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# Revisiting the flaws and pitfalls using simulation in the analysis of aviation capacity problems

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ABSTRACT

The aviation industry is a changing industry in which several factors influence the performance of the airport and the network of airports that are interconnected. Business models, technical operations in airspace and in the airfield, societal conditions among others are some of the ones that must be taken into account in order to get a full understanding of the cause-effect relationships that hinder the proper management of the system. In recent times with the evolution of the computer technology and the level of maturity of the algorithms used to simulate and analyse dynamic systems, simulation has gained more importance than before. Simulation approaches emerge as the ones that are able to take into account the stochastic nature of dynamic systems besides all the different factors that impact the systems under study. This is something that traditional analytical approaches could not evaluate and therefore under the constant change of the systems they lack of the proper flexibility to provide timely solutions. However with the popularity that simulation has gained, the different steps and good practices that must be taken into account are commonly forgotten when the simulation model is developed and then the system is analysed; in the particular case of the aviation industry this situation has gained particular importance.

The current paper addresses some of the common flaws and pitfalls incurred when simulation is used for analysis of aeronautical systems. Pitfalls' classification and suggestions for avoiding them are presented. Some flaws are exemplified through cases in which the conclusion from the analysis might differ depending on the angle of the analysis performed with the implications of different economic consequences for the decision makers. The main objective of this paper is that it serves as an eye-opener for a relatively novel researcher or practitioners in the art of simulation. It will serve for avoiding these common flaws when using simulation for addressing aviation problems.

## 1. Introduction

The air mode is a growing mode which gains more and more importance, and in 2014, the number of flights in Europe increased by 1.7% compared to 2013 (Eurocontrol, 2015) and the number of passengers grew by 5.4% compared to 2013 reaching 3.3 billion of passengers in that year (IATA, 2014).

According to these trends, an increment in volume of flights and number of passengers for the next coming years is expected. This situation is translated in a massive use of resources at both air and ground levels; for these reasons, it is highly likely to encounter congestion problems in many airports worldwide and in particular in the most important hubs. In order to avoid the mentioned situation, the improvement of capacity has become a challenge which must be addressed in the best possible way, taking into account all the different factors and variables that disrupt the system making it more difficult to manage.

In order to cope with capacity issues, the analysts use different techniques that range from the typical scenario-based EXCEL sheets to thorough studies about the movements and operations in the system using a specific-purpose simulator. In recent years and with the evolution of digital computers techniques such as simulation-based analysis has become popular and consultancy companies are using them for analysing aviation operations performance such as Mott MacDonald (UK), NACO (The Netherlands), ARC-Consultants (Germany), Arup (UK) among others. In addition to the consultant companies that are using simulation-based analysis for addressing capacity problems, the airports and airport operators are becoming keen also to the use of these novel technologies (ARC, 2015).

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## 2. Simulation approach

Nowadays, simulation alone and sometimes combined with optimization techniques are used in diverse industries to deal with the decision-making activity by searching optimal or feasible solutions to real problems. The use of simulation as an analysis tool facilitates the design and assessment of strategies reducing the risk of poor outcomes. Furthermore, simulation models have proved to be useful for examining the performance of different system configurations and/or alternative operating procedures for complex logistic or manufacturing systems among other applications (Longo, 2013). However in the aviation industry, its use is not common practice yet but it is becoming an approach that some stakeholders and researchers are exploring (Mujica, 2015; Mujica et al., 2014; Zuniga et al., 2011).

Simulation provides an environment for studying the dynamic behaviour of a system with uncertainty under different operating conditions, using continuous, discrete or hybrid models to represent it (Banks et al., 2010).

There are different modelling approaches such as system dynamics, agent technology or discrete-event systems (DES). The former is applied in systems in which the state variables change continuously in time such as the level in a tank or the temperature in a chemical reactor; agent technology is a relatively novel approach in which the power of computers are used to calculate independent behaviour of the entities within a system during specified intervals of time (Becu et al., 2003) while DES are suitable for analysing systems in which the variables that represent the state of the system (state variables) change at particular instants of time. Under the DES approach, the change in the system takes place due to the occurrence of events that modify the values of the state variables. This makes the resulting models asynchronous, inherently concurrent, and nonlinear, rendering their modelling potential for modelling real systems (which in most of the cases behave in a nonlinear and stochastic fashion). The simulation-based analysis methodology has been so far applied successfully in different industrial fields and its steps vary depending on the objective pursued but the basic ones are presented in Fig. 1 (Banks et al., 2010).

Banks et al. (2010) determine that the behaviour of a system which evolves over time and where uncertainty plays an important role in the outcome can be studied by developing a simulation model. This model takes the form of a set of assumptions concerning the operation of the system; such assumptions are expressed in mathematical, logical, and symbolic relationships between the entities of the system. Simulation involves the generation of an artificial history of a system, and the observation of that artificial history to draw inferences concerning the operating characteristics of the real or future system.

There are a lot of simulation advantages, some of them involve the possibility of exploring new policies and procedures without disrupting ongoing operations of the real system; new systems can be tested without committing resources for their acquisition; and time which is a very important resource nowadays, can be compressed or expanded with the simulation. Another key characteristic is that it is useful for getting insight into the interaction of stochastic variables within the system. A simulation study can help therefore to understand how the system operates rather than how the system is perceived by the analysts or user of the system.

Due to these characteristics, simulation-based analysis is a powerful technique which when properly used can give answers to different questions about the system under study such as:

- What is the impact of variability in the system?
- Do the systems have enough capacity throughout the seasons?
- What would be the best configuration for the objective pursued?
- What would be the impact of changes in the system?
- How can we manage the resources at hand in order to minimize disruption?
- Do we need to increase facilities?

