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# Applying discrete event simulation to the design of a service delivery system in the aerospace industry: a case study

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**Abstract** This paper presents the results of a simulation study concerned with the design of a service delivery system. In particular, it shows how discrete event simulation can be used at the point of signing a long-term service contract to assess whether a service delivery system will be able to comply with the contractual terms over time. This study also proposes a methodology based on the Monte Carlo simulation to estimate the service demand in a context where the installed base evolves dynamically over time. Such a methodology has been used to verify the discrete event simulation model. This research is based on real data from a leading global supplier of human to machine electronic controls operating in the aerospace industry. This supplier has recently signed a major contract for the provision of several devices and related services. These devices will be installed on aircrafts progressively entering service over the next seven years.

**Keywords** Simulation · Aerospace industry · Service delivery systems · Service level agreement

## Introduction

Aerospace is a growing, global, complex, and highly regulated industry (Harun and Cheng 2010; Williams et al. 2002). The growth of the civil aviation market, coupled with the commissioning of new aircrafts such as the Airbus A380, are intensifying the competition among airline operators, maintenance repair overhaul (MRO) service providers, original equipment manufacturers (OEMs), and third party suppliers, to increase their share in the service and maintenance market (Brintrup et al. 2009). Despite this fierce competition, the emergence of on-time performance (i.e., performance based on the on-time departure of the aircraft) as the key success factor of the airline industry (Lendermann et al. 2010), as well as the increase of fuel costs (Brintrup et al. 2009), is orienting the whole service supply chain toward common strategic goals. These goals include the reduction of late departures due to technical delay, maximization of the aircraft availability, minimization of the *time on ground*, reduction of so-called *no fault found* (NFF) delays (i.e., alarms that result in no fault found after the investigation), and of course, reduction in costs. To fulfill these objectives, the provision of services and parts in this industry is regulated by extremely detailed service-level agreements (SLAs). These contracts define rigorous service-related requirements that amount to strict production-related requirements (Harun and Cheng 2010; Stringer et al. 2012) that the suppliers are traditionally obliged to fulfill to obtain certification of the airworthiness of the parts they design, manufacture, and/or maintain (e.g., the European Aviation Safety Agency [EASA] Form One). A high level of competition, exacting regulations, and demanding performance-based service contracts make it particularly complex for suppliers to design and operate their service delivery systems. In particular, one of the greatest challenges is to estimate, at the point of signing a contract, the resources that will be needed to provide the agreed parts and services over a period that can stretch 20, 30, or even 40 years into the future (Romero Rojo et al. 2009). Because of these characteristics, the aerospace industry represents an interesting setting to study the issues concerned with the service delivery systems modeling and design. In this paper, we discuss the use of discrete event simulation as a design tool. In particular, we show the results of a study where simulation has been applied to support the design of the service delivery system of a leading OEM operating in the aerospace industry.

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The paper is organized as follows: in the next section, we provide a literature review, in "Case description" section we present the unit of analysis, which for confidentiality reasons will be referred to as ALFA company. In "Model development" section, we present the simulation model and discuss its verification and validation; we describe the results of the simulation study in "Results" section. Finally, in "Conclusions, limitations and future research" section, we draw conclusions, illustrate the study limitations and delineate future research steps.

## Literature review

The literature proposes several models to address issues typical of the design of service delivery systems in aerospace. Simao and Powell (2009), for example, use approximate dynamic programming to assess inventory policies to meet target service levels. Safavi (2005), instead, provides an overview of the forecasting method adopted in the aerospace and defense industry, and of the problems which this industry encounters in its forecasting efforts. MacDonnell and Clegg (2007), in turn, discuss how the spare parts mean time between unscheduled removal and costs can be optimally traded off. However, because of the large number of decision variables and constraints that influence the system's behavior, the complex and (often) nonlinear interactions occurring among them, and the presence of multiple and conflicting objectives, it has been found that service systems can be sufficiently understood only through simulation analysis (Lendermann et al. 2010; Longo 2011). As Longo (2011) points out, in these contexts, mathematical or stochastic models alone do not allow a sound understanding of the system under study to be gained. Moreover, these models are often based on a high number of restrictive assumptions, making them inapplicable in real settings. Simulation, on the other hand, permits both the creation of artificially real complex systems (Longo 2011; Gagliardi et al. 2012; Zhang and Anosike 2012) and the compression of time. This, in turn, allows many different performance measures to be monitored; in a matter of hours, the system's behavior over long periods of time (many years) can be delineated. Thus, in the fields of operations and supply chain management, simulation represents a tool that is powerful both for research and decision making (Manuj et al. 2009; Longo and Mirabelli 2008). In particular, Manuj et al. (2009) points out that simulation as a decision making tool is most useful when: (1) it is not possible to find analytical solutions; (2) it is either too costly or impossible to obtain real-world observations; or (3) a limited number of alternatives are considered, and the goal is to understand the effects of change brought about by a limited number of variables. Simulation models, in fact, do not provide optimal results; rather, they allow understanding and comparison of a fixed number of alternatives (Law 2006; Banks 1998). The literature, indeed, thoroughly discusses the use of simulation as a tool to support supply chain management decisions (Terzi and Cavalieri 2004; van der Zee and van der Vorst 2005; Manuj et al. 2009; Cimino et al. 2010; Longo 2011; Carvalho et al. 2012). For example, Persson and Olhager (2002) propose a study, based on the case of a company in the mobile communications industry, where simulation is used together with other quantitative techniques to compare alternative supply chain designs with respect to quality, lead-times and costs. Similarly, Carvalho et al. (2012) use simulation to evaluate alternative strategies to increase supply chain resilience in the automotive supply chain. Manzini et al. (2005), in its turn, show the benefits associated with the application of discrete/continuous hybrid simulation tools in the design and management of different types of supply chains (namely, machinery, iron metallurgy, apparel and dairy products). Finally, Reiner (2005), referring to a case in the telecom industry, describes how supply chain process improvements can be dynamically evaluated and supported by integrating discrete-event simulation and system dynamics models. However Manuj et al. (2009) claim that the published studies often do not satisfactorily describe the efforts taken to maintain methodological rigor. Moreover, the literature still lacks of studies, based on real cases, where simulation is used to analyze the behavior of complex systems devoted to the provision of field services (Jahangirian et al. 2010; Agnihothri and Mishra 2004). In particular, there is still a paucity of studies investigating how simulation can be applied to support the design of systems that are globally dispersed and need to evolve over the long term to cope with the growth and the ageing of the installed base. However, assessing whether a field service delivery system will be able to comply with certain SLA over the long run is a compelling need in the aerospace industry (MacDonnell and Clegg 2007) as well as in many other industries (Blumberg 1991). With this study we contribute to the literature by showing how discrete event simulation can effectively support companies in performing such a challenging assessment.

## Case description

### The company

ALFA is a company leader in the provision of human to machine electronic controls for commercial and military aircrafts. In 2010, ALFA employed 230 people and had a turnover of 45 million. ALFA's customers are leading companies producing aircrafts and helicopters. In addition to providing state-of-the-art devices for application in top-level rotary and fixed wing aircrafts, ALFA is required to provide customer service in strict compliance with the laws and stringent regulations in force in the aerospace industry. The service activities of ALFA are coordinated by an independent function called Customer Service. This function has the duty to plan, coordinate, and execute service activities. It is led by a Customer Service manager. Recently, ALFA signed a contract with BETA for the provision of 26 different types of devices and related services. These devices will be part of a new type of aircraft for which BETA has already received more than 600 orders. The terms of supply for these devices mandate conditions relating to the following: stringent requirements for equipment reliability; precise conditions for supply lead-times; precise infrastructural requirements for the service delivery system; and precise target values for certain service performances. With regards to this contract, the actual customers of ALFA are as follows: BETA; the airline and leasing companies that actually buy BETA's aircrafts; and so-called customer nominees, i.e., third party MRO companies that carry out the maintenance activity on BETA's aircrafts. The terms of supply are exactly the same for all of these customers. As the Customer Service manager of ALFA has pointed out, the main practical problem ALFA faces is ascertaining whether its service delivery system will be able to meet the agreed conditions over time, and if not, what types of changes will be needed to achieve this goal. In this study, we show how simulation can support this type of evaluation. A detailed description of the contractual conditions is provided in the following section.

## Contractual requirements

The contract clearly defines stringent requirements in terms of both the service delivery system's *infrastructural* and *service performances*.

### *Infrastructural requirements*

According to the contract, ALFA's service delivery system must include the following: a centralized warehouse open 24/7 from which spare parts can be rented or bought by customers on a year-round basis; at least four service stations located, respectively, in the European Union (EU), United States (US), Middle East (ME), and Far East (FE) open 24/7. The service stations must be certified by the EASA, and must provide repair services to fix failed devices coming from the field. Furthermore, a dedicated hotline must be available all year round and 24/7 to respond to technical enquiries. In addition, each service station must keep at least one item of each type of the supplied equipment in stock, to be used in the case of aircraft on ground (AOG) requests. AOG occurs when an aircraft is unable to take off because of the unavailability of devices provided by ALFA. In such a case, ALFA must ship to the customer a functioning backup equipment, ready to be installed on the aircraft. Such ready-to-install devices are not used in the case of a repair request. To repair failed devices coming from the field, ALFA instead uses maintenance kits that contain replaceable spare parts and other tools needed for the repair. Each type of equipment requires a different kit, and each repair request requires one kit. The contract does not, however, prescribe the number of kits to keep in stock.

### *Service performance requisites*

The contract clearly sets targets for four main types of performance.

1. *Spare parts procurement lead time*: This is the time required to produce a piece of equipment. It must be less than 7 days for critical items, i.e., those items classified as "no go/go if" or shelf stock according to the World Airlines and Suppliers Guide (WASG); and 45 days for noncritical items. The lead time refers to the initial provisioning of the parts, which is clearly not a task performed by the service stations. As a result, this provisioning is not considered in the present study.
2. *Spare parts delivery time (SPDT):* This is the time required to deliver functioning backup equipment to the nearest airport as a consequence of an AOG service request. The device will subsequently be shipped from this airport to the airport where the aircraft is blocked. According to the contract, the *SPDT* must be shorter than 4 h.
3. *Response time (RT)*: This is the time required to create a service ticket and its associated documentation. The contract prescribes that the *RT* to technical enquiries must be 4 h if the enquiry arrives by telephone or fax, and 10 days for enquiries arriving via letter. The same contractual terms apply to requests for remote support (*RTr*) and on-field support (*RTo*). In case of repair requests, the service ticket is created when the failed equipment arrives at the service station.
4. *Shop process time (SPT)*: This is the time required to repair a piece of equipment. The shop process time is 10 days for avionic devices, 15 days for nonavionic ones (lighting systems), and 3 days for NFF items.

The contract also defines the documentation (test reports, certificates of conformity, equipment maintenance manuals, ground equipment manuals, etc.) relevant to the supplied devices that ALFA has to produce. In addition, it defines precise policies to manage buy-back and retrofit of the devices, policies to manage the spare parts obsolescence, and finally, the amount of training activities that ALFA has to impart to its customers so that they can perform certain maintenance tasks autonomously.

### The organizational structure and processes

To comply with the terms of supply, ALFA organizes each service station into six departments:

1. *Technical service (TS):* This department's duty is to perform on-field technical interventions and to provide technical remote support.
2. *After sales service (ASS):* This department handles incoming service requests, inspects failed devices coming from the field, and writes the documentation that certifies the correct functioning of the repaired devices.
3. *Spare parts management (SPM):* This department performs the actual material handling activities. More specifically, it carries out the spare parts picking activities, keeps the spare parts inventory under control, reorders parts when needed and manages the reception of the spare parts coming from the production facility.
4. *Administration (ADM):* This department produces the documentation that must accompany new or repaired devices when they are shipped to customers.
5. *Shipment (SH):* This department is responsible for actually packing the devices and shipping them to customers.
6. *Repair (REP):* This department actually performs the repair activities.

Each service station is involved in four main processes.

1. *The AOG process:* This consists of the transfer of functioning backup equipment from the service station to the nearest airport. The equipment will subsequently be shipped from this airport to the airport where the aircraft is actually blocked.
2. *The repair process:* This is the process through which ALFA repairs a failed piece of equipment that the customer sends to the service station.
3. *The remote technical assistance process:* This is the process through which ALFA provides remote support to customer to allow them to fix (minor) failures on their own.
4. *The on-field technical assistance process:* This is the process through which ALFA provides support to customers directly at the customer site. Requests for on-field interventions are very rare.

Simplified maps of these processes are illustrated in Figs. 1, 2, 3 and 4. Each map represents a process and identifies (1) the main activities of which each process is composed of (rectangular box) and (2) the department (horizontal lanes) that has the duty to perform such an activity.

Although not mentioned in the contract, to comply with a common benchmark for the aerospace industry (Lendermann et al. 2010), ALFA wants to achieve a service level (*SL*) for each process—i.e., a ratio between the service requests fulfilled on time and total requests—that is higher than 0.97 at a level of significance of 0.05.

As a final remark, it is worth to point out that due to its infrastructural characteristics and to the nature of the service demand, the service delivery system of ALFA can be considered *asset-centric* (Aberdeen Group 2005). The system, in fact, is characterized by a relatively small number of field technicians, each performing few on-site interventions (e.g., less than one per week) on a relatively small number of assets spread over a wide territory. In this type of systems the scheduling, routing and dispatching of field technicians do not represent a relevant issue (Aberdeen Group 2005). Consequently these systems can be correctly modeled without implementing sophisticated field force scheduling and routing algorithms. In the next sections we describe how we modeled the ALFA service delivery system and how the model has been used to verify whether ALFA will be able to meet its contractual requirements and achieve the desired *SL*.

## Model development

The simulation model has been developed following a four-stage process: (1) data collection, (2) definition of the output and control variables, (3) definition of the model structure and logic, (4) model verification and validation. These stages are summarized in Table 1 and discussed in greater detail in the following sections.

### Data collection

The data used in this study were provided by ALFA's Customer Service manager. They can be divided into the following categories: (1) *reliability-related*, (2) *demand-related*, and (3) *resource consumption-related*. These data are described in the following subsections.

#### *Reliability-related data*

We considered 26 devices. For each supplied device, ALFA provided the failure rate $\lambda$, which was assumed to be constant, and the mean time between failures (MTBF). ALFA calculated the failure rates of each device by adding up the failure rates of its components, thereby assuming a series system. These assumptions are justified by the fact that the devices are made of electronic parts and the failure of any single component results in a malfunctioning of the device as a whole.

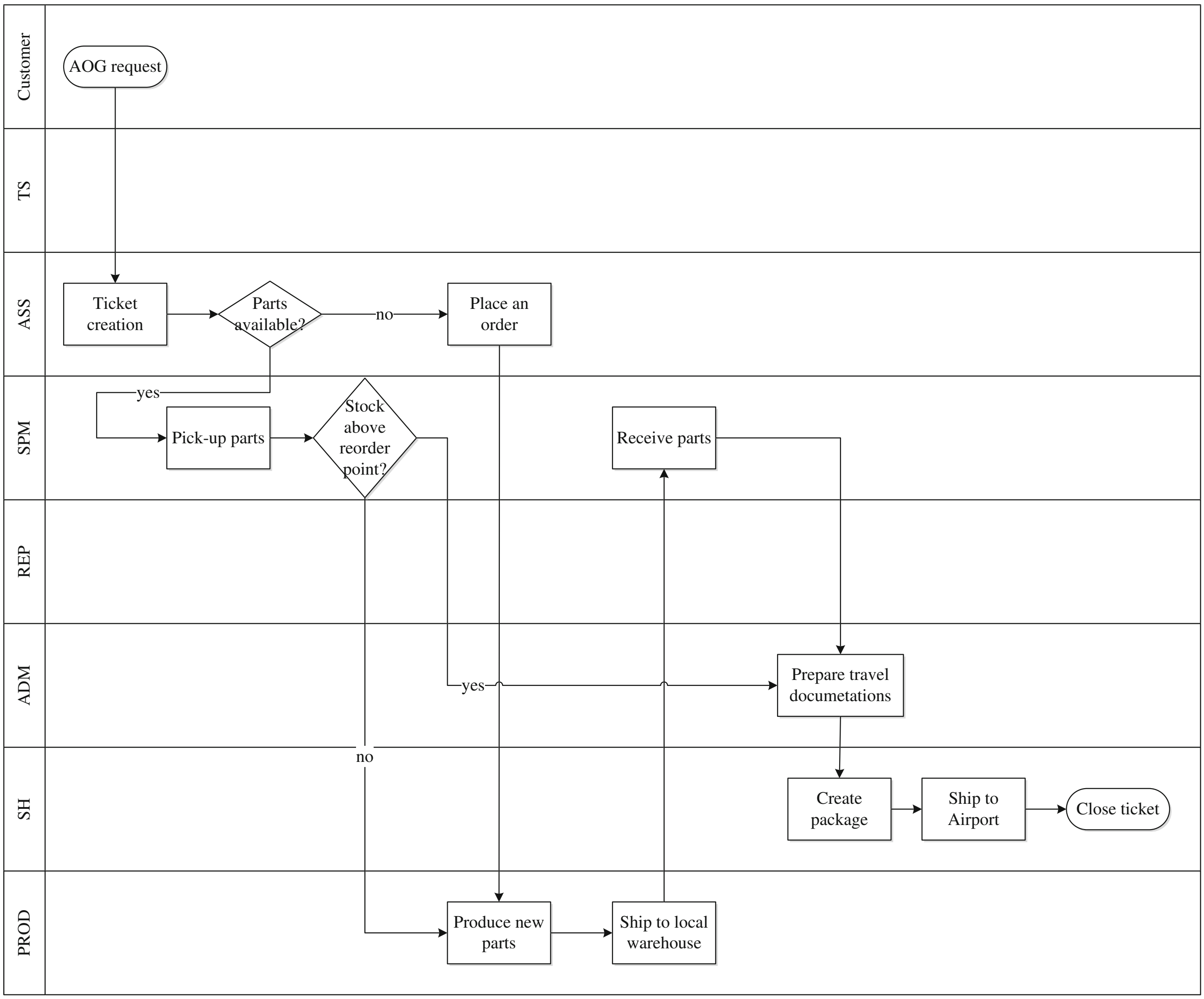


**Fig. 1** "Aircraft on ground" process

*Demand-related data*

ALFA provided an estimate of the number of aircrafts that would enter into service in the next seven years (year by year, see Table 2). All of these aircrafts will have 38 devices on board, since some of the 26 devices mentioned above are installed more than one time in each aircraft.

ALFA also provided an estimate of the number of flight cycles (FC) that each aircraft is expected to perform every year, the flight hours (FH) associated with each cycle, and the average time between two consecutive flights (TBF) (FC = 940 flights/year; FH = 5 h/flight; TBF = 4.3 h/flight). This information is extremely relevant because failures can occur only when the aircraft is on flight. ALFA also identified the possible routes that aircrafts would likely use. This information is very relevant as well, since it can help to identify where the demand for technical assistance and parts is likely to emerge. However, the routes cannot be determined in advance, since ALFA has no information about the airline companies (BETA's customers) that will operate the aircrafts. A rough estimate has been provided with the assumption of four generic destinations: the US, EU, ME, and FE. Hence, given the characteristics of the aircrafts, we have identified the following possible "macro" routes:

- EU-EU; EU-US; EU-ME for aircrafts departing from the EU;
- US-US; US-EU; US-FE for aircrafts departing from the US;
- ME-EU; ME-FE for aircrafts departing from the ME;
- FE-US; FE-ME for aircrafts departing from the FE.

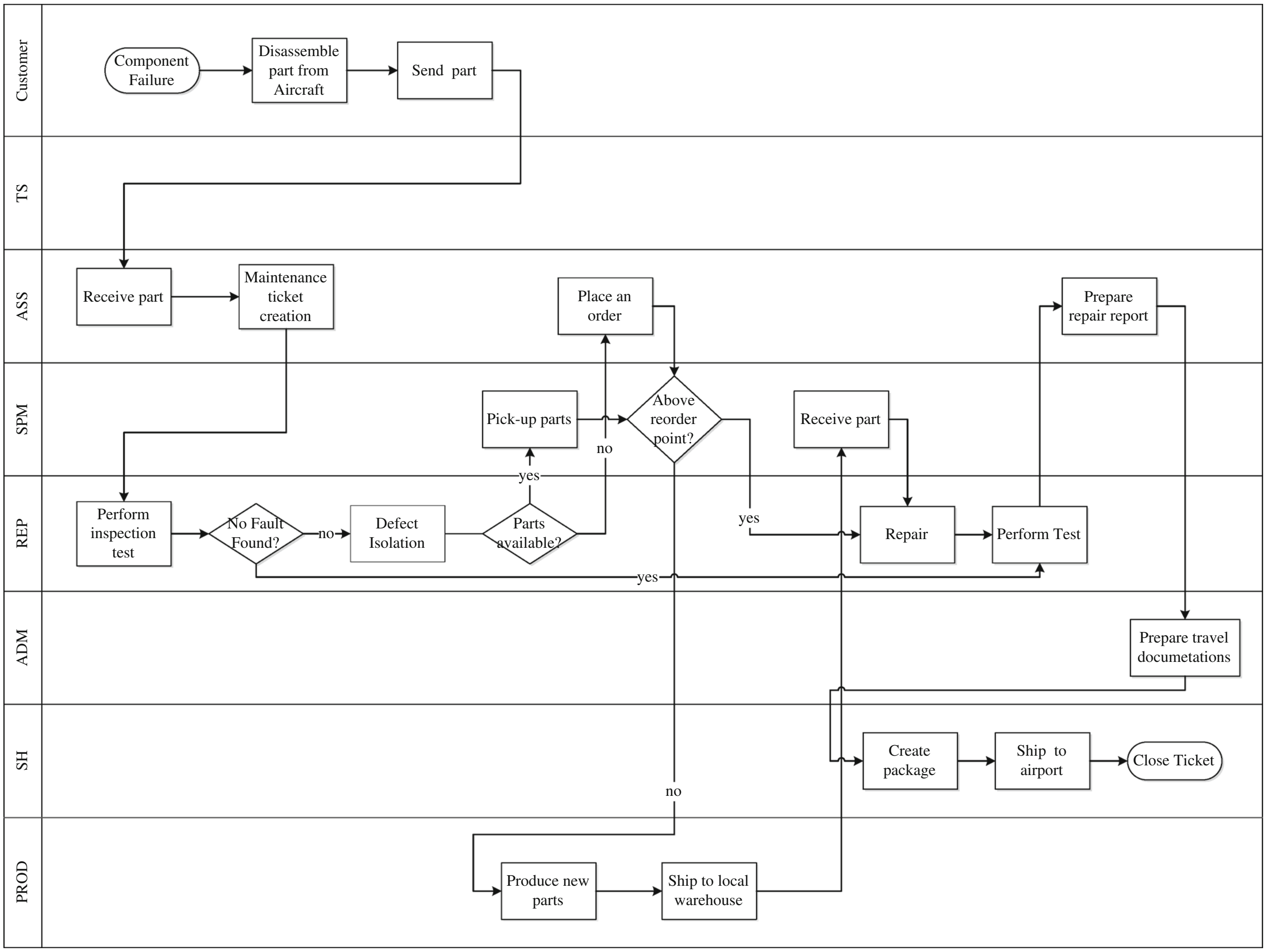


**Fig. 2** Repair process

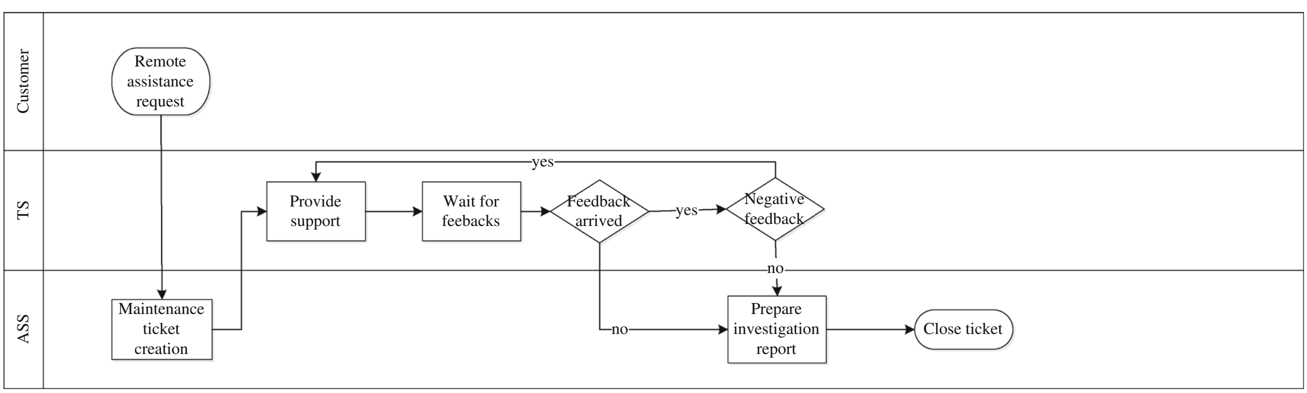


**Fig. 3** Remote technical assistance process

Each route is considered equiprobable. Such an assumption obviously implies that more intense air traffic will be evident in the EU and US. Finally, ALFA has estimated, for each device, the percentage of NFF service requests and the probability with which the device's failure will trigger one of the aforementioned processes.

*Resource consumption-related data*

ALFA provided an estimate of the minimum, modal, and maximum value of the time required to perform the activities that each process is composed of (rectangular blocks in Figs. 1, 2, 3 and 4). We thus estimated the time required

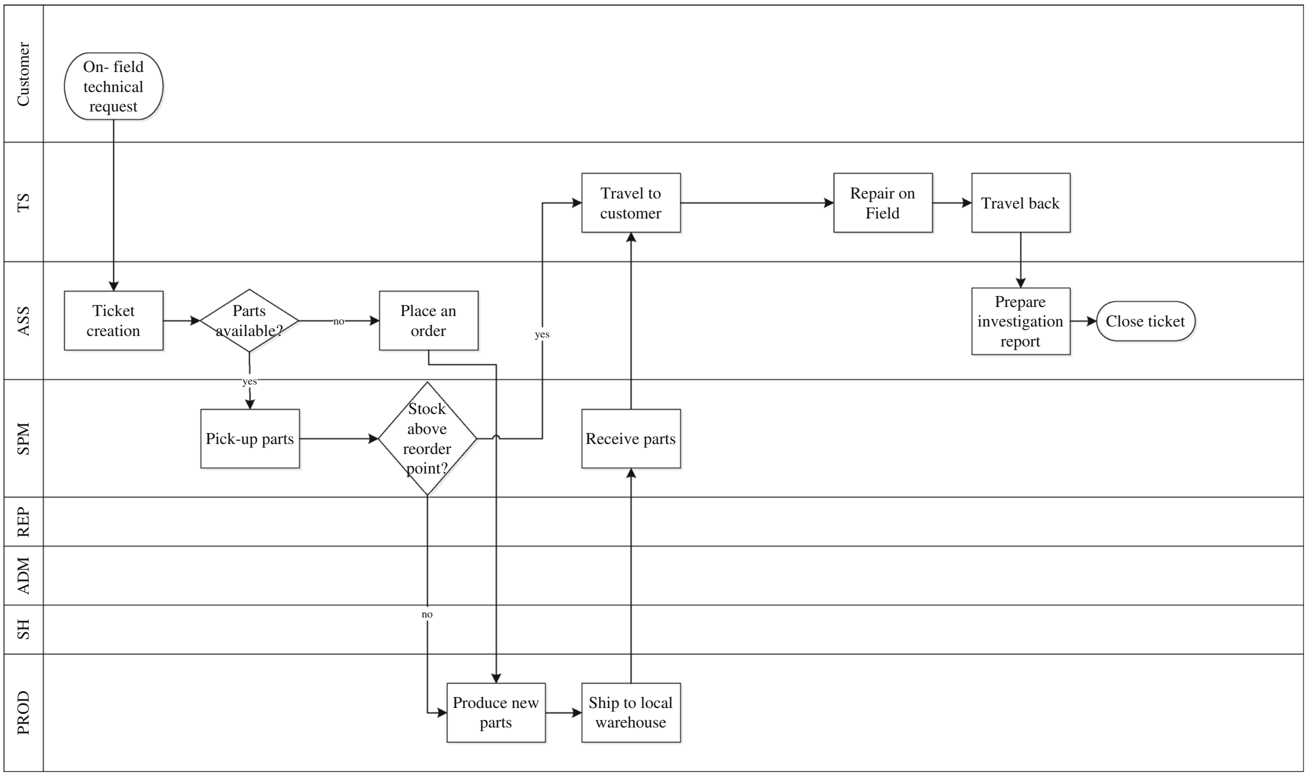


**Fig. 4** On-field technical assistance process

to perform each activity as distributed according to a triangular (TRIA(min, mode, max)) distribution model (Kelton et al. 2009). ALFA also provided an estimate of the time (minimum, modal, and maximum value) that carriers require to bring the spare parts from the central production facility to the service stations and from each service station to the nearest airport. We hypothesize that these times will also be distributed according to a triangular distribution. In addition, we assumed that one item of each device would be kept in stock at each repair station to be used in case of AOG, plus one maintenance kit for each device to be used in case of a repair request. The reorder point for each device and maintenance kit is supposed to be zero. These hypotheses were suggested directly by ALFA and reflect the policy that ALFA intends to use, in the short-term.

## Definition of the output and control variables

To assess whether ALFA will be able to meet its contractual requirements we have considered the following output variables: the number of failures ($N_i$) and the number of NFF requests ($Nn_i$) associated with each device $i$; *RTr* and *RTo*; *SPT*, both for regular (*SPT*) and NFF items (*SPTn*); *SPDT*; and finally, the work load that the service requests associated with BETA create for each department in each service station. In addition, as will be illustrated in greater detail in "Scenario analysis" section, we have considered the reorder point of the maintenance kits, the reorder point of the devices and the time required to transfer parts from the service station to the nearest airport as control variables.

## Definition of the model structure and logic

The ALFA service delivery system was modeled using Rockwell Arena 13. Arena, indeed, combines the user-friendliness of high layer simulator and flexibility of simulation language (Kelton et al. 2009). In addition it can be easily integrated via VBA with other office applications, i.e., MS Excel, making the analysis of the simulation output easier. The model is made up of six submodels. The first generates the aircraft entities following the demand pattern illustrated in "Demand-related data" section. In addition, it models the aircraft flight activities, allowing tracking the aircraft status (idle-on flight) as well as its route. The second submodel generates the device entities and simulates their failures according to the devices' MTBF. Each device, and consequently each failure, is randomly assigned to an aircraft, and can give rise to different types of service requests (AOG, on-field support, remote support, repair) according to the probability provided by ALFA. These requests are handled by the service station located in the region where the aircraft will land. The third, fourth, fifth, and sixth submodels reproduce the AOG, repair,

**Table 1** Model development stages

| Stage | Relevant information |
|---|---|
| Data collection | Reliability-related data |
| | Components failure rates and MTBFs |
| | Demand-related data |
| | Flight cycles and Flight hours |
| | Average time between two consecutive flights |
| | Routes |
| | Resource consumption-related data |
| | Activities' durations |
| Definition of the output and control variables | Output |
| | Number of failures for each device |
| | Number of NFF requests for each device |
| | RTr and RTo |
| | SPT and SPDT for regular and NFF items |
| | Service stations work load |
| | Control variables |
| | Reorder points |
| | Travel times |
| Definition of the model structure and logic | 6 submodels simulating, respectively: |
| | 1. Aircraft commissioning and flight activities |
| | 2. Devices failures |
| | 3. AOG process |
| | 4. Repair process |
| | 5. Remote technical assistance process |
| | 6. On-field technical assistance process |
| Model verification and validation | Verification |
| | Model debugging |
| | In-depth verification of submodel 2 through Monte Carlo simulation |
| | Validation |
| | Structured walkthrough of the simulation model with academic expert |
| | In-depth discussion of the results with ALFA management |

remote technical assistance, and on-field technical assistance processes, respectively, according with the maps in Figs. 1, 2, 3 and 4.

## Model verification and validation

### *Model verification*

Model verification is the process of examining the outputs of each submodel and of the complete model to ensure that they are executing and behaving acceptably, i.e., according to the modeler's expectation (Manuj et al. 2009). Thus, model verification involves the debugging of any error in programming logic and code. In this study, the model has been verified utilizing the debug features of Rockwell Arena 13. To improve the quality of the verification process, the model logic was checked by two people other than the one who actually coded the model. Moreover, we performed an in-depth verification of the submodel generating the device failures. To accomplish this, we compared the data produced by such a submodel with manually calculated data, as suggested by Fishman and Kiviat (1968). In particular, we assessed whether the number of device failures generated by the submodel over the time was coherent with the homogeneous Poisson process the submodel was intended to reproduce. To do this, we considered seven aircraft batches, respectively representing the aircrafts that will enter service in the first, second, third, fourth, fifth, sixth, and seventh year (Table 2). Since the devices installed on the aircrafts are independent from one another, we calculated, for each batch $j$, the total failure rate $\lambda b_j$ as:

**Table 2** Aircrafts to be commissioned

| Years | New aircrafts | Total number of aircrafts |
|---|---|---|
| 1 | 3 | 3 |
| 2 | 15 | 18 |
| 3 | 24 | 42 |
| 4 | 46 | 88 |
| 5 | 78 | 166 |
| 6 | 114 | 280 |
| 7 | 134 | 414 |

$$\lambda b_j = \sum_{i=1}^{26} \lambda_i \times c_i \times a_j, \qquad (1)$$

where:

$\lambda_i$ is the failure rate of the device of type $i$;
$c_i$ is the number of devices of type $i$ installed in each aircraft;
$a_j$ is the number of aircrafts in the batch $j$.

Using MS Excel, we carried out a Monte Carlo simulation to obtain 30 different realizations of random Poisson processes characterized by an intensity equal to $\lambda b_{j,}$ for each batch $j$. Starting from these realizations we have calculated for each year $y(y = 1, \ldots, 20)$, the mean value $M$ and the standard deviation $S$ of: (1) the number of failures $\tilde{N}b_{j,y}$ occurring during the $y$th year due to devices installed on the aircrafts in the $j$th batch and (2) the total number of failures $\tilde{N}_y$ occurring during the $y$th year. In doing so, we took into account the fact that the aircrafts in the first batch will start to fly the first year, those in the second batch the second year, and so on. The mean values $M$ and standard deviation *StDev* of the failures obtained through the Monte Carlo simulation are reported in Table 3. For each year $y$, we have subsequently performed two-tailed $t$ tests (Montgomery and Runger 2002) to determine whether the mean values $M(\tilde{N}_y)$ obtained with the Monte Carlo simulation were statistically different from the number of failures $M(N_y)$ obtained with the discrete event simulation model. In statistical terms, we have tested the null hypothesis $H_0 : M(\tilde{N}_y) - M(N_y) = 0$ against the alternative hypothesis $H_1 : M(\tilde{N}_y) - M(N_y) \neq 0$ for each year $y$. The results of the $t$ tests are presented in Table 4, where we report the degrees of freedom (*dof*), $t$ statistics, and $p$-values for each test. As can be observed for all the tests, the $p$-value is greater than or equal to 0.1. We also tested whether the cumulative number of failures obtained with Monte Carlo simulation $M(cum\tilde{N}_y)$ was statistically different from the cumulative number of failures $M(cumN_y)$ obtained with the discrete event simulation model. The results are presented in Table 5. Also in this case, the $p$-value was greater than or equal to 0.1 for all of the tests. We can thus conclude that at a level of significance of 0.1, there is no convincing evidence for a difference in the number of failures generated by the two models; consequently, we can consider the submodel *verified* (Law 2006). It is worth noticing that the number of failures increases from year 1 to 7 because of the increase of the number of aircraft in service. After the seventh year, the number of failures remains fairly stable.

### *Model validation*

Model validation is the process of determining whether a simulation model is an accurate representation of the system under investigation (Law 2006). Validation is always desirable, but unfortunately, it is not always possible (Fishman and Kiviat 1968). In our study, the simulation model represents a system that has been recently deployed. Consequently, we could not validate the model by comparing real data with the simulation output. Nonetheless, as suggested by Manuj et al. (2009), we performed a structured walkthrough of the simulation model with one academic expert in the field, and we thoroughly discussed the simulation results with the ALFA's Customer Service manager. The results were judged *reasonable* and the overall model *credible*. As a result, we concluded that the model had satisfactory *face* validity (Banks 1998).

## Results

### AS-IS analysis

To verify whether ALFA is able to fulfill its contractual requirements, we performed 30 runs of 14 years each, and analyzed the simulation results with consideration of both the separate service stations and the service delivery system as a whole. The graph in Fig. 5 shows the mean value of the number of service requests in each region for each year. It also distinguishes between requests due to failed items (black dots) and to NFF items (white dots).

Comparing the different regions, we found that the number of service requests coming from the EU and the US were both significantly higher ($p < 0.05$) than those coming from the ME and FE. Moreover, the number of requests coming from the EU was not significantly different from the number from the US ($p > 0.1$), while ME and FE were also not significantly different from one another ($p > 0.1$). This is coherent with the hypotheses we presented in "Demand-related data" section regarding the aircrafts' routes. Since the resources deployed in each region are the same, the system runs in a slightly different way in each region. Consequently, the work load generated by BETA will not be the same for each service station. Table 6 reports the mean, standard deviation, and lower and upper bounds of the 95 % confidence interval for the mean of the time (hours per year) required by each department in each service station to support the service requests related to BETA.

In Tables 7, 8 and 9, we report the mean, standard deviation, maximum, and lower and upper 95 % confidence interval for the mean of each contractual performance. The maxima are calculated as the maximum across years of the individual replications maxima (Kelton et al. 2009). As such, they represent extreme cases.

If we look at Table 7, we notice that the maximum value of the *RTr* and *RTo* is always smaller than the contractual threshold. This means that the service tickets are always created on time in the case of technical assistance requests. Therefore, it can be determined that neither the remote nor the on-field technical assistance process is critical. Unfortunately, the same conclusion cannot be drawn for the repair and AOG processes. In fact, looking at the *SPT* (Table 8), we observe that the maximum values and the standard deviations are extremely high. These high values are due to the stock-outs that occur when the same type of device fails more than once within a few days in the same region. ALFA keeps just one item for each maintenance kit in stock. Hence, in case of stock-out, ALFA has to produce a new maintenance kit and send it to the repair station. This prevents the repair from being executed within the contracted times (on average, the *SPT* is less than 12 h if the maintenance kits are available and greater than 850 h if they are not). Looking at the different regions, we noticed that on average, the *SPT* is higher in the US than the EU, although the demand for service in these two regions is not significantly different. This is because the production facility where the devices and the maintenance kits are actually produced is located in the same facility, which also hosts the EU service station.

Similarly to the *SPT*, the *SPDT* is characterized by extremely high maximum values (Table 9). Such values arise

**Table 3** Monte Carlo simulation results

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M(\tilde{N}b_{1,y})$ | 2.4 | 2.5 | 3.2 | 2.5 | 2.6 | 2.5 | 2.4 | 2.5 | 2.1 | 2.4 | 2.8 | 2.4 | 2.2 | 2.8 | 2.5 | 3.1 | 2.2 | 1.9 | 2.9 | 2.4 |
| $StDev(\tilde{N}b_{1,y})$ | 1.6 | 1.4 | 2.0 | 1.4 | 1.2 | 1.6 | 1.5 | 1.8 | 1.1 | 1.9 | 1.7 | 1.4 | 1.4 | 1.7 | 1.7 | 1.7 | 1.5 | 1.2 | 2.0 | 1.1 |
| $M(\tilde{N}b_{2,y})$ | | 11.7 | 12.2 | 11.3 | 13.2 | 11.8 | 11.8 | 12.3 | 12.8 | 11.7 | 12.9 | 12.1 | 12.7 | 12.3 | 12.1 | 11.8 | 12.2 | 12.4 | 12.9 | 12.8 |
| $StDev(\tilde{N}b_{2,y})$ | | 3.5 | 3.6 | 3.1 | 3.7 | 3.7 | 2.9 | 4.2 | 3.5 | 2.7 | 3.4 | 3.5 | 3.6 | 3.3 | 3.5 | 3.5 | 3.8 | 3.9 | 3.8 | 4.3 |
| $M(\tilde{N}b_{3,y})$ | | | 19.8 | 19.1 | 19.8 | 20.8 | 18.8 | 19.4 | 20.5 | 21.0 | 19.1 | 18.4 | 19.8 | 19.6 | 20.0 | 18.7 | 19.2 | 19.4 | 18.4 | 19.5 |
| $StDev(\tilde{N}b_{3,y})$ | | | 4.4 | 5.4 | 4.3 | 4.3 | 4.2 | 5.1 | 4.5 | 5.4 | 3.8 | 5.3 | 4.3 | 3.9 | 3.9 | 4.2 | 4.7 | 4.7 | 5.1 | 4.1 |
| $M(\tilde{N}b_{4,y})$ | | | | 37.8 | 38.4 | 39.3 | 37.9 | 36.1 | 38.1 | 37.6 | 38.1 | 35.6 | 38.3 | 36.4 | 37.8 | 40.2 | 35.5 | 36.1 | 37.9 | 37.9 |
| $StDev(\tilde{N}b_{4,y})$ | | | | 4.8 | 6.0 | 6.5 | 4.6 | 5.4 | 5.9 | 6.1 | 6.0 | 5.1 | 6.0 | 6.5 | 6.3 | 6.5 | 6.2 | 7.0 | 6.3 | 6.6 |
| $M(\tilde{N}b_{5,y})$ | | | | | 61.5 | 63.2 | 64.0 | 63.0 | 67.2 | 61.6 | 63.7 | 61.8 | 65.7 | 65.0 | 64.2 | 65.4 | 65.4 | 62.3 | 63.1 | 65.5 |
| $StDev(\tilde{N}b_{5,y})$ | | | | | 8.8 | 8.7 | 6.9 | 8.7 | 8.8 | 6.8 | 7.6 | 8.6 | 7.0 | 9.1 | 8.8 | 7.8 | 8.4 | 9.5 | 8.3 | 6.9 |
| $M(\tilde{N}b_{6,y})$ | | | | | | 92.9 | 95.1 | 92.0 | 95.3 | 96.8 | 93.4 | 92.6 | 91.3 | 94.6 | 90.3 | 90.8 | 94.0 | 92.5 | 94.4 | 93.9 |
| $StDev(\tilde{N}b_{6,y})$ | | | | | | 8.9 | 7.7 | 8.3 | 9.2 | 8.3 | 10.1 | 10.1 | 9.8 | 10.2 | 8.9 | 9.0 | 10.1 | 13.4 | 9.3 | 8.5 |
| $M(\tilde{N}b_{7,y})$ | | | | | | | 103.8 | 110.3 | 105.4 | 106.8 | 109.3 | 110.4 | 110.5 | 110.6 | 110.3 | 108.1 | 113.4 | 115.1 | 110.1 | 113.8 |
| $StDev(\tilde{N}b_{7,y})$ | | | | | | | 10.9 | 11.6 | 9.0 | 11.2 | 8.6 | 10.3 | 11.9 | 10.5 | 7.3 | 10.3 | 14.3 | 9.1 | 10.7 | 10.0 |
| $M(\tilde{N}b_{y})$ | 2.4 | 14.3 | 35.1 | 70.7 | 135.6 | 230.5 | 333.8 | 335.5 | 341.4 | 337.7 | 339.3 | 333.4 | 340.6 | 341.2 | 337.2 | 338.1 | 341.9 | 339.6 | 339.8 | 345.9 |
| $StDev(\tilde{N}b_{y})$ | 1.6 | 3.5 | 6.6 | 6.9 | 13.5 | 10.4 | 15.4 | 13.5 | 16.9 | 23.0 | 15.1 | 17.9 | 16.7 | 20.3 | 20.1 | 18.9 | 19.1 | 20.6 | 22.2 | 19.0 |

**Table 4** Comparison between Monte Carlo and discrete event simulation results, failures per year

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M(\tilde{N}_y)$ | 2.4 | 14.3 | 35.1 | 70.7 | 135.6 | 230.5 | 333.8 | 335.5 | 341.4 | 337.7 | 339.3 | 333.4 | 340.6 | 341.2 | 337.2 | 338.1 | 341.9 | 339.6 | 339.8 | 345.9 |
| $StDev(\tilde{N}_y)$ | 1.6 | 3.5 | 6.6 | 6.9 | 13.5 | 10.4 | 15.4 | 13.5 | 16.9 | 23.0 | 15.1 | 17.9 | 16.7 | 20.3 | 20.1 | 18.9 | 19.1 | 20.6 | 22.2 | 19.0 |
| $M(N_y)$ | 2.8 | 14.6 | 34.4 | 72.2 | 132.9 | 226.8 | 336.6 | 336.2 | 334.9 | 336.3 | 334.1 | 335.0 | 335.8 | 335.6 | 331.9 | 344.2 | 335.6 | 337.3 | 337.6 | 338.4 |
| $StDev(N_y)$ | 2.0 | 3.9 | 6.1 | 7.3 | 11.1 | 10.1 | 21.5 | 20.9 | 19.1 | 21.4 | 16.8 | 18.2 | 20.1 | 17.8 | 19.6 | 20.0 | 18.6 | 22.0 | 15.0 | 17.2 |
| dof | 55.0 | 57.0 | 57.0 | 57.0 | 55.0 | 57.0 | 52.0 | 49.0 | 57.0 | 57.0 | 57.0 | 57.0 | 56.0 | 57.0 | 57.0 | 57.0 | 57.0 | 57.0 | 50.0 | 57.0 |
| t | −0.9 | −0.4 | 0.4 | −0.9 | 0.8 | 1.4 | −0.6 | −0.2 | 1.4 | 0.3 | 1.3 | −0.4 | 1.0 | 1.1 | 1.0 | −1.2 | 1.3 | 0.4 | 0.4 | 1.6 |
| *P* | 0.4 | 0.7 | 0.7 | 0.4 | 0.4 | 0.2 | 0.6 | 0.9 | 0.2 | 0.8 | 0.2 | 0.7 | 0.3 | 0.3 | 0.3 | 0.2 | 0.2 | 0.7 | 0.7 | 0.1 |

**Table 5** Comparison between Monte Carlo and discrete event simulation results, cumulative failures

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $M(Cum\tilde{N}_y)$ | 2.4 | 16.6 | 51.7 | 122.4 | 258.0 | 488.4 | 822.3 | 1,157.8 | 1,499.2 | 1,836.9 | 2,176.3 | 2,509.6 | 2,850.2 | 3,191.4 | 3,528.6 | 3,866.7 | 4,208.6 | 4,548.2 | 4,887.9 | 5,233.8 |
| $StDev(Cum\tilde{N}_y)$ | 1.6 | 3.7 | 7.8 | 11.2 | 16.3 | 17.4 | 19.0 | 21.6 | 28.6 | 42.3 | 44.9 | 48.4 | 47.2 | 54.9 | 53.9 | 61.5 | 68.5 | 78.0 | 83.8 | 82.6 |
| $M(CumN_y)$ | 2.8 | 17.4 | 51.8 | 124.0 | 256.9 | 483.7 | 820.3 | 1,156.5 | 1,491.3 | 1,827.6 | 2,161.7 | 2,496.8 | 2,832.6 | 3,168.2 | 3,500.1 | 3,844.3 | 4,179.9 | 4,517.2 | 4,854.8 | 5,193.2 |
| $StDev(CumN_y)$ | 2.0 | 4.0 | 8.3 | 10.1 | 15.9 | 18.5 | 30.2 | 39.5 | 44.2 | 54.5 | 59.5 | 61.3 | 64.8 | 68.2 | 72.4 | 66.6 | 71.9 | 76.3 | 80.5 | 83.0 |
| dof | 55.0 | 57.0 | 57.0 | 57.0 | 57.0 | 57.0 | 48.0 | 44.0 | 49.0 | 54.0 | 53.0 | 55.0 | 53.0 | 55.0 | 53.0 | 57.0 | 57.0 | 57.0 | 57.0 | 57.0 |
| t | −0.9 | −0.8 | 0.0 | −0.6 | 0.2 | 1.0 | 0.3 | 0.2 | 0.8 | 0.7 | 1.1 | 0.9 | 1.2 | 1.5 | 1.7 | 1.4 | 1.6 | 1.6 | 1.6 | 1.9 |
| $P$ | 0.4 | 0.4 | 1.0 | 0.6 | 0.8 | 0.3 | 0.8 | 0.9 | 0.4 | 0.5 | 0.3 | 0.4 | 0.2 | 0.2 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 |

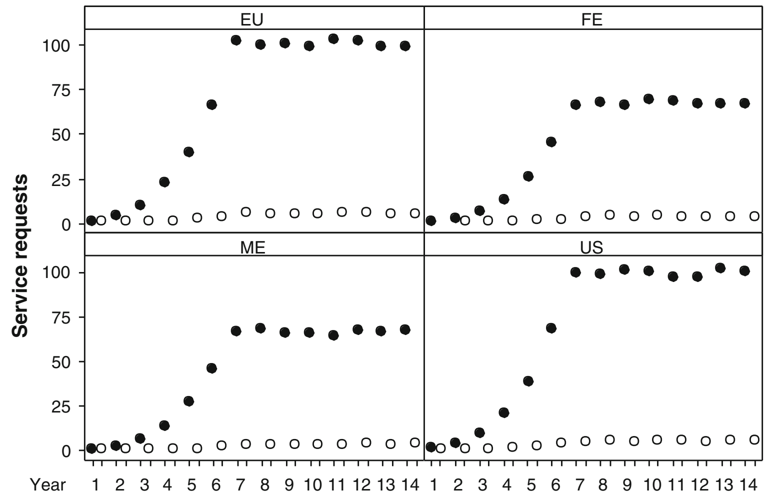


**Fig. 5** Service requests due to failed items (*black dots*) and to NFF items (*white dots*)

**Table 6** Hours per year worked on service requests related to BETA in each department

| | EU | ME | FE | US |
|---|---|---|---|---|
| ADM | | | | |
| Mean | 6.5 | 4.3 | 4.3 | 6.5 |
| StDev | 0.3 | 0.2 | 0.2 | 0.2 |
| Lower | 6.4 | 4.3 | 4.2 | 6.4 |
| Upper | 6.6 | 4.4 | 4.4 | 6.5 |
| ASS | | | | |
| Mean | 27.2 | 18.2 | 18.2 | 27.1 |
| StDev | 1.1 | 0.8 | 0.9 | 0.9 |
| Lower | 26.8 | 18.0 | 17.9 | 26.7 |
| Upper | 27.6 | 18.5 | 18.5 | 27.4 |
| REP | | | | |
| Mean | 348.5 | 233.1 | 231.7 | 345.4 |
| StDev | 14.5 | 9.4 | 11.3 | 11.9 |
| Lower | 343.1 | 229.5 | 227.5 | 340.9 |
| Upper | 353.9 | 236.6 | 235.9 | 349.8 |
| SPM | | | | |
| Mean | 29.7 | 20.5 | 20.5 | 28.3 |
| StDev | 1.1 | 0.7 | 0.8 | 1.0 |
| Lower | 29.3 | 20.3 | 20.1 | 28.0 |
| Upper | 30.1 | 20.8 | 20.8 | 28.7 |
| SH | | | | |
| Mean | 48.8 | 32.5 | 32.5 | 48.5 |
| StDev | 2.1 | 1.2 | 1.6 | 1.6 |
| Lower | 48.0 | 32.0 | 31.9 | 47.9 |
| Upper | 49.6 | 33.0 | 33.1 | 49.1 |
| TS | | | | |
| Mean | 102.2 | 72.2 | 70.1 | 109.3 |
| StDev | 19.1 | 15.3 | 14.5 | 19.8 |
| Lower | 95.1 | 66.5 | 64.7 | 101.9 |
| Upper | 109.3 | 77.9 | 75.5 | 116.7 |

when two AOGs occur in the same region within a few days. If this happens, the devices go out of stock and ALFA has to produce a new device. Moreover, in contrast to the *SPT*, the *SPDT* has a mean value that is always significantly ($p < 0.05$) higher than the contractual target of 4 h, even for the cases for which the devices are actually in stock. This is because, due to a lack of responsiveness of the carrier, transfer of parts from the service station to the nearest airport can take up to 5 h, even though the service stations are located within 1 h drive from the nearest airport. Obviously, as for the *SPT*, when a stock-out occurs, the *SPDT* assumes an extremely high value (up to 1,094 h, see Table 9). In any case, the mean value of the *SPDT* is on average significantly ($p < 0.05$) smaller than the mean value of the *SPT*. In fact, AOG rarely occurs, and therefore stock-outs are less likely to happen.

Since the AOG and the repair processes are critical, hereafter we present the simulation results relevant to these processes in more depth. In particular, we focus on two main performances, the *SL* and the total delay (*TD*). As pointed out in "The organizational structure and processes" section, the *SL* represents the ratio between the service requests fulfilled on time and the total number of service requests. In contrast, the *TD* represents the sum of the delays accumulated every time service requests are not fulfilled on time. Both types of performance are extremely relevant. In fact, on the one hand, ALFA wants to obtain a *SL* higher than 0.97 with a level of significance of 0.05. On the other, the penalty that ALFA has to pay to its customers every time a service request is not fulfilled on time is proportional to the difference between the time actually spent fulfilling the request and the contractual target. Hence, for both the repair and the AOG process we performed a one-tiled $t$ test to determine whether, at a level of significance of 0.05, the *SL* was higher than the target level ($SL_{tg}$) of 0.97 for each year. In statistical terms we tested the null hypothesis $H_0 : M(SL) = 0.97$ against the alternative

**Table 7** Simulation results: response times

| | RTr(h) [$RTr_{tg} = 4\,h$] | | | | | RTo (h) [$RTo_{tg} = 4\,h$] | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | EU | ME | FE | US | TOT | EU | ME | FE | US | TOT |
| Mean | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| StDev | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Max | 0.43 | 0.41 | 0.41 | 0.44 | 0.44 | 0.41 | 0.39 | 0.40 | 0.44 | 0.44 |
| Lower | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Upper | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |

**Table 8** Simulation results: shop process times

| | SPT(h) [$SPT_{tg} = 240/360\,h$] | | | | | SPTn(h) [$SPTn_{tg} = 72\,h$] | | | | | TOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | EU | ME | FE | US | TOT | EU | ME | FE | US | TOT | |
| Mean | 165.5 | 171.7 | 174.4 | 232.1 | 188.4 | 8.7 | 8.6 | 8.6 | 8.6 | 8.6 | 177.2 |
| StDev | 298.9 | 344.9 | 346.4 | 387.0 | 346.8 | 1.0 | 0.9 | 0.9 | 1.0 | 1.0 | 338.6 |
| Max | 967.7 | 1,186.4 | 1,178.2 | 1,182.6 | 1,186.4 | 16.9 | 14.6 | 13.8 | 15.9 | 16.9 | 1,186.4 |
| Lower | 162.6 | 167.5 | 170.3 | 228.3 | 186.5 | 8.6 | 8.6 | 8.6 | 8.6 | 8.6 | 175.4 |
| Upper | 168.4 | 175.8 | 178.6 | 235.9 | 190.3 | 8.7 | 8.6 | 8.7 | 8.7 | 8.7 | 178.9 |

**Table 9** Simulation results: spare part delivery times

| | SPDT(h) [$SPT_{tg} = 4\,h$] | | | | |
|---|---|---|---|---|---|
| | EU | ME | FE | US | TOT |
| Mean | 16.7 | 14.6 | 17.6 | 18.7 | 17.1 |
| StDev | 92.2 | 92.1 | 106.3 | 109.1 | 100.4 |
| Max | 958.0 | 1,027.1 | 1,093.8 | 1,107.2 | 1,107.2 |
| Lower | −132.2 | −78.9 | −74.0 | −118.7 | −439.9 |
| Upper | 165.7 | 108.1 | 109.1 | 156.1 | 474.0 |

hypothesis $H_1 : M(SL) > 0.97$ and controlled whether the corresponding $p$-values were smaller than 0.05. To display the results of these tests, in Fig. 6 we report the value of the lower bound (LB) of the 95 % one-sided confidence interval for the *SL* mean for each year. Obviously, when LB is higher than 0.97, the $p$-values are smaller than 0.05. In these cases, we can reject the null hypothesis, and consider *SL* to be higher than 0.97 at a level of significance of 0.05.

If we consider the repair process, *SL* is significantly higher than 0.97 only for the first two years. In contrast, for the AOG requests, *SL* is never significantly higher than 0.97 and is always significantly smaller than the *SL* of the repair process. This latter result is not surprising. As we have already pointed out, in fact, the expected value of the *SPDT* is higher than the contractual target (Table 9). In Fig. 7, we report the mean value of *TD* and the 95 % confidence band for each year. As can be observed, *TD* assumes a value that is remarkably higher for the repair process, especially after the second year. The *TD* of the AOG process, however, is still high, especially after the fourth year.

The simulation data also revealed that the repair requests that were not fulfilled on time were those (and only those) for which ALFA went out of stock. In contrast, AOG requests were often not fulfilled on time even when the spare parts were actually available. However, since stock-outs are rarer in the AOG process, the average delay associated with the AOG requests was usually smaller than that associated with the repair requests.

In sum, ALFA's ability to meet its SLA is compromised by two major issues: first, the excessive time required to transfer parts from the repair station to the nearest airport in the case of AOG; second, the emergence of stock-out situations, which cause a reduction in *SL* and dramatically increases *TD*. The first issue can only be addressed by reducing the transfer time, e.g., by contracting a shorter transfer time with the specialized carriers that actually pick up the devices at the

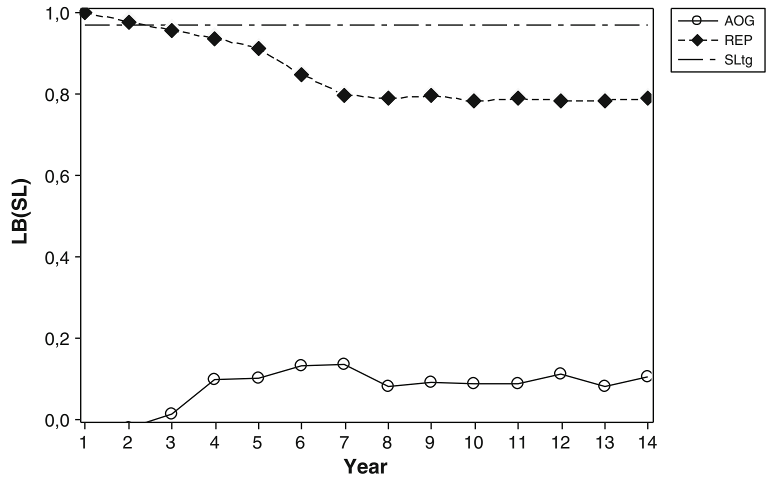


**Fig. 6** Lower bound of the 95 % one-sided confidence interval for the *SL* mean

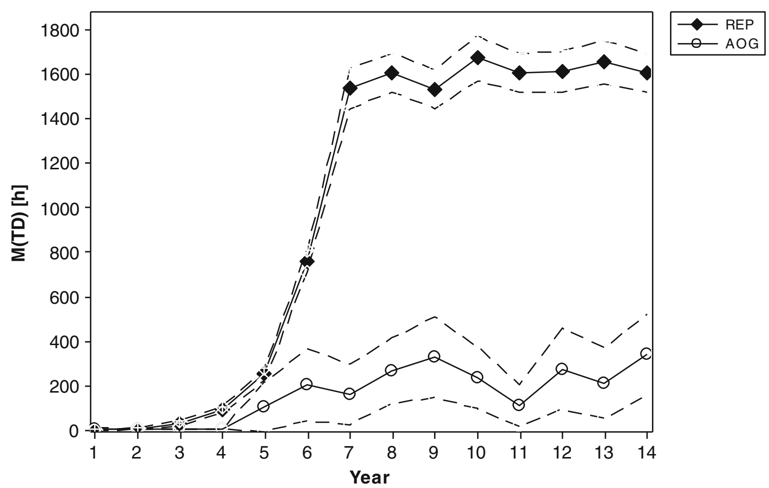


**Fig. 7** Mean and 95 % confidence band for the *TD* mean

service station and bring them to the nearest airport. As we have already pointed out, the time required to bring a part from the service station to the airport can be up to 5 h, although the airports are placed one hour's drive from the service stations. Therefore, there is room for improvement here. In contrast, resolving the second issue requires changing the inventory policies. The definition of optimal inventory policies would require many variables to be taken into consideration (e.g., the failure rates of each type of device, the expected demand for devices from each region, the cost of keeping each type of device in stock, the costs associated with the penalties, etc.), and defining safety stocks, reorder points, etc., for each time period, region, and device. The development of sophisticated inventory models is out of the scope of this study. Nevertheless, in the next section we present a scenario analysis to illustrate how changes in the reorder points and in the transfer time can affect the performance of the repair and AOG processes.

Scenario analysis

In this section we show the results of a scenario analysis where, starting from the AS-IS scenario, we investigate the impact of a reduction of the transfer time and of an increase of reorder point of the maintenance kits *R(Kit)* and of the reorder point of the devices *R(Dev)* on the *SL* and *TD* of both the repair and AOG processes. The analyzed scenarios are summarized in Table 10 and described hereafter.

To improve the performance of the repair process, in the first scenario, we increased *R(Kit)* from 0 to 1 at the beginning of the third year (when the *SL* of the repair process became smaller than 0.97, see Fig. 6). In contrast, in second and third scenarios, we increased the *R(Kit)* from 0 to 1 at the beginning of the third year and from 1 to 2 at the beginning of the seventh year (when the *SL* of the repair process became smaller then 0.8, see Fig. 6). To increase the performance of the AOG process, we reduced the modal and

**Table 10** Scenario analysis: data

| Variables | AS-IS | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| Transfer time | TRIA(1.5, 3.25, 5) | TRIA(1.5, 1.75, 2) | TRIA(1.5, 1.75, 2) | TRIA(1.5, 1.75, 2) |
| R(Kit) | R = 0 | R = 0 from year 1 to 2 | R = 0 from year 1 to 2 | R = 0 from year 1 to 2 |
| | | R = 1 from year 3 to 14 | R = 1 from year 3 to 6 | R = 1 from year 3 to 6 |
| | | | R = 2 from year 7 to 14 | R = 2 from year 7 to 14 |
| R(Dev) | R = 0 | R = 1 from year 1 to 14 | R = 0 from year 1 to 14 | R = 0 from year 1 to 14 |
| | | | R = 1 from year 8 to 14 | R = 1 from year 5 to 14 |

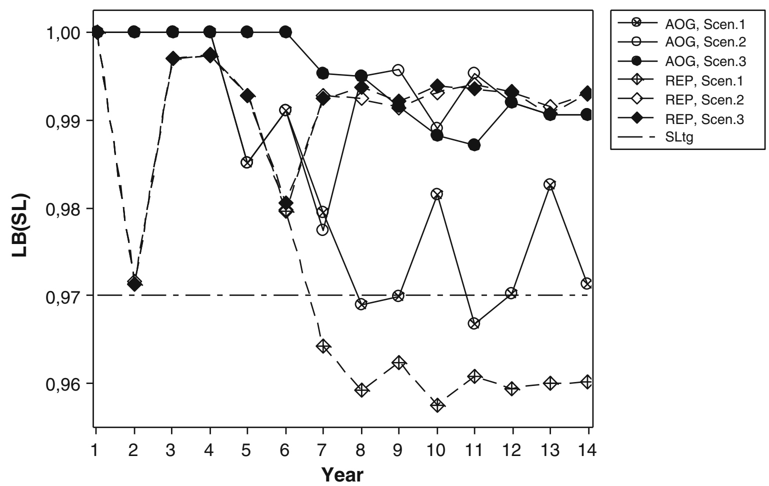


**Fig. 8** Scenario analysis: lower bound of the 95 % one-sided confidence interval for the *SL* mean

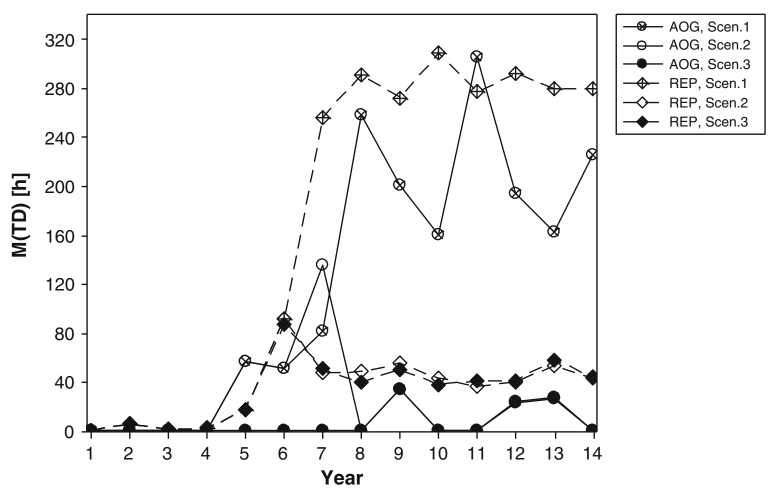


**Fig. 9** Scenario analysis: mean *TD*

maximum value of the transfer time in all three scenarios, which shifted from 3.25 and 5 h to 1.75 and 2 h, respectively. The minimum value of the transfer time was held constant (1.5 h) across all scenarios. These new values of the transfer time have been judged reasonable by ALFA. In addition, in the second and third scenarios, respectively, we increased *R(Dev)* at the beginning of the eighth year (when the *TD* of the AOG process became higher than 250 h, see Fig. 7) and at the beginning of the fifth year (when *TD* became higher than 100 h, see Fig. 7). The results of the scenario analysis are presented in Figs. 8 and 9.

As can be observed, the *SL* of the repair process in the first scenario is significantly higher than 0.97 for only the first six years (Fig. 8). This means that increasing *R(Kit)* only one time, at the beginning of the third year, does not allow a satisfactory *SL* to be obtained after the first 6 years.

**Table 11** Scenario analysis: years when ALFA is expected to achieve unsatisfactory performances

| Variables | AS-IS | Scenario 1 | Scenario 2 | Scenario 3 |
|---|---|---|---|---|
| $TD_{AOG}$ | 5–14 | 5–14 | 5–7 | None |
| $TD_{REP}$ | 5–14 | 7–14 | None | None |
| $SL_{AOG}$ | 1–14 | 8, 9, 11 | None | None |
| $SL_{REP}$ | 3–14 | 7–14 | None | None |

Similarly, by reducing the travel time, but not changing the *R(Dev)* (Scenario 1), we obtain a satisfactory *SL* of the AOG process for only the first seven years. To obtain the desired *SL* for both the repair and the AOG process, it is thus necessary to again increase *R(Kit)* starting from the seventh year and *R(Dev)* starting from the eighth year. In fact, if we consider the second scenario, we notice that the *SL* values of both processes are always significantly higher than 0.97 (Fig. 8). Unfortunately, however, in the second scenario, the AOG process's *TD* assumes mean values of 57, 51, and 136 h in the fifth, sixth, and seventh years, respectively (Fig. 9). Given the emergency nature of the AOG requests, ALFA considers these values to be too high. To address this issue, we increased *R(Dev)* in the fifth year instead of the eighth (third vs. second scenario). By doing so, in addition to obtaining a satisfactory *SL* (Fig. 8), we obtained a mean *TD* (Fig. 7) that was always smaller than 35 h, which is definitely more acceptable. Of course, if compared with that in the second scenario, this latter solution implies a higher inventory investment from the fifth to the seventh year. The results of the scenario analysis are summarized in Table 11. In this table we identify for each scenario, critical process and performance the years when ALFA is expected to achieve unsatisfactory results.

It is worth pointing out, however, that having identified the scenarios (i.e., scenario 2 and 3) where the *SL* of the repair and AOG processes are *disjointedly* higher than 0.97 still it does not allow us to conclude that operating according to these scenarios the *SL* of these processes will be *simultaneously* higher than 0.97. In statistics, when one considers a set of statistical inferences simultaneously, it is not sufficient to ascertain whether the $p$-values $p_i$ of each test are smaller than the desired significance level (e.g., $p < 0.05$). Rather, it is also necessary to verify whether the experiment-wide $p$-value $p_{tot}$ is smaller than the desired significance level (i.e., $p_{tot} < 0.05$). If we perform $n$ independent tests $j$, $p_{tot}$ can be calculated as (Field 2005):

$$p_{tot} = 1 - \prod_{j=1}^{n} (1 - p_j). \tag{2}$$

In our study, to calculate $p_{tot}$, we proceeded as follows. Since we knew that the technical assistance requests were always handled on time (*SL=1, P=0*), to calculate $p_{tot}$, we considered the AOG and repair processes only. For each year $y$, we knew the $p$-values $(p_{REP}(y), p_{AOG}(y))$ of the $t$ tests through which we tested, respectively, whether the *SL*s of the repair and AOG processes were significantly smaller than 0.97. Hence, since these processes are independent, for each year, we computed $p_{tot}$ as:

$$p_{tot}(y) = 1 - [(1 - p_{REP}(y))\, x\, (1 - p_{AOG}(y))]. \tag{3}$$

$p_{tot}$ represents the probability of considering both the *SL*s to be higher than 0.97 when at least one is not. Table 12 reports the mean and the standard deviation of the *SL* for each year and process, as well as the values of $p_{REP}$, $p_{AOG}$, and $p_{tot}$. The table refers to the third scenario.

As can be observed, $p_{tot}$ is always smaller than 0.05. Hence, we can conclude at a significance level of 0.05 that ALFA, operating as described in scenario 3, will be able to

**Table 12** Experiment-wide significance level $P_{tot}$, scenario 3

| Process | Years | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| Repair | | | | | | | | | | | | | |
| Mean(SL) | 1.00 | 0.98 | 1.00 | 1.00 | 0.99 | 0.98 | 0.99 | 1.00 | 0.99 | 1.00 | 0.99 | 0.99 | 0.99 |
| StDev(SL) | 0.00 | 0.04 | 0.01 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 |
| $p_{REP}$ | – | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| AOG | | | | | | | | | | | | | |
| Mean(SL) | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | 0.99 | 1.00 | 1.00 |
| StDev(SL) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.01 | 0.01 |
| $p_{AOG}$ | – | – | – | – | – | – | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| TOT | | | | | | | | | | | | | |
| $p_{tot}$ | – | – | – | – | – | – | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

fulfill all types of service requests with a service level of at least 0.97 for each year.

## Conclusions, limitations and future research

This study suggested that simulation can be a powerful tool to support the design of service delivery systems and to reduce the risks that suppliers face when they sign long-term service contracts. The study also proposed a methodology, based on Monte Carlo simulation, of estimating the yearly failures and therefore the service demand in a context where the installed base evolves dynamically over the time. In this study, such a methodology was successfully employed to verify the (discrete event simulation) submodel, through which we simulated the devices failures and thus the demand for service over time. Such a methodology can be applied in many different contexts to plan the resources (inventory, service staff, support staff, etc.) involved in the service delivery process. For example, it can be used by manufacturers to forecast the warranty costs (Shokohyar et al. 2012) associated with the launch of different batches of products on the market over time. The sale of extended warranties and the adoption of SLA that stretch several years into the future, in fact, are becoming common practices in a growing number of markets (Li et al. 2012; Chen et al. 2012). Consequently, manufacturers and service providers are increasingly more concerned with the medium and long-term consequences of the ageing and growth of their installed base (Jin and Liao 2009). This study, indeed, also gave a detailed account of how the simulation's output can be analyzed to make inferences about the service system's capability to fulfill certain SLA. In addition, this study identified a solution (corresponding to the third scenario) which would allow ALFA to obtain the desired performance. Of course, such a solution is far from being optimal. Identifying an optimal solution would have required, for example, implementing different inventory policies in different regions and for different types of devices. However, the objective of this study was not to find an optimal solution, but rather to show how simulation can help in interpreting the effects that the implementation of certain policies has on service delivery system performance. The analysis, for example, has demonstrated that the inventory policies that ALFA is considering will cause increasing problems starting from the third year. Another limitation of the proposed model is that it is highly tailored to the ALFA case (except for the submodel generating the failures). Hence, the proposed modeling approach can only be adopted to study asset-centric delivery systems like the ALFA one. Such an approach, in fact, it is by no means applicable to model *dispatch-centric* (Aberdeen Group 2005) delivery systems. This latter type of systems, which are quite common in the utility and telecom industries, are characterized by a high number of field technicians, permanently deployed on-field and performing several interventions every day (Aberdeen Group 2005). Dispatch-centric delivery systems need to be modeled taking into consideration the (sophisticated) algorithms used to schedule, dispatch and route the field force. These aspects, however, are not considered in this study.

Despite its limitations, this study can still be expanded in several ways. For example, the simulation model could be used to test the effectiveness of more sophisticated analytical inventory models already available in the literature (Bacchetti and Saccani 2012) or still to be purposely developed. Similarly, it could be used to assess whether satisfactory performance could be obtained by implementing different spare part management policies (Cavalieri et al. 2008; Cheng and Prabhu 2010), e.g., the transshipment of parts between service stations.

## References

Aberdeen Group. (2005). *The mobile field service solution selection report: Strategy and technology selection handbook*. Boston, MA: Aberdeen Group Inc.

Agnihothri, S. R., & Mishra, A. K. (2004). Cross-training decisions in field services with three job types and server-job mismatch. *Decision Sciences*, *35*(2), 239–257.

Bacchetti, A., & Saccani, N. (2012). Spare parts classification and demand forecasting for stock control: Investigating the gap between research and practice. *Omega*, *40*(6), 722–737.

Banks, J. (1998). *Handbook of simulation*. New York: Wiley.

Blumberg, D. F. (1991). *Managing service as a strategic profit center*. New York: McGraw-Hill.

Brintrup, A. M., Ranasinghe, D. C., Kwan, S., Parlikad, A., & Owens, K. (2009). Roadmap to self-serving assets in civil aerospace. In *Proceedings of the CIRP IPS2 conference 2009* (pp. 323–239).

Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, *62*(1), 329–341. doi:10.1016/j.cie.2011.10.003.

Cavalieri, S., Garetti, M., Macchi, M., & Pinto, R. (2008). A decision-making framework for managing maintenance spare parts. *Production Planning and Control*, *19*(4), 379–396.

Chen, X., Li, L., & Zhou, M. (2012). *Manufacturer's pricing strategy for supply chain with warranty period-dependent demand*. Omega.

Cheng, C. Y., & Prabhu, V. (2010). Evaluation models for service oriented process in spare parts management. *Journal of Intelligent Manufacturing*, *23*(4), 1403–1417. doi:10.1007/s10845-010-0486-0.

Cimino, A., Longo, F., & Mirabelli, G. (2010). A general simulation framework for supply chain modeling: State of the art and case study. *International Journal of Computer Science Issue, 7*(2), 1–9.

Field, A. (2005). *Discovering statistics using SPSS* (2nd ed.). London: Sage.

Fishman, G. S., & Kiviat, P. J. (1968). The statistics of discrete event simulation. *Simulation*, *10*(4), 185–195.

Gagliardi, J. P., Renaud, J., & Ruiz, A. (2012). A simulation modeling framework for multiple-aisle automated storage and retrieval systems. *Journal of Intelligent Manufacturing*. doi:10.1007/s10845-012-0686-x.

Harun, K., & Cheng, K. (2010). An integrated modeling method for assessment of quality systems applied to aerospace manufacturing supply chains. *Journal of Intelligent Manufacturing*, *23*(4), 1365–1378. doi:10.1007/s10845-010-0447-7.

Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K., & Young, T. (2010). Simulation in manufacturing and business: A review. *European Journal of Operational Research*, *203*(1), 1–13.

Jin, T., & Liao, H. (2009). Spare parts inventory control considering stochastic growth of an installed base. *Computers & Industrial Engineering*, *56*(1), 452–460.

Kelton, W. D., Sadowski, R. P., & Swets, N. B. (2009). *Simulation with arena*. New York: McGraw-Hill.

Law, A. M. (2006). *Simulation modeling and analysis*. New York: McGraw-Hill.

Lendermann, P., Schirrmann, A., Ping Gan, B., Fromm, H., & Julka, N. (2010). Unlocking value from equipment exchange contracts in aviation using simulation-based optimization. In *Proceedings of the 2010 winter simulation conference* (pp. 2034–2045).

Li, K., Mallik, S., & Chhajed, D. (2012). *Design of extended warranties in supply chains under additive demand*. Production and Operations Management.

Longo, F. (2011). Advances of modeling and simulation in supply chain and industry. *Simulation*, *87*(8), 651–656. doi:10.1177/0037549711418033.

Longo, F., & Mirabelli, G. (2008). An advanced supply chain management tool based on modeling and simulation. *Computers and Industrial Engineering*, *54*(3), 570–588.

MacDonnell, M., & Clegg, B. (2007). Designing a support system for aerospace maintenance supply chains. *Journal of Manufacturing Technology Management*, *18*(2), 139–152.

Manuj, I., Mentzer, J. T., & Bowers, M. R. (2009). Improving the rigor of discrete-event simulation in logistics and supply chain research. *International Journal of Physical Distribution & Logistics Management*, *39*(3), 172–201. doi:10.1108/09600030910951692.

Manzini, R., Ferrari, E., Gamberi, M., Persona, A., & Regattieri, A. (2005). Simulation performance in the optimisation of the supply chain. *Journal of Manufacturing Technology Management*, *16*(2), 127–144.

Montgomery, D. C., & Runger, G. C. (2002). Applied statistics and probability for engineers. New York: Wiley.

Persson, F., & Olhager, J. (2002). Performance simulation of supply chain designs. *International Journal of Production Economics*, *77*(3), 231–245.

Reiner, G. (2005). Customer-oriented improvement and evaluation of supply chain processes supported by simulation models. *International Journal of Production Economics*, *96*(3), 381–395.

Romero Rojo, F. J., Roy, R., Shehab, E., & Wardle, P. J. (2009). Obsolescence challenges for product-service systems in aerospace and defence. In *Proceedings CIRP IPS2 conference 2009* (pp. 255–260).

Safavi, A. (2005). Forecasting demand in the aerospace and defense industry. *Journal of Business Forecasting*, *24*(1), 2–7.

Shokohyar, S., Mansour, S., & Karimi, B. (2012). A model for integrating services and product EOL management in sustainable product service system (S-PSS). *Journal of Intelligent Manufacturing*, 1–14. doi:10.1007/s10845-012-0694-x.

Simao, H., & Powell, W. (2009). Approximate dynamic programming for management of high value spare parts. *Journal of Manufacturing Technology Management*, *20*(2), 147–160.

Stringer, D. B., Sheth, P. N., & Allaire, P. E. (2012). Physics-based modeling strategies for diagnostic and prognostic application in aerospace systems. *Journal of Intelligent Manufacturing*, *23*(2), 155–162.

Terzi, S., & Cavalieri, S. (2004). Simulation in the supply chain context: A survey. *Computers in Industry*, *53*(1), 3–16. doi:10.1016/s0166-3615(03)00104-0.

van der Zee, D. J., & van der Vorst, J. G. A. J. (2005). A modeling framework for supply chain simulation: Opportunities for improved decision making. *Decision Sciences*, *36*(1), 65–95.

Williams, T., Maull, R., & Ellis, B. (2002). Demand chain management theory constraints and development from global aerospace supply webs. *Journal of Operations Management*, *20*, 691–706.

Zhang, D., & Anosike, A. (2012). Modelling and simulation of dynamically integrated manufacturing systems. *Journal of Intelligent Manufacturing*, *23*(6), 2367–2382.