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D24.5

Prototype assessment

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Abstract:	The analysis of real MRO performance and of demand satisfaction in consumer good industry highlights the industrial motivation for collaborative SCM. The prototype application, applied to test case, present suitable functionalities and good performances. The secure cloud SCM system will improve the performance of the whole supply chain.
Keywords:	Pilot case, Prototype application, assessment, benefit simulation

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Executive Summary

This report – the fifth and final deliverable of WP 24 – provides an assessment of the pilot cases and of the prototypes that were implemented for the two industrial pilot cases: the aeronautic fleet management and the consumer goods setting.

The first setting is provided by an aeronautical Maintenance, Repair and Overhaul service provider, industrial partner of DTA (Distretto Tecnologico Aerospaziale) and of University of Salento - CCII (Centro Cultura Innovativa d'Impresa). A number of analysis was carried out on this dataset in order to study the process performance, the troubles and their (potential) causes, and the opportunities for improvements in order to move from a MRO business model to a 'fleet management' service provision. As conclusion we can say that the current process suffers from a lack of collaboration; the reason for this is twofold: for one thing, the supply chain actors are not willing to share data due to fear of misuse or data leakage. For another thing, some data is currently not yet available in the granularity, quality and timeliness that would be required for data-driven collaborative planning.

The second setting is provided by Arcelik AS, a large international manufacturer and retailer, and focusses on their white goods branch, where variable customer demands cause substantial inefficiencies in their supply chain. As conclusion we can say that the current process suffers from poor accuracy in pre-orders provided by Arceliks customers. Our solution tackles this issue by avoiding the manual influence of the customers. Via the secure cloud platform we are able to leverage additional data from the customers for aggregate forecasting without the need to openly access this data.

With our prototypes we achieve reasonable computational performance measures. The initial encryption of realistically sized database on a local machine takes under 14 minutes in the aerospace setting and under 7 minutes in the retail setting. In both settings computation time grows linear in the number of instances. We note that these computational costs could be further reduced by parallelisation. Furthermore, initial encryption of entire database is not a frequent task (typically once a week is enough). The secure evaluation on encrypted data on cloud system is performed much more often and needs much faster response times. Here we achieve in the aerospace setting a time under 5 seconds. The aggregation of up to 8000 encrypted values which is required in the retail settings is done in around 300ms.

The economic evaluation shows promising results for both settings. Both prototypes principally aim at improving forecast accuracy. For each setting we analyse the impact of improved forecast on costs. For the aerospace setting, we can show that a 10% improvement in the forecasts for some categories of spare parts leads to 10.5% cost reduction in combination with a significant increase in customer service level. In the retail setting, we achieve, for some product categories, an effective cost reduction of 8.6% in combination with a significant increase in customer service levels. In addition, for both settings we provide a categorization of parts/products along with a prioritisation with respect to the potential cost reduction achieved by improved forecasting performance.

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Chapter 1 Introduction

In this report – the fifth and final deliverable of WP 24 – we assess the two pilot cases and prototypes that were implemented for both industrial pilot cases. In the subsequent sections of the introduction we revisit the aeronautic fleet management as well as the consumer goods setting. We then proceed, according to the description of work, with evaluating the prototypes with respect to several aspects: the application performances in term of security and of functionalities were measured, while the economic impacts of the collaborative forecast computation models are evaluated in conjunction with the pilot cases analysis. The capabilities and remaining obstacles towards an effective application and acceptance in industries are addressed in Chapters 2.1 and 3.1. Therefore, we analyse current supply chain performances in both industrial settings by exploiting provided datasets. The economic performance is assessed in Chapters 2.2 and 3.3. For this, we apply a benefit assessment simulation tool that was developed by UWUERZ. It models the specific supply chain setting and provides robust estimates for distributions of cost reductions with respect to an improved forecast. The functional performance is covered in Chapter 4. The prototypes' algorithms are tested with different datasets varying in size and complexity. Chapter 5 provides a conclusion and recommendation for industrialization. We provide additional business opportunities of the innovative supply chain models and systems and outline future research and open development issues.

1.1 Industrial scenarios and prototype applications

The two industrial scenarios, which are taken into consideration in this project for secure cloud supply chain management systems, stem from two different sectors; however, they share some common business features that are pushing industrial players in developing innovative SCM models and technologies. The common features are listed below:

- A global, layered and tangled supply chain,
- The need of sizeable customization of supply chain management systems due to specific properties of products (i.e. complexity of configuration) and processes,
- Very expensive flow of products in the supply chain (large quantity of products, quick obsolescence, costly products and costly product handling),
- A widespread awareness that important improvements of business performances are driven by the orchestration of the supply chain system as well as the optimization of local production processes,
- A widespread awareness that automating frequent data flow in supply chain will provide benefits to all participants and will be experienced by end users too,
- A widespread awareness that security is the most challenging obstacle to data flow in the supply chain and to other kind of ICT-based collaboration among customers and suppliers,

In the aeronautical and consumer goods industries (but also in any other industrial contexts sharing the same features) the need of secure cloud supply chain management systems is a pressing matter. The following subchapters carve out the details of each industrial setting.

1.1.1 Aeronautic fleet management

In the aeronautic industry, the specific after-sale service (Maintenance, Repair and Overhaul - MRO) management was selected as pilot case in this project as a number of facts, occurred in the last decade, are pushing players to improve forecasts and planning capabilities and systems:

- **new business model diffused**, it is based on the actual service performance more than on costs sustained to execute the service (performance based contracts), the profit margin of the service provider is strongly related to its capability to forecast demand,
- **huge amount of product data available** (in the most recent aeronautic products) that is improving service forecast accuracy, for example data connected from the engine sensor system during flights,
- **increased complexity of the products**, in terms of configuration and number of parts. This translates into complex after-sale service supply chains, characterized by a big number of spare parts providers and different inventory management policies,
- **increased business competition for incumbents (European) SMEs**, due to new service providers in China, Brazil, India and other low cost States where the aviation industry and business is developing and growing.

Since a long time that the concept of 'fleet management' is used in opposition with that of MRO. The concept of MRO is directly related to the service executed, time after time, by the service provider on a specific product, under the request of the product owner or operator. As the scarce competence of the airlines in managing the health status of the aircraft fleet, and in particular of the engine fleet, more and more responsibility on service execution was moved towards the service provider. Indeed, the concept of 'fleet management' highlights the business role of the service provider towards its whole community of customers and its capability to manage their business needs by directly taking decisions about the (type of) services execution and the spare parts management. The decisions are about which engine or component servicing, when servicing, and which kind of service (repair or replacement). Service cost model changes also, moving from the 'time and resources' used during the service execution to the 'fleet availability' provided by the service provider.

In this business relationship, since the service demand can be foreseen and planned only in part, the profits of the 'fleet management' service provider are directly determined by its capability to forecast the unexpected demand. Forecasts indeed lead decisions about resource and inventory management and related service plans. Forecast capability is based on the availability of updated data about the engine health status, which is confidential and requires slow, monitored and limited flow in the service provider node.

To improve this process, the prototype of secure cloud supply chain management system will manage communication processes between engine operators and service provider, and compute on all health status data by leveraging secure computation technology. It guarantees that private data belonging to several customers and private data belonging to the service provider can be processed altogether without any risks to leak confidential data towards competitors, business partners, or other third parties, SCM system administrator included. The outputs of the computations, demand forecast for future time slots, is input for spare parts purchasing policy and for resource management in the service provider node, as well as the fleet service plans in the customer nodes.

1.1.2 Vendor management inventory for household appliances industry

The household appliance manufacturing industry consists of cooking appliances, laundry appliances, refrigeration, home comfort appliances and the other product groups. Arçelik supplies household appliances to its subsidiaries and direct customers in many markets.

At present, due to the long lead times of approximately 6 weeks all customers have to place pre-orders. Arcelik’s supply chain, purchasing and production management departments work in coordination to allocate or to place pre-orders to components suppliers, to make necessary capacity reservations in Arçelik’s various plants and warehouses based on the ordered product groups and reserve necessary capacity with transport and service providers. The customers place their binding real orders about four to eight weeks after their pre-orders. There are significant deviations between pre-orders and binding real orders in product groups and markets. There are various reasons for these deviations:

1. volatile market situations which cause fluctuation in demand;
2. customers have not enough resources or capacity to make proper forecasting;
3. some customers intentionally keep high pre-orders to guarantee their actual orders on time.

The deviations between pre-orders and binding real orders bring many additional cost to Arçelik and thus the vendor management inventory approach will reduce these unnecessary cost, up to an acceptable level.

Arcelik has selected and provided data set covering two years period for over 1800 different products which are identified by SKUs (stock keeping units) to test vendor management inventory approach in household appliances industry. The data set includes inventory levels and sales numbers on a monthly basis for two years duration.

The provided data set is analysed to select products for the applicability of vendor managed inventory approach. Thus, the products to be selected have to be sold to two or more customers in the same area/region to apply secure vendor managed inventory approach. After the analysis four products were selected with typical characteristics in terms of margin, demand volume, demand irregularity and cost structure to test in vendor managed inventory approach.

Chapter 2 Fleet management

2.1 Description of the case study (MRO Programme JT8D)

In this section, we focus our attention on a dataset extracted from the MRO service provided by an aeronautical Maintenance, Repair and Overhaul service provider, industrial partner of DTA (Distretto Tecnologico Aerospaziale) and of University of Salento - CCII (Centro Cultura Innovativa d'Impresa). Numerous analysis were carried out in order to study the process performance, the related issues and their (potential) causes, and the opportunities for improvements to remain profitable moving from a 'time and material' cost definition to a 'fleet management' service provision.

Before describing the dataset and the analysis, for completeness and clarity reasons, a brief overview on the main activities related to the Maintenance, Repair and Overhaul process is provided (Figure 1).

The MRO process starts at the arrival and the storing of the engine to be serviced. It follows the macro-activity Non Destructive Inspection, which includes engine disassembling, cleaning, non-destructive tests (NDT) and accurate inspection for all components. At the end of this phase, for each engine part, it is decided how to proceed: repair, replacement, or re-assembly in the case it recognized as a 'good one' (thus it is stored in the warehouse, waiting for next assembly task). Once all components (new, repaired, and the good ones) are available for kitting, the assembly task starts. Before being given back to the airline/air force owner, the engine is tested to obtain all quality certifications.

More detailed information of the process are available in Deliverable 24.2 – Business modelling.

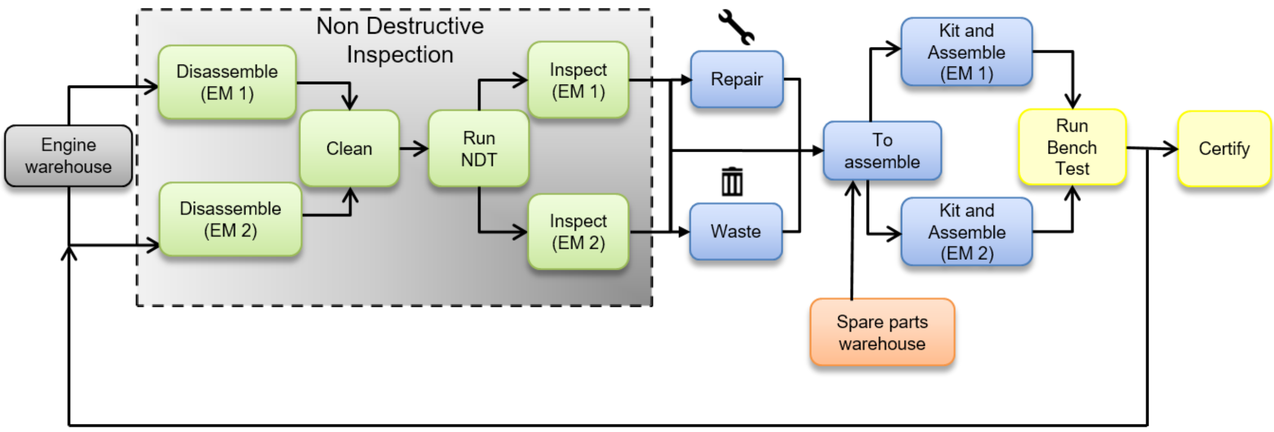

Figure 1. Engine MRO process model.