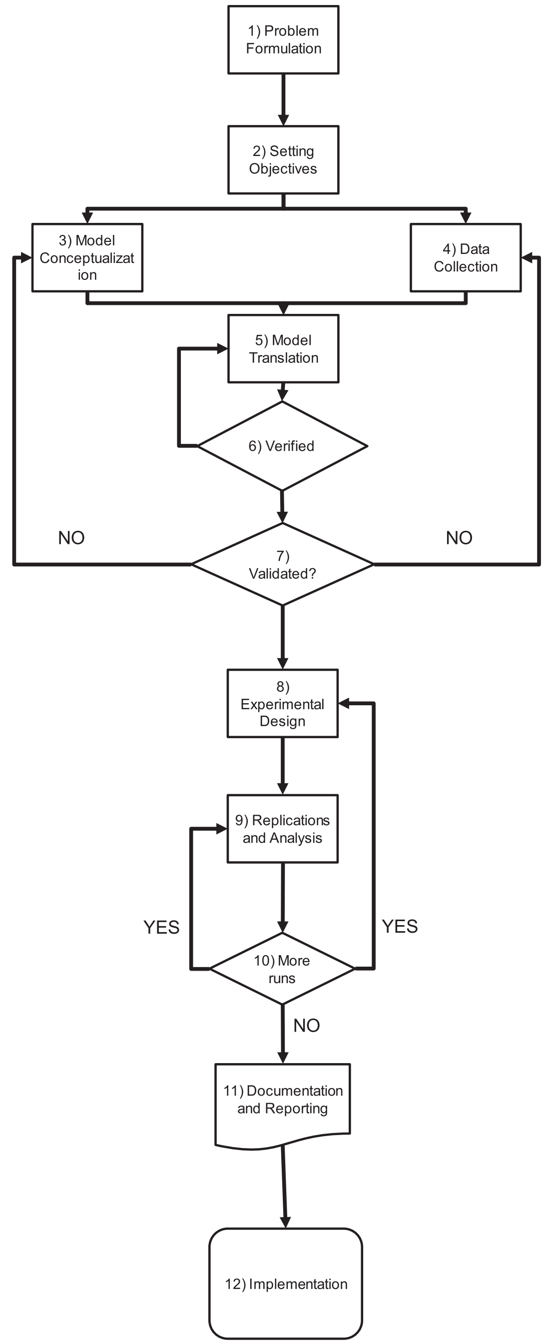


**Fig. 1.** The basic steps in the simulation-based methodology.

- Where is the bottleneck in the system?
- How can capacity be increased?
- How can throughput be increased?
- How can waiting times and queuing be reduced?

The advantages and potential of simulation or simulation-based analysis for the study and improvement of aviation performance are increasingly recognized in a wide range of activities such as passenger flow, logistics and study of airspace among others. However, as it has been mentioned, the methodology must be properly implemented in order to reduce the risk of ending up with unfeasible or poor solutions.

In the next sections some of the flaws that any analysts can incur when performing a simulation-based study are revisited and for the case of aviation problems emphasis is put on some of the flaws that have been identified by the authors. Finally, the authors enhance the

**Table 1**
Pitfalls of simulation (Ulgen and Shore, 1996).

| Process Related Pitfalls | |
|---|---|
| 1 | Unclear project objectives |
| 2 | Keeping the customer uninformed |
| 3 | Not establishing a base for comparison |
| 4 | Unrealistic expectations from the study |
| 5 | Too much faith in the input data |
| 6 | Infrequent reporting and lack of documentation |
| 7 | Lack of frequent customer interaction |
| 8 | Inadequate reporting and lack of documentation |
| 9 | Frequent scope changes |
| 10 | Too much faith in the simulation output |
| 11 | Inadequate review of the project while it is ongoing |
| 12 | Spending more time on the model rather than the problem |
| 13 | Not knowing when to stop |
| Model Related Pitfalls | |
| 1 | Model assumptions not validated |
| 2 | Starting with an overly complex model |
| 3 | Losing sight of the implementation issues |
| 4 | Using the model sparingly |
| 5 | Not understanding the model's limits |
| | People Related Pitfalls |
| 1 | Lack of teamwork |
| 2 | Not involving the key decision makers in the project |
| 3 | Not knowing and/or listening to the costumer |
| 4 | Providing a small list of alternatives to the costumer |
| 5 | Being afraid of advocating change |

discussion with the presentation of two cases in which at first glance one could incur wrong conclusions.

## 3. Common pitfalls in simulation projects

In order to develop a simulation project properly, it is necessary to identify the pitfalls in which its development and execution may be incurred. In this section, a list of some errors given from different authors point out which ones of them can be present in aviation research.

Some of the first authors that have written about this topic are Ulgen and Shore (1996) that presented a methodology to avoid pitfalls and a table with a pitfalls' classification as the next one (Table 1):

Other authors as Schmeiser (2001) based their analysis on the statistical mistakes done when working with input and output data.

Jain (2008) mentioned that common mistakes are:

- Inappropriate level of detail: may think more detail is always better, but More detail = > More time, Bugs, & CPU time
- More parameters ≠ More accurate (if unable to precisely model a parameter)
- Unverified simulation models: e.g., due to software bugs
- Invalid models (e.g., for parameters): model vs. reality
- Improperly Handled Initial Conditions
- Initial part of a simulation is usually not the same as steady state, and thus should be treated separately
- Too Short Simulations
- Length of simulation should depend on the required accuracy and the variance of observed quantities
- Poor Random Number Generators: Safer to use a well-known generator
- Improper Selection of Seeds. E.g., zero seeds or same seeds for all streams = > correlated random streams

Then Law (2003) classified seventeen pitfalls in simulation modelling and they were classified into four categories as follows:

a. Modelling and validation
- Failure to have a well-defined set of objectives at the beginning of the study
- Misunderstanding of simulation by management
- Failure to communicate with the decision-maker on a regular basis
- Failure to collect good system data
- Inappropriate level of model detail – this is one of the most common errors, particularly among new analysts
- Treating a simulation study as if it were primarily an exercise in computer programming
- Lack of knowledge of simulation methodology and also probability and statistics

b. Simulation software
- Inappropriate simulation software – either too inflexible or too difficult to use
- Belief that so-called “easy-to-use software” requires a lower level of technical competence – regardless of the software used, one still has to deal with such issues as problem formulation, what data to collect, model validation, etc.
- “Blindly” using software without understanding its underlying assumptions, which might be poorly documented
- Misuse of animation – making an important decision about the system of interest based primarily on viewing an animation for a short period of time, rather than on the basis of a careful statistical analysis of the simulation output data

c. Modelling system randomness
- Replacing an input probability distribution by its mean
- Incorrect choice of input probability distributions – normal or uniform distributions will rarely be correct
- Cavalier use of the triangular distribution when system data could be collected – triangular distributions cannot accurately represent a source of randomness whose density function has a long right tail, a common situation in practice

d. Design and analysis of simulation
- Misinterpretation of simulation results – treating simulation output statistics as if they were the true model performance measures
- Failure to have a warm-up period when the steady-state behaviour of the system is of interest
- Analysing (correlated) output data from one replication of a simulation model using formulas that assume independence – variances might be grossly underestimated.

Banks and Chwif (2010), compiled some warnings for simulation modelling and they are grouped into seven categories as follows: Data Collection, Model Building, Verification and Validation, Analysis, Simulation Graphics, Managing the Simulation Process, and Human Factors, Knowledge, and Abilities.

- **Data collection**
  Anticipate having problems with input data.
  Choosing the wrong input distribution may hurt, but it may not be that harmful.
  Choosing the wrong input distribution may hurt, but it may be harmful.
  Use up time, not time between breakdowns when modelling.
  All forecasts are wrong!
  The amount of data that you have is important.
  Collect your input data properly.
- **Model building**
  Keep the model simple, but not too simple. Make the model complex, but not too complex.
  Create a conceptual model prior to the implementation of the computerized model.
  Start simply, verify, validate, and grow the model, verify, validate,

and grow the model, etc.
Validate the conceptual model before proceeding with model building.
Maintain frequent interaction with the client.

- **Verification and validation**
Do a lot of verification and validation, not a little.
It's possible to invalidate a simulation model, but impossible to validate a simulation model.
Check basic principles of queuing before the simulation commences so that you can examine the appropriate range of policy options.
- **Analysis**
Do not simulate outputs when you should not simulate outputs.
Avoid point estimates.
Know when to warm up a system (non-terminating) and when not to warm up a system (terminating).
Steady-state to me may not be steady-state to you because it is usually determined visually.
Have an appropriate performance measure. It is not always appropriate to find the system that has the lowest average number of loads (or, lowest average time that loads spend in the system), but the one that minimizes cost or maximizes profit.
If you have a 'push' system, production is not an appropriate output measure.
Avoid a type III error.
- **Simulation graphics**
Do not get over impressed by fancy graphics.
Organize the model on the screen so that viewers have a general view of the process.
- **Managing the simulation process**
The simulation process is a project and thus all principles of project management should be followed.
One of the first definitions in a simulation study is its objective.
Do not promise the sun and deliver only the moon. Simulation is not a panacea that will solve every problem.
Do not accept any assignments unless the resources are there to make it happen.
Do not cut phases of the simulation modelling process in order to reduce the time and cost of a simulation study.
Determine how close to reality you need to represent. Acquire the right level of power in your software.
The manager of the simulation project should understand the simulation process in order to adequately manage it.
- **Human factors, knowledge, and abilities**
Relearn your basic statistics so that you can explain a Type I error, Type II error, confidence interval, and so on.
We communicate through spreadsheets. Do become very good at using them.
The most critical component of a simulation project is not software. Neither is it hardware. It is 'human ware'. Beware of the SINSFIT principle: Simulation is no substitute for intelligent thinking.
Becoming a good modeller takes time and experience.

Barth et al. (2012) specified five typical pitfalls that are associated with the process of applying simulation models and characterize the "logic of failure" (Dörner, 1996) behind the pitfalls.

1. **Distraction Pitfall.** The involvement of other stakeholders in the modelling process is likely to be a main driver for the distraction pitfall. In a business environment as well as in the armed forces, clients or superiors might request to have several questions addressed in one model. In science, similar pressures might be exerted from fellow scientists in an audience, supervisors, reviewers, etc. Inexperienced modellers, in particular, can succumb to believing that they are "not accomplishing enough" in the project.
2. **Complexity Pitfall.** The model structure has to represent reality with sufficient precision for the simulation to yield applicable results. It is a balancing act between simplifying and exact representation. Trying to do the second sometimes even causes a simulation project to fail.
3. **Implementation Pitfall.** Software support is often needed to generate the actual simulation model once the conceptual design is finalized. As the domain experts involved in modelling are often laymen with regard to IT implementation, they are at risk of choosing unsuitable software for the simulation.
4. **Interpretation Pitfall.** Upon completing and testing an implemented simulation model, one can finally work with it. However, one can often observe that users are prone to losing their critical distance to the results produced by a simulation. It happens for example when the analysed aspect is not part of the reality represented by the model or when the model is too simple and does not allow for valid interpretations. These wrong conclusions resulting from a loss of critical distance is what we call the interpretation pitfall.
5. **Acceptance Pitfall.** Even if one is convinced of the simulation results' validity and accuracy, this may not be true for third-party decision makers. In many settings, third-party decision-makers have the final word and hardly know the model. The more distant they are to the modelling process and the more complex the simulation model is, the more sceptical they tend to be about the results.Uhrmarcher (2012) showed seven pitfalls in the success of a PhD project in modelling and simulation. These pitfalls are listed below:

1. **Don't know whether it is modelling or simulation.** "Simulation is an experiment performed on a model" – this definition is attributed to Granino Korn and John Wait in Cellier (1991, p. 6). It is a quite commonly agreed upon interpretation of simulation and clarifies the relationship between modelling and simulation.
2. **No separation of concerns.** That means according to the author: separation of concerns facilitates to focus your research, to make a contribution to a particular field, and to use the work of others. There is a huge portfolio of methods already available. Without separation of concerns, it is very likely to redo what others have already done, and even to do this poorly.
3. **No clear scientific question.** Independently whether you are developing or applying modelling and simulation methods, it is important to clarify the reasons you selected a particular formalism or method to work with.
4. **Implementing everything from scratch.** The effort in developing a modelling and simulation tool is often underestimated. In addition to providing support for modelling, e.g., providing a model editor and implementing an execution algorithm, means to observe, store, and analyse data needs to be realized or integrated. In order to overcome this situation, one alternative is to use one of the modelling and simulation frameworks around that are aimed at facilitating the development of modelling and simulation tools by reusing.
5. **Unsupported claims.** A prerequisite for any meaningful claim (and thus for circumventing Pitfall 5) is to have a clearly defined scientific question (see Pitfall 3).
6. **Toy duck approach.** Deficiencies in validity referring to model, experiments, and software (see also Pitfall 4) will endanger the credibility of the simulation study. The lack of valid experiments has been identified as a reason for the credibility crisis of simulation in the area of performance evaluation (Pawlikowski, 2002; Kurkowski et al., 2005).
7. **The tunnel view.** The interdisciplinary nature of modelling and simulation should help looking across the boundaries of his or her research, however, interestingly it seems to have the opposite effect. The different vocabulary used in different disciplines makes it harder to locate related work.

These are common pitfalls when someone is applying simulation for the analysis of dynamic stochastic systems such as manufacturing, logistics, and supply chain among others. According to this review of the literature and the experience of the authors, we identified that some of them are appearing recurrently in the simulation studies performed in the aviation industry as we present in the following section. So the contribution of this paper is mainly on the methodological application of the simulation methodology in the field of aviation industries; in addition, the authors have identified some situations that can be recognized as flaws or pitfalls in the particular case of aviation and that are marginally mentioned in the previous review.

## 4. Common flaws when using simulation-based analysis in aviation

Ulgen and Shore (1996) published their article 21 years ago, since then other authors have been written on the subject, and some of the flaws detected still remain. According to the classification that Ulgen and Shore gave about the type of failures based on processes, models and people, later authors focused their attention on some of them and went deeper, others had a more general vision, and what must also be noted is that depending on the type of simulation and where it is going to be applied is where you can find more frequent errors. For what concerns this article, Table 2 presents the categories proposed in this work and it shows which of the failures coincide with the authors mentioned. Many of the flaws reported in this review have been overcome over time, others persist and it is of utmost importance to point them out regularly so as not to lose sight of the importance of considering them when applying the simulation methodology. The different categories of flaws in aviation are elaborated in this section so it is clear for the analyst where to pay attention when analysing an aviation system.

The following are the common flaws identified when simulation-based analysis is put into practice in the analysis of aviation systems. These flaws must be avoided if the system is going to be properly understood and when possible improved.

*Flaw A) Not knowing the objective of the study.*

The first step in the use of the methodology is to clearly define the objective pursued. Once we have the objective stated clear it is relatively easy to identify which tool/technique would be sufficient for it. It is common to find practitioners that think the tool that was useful for some companies could be useful for theirs. With a clear objective of the study it becomes easier to define or decide whether we need a high-detailed simulation program (CAST [ARC, 2015], AirTop [AirTopSoft, 2017], Quest [Dassault Systems, 2016] or other), a general-purpose one (SIMIO [SIMIO, 2017], ARENA [Arena, 2017], Anylogic [Anylogic, 2017]) or a high-level decision-support tool for planning (Beontra's scenario planning [Beontra, 2017], EXCEL, etc.). This initial decision has important implications in the time, the quality of the results and the ratio price/quality. In addition, the success of the project or study might be at risk if a bad decision is made when the objective is not known. Thus for the different decision levels (strategic, tactical and operational) different simulation-based tools must be selected. One size DOES NOT fit all.

*Flaw B) Not performing a properly conceptual design.*

It is common that when starting a simulation-based study, the analysts are anxious to start playing around with the software tool recently purchased (CAST, SIMIO, AirTop, Anylogic, etc.). Since the cost of the simulation software programs is relatively high in comparison with other tool like Office or AutoCAD is normal to expect to have benefited from it as soon as possible. However, the correct technical use of the tool does not imply that the analyst is skilled for performing simulation studies. The simulation-based analysis is a methodology that has different important steps that must be followed in order to be successful in performing the study. The translation of the conceptual model to the computer tools (i.e. software) is just another step of the methodology which is required for properly mastering the methodology (see Fig. 1, step 5). Not understanding the simulation-based methodology might involve high risk of failure in the study and/or the failure of the implementations proposed after the results and conclusions are taken from the model (garbage-in- garbage-out).

*Flaw C) Confusing verification with validation.*

We must differentiate between verification and validation and we explain the difference in order to make them clear. Fig. 2 shows the process of verification and validation (Sargent and Goldsman, 2016).

Conceptual model verification is defined as ensuring that the theories and assumptions underlying the conceptual model are correct and the model representation of the problem entity is "reasonable" for the intended purpose of the model. Computerized model verification thus is defined as assuring that the computer programming and implementation of the conceptual model are correct. In the particular case of aviation models, this means that the analyst should verify that the logic of the entities (passengers, aircraft, and vehicles) is reasonable according to the system at hand and the process they follow within the model makes sense; in other words it is a superficial check of the logic of the computer model (e.g. checking that from arrival to departure of an aircraft it follows speeds according to reality or that the speeds of passengers within a terminal model are not constant or too fast). For this verification step it should be an easy and fast evaluation, for instance, if we are developing an airside simulation we would suggest that the analyst follows the complete route of an aircraft to check that all the speed, logic, route are logical.

On the other hand, operational validation is defined as determining whether the model's output behaviour has a satisfactory range of accuracy for the model's intended purpose over the domain of the model's intended applicability. This is where much of the validation testing and evaluation take place. Since the computerized (simulation) model as

**Table 2**
Comparison seven flaws and literature review.

| Mujica Mota-Flores | Ulgen (1996) | Law (2003) | Jain (2008) | Banks (2010) | Barth (2012) | Uhrmarcher (2012) |
|---|---|---|---|---|---|---|
| Flaw A<br>Not knowing the objective of the study | ✓ | ✓ | | | | |
| Flaw B<br>Not performing a properly conceptual design | | | | ✓ | | |
| Flaw C<br>Confusing verification with validation | | | | ✓ | | |
| Flaw D<br>The habit of drawing conclusions from a deterministic value | | ✓ | | ✓ | | |
| Flaw E<br>Getting lost in numbers | | | | ✓ | | |
| Flaw F<br>Proposing solutions in non-priority areas | | ✓ | | | ✓ | |
| Flaw G<br>Lack of rigor when analysing the outcome | | | | ✓ | ✓ | |

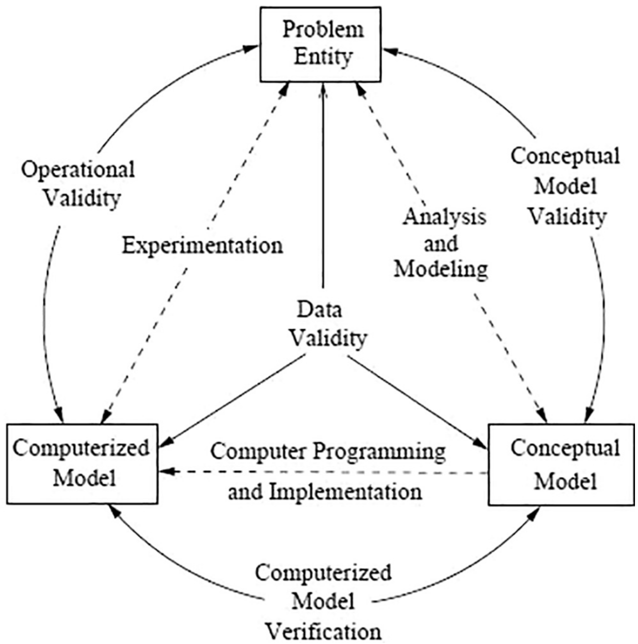


**Fig. 2.** Simplified version of modelling process. Sargent and Goldsman (2016).

shown in Fig. 2 is used in operational validation, any deficiencies found may be caused by what resulted from any of the earlier steps that are involved in developing the simulation model, including developing the system's theories or having invalid data. The validation then is a procedure which is supported by quantitative analysis (statistical tools) and it will be fundamental for getting the confidence levels we need from the models in order to use them for experimenting and making decisions over the real system.

Table 3 presents a classification of validation approaches for operational validity. In this table, comparison means comparing/testing the model and system input-output behaviour. The validation suggested for aviation systems is basically quantitative analysis in which both the directions and the precise magnitudes of the output behaviours are examined. Sometimes when data are not available it is necessary to approach Experts (e.g., subject matter experts) on the system who often know the directions and frequently know the "general values" of the magnitudes of the output behaviours.

There are different approaches for performing a validation of the different element of the models, Fig. 3 illustrates most of the common ones.

For the operative analysis and in particular for the aviation systems, it is recommended to look always for an objective approach, in the Fig. 3 it would correspond to the left branch. In earlier years the subjective approach such as face validity (expert one), or Turing test had been widely used since the availability and capacity for storing data were very limited. Nowadays the situation has changed and the subjective validation is not enough to get confidence in the model developed. For that reason, it is necessary to have statistically-skilled people within the industry. It is not common to find analysts trained in the hard statistical techniques used for validation, therefore, that type of people are valuable more and more. Regarding the quantitative tests,

**Table 3**
Operational validation classification.

| Decision Approach | Observable System | Non-observable System |
|---|---|---|
| Objective Approach | -Comparison using statistical tests and procedures | -Comparison to other models using statistical tests |

some common ones are the *t*-test, chi2, ANOVA, *Z*-test and hypothesis tests. They are the key to get objective confidence in the results obtained from the model. Therefore these tests are the equivalent to the experiments performed by scientists in history to demonstrate that the theory (model) can be applied with confidence.

As it has been mentioned, the visual comparison was part of the old methods for validating a model and is still part of the verification procedure. Then the flaw C consists that instead of performing the statistical analysis required some prefer to compare the qualitative performance (sometimes obtained in the animation which must be used for verification) with qualitative performance perceived in the system (see Fig. 4).

*Flaw D) The habit of drawing conclusions from a deterministic value.*

This flaw is also known as *the flaw of averages* (Zavage et al., 2012); it consists of putting focus only on the average value obtained from the results such as KPIs values instead of analysing the whole picture (average, standard deviation, skewness, etc.) and the outcomes including the variability of the system which in dynamic systems is a fundamental part of them. In the particular case of aeronautical systems, variability should be an important factor to address if we want to improve the performance of these systems. In order to avoid this error, it is necessary to analyse how important the variability is and what the implication would be if we reduced it and in addition how it would impact the performance of the system.

*Flaw E) Getting lost in numbers.*

This error implies that when we have a model at hand it is easy to generate all kinds of information such as waiting times, throughput, standard deviations, delays in different parts and all kinds of KPIs and their average, minimum and maximum values. Under these circumstances, it is easy to get lost in numbers and be overwhelmed with the information. Therefore it is necessary to have a structural approach that allows us to identify the different constraints in the system, identify how the system behaves, identify the bottleneck and only then it would become natural to look for the information in order to propose solutions. For overcoming these flaws it is suggested that the analyst understands the theory of constraints, masters the techniques of design of experiments and spends enough time developing a conceptual design where the expected outcomes and performance indicators have been properly identified ahead of the development of the computer model.

*Flaw F) Proposing solutions in non-priority areas.*

As a natural consequence of the previous flaw, it is very common to propose solutions in areas that would not significantly impact the performance of the whole system. For example, in many terminals, it is common to see that the most congested area is at passport control or security and in addition, it is also easy to perceive the unbalance of the system. However, by just pure observation it is not possible to conclude that a particular functional area of a terminal or a system is the bottleneck. We need to perform a structured analysis for identifying it. This is relatively easy to evaluate using simulation-based analysis, thus it is proposed to perform a structured analysis of the throughput (entities/time) of the different areas or processes within the system, obtain the capacity limitations of the different elements in the system and with those values at hand, identify the correct bottleneck of the system. Once we have identified it we can act in consequence to increase as much as possible the utilization of the resources of the bottlenecks.

*Flaw G) Lack of rigour when analysing the outcome.*

One of the key advantages of simulation is its capacity to stretch or compact time; therefore we can verify easily the performance of the system under diverse circumstances. However, depending on the type of tool used for the study it would take more or less time to achieve results. With high-detailed simulation, it takes a long time to run a simulation (due to all the calculations needed by the computer) and so the time needed to perform a relevant number of replications in order to achieve the proper level of confidence that allows us to draw reliable conclusions. For that reason, analysts prefer or are commonly tempted to run few replications with the consequent time-saving. However this

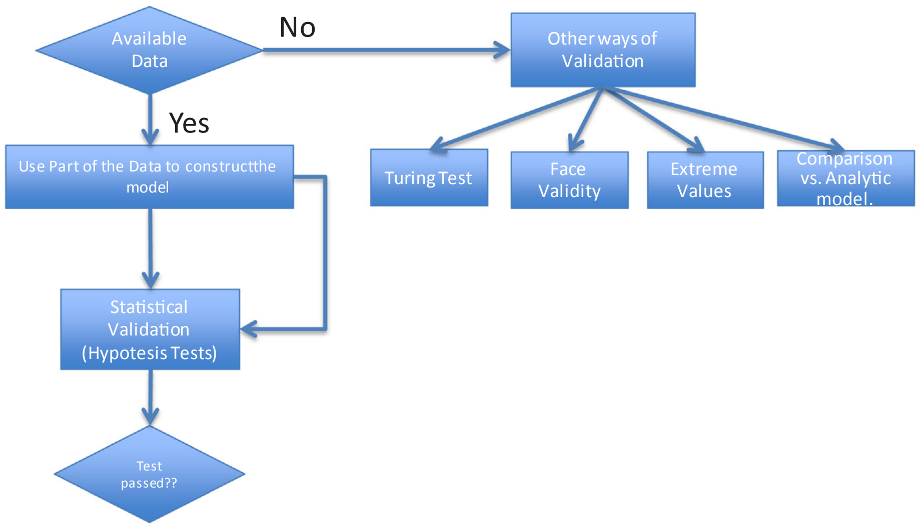


**Fig. 3.** Methodology for validation.

**Fig. 4.** Qualitative comparison between a simulation program and reality (LHR: Rosenthal, 2008).

**Table 4**
Information of the current process.

| | Cleaning Operation | | | |
|---|---|---|---|---|
| | AVG | Min. | Max. | STD. Dev. |
| Max. No. of Extra Cleanings | 6.7 | 3 | 12 | 2.306 |
| Max. No. of Delays | 37.43 | 13 | 81 | 15.904 |
| Avg. Turnaround Times | 38.59 | 37.17 | 40.9 | 0.8262 |
| Max. Turnaround Times | 54.38 | 49.14 | 59.31 | 1.8539 |

practice is not recommended since one of the foundations of simulation lies in the integration of stochastic processes and for concluding something about a system with uncertainty we need to perform several replications of the system under study. Therefore it is necessary to run enough simulations so that the potential problems can be clearly identified and bad consequences could be avoided in the simulation-based planning phase instead of during the operation. The objective of simulation-based studies should be beside obtaining only the performance indicators of the system to identify those rare situations that could lead to a collapse of the system, and those situations can only be identified when variability is left to play. For this reason, it is suggested to run enough replications and perform a scientific-based analysis using statistics and data analysis.

In the next section, we will present two case studies which will illustrate the potential problems we can incur if we do not pay the right attention to the elements mentioned above. It is also fair to mention that Ulgen and Shore (1996) proposed a series of steps for avoiding potential errors that are worth to review in order to avoid falling into the errors or pitfall mentioned in this article.

## 5. Case studies

In this section, a couple of examples are presented in order to exemplify some of the common mistakes during the analysis of aviation systems.

**Case I. A new procedure for cleaning an aircraft**

This study has been performed for a LCC in Spain (Mujica et al., 2013) in which a new cleaning schema was proposed for reducing the turnaround time. We identified that with different types of cleaning services based on the flight history of the aircraft, it was possible to achieve important reductions in the turnaround time.

Table 4 presents some performance indicators of the operation previous to the implementation of the proposed cleaning procedure.

In the table, the statistics of the current process are presented. The first two rows represent the maximum number of extra cleanings (an extra cleaning is a cleaning operation that was not originally scheduled during the stopover of the aircraft; instead it was requested by the crew) and maximum number of delays. The information from the columns is the average values, the limits of the range and the standard deviation of the values. The last two rows represent the average values of the turnaround time and the maximum turnaround times achieved during the simulations correspondingly.

After implementing more specific cleaning operation for specific situations during the stopover (Mujica et al., 2013) the following performance (Table 5) was achieved.

Perhaps at the first sight the numbers do not say a lot about the performance, for example concerning the turnaround times if we put focus on the average value one can perceive that only one minute in average was reduced with the new procedure and it might lead the analyst to think that it is not really relevant or significant this

**Table 5**
Proposed Schema.

| | Cleaning Operation | | | |
|---|---|---|---|---|
| | AVG | Min. | Max. | STD. Dev. |
| Max. No. of Extra Cleanings | 1.65 | 1 | 4 | 0.8846 |
| Max. No. of Delays | 12.42 | 1 | 56 | 18.69 |
| Avg. Turnaround Times | 37.57 | 36.03 | 39.47 | 0.9127 |
| Max. Turnaround Times | 40.4 | 38.57 | 43.47 | 1.235 |

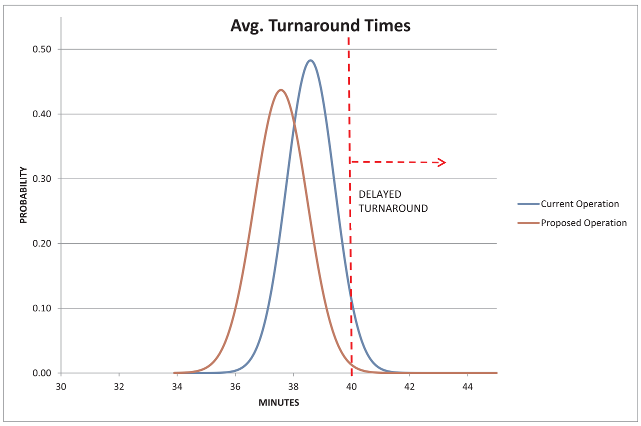


**Fig. 5.** The reduction of average times.

improvement (Flaw D). However, by analysing the whole picture (average, range and standard deviation), we come up with the following reasoning.

By plotting the two performances (before and after), for having a complete graph of the distribution of the turnaround values of the operation, we obtain Fig. 5. The figure allows to illustrate the performance of the operation once it is performed several times; furthermore, it can be appreciated that the mean value moved a minute to the left in the horizontal axis and so the whole distribution of turnaround times. Under this situation, the percentage of expected flights with potential delays (more than 40 min) has been reduced to 0.2% while without the implementation the expected delay had been around 2% of the total flights. Therefore after implementation it is possible to understand the true impact (which must be based on the expected values from the probability distribution) in which the expected reduction in delayed flights is of 90%. What can be illustrated with this example is that when variability is present the punctual values provide little information. For this reason, the suggestion is to evaluate the impact of the distributions instead of just the indicators of the central tendency values in order to come to a better analysis of the operations when variability is present.

**Case II. The analysis of a future airport**

We have studied the case of the new development of Lelystad Airport in The Netherlands (Mujica et al., 2017). The objective of the study was to identify potential problems when commercial traffic is operative in the airport. For that purpose, it was necessary to develop a simulation model that included the ground handling vehicles and the airside elements of the airport such as taxiways, runway, stands, all together with the corresponding technical restrictions. In addition, three different configurations were evaluated (L-shape apron, Linear with Nose In parking positions, Linear with parallel positions). In addition to the layout, we designed experiments on the model varying the number of handling vehicles and the amount of traffic. Table 6 illustrates the domain of the variables used in the analysis.

The first two rows refer to the layout of the Apron and to the number of ground handling vehicles respectively, while the last two refer to the traffic demand (from low to high) and the allocation of aircraft once they enter into the apron. The combinatorial analysis of

**Table 6**
Experimental Design for the Lelystad Case.

| Input Variable | Domain |
|---|---|
| Airside Layout | Configuration A: L-shaped apron with Nose In parking positions<br>Configuration B: Linear configuration with Nose In parking positions<br>Configuration C: Linear with parallel parking positions (Taxi-In- Taxi Out) |
| Ground Handling Vehicles | Group 50%: 4 sets of 8 vehicles<br>Group Normal: 8 Sets of 8 Vehicles<br>Group FLEXIBLE: 8 loaders, 8 Baggage, 8 stairs, 6 Fuel, 6 water, 6 cleaning |
| Traffic Demand | 1. Scenario 40K: 40,000 Air traffic movements annually<br>2. Scenario 45K: 45,000 Air traffic movements annually<br>3. Scenario 50K: 50,000 Air traffic movements annually |
| Stand Allocation | Allocation 1: Left-Right (L-R)<br>Allocation 2: Centre– Out (C-O) |

the different domain variables was performed and the graphical results of the most relevant of them are presented in Figs. 6 and 7.

Fig. 6 depicts the dependency of the average times at Apron with linear configuration and Nose-In parking positions with the different variables (left-hand side) and the variability (half width of the 95% confidence interval) of those average values (right-hand side). In this case, the turnaround times that can be achieved range in the best case between 30 and 35 min with a corresponding variability (95% confidence interval) of 1–2 min.

On the other hand, Fig. 7 illustrates the performance that can be obtained by a linear configuration in which the use of pushback trucks is eliminated through the implementation of a parallel allocation of stands where the aircraft uses its engines for the taxi-in taxi-out procedures. With this configuration, the interaction between aircraft and service vehicles is high with the corresponding impact in variability as it can be appreciated in the right-hand side of Fig. 7.

When interpreting the figures, again, at first sight, the reader could incur in flaws D, E and G. If one only pays attention to average values then one could conclude that the configuration of Fig. 6 is much better than the taxi-in-out configuration (Fig. 7) since the average values are smaller. However if we pay attention to the variability of Fig. 7 (right-hand side), it can be appreciated that in spite of the present variability it is possible to achieve as low turnaround operations as 32 min with standard deviations of 3 or 4 min. The latter means that in some cases it is possible to get 28 min of turnaround time which could be very competitive for the airport under study. Furthermore, the analysis can drive the decision makers to investigate how to better coordinate the operations of the vehicles in order to reduce the variability of the system so that it is possible to maintain the turnaround times of 28 min or even less. In other words, by running the simulations it was possible to reveal the configuration with the shortest turnarounds (Fig. 7); and it also raises the questions on how to reduce the variability for maintaining the short turnaround times while making it economically attractive for the potential airlines to come.

## 6. Conclusions

In this article, the authors have made a review of the common mistakes when applying simulation in the analysis and evaluation of systems and infrastructures. Since simulation has become more and more important and popular in the study of aviation systems, the authors have put emphasis on how to avoid common mistakes in its application in this realm. Some of the common mistakes when performing a simulation-based analysis have been presented and discussed. These types of errors have been identified during the years by the authors.

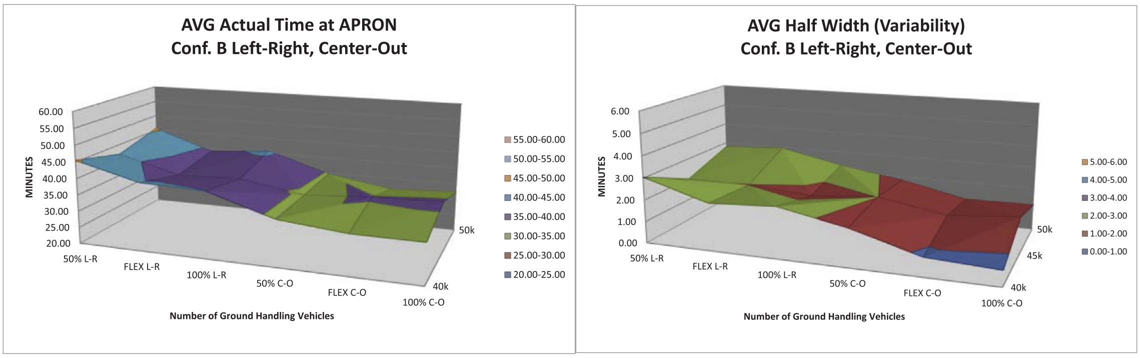


**Fig. 6.** Linear configuration with Nose In parking position.

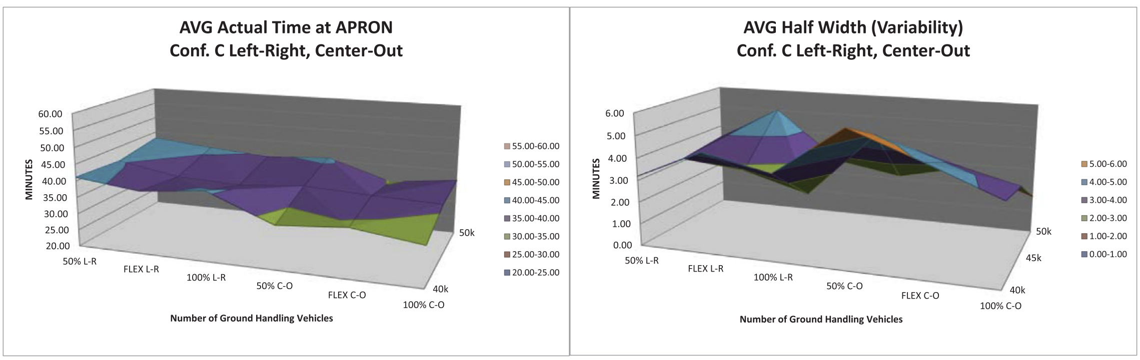


**Fig. 7.** Linear configuration with parallel parking positions.

Simulation is a powerful methodology which is composed of different steps, however with the rise of the machines and computer power many software programs have been developed for easily constructing simulation models. As it has been pointed out, the use of computer programs have become very popular and sometimes their popularity shadows the other key steps required for robust analysis which are necessary for the success of a simulation project, and for its proficiency to provide value to the industry. We strongly suggest practitioners, students and academics in the aviation industry interested in applying the simulation methodology to use this article prior to the deployment and application of the methodology; we are confident that by reading the presented flaws, pitfalls and examples it will increase the chance of providing a valuable result when applying the methodology.

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