2.1.1 Dataset

The dataset provided by the MRO Service Provider collects data on MRO events on the Pratt & Whitney JT8D[1] engine family, in a time span of 8.7 years (from March 1998 to October 2006). The selected pilot case is representative of a wide part of the market being characterized by the following features:

1. Health data not directly available to the service provider (in part they are not available at all due to missing sensor, in part because they are not digitally managed),
2. Numerous airlines manage that engine model,
3. It is an old product, but yet produced, so that there are several SMEs (usually assemblers of main modules) competing in the service provision market.

The JT8D is a highly durable and reliable engine: it has completed more than 673 million dependable flying hours since entering service. The first application of the JT8D was in 1963 within a Boeing 727; since that date, more than 14.750 JT8D engines have flown (among these there are engines belonging to the standard JT8D family and updated programs, such as JT8D-200, JT8D-217 and -219). Today, 2.400 JT8D engines are in use, and their major applications are in Boeing 727, Boeing 737-100/-200, McDonnell Douglas DC-9, and McDonnell Douglas MD-80.

The Company provides the MRO service for a number of customers whose fleet goes from few to a quite large number (about 200 engines) of engines. The Company has serviced the following JT8D models: JT8D-15, JT8D-15A, JT8D-17, JT8D-17A, JT8D-217, JT8D-217A, JT8D-217C, JT8D-219, JT8D-7B, and JT8D-9A. The difference is in the specific engine configuration and regards minor parts. Actually it doesn't affect the conclusion of this study.

The dataset was created by the Service Provider and contains data about the serviced engine. Data were entered manually in the ICT system of service provider company as the engine arrives in the plant; this means that these data (as well as any other data related to health status of the engine) are not available in advance to compute any demand forecast. The main motivation is the confidentiality of that data, as discussed in D24.1 and D24.2. In particular, for each serviced engine, uniquely named with a specific Serial Number (SN), some data describing the status of the engine and some data describing the timeline of the process are connected. The following parameters are reported[2] in the dataset:

- *Engine Owner (EO)*: the code identifying the owner/operator of the engine.
- *Date of the Event (attribute name: DATEVE):* date in which the MRO service provider records the event related to the engine shop visit[3]. In this date, the engine arrives into the MRO plant and the service provider starts planning the next activities to carry out on it.
- *Date In Workshop (DATINWOR)*: date in which the engine comes into the MRO workshop.

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[1] Here the product section on the Pratt and Whitney web portal: http://www.pw.utc.com/JT8D_Engine

[2] Actually, the dataset contains few more data identifying engines on a global basis, which are not reported here to save privacy. However, this does not reduce the validity of the analysis. Moreover, all data pointing to individual engines and the engine owner were obfuscated.

[3] A shop visit is classified as removal whether the subsequent engine maintenance performed prior to reinstallation entails separation of pairs of major mating flanges, or removal of a disk hub or spool (Ackert S., "Basics of Aircraft Maintenance Reserve Development and Management", Aircraft Monitor, http://www.iata.org/whatwedo/workgroups/Documents/Paperless%20Supply%20Chain/Basics-AC-MR.pdf).

- *Date Out Workshop (DATOUTWOR)*: date in which the engine leaves the MRO workshop.
- *Type of task (CODTSK):* four different types of tasks are performed during the engine shop visit; they are: general inspection (U); repair (P); test bench (T); and visual inspection (Z).
- *Date of Order Creation (DATCREORD)*: date in which the activities to be performed on the engine are approved[4]. Since that date, the MRO operations can start.
- *Start-Date of the Activities (STARTDATWIP)*: date in which the MRO service operations on the engine really start.
- *End-Date of the Activities (ENDDATWIP):* date in which the MRO service operations on the engine are really completed.
- *Total Flight Hours (TOTHOURS)*: total engine flight hours, at the moment of the shop visit.
- *Total Flight Cycles (TOTCYCLES)*: total engine flight cycles, at the moment of the shop visit.
- *Hours from last general inspection (HOURGEINS)*: engine flight hours from the last general inspection task, at the moment of the shop visit.
- *Cycles from last general inspection (CYCGEINS)*: engine flight cycles from the last general inspection task, at the moment of the shop visit.
- *Hours from last service not of general inspection (HOURLASTASK)*: engine flight hours from the last not general inspection service (what it was), at the moment of the shop visit.
- *Cycles from last task not of general inspection service (CYCLASTASK)*: engine flight cycles from the last not general inspection service (what it was), at the moment of the shop visit.

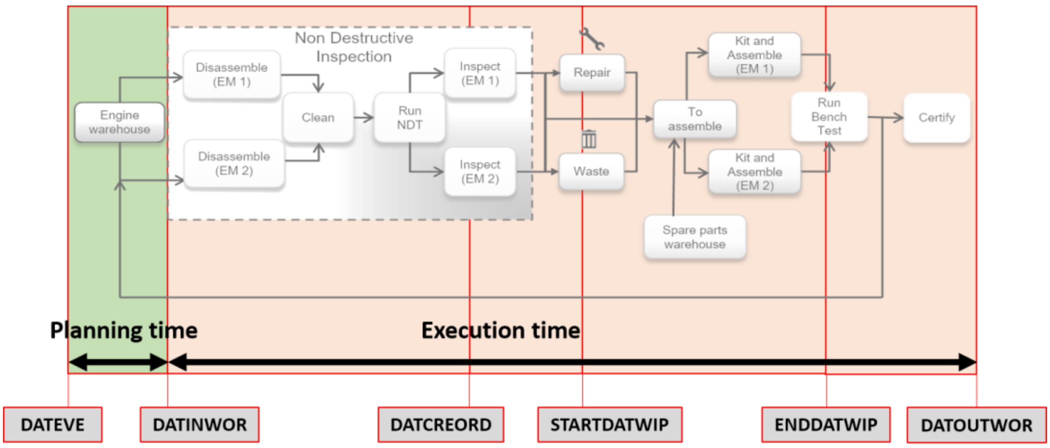

Figure 2. Dates recorded for each service event.

[4] In the 'Time and Material' business relationship, the customer has to approve the maintenance activities and the replacement identified during the inspection.

In order to make clearer the sequence of the dates recorded in the dataset, in the Figure 2 all dates are depicted in relation to the MRO process. It is possible to recognize two phases:

1. **Planning phase**: the time spent by the engine in the MRO warehouse waiting for it being serviced, and computed as the difference between DATINWOR and DATEVE;
2. **Service execution phase**: the time spent by the engine in the MRO workshop, it was computed as the difference between DATOUTWOR and DATINWOR in the dataset.

The sum of planning and execution times is the time necessary to fulfil the engine MRO demand (Turn Around Time, TAT). Figure 3 shows that the planning and execution phases are independent each other, since no correlation between the two time periods is evident.

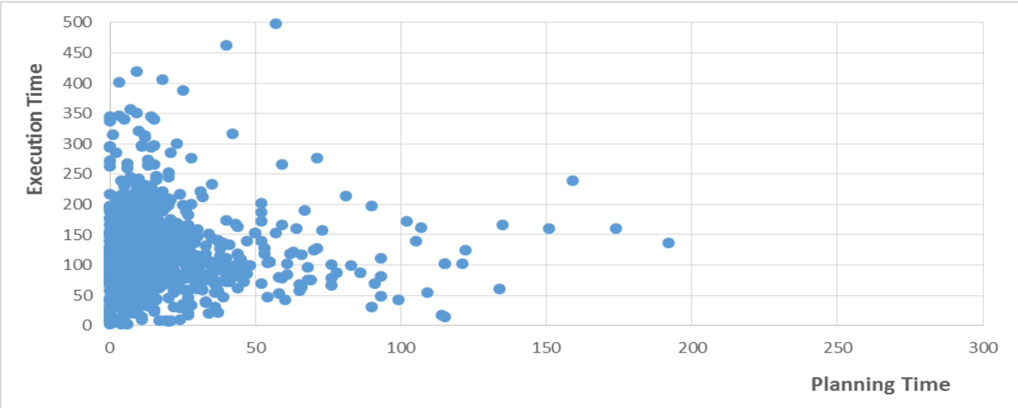

Figure 3. Relation between planning and execution phases.

The dataset provided by the Company contained initially 1.068 service events. The great majority of the service events (999 events) are of ‘repair’ type; they are followed by ‘general inspection’ events (55), and by ‘visual inspection’ and ‘test bench’[5] ones, which are respectively 10 and 4 events (see Figure 4).

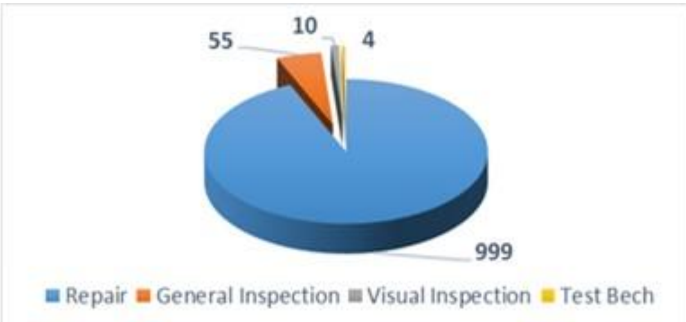

Figure 4. Share of all MRO events.

[5] Visual inspection and test bench are specific services required by customers when the troubles of the engine are not immediately recognizable; moreover, in some case, they are managed separately with respect to the possible other tasks due to administrative constraints.

Since visual inspection and test bench events are numerically negligible compared to repair and general inspection ones, as well as having a low impact on the overall execution times of the process, they are not considered in our following analysis.

Moreover, during the analysis on repair and general inspection subdatasets, 14 events inconsistently reported were recognized and eliminated; furthermore other MRO events contains partial inconsistent data. The inconsistency is motivated by the following facts:

1. The event is represented by not valid data;
2. Two different data entries for the same engine at the same period. For example, the engine is delivered to the MRO service provider with a specific motivation (for example inspection of a part), but during the service a new trouble (need of repair) was recognized;
3. Data are clearly not consistent with the history of the engine (total flight hours or cycles) that can be recognized in the dataset.

In that case the event was not definitively deleted, on the contrary the correct data were used in specific analysis. Such inconsistencies are motivated by the fact that data is entered manually by operators, so a certain number of human errors are introduced.

In the dataset prepared for the analysis, there are 468 engines, belonging to 37 different engine owners (see Figure 5). Many of the engines were subjected to more than one shop visit, the highest number of shop visits being 8 (only for one engine). The Engine Owner 4 (EO4) owns 269 engines; the EO20 owns 41 engines, both EO8 and EO37 owns 29 engines; while, the remaining part of the fleet (100 engines) is divided among all other 33 Engine Owners.

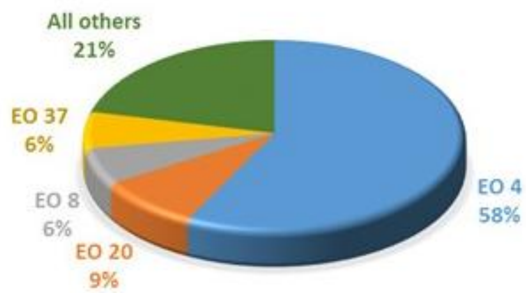

Figure 5. Distribution of the fleet in the customer community.

2.1.2 Introduction to the analysis

The aim of the analysis is to evaluate the planning and execution times of the MRO service process, and to analyse the MRO process predictability.

In particular, in the subsections 2.1.2.1 and 2.1.2.2 below, the impact of the fleet size on the service performance will be investigated. For example, we will examine whether service planning and execution timetables change with respect to the performed service, or to the customer's fleet size. In order to carry out this analysis, four different subgroups of data will be considered (see Table 1):

- **DG1**, which includes all Repair events of the dataset;
- **DG2**, which include all General Inspection events of the dataset;
- **DG3**, which includes all Repair and General Inspection events in the dataset associated with the EO4 fleet;
- **DG4**, which includes all repair and general inspection events in the dataset associated with the EO20 fleet.

Repair and General Inspection are the event types with the highest number of events in the database; in the same way, EO4 and EO20 are the two engine owners with the biggest fleet.

Data group name	Group description	Group size
DG1	Total number of repair events	992 events
DG2	Total number of general inspection events	48 events
DG3	Total number of repair and general inspection events associated with the EO4 fleet	632 events
DG4	Total number of repair and general inspection events associated with the EO20 fleet	89 events

Table 1. Data groups – Planning and execution times.

In the subsection 2.1.2.3, instead, we will analyse the relationship between engine Total Flight Hours and Cycles, and the date of the shop visit. This study was conducted on all engines with more than two shop visits, in order to find out (if any) the conditions triggering a shop visit. In this case, four subgroups of data will be taken into consideration (see Table 2):

- **DGa**, which includes all engines in the dataset with three repair and/or general inspection events;
- **DGb**, which includes all engines in the dataset with four repair and/or general inspection events;
- **DBc**, which includes all engines in the dataset with five repair and/or general inspection events;
- **BDd**, which includes all engines in the dataset with six repair and/or general inspection events.

Data group name	Group description	Group size
DGa	Total number of engines with three repair and/or general inspection events	95 events
DGb	Total number of engines with four repair and/or general inspection events	49 events
DGc	Total number of engines with five repair and/or general inspection events	21 events
DGd	Total number of engines with six repair and/or general inspection events	3 events

Table 2. Data groups - Process predictability.

As part of the preliminary analysis, the frequency distribution of actual service demand for month and of TAT are depicted in Figure 6 and Figure 7, respectively. The first graph shows that the customers' demand is not stable over time (there are a number of peaks and troughs); it is expected that periods of under-utilization of human and technical resources follow periods in which demand exceeds the service capacity. On the contrary, TAT distribution is an evidence that 69% of values appear between 80 and 185 days. Moreover, higher TAT values can be also observed. The high values of mean, median and standard deviation of TAT distribution are specified in Figure 7.

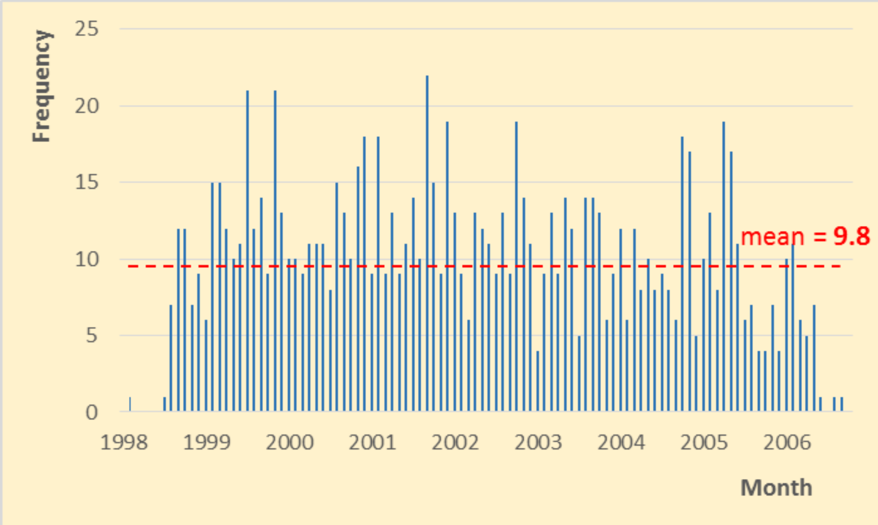

Figure 6. Overhaul demand per month.

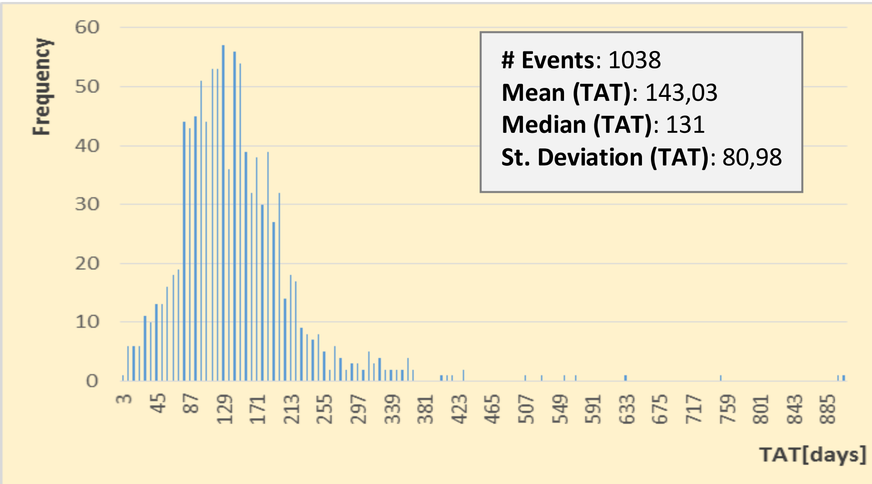

Figure 7. Distribution of TAT to fulfil the overhaul demand.

2.1.3 Planning time

In the analysis, it is assumed that the time spent by the engine in the Company's warehouse, waiting for it being serviced, is the time required by the Company to plan the service itself, that is to assign the task to resources and plan for spare spare provision. For this reason, this will be considered the *planning period*.

The analysis on the planning time period (in the following named PT) aims to investigate the possible correlation between time necessary to plan the next activities on the engine and the type of event to be performed in the engine shop visit, or the fleet size of the engine owner. As a consequent, the PT is analysed referring to DG1, DG2, DG3 and DG4. For each data group, the frequency distribution of the planning times is measured, and the values of the median, mean, and standard deviation[6] are computed[7].

It is important to emphasize that, for the planning time analysis, a number of events for each data group were not considered, due to inconsistent values for the attributes DATINWOR and DATEVE. These events are included in other analysis conducted on the dataset, since values for the other attributes are correct and coherent.

DG1 analysis

DG1 consists of 973 data entries related to all repair events in the dataset, in a time frame of about 9 years (from 1998 to 2006). As mentioned before, this group was cleaned from 19 inconsistent events, due to clear errors in the manual transcription of data related to DATINWOR and DATEVE attributes. The Figure 8 shows the frequency distribution of PT. Moreover, the values of the mean, median and standard deviation of the entire data group are provided. Although the range of values for the planning time is quite broad (from 0 to 494), the majority of them (953 events) fall between 0 and 33 days. To understand better the shape of the graph, in Figure 9 we show only part of the frequency distribution with planning time less than 90 days (PT'').

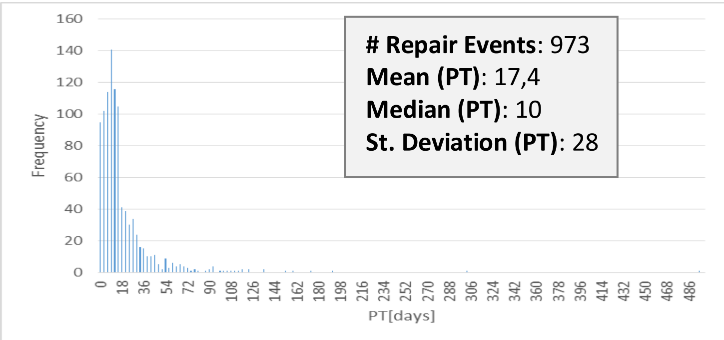

Figure 8. PT distribution - DG1.

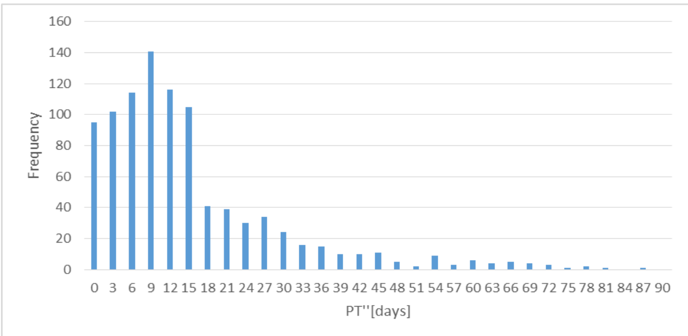

Figure 9. PT'' distribution - DG1.

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[6] The mean summarizes the whole (sub) dataset in a single value, giving a fairly good idea about it; the median represents the middle value of the (sub) dataset: it separates the higher half of the data sample from the lower one; at last, the standard deviation provides the measure of dispersion of values in the dataset.

[7] Computations were executed using the functionalities of MSExcel tool.

DG2 analysis

The second group, DG2, collects all 43 general inspection events in a time frame from 1998 to 2004. This group was cleaned from 5 new inconsistent data, due to clear errors in the data manual transcription for DATINWOR and DATEVE attributes. Figure 10 shows the frequency distribution of PT, and the values of the mean, median and standard deviation of the entire data group.

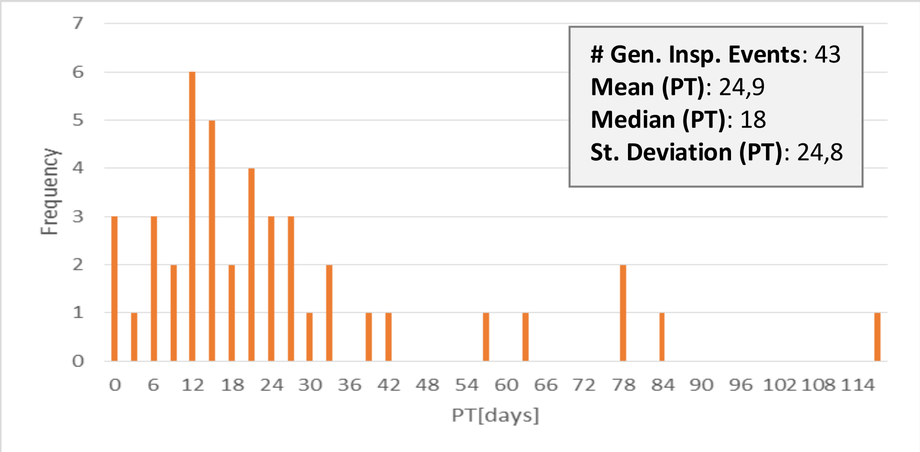

Figure 10. PT distribution - DG2.

DG3 analysis

DG3 refers to all repair and general inspection events associated with EO4 fleet. In this data group, the number of data rows considered is 622 (ten inconsistent data). The Figure 11 below depicts the frequency distribution of PT, and the values of mean, median and standard deviation of the data sample in exam. As in DG1, the range of values for the planning time is here rather broad (from 0 to 301); however the majority of values (604 events) fall between 0 and 36 days. With the aim to better understand the graph shape, in Figure 12 only the part of the frequency distribution with planning time less than 90 days (PT'') is showed. Even in this case, based on 615 repair events, mean, median and standard deviation values were calculated.

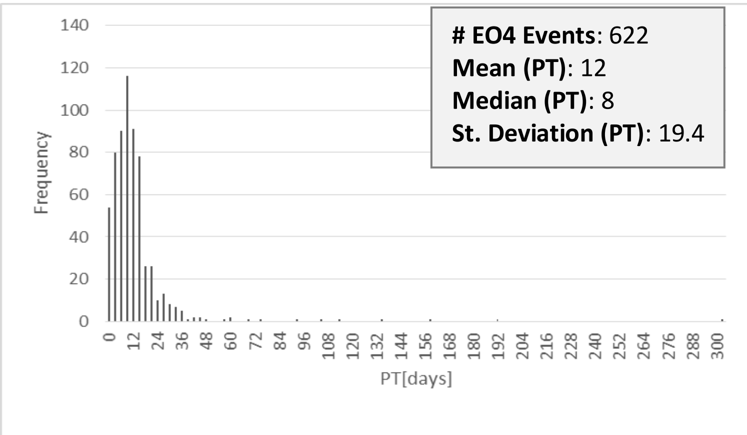

Figure 11. PT distribution - DG3.

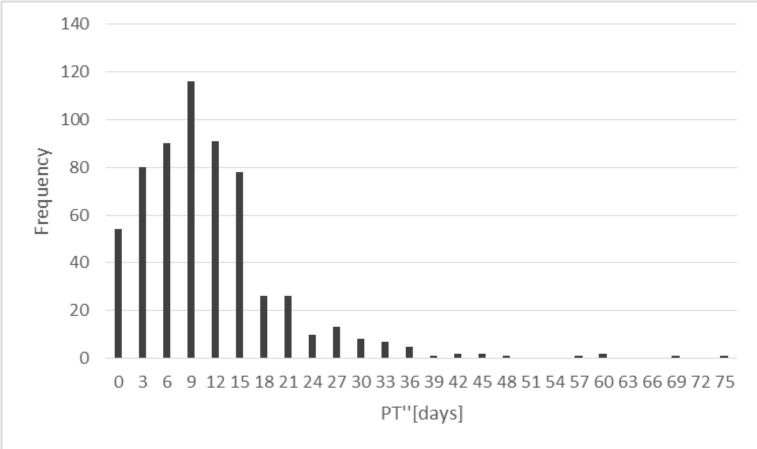

Figure 12. PT’’ distribution – DG3.

DG4 analysis

At last, DG4 refers to all repair and general inspection events associated with EO20 fleet. This group collects 86 events in 8 years time frame (from 1998 to 2005). Only three of them are reported with inconsistent data. In Figure 13, PT distribution of frequency, as well the values of the mean, median and standard deviation are shown.

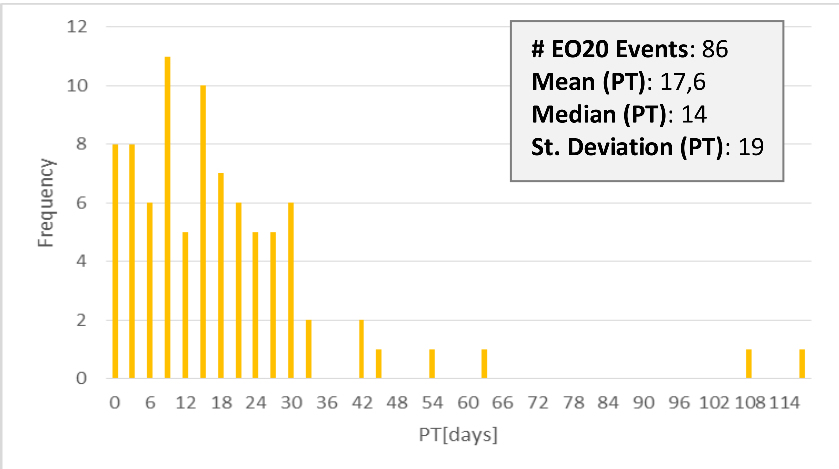

Figure 13. PT distribution - DG4.

Data groups’ comparison

In this part, mean, median and standard deviation of the previous data groups are compared, in order to analyse the relation between the time necessary to plan the engine shop visit, and the type of event that will be performed during the shop visit, or the fleet size of the engine owner (see Figure 14, Figure 15 and Figure 16). Mean and median values show performance of the planning process are better in the case of repair events than general inspection one, and in the case of the engine owner with the largest fleet (EO4 VS EO20). These results can be justified respectively by the higher urgency associated with maintenance (repair) events generally, and by the higher pressure that the engine owner with the largest fleet is able to play on the service provider.

Standard deviation shows a quite similar dispersion of values in the case of repair and general inspection events, and for the EO4 and EO20; the difference being justified by the different dimension of the subdataset.

Table 3 collects mean, median and standard deviation values for DG1, DG2, DG3 and DG4.

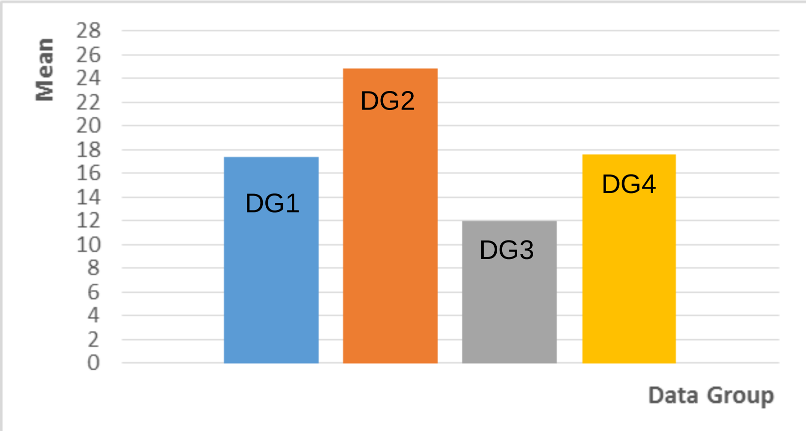

Figure 14. Mean comparison.

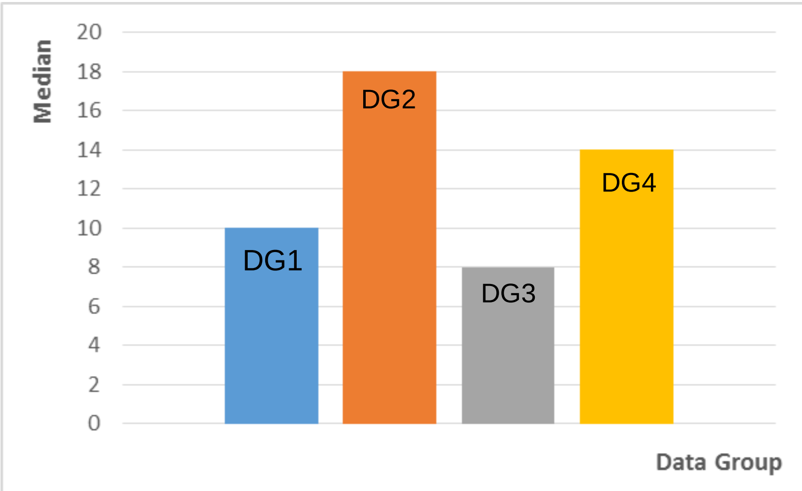

Figure 15. Median comparison.

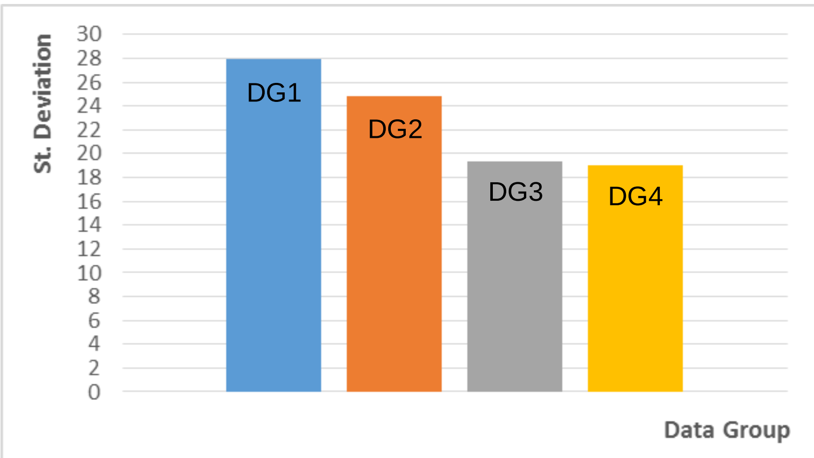

Figure 16. Standard deviation comparison.

	DG1	DG2	DG3	DG4
Mean (PT)	17.4	24.9	12	17.6
Median (PT)	10	18	8	14
St. Deviation (PT)	28	24.8	19.3	19

Table 3.Mean, median and standard deviation of planning time – DG1, DG2, DG3 and DG4

2.1.4 Execution time

The service execution time of the MRO process is evaluated through the measurement of the time spent by the engine in the MRO workshop.

The goal of this subsection is to understand whether the service execution time (in the following named ET) changes in function of the event type performed during the engine shop visit, or with respect to the fleet size of the engine owner. In order to achieve these goals, the execution time, as it has happened for the planning time, was analysed considering DG1, DG2, DG3 and DG4. For each data group, the frequency distribution of the execution time was defined, as well as the values of median, mean, and standard deviation of the sample.

DG1 analysis

The first data group, DG1, consists of 992 events. Its big size allows us to study the change of the values with time. For that reason, G1 was split in five subgroups, each of them spanning over two years. The following graphs (Figure 17 - Figure 21) show ET distribution within all the different periods. Moreover, for each distribution, the values of mean, median and standard deviation are reported.

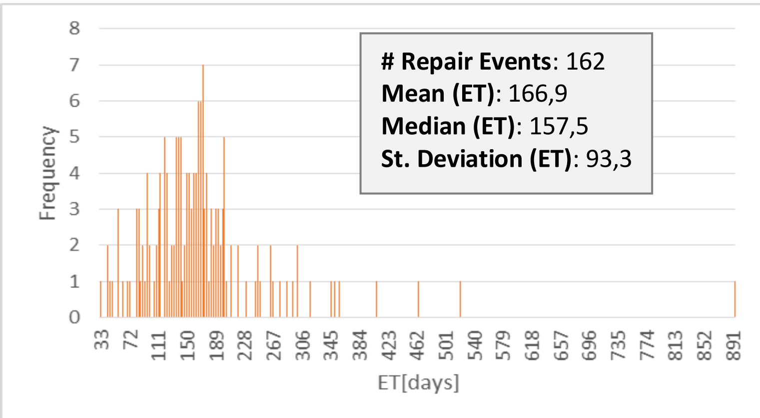

Figure 17. ET distribution of DG1 (1998-1999).

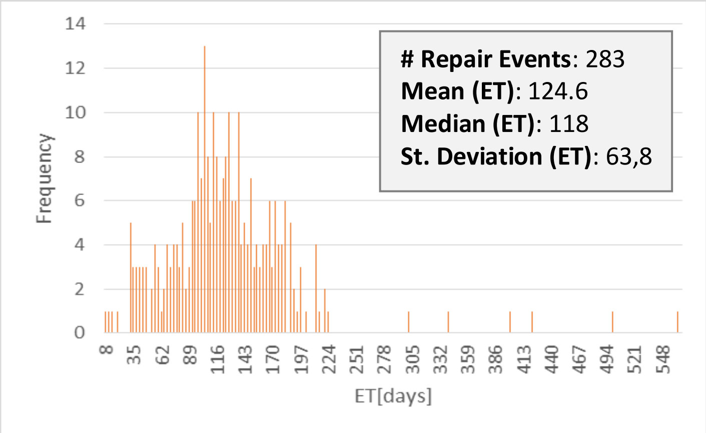

Figure 18. ET distribution of DG1 (2000-2001).

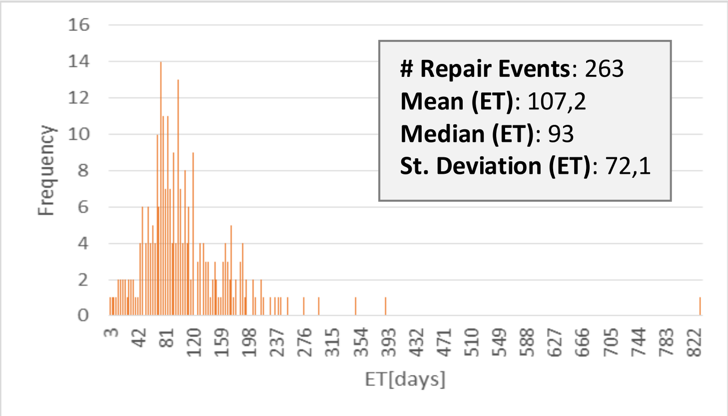

Figure 19. ET distribution of DG1 (2002-2003).

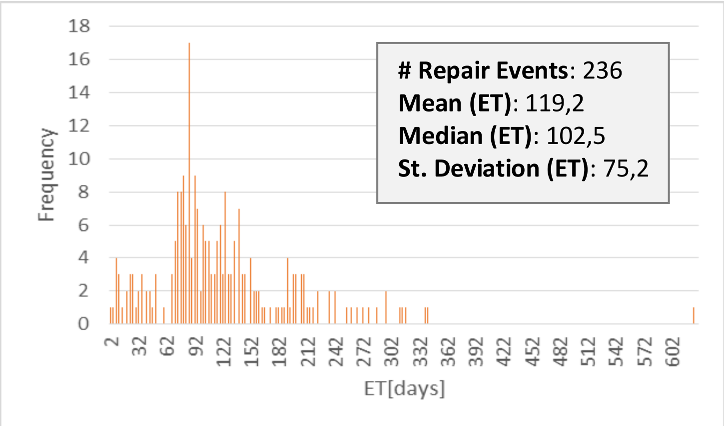

Figure 20. ET distribution of DG1 (2004-2005).

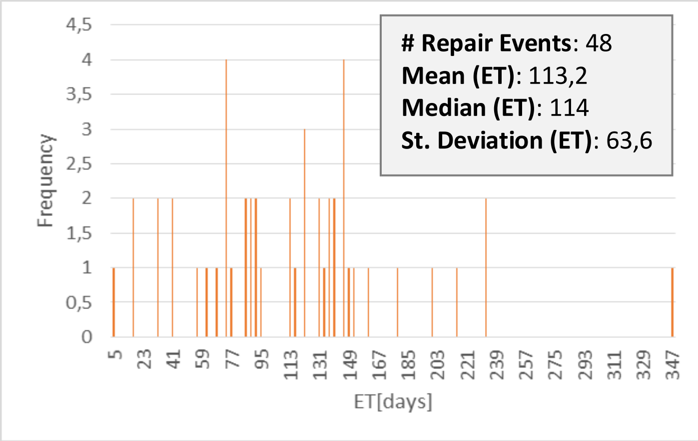

Figure 21. ET distribution of DG1 (2006).

In Figure 22, the values over time for median, mean and standard deviation computed in all two-year periods are depicted. The graph shows the median and mean decrease from 1998 to 2003, after which it stabilizes. This trend means that from 1998 to 2003 relevant improvement in the process management was achieved, in the next period instead there were no significant changes in the process performance.

Standard deviation, instead, although characterized by lower changes in value over time, assumes quite high values (between 64 and 93 days); this means that the variability of the service process is very high. The variability of the process can be justified in part by the fact that modules to be repaired or replaced are identified during the process, and in part by scarce information on the service demand and on the status of the engine. Both information, indeed, impacts on the capability to plan the service and spare parts provision. The impact of forecast capabilities on the inventory management policy and costs is further discussed in the section 2.2.

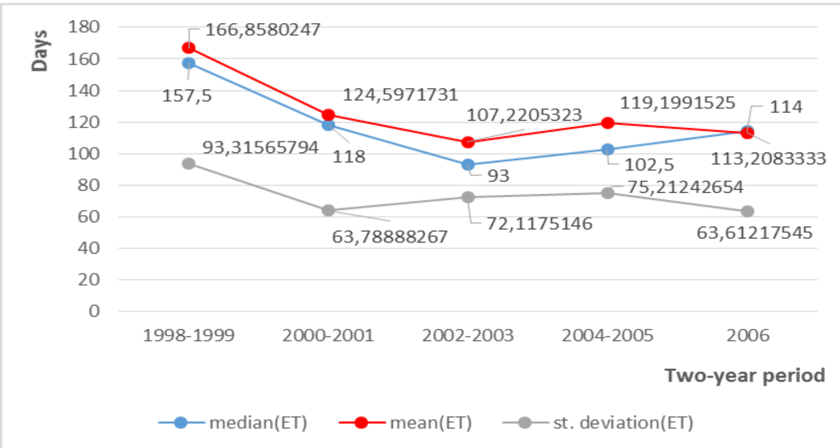

Figure 22. Comparison of mean, median and standard deviation - DG1.

DG2 analysis

The second group, DG2, collects all 48 general inspection events. This group spans over a shorter time frame: from 1998 to 2004. In order to have a statistical relevance of the data sample, ET distribution is not split in two-year periods (see Figure 23).

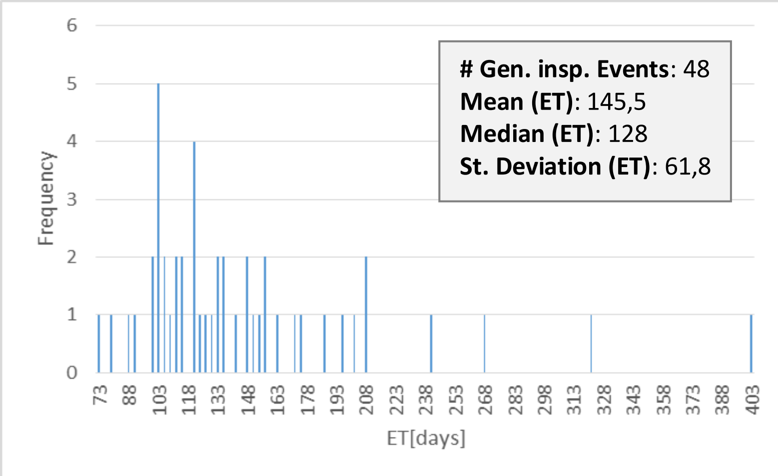

Figure 23. ET distribution of DG2 (1994-2004).

In the following graphs (Figure 24, Figure 25 and Figure 26), the attributes of ET distribution (mean, median and standard deviation), associated with DG1 and DG2, are compared. Moreover, the grey dotted line, named DG2', comes to show how the line associated with DG2 would be if the highest data in the sample (ET=401) was not in the dataset. It is important to underline that such a high value does not depend on the process execution, but is related to business issues in the customer-supplier relationships. In DG2, which consists of a few number of events, the presence of a high data affects the trend of the line.

If the ET=401 is not considered, no significant differences in the performance of the two type of service (repair and general inspections) appear, in particular in the second half of the analysed period (from 2002 to 2006). This result authorized authors to state that the service provider tries to manage homogeneously the two services. This implies also that we are right in managing the two case together.

On the contrary, as the two event's type are quite different in their motivations (ordinary after-sale service against unexpected damage or engine underperformance) and in the forecast opportunities (leveraging private data connected by the engine owner), it should be expected that general inspections events were better planned leading to a quicker service.

Regarding to standard deviation values, instead, they follow a more regular trend in DG1 than in DG2, where a visible peak in 2002-2003 appears; actually, this is not very significant since only six events belong to that two-year period and, deleting the mention of high ET value from the dataset allows for a more aligned value to be obtained.

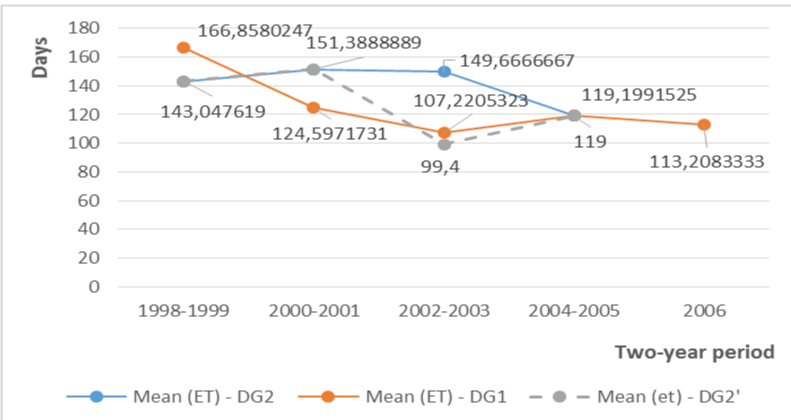

Figure 24. Comparison between DG1 and DG2 - Mean.

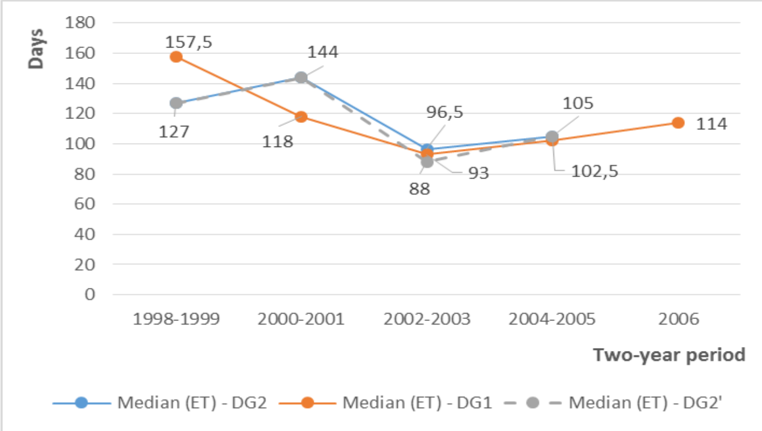

Figure 25. Comparison between DG1 and DG2 - Median.

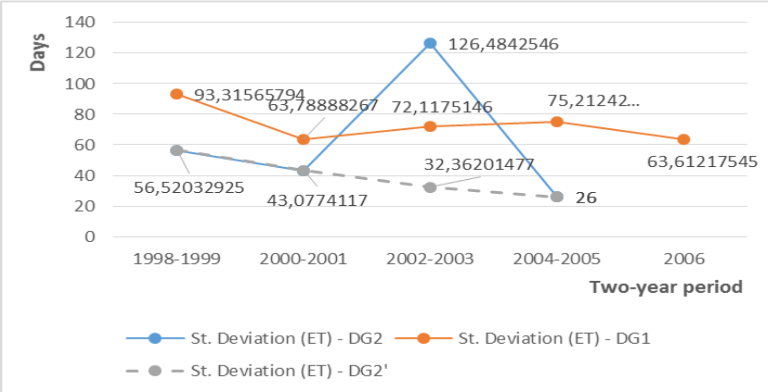

Figure 26. Comparison between DG1 and DG2 - Standard deviation.

DG3 analysis

As said above, DG3 refers to all repair and general inspection events associated with EO4 fleet, which is the biggest fleet (269 engines) in the dataset.

In this data group, the number of events is high (632), so that ET distribution can be analysed on a two-year periods (see Figure 27 - Figure 31).

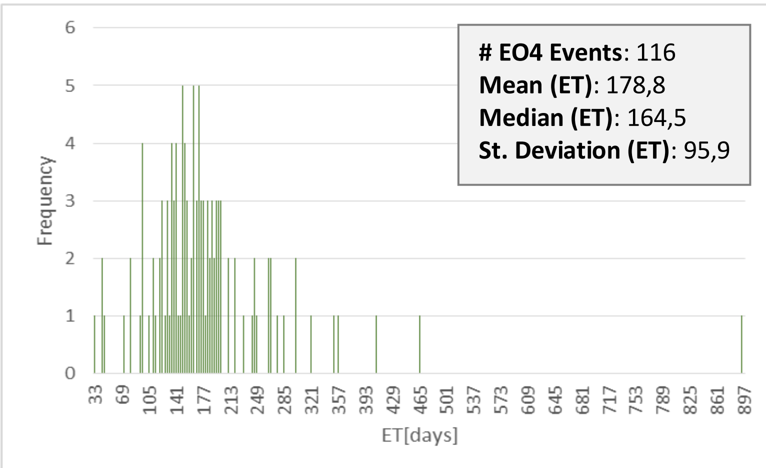

Figure 27. ET distribution of DG3 (1998-1999).

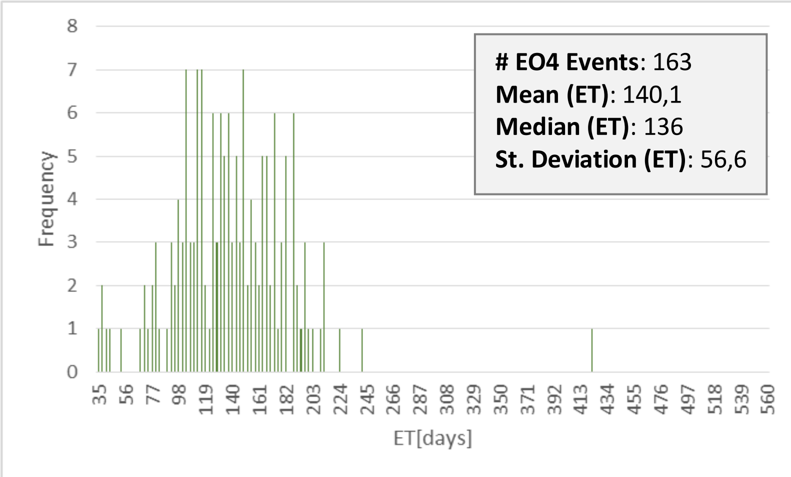

Figure 28. ET distribution of DG3 (2000-2001).

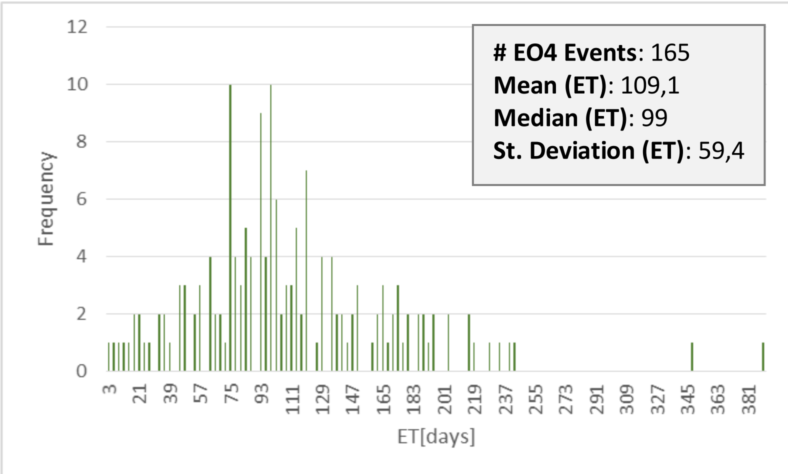

Figure 29. ET distribution of DG3 (2002-2003).

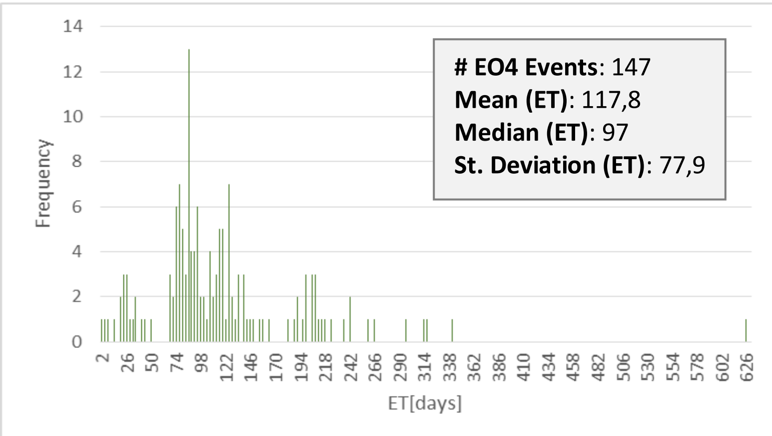

Figure 30. ET distribution of DG3 (2004-2005).

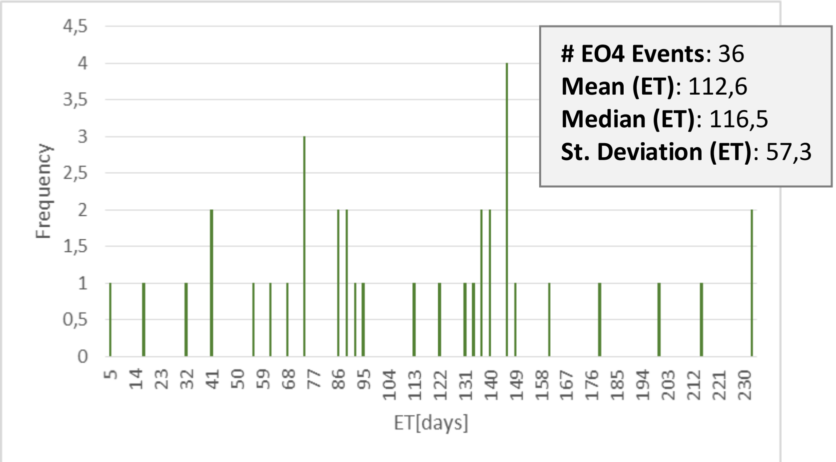

Figure 31. ET distribution of DG3 (2006).

In Figure 32, values of mean, median and standard deviation of ET distributions are depicted. As it could be expected, the ET trend over time of DG3 is similar to that of DG1: median and mean decrease from 1998 to 2003, then stabilize from 2004 to 2006; standard deviation has a more regular trend, even though assumes quite high values (between 57 and 98 days). This is because the great majority of the engine shop visits are of repair type.

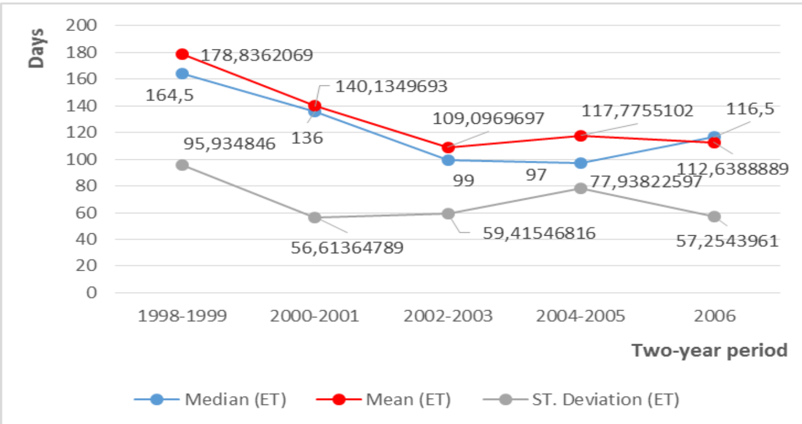

Figure 32. Comparison of median, mean and standard deviation - DG3.

DG4 analysis

DG4 refers to all repair and general inspection events associated with EO20 fleet, which is the second biggest fleet in the dataset (41 engines).

This group collects 89 events in 8 years of time frame (from 1998 to 2005). In Figure 33, ET distribution, as well the values of mean, median and standard deviation are shown.

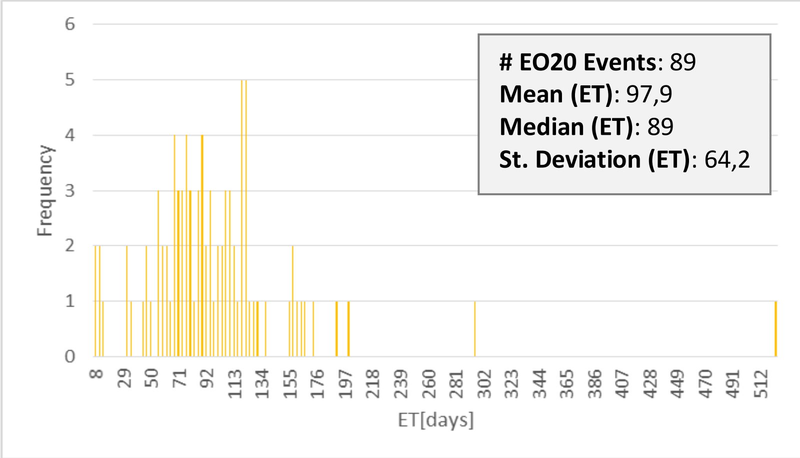

Figure 33. ET distribution of DG4 (1998-2005).

The graph comparing the values of mean, median and standard deviation computed on the DG3 and DG4 (Figure 34, Figure 35 and Figure 36) show that lower values (that is better service performance) are associated with lower fleet. In our opinion, this result depends more on the lower number of 'exceptional' events, leading to service delay, that occur in a smaller fleet than on a specific service policy.

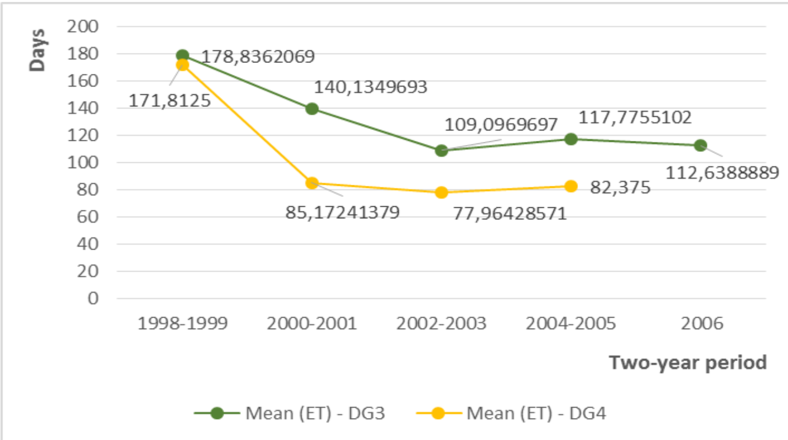

Figure 34. Comparison between DG3 and DG4 - Mean.

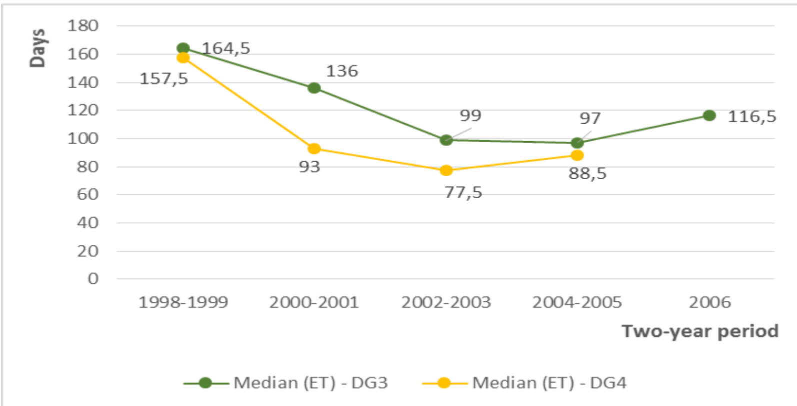

Figure 35. Comparison between DG3 and DG4 - Median.

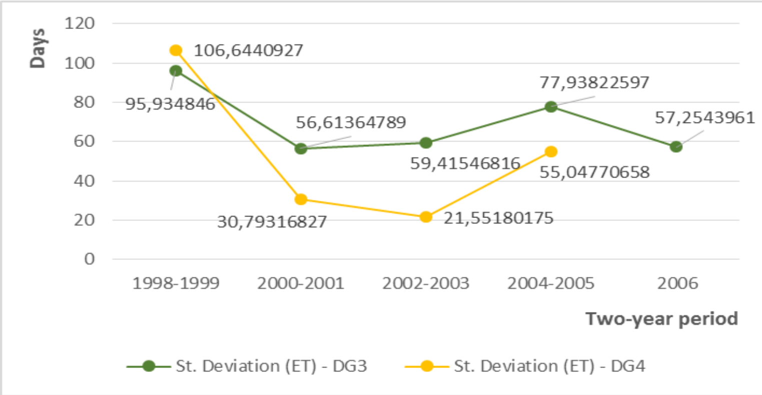

Figure 36. Comparison between DG3 and DG4 - St. Deviation.

2.1.5 Process predictability

In this subsection, the relationship between the engine usage parameters and the date of the MRO events is analysed, with the aim to study the predictability of future shop visits. In particular, we will investigate the relation between total flight hours and total flight cycles – y axis – of the engines (named *TOTHOURS* and *TOTCYCLES* in the dataset), and the date of shop visit – x axis – (*DATEVE* in the dataset). As said before, DGa, DGb, DGc and DGd will be the subgroups of data to be analysed.

DGa analysis

In DGa, 95 different engines with only three events of repair and general inspection are collected. Figure 37 shows the relation between *TOTHOURS* and *DATEVE,* where dotted lines represent the linear regression line for events related to the specific engine*;* in the same way, Figure 38 shows the relation between *TOTCYCLES* and *DATEVE*[8]*.*

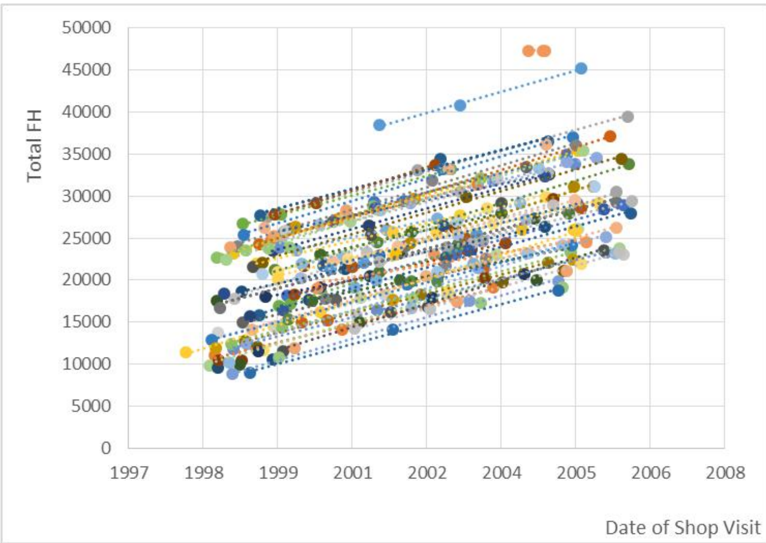

Figure 37. Relation between engine Total Flight Hours and date of shop visit - 3 Shop Visits.

[8] Reader has to take in consideration that these engines are not new, so the first event here reported is not the firts service for the engine.

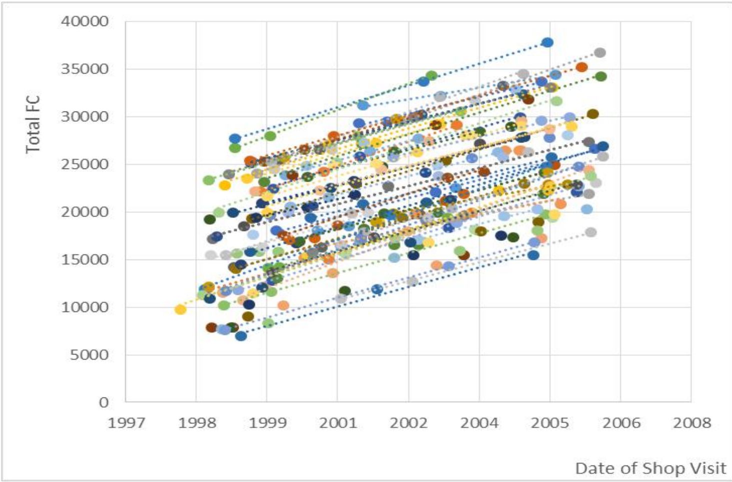

Figure 38. Relation between engine Total Flight Cycles and date of shop visit - 3 Shop Visits.

It can be assumed that there is a linear relationship between engine usage (measured through the total flight hours and cycles) and its MRO events. In order to measure the strength of the linear relationship between *TOTHOURS* and *DATEVE*, as well as between *TOTCYCLES* and *DATEVE*, the coefficient of determination[9] is computed for each events' group associated with an engine (see Figure 39 and Figure 40). Since the great majority of points, representing the coefficient value, are very close to 1 (only one engine presents a value lower than 0.9, but however higher than 0.85 in the case of flight hours, and lower than 0.8 in the case of flight cycles), it is possible to confirm the linear trend of the usage parameters over time.

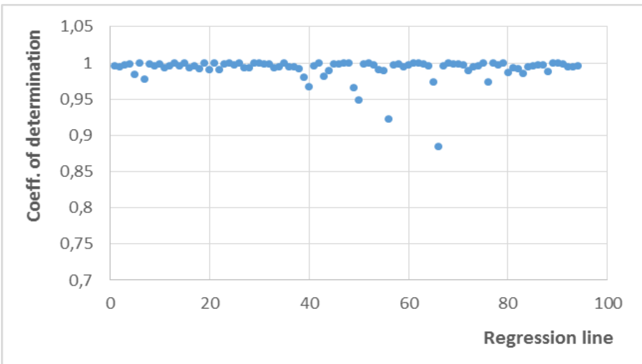

Figure 39. Coefficient of determination (TOTHOURS and DATEVE) - 3 Shop Visit.

[9] The coefficient of determination, measures how well the regression line represents the data, can assume values between 0 and 1. The higher the coefficient, the higher percentage of points the line passes through when data point and line are plotted. Values 1 or 0 indicate the regression line represents all or none of the data, respectively. For example, whether the coefficient is 0.80, this means that 80% of the points fall within the regression line.

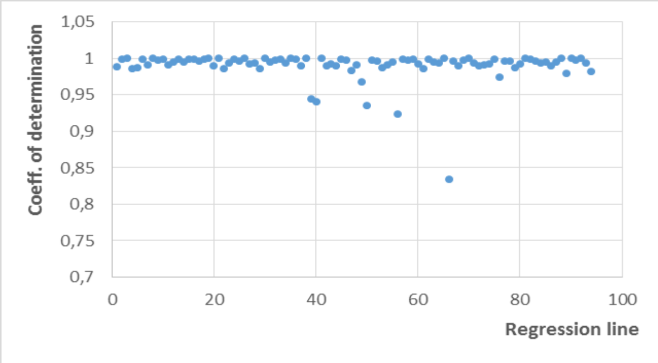

Figure 40. Coefficient of determination (TOTHOURS and DATEVE) - 3 Shop Visits.

DGb analysis

The second group, DGb, collects 49 different engines with four events of repair and general inspection. In Figure 41 and Figure 42, the relation between *TOTHOURS* and *DATEVE*, and between *TOTCYCLES* and *DATEVE* is shown, respectively, with the associated regression lines.

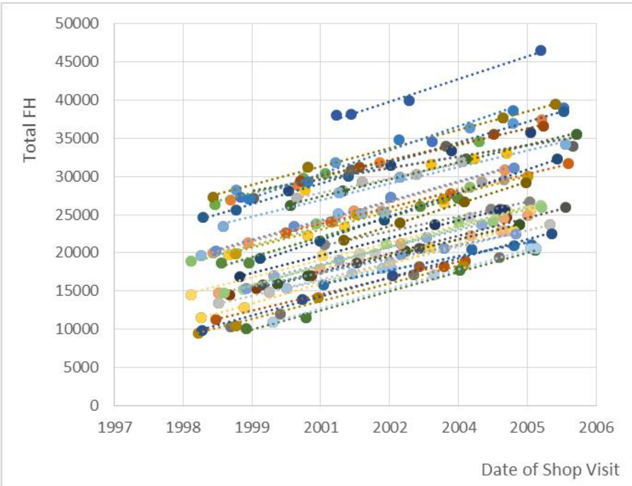

Figure 41. Relation between engine Total Flight Hours and date of shop visit - 4 Shop Visits.

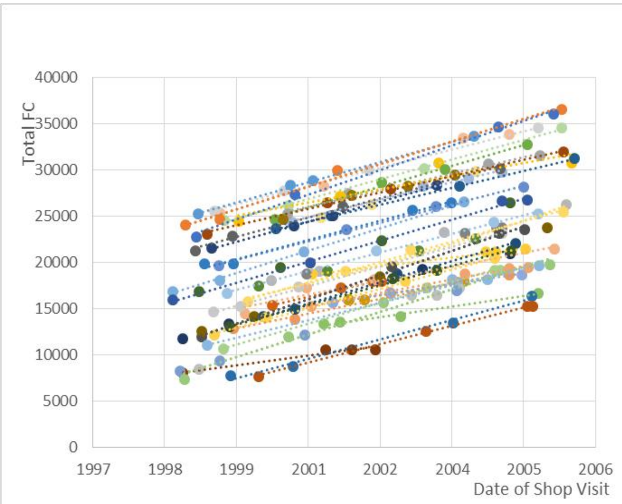

Figure 42. Relation between engine Total Flight Cycles and date of shop visit - 4 Shop Visits.

As for DGa, also in this case the linear trend between engine flight hours and cycles, and the date of shop visits is verified through the coefficient of determination: the great majority of coefficient of determination values (depicted in Figure 43 and Figure 44) is close to 1.

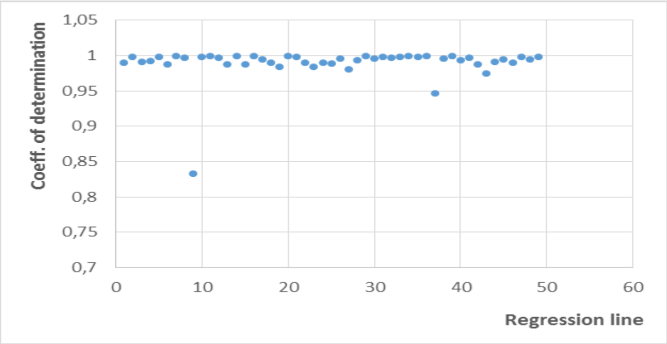

Figure 43. Coefficient of determination (TOTHOURS and DATEVE) - 4 Shop Visits.

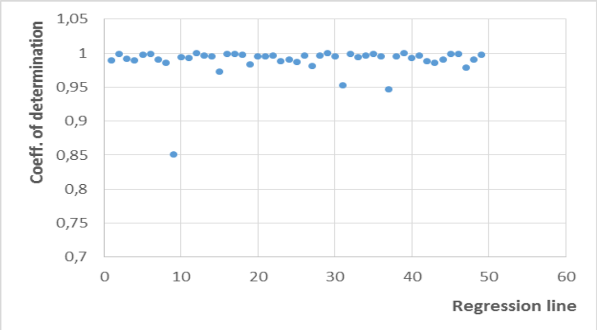

Figure 44. Coefficient of determination (TOTCYCLES and DATEVE) - 4 Shop Visits.

DGc analysis

In DGc, 21 different engines with only five events of repair and general inspection take part. In Figure 45 and Figure 46, the relation between TOTHOURS and DATEVE, and between TOTCYCLES and DATEVE is shown; while Figure 47 and Figure 48 depict the values of the coefficient of determination. For all engines with five shop visits recorded, also in this case, as expected, there is a linear relation between the parameters of engine usage and the date of the shop visits.

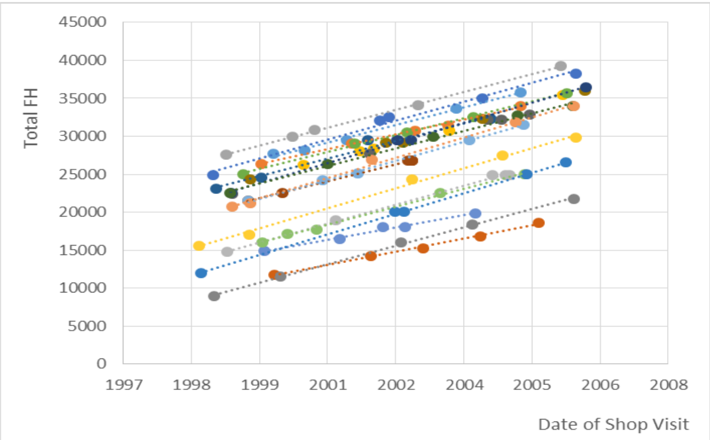

Figure 45. Relation between engine Total Flight Hours and date of shop visit - 5 Shop Visit.

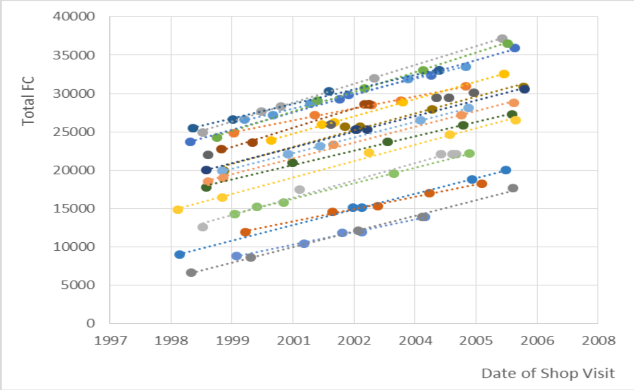

Figure 46. Relation between engine Total Flight Cycles and date of shop visit - 5 Shop Visits.

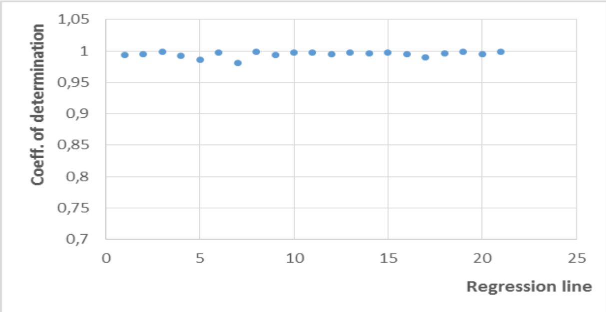

Figure 47. Coefficient of determination (TOTHOURS and DATEVE) - 5 Shop Visit.

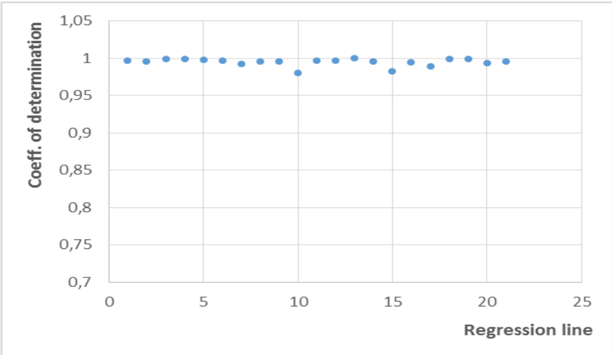

Figure 48. Coefficient of determination (TOTCYCLES and DATEVE) - 5 Shop Visits.

DGd analysis

In the last group, characterized by the engines with six events of repair and general inspection, there are only 3 different engines. Although the small size of the group, the relationships between *TOTHOURS* and *DATEVE,* and *TOTCYCLES* and *DATEVE* are studied (see Figure 49 and Figure 50). By the graphs analysis, it is clear the linear trend between the engine usage parameters and the shop visits. We give evidence of this by showing in Figure 51 and Figure 52 the values of the coefficients of determination.

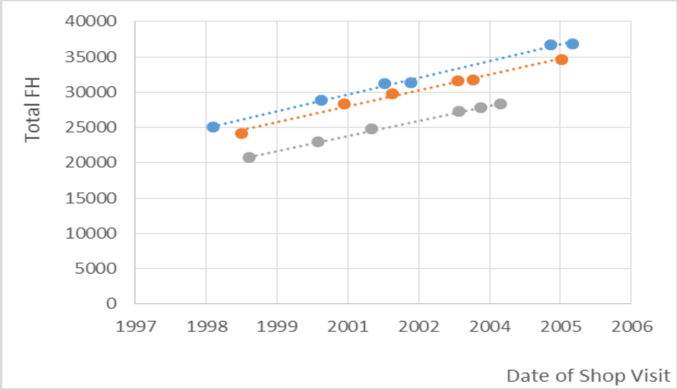

Figure 49. Relation between engine Total Flight Hours and date of shop visit - 6 Shop Visits.

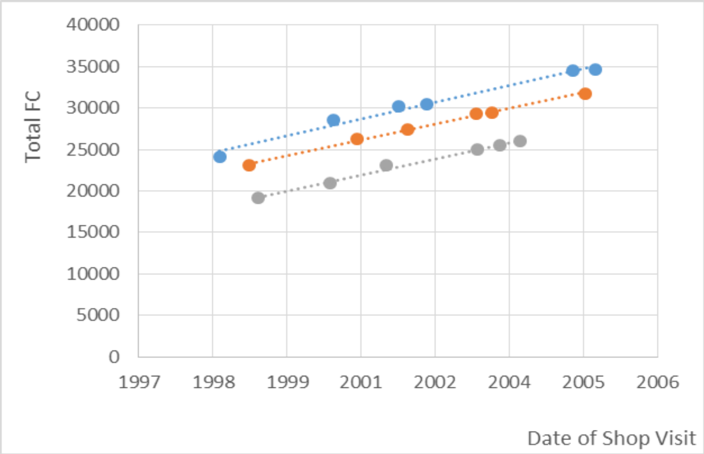

Figure 50. Relation between engine Total Flight Cycles and date of shop visit - 6 Shop Visits.

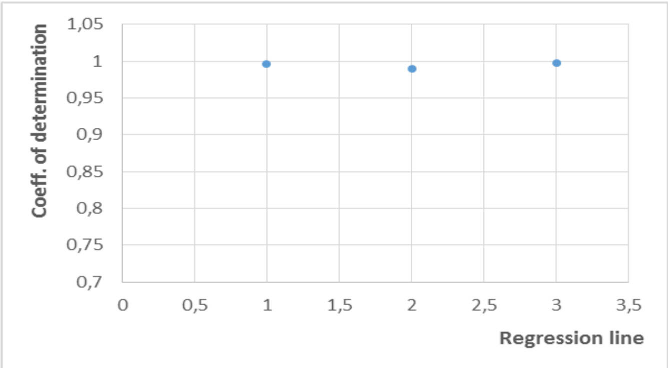

Figure 51. Coefficient of determination (TOTHOURS and DATEVE) - 6 Shop Visits.

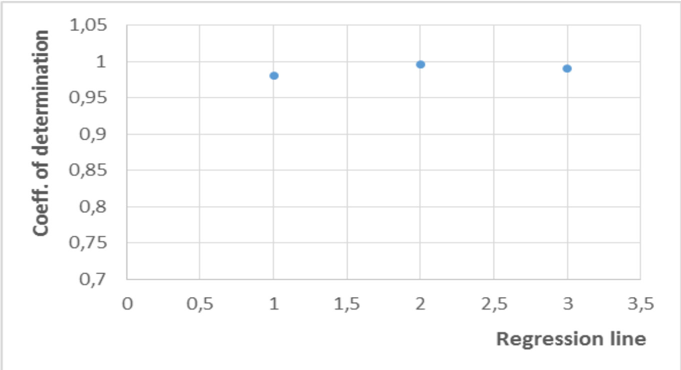

Figure 52. Coefficient of determination (TOTCYCLES and DATEVE) - 6 Shop Visits.

Overall, each engine has its own regression line, to which the repair or general inspection events belong. The regression lines differ with respect to the intercept on the Y axis, meaning that each engine differs for the usage (Flight hours and cycles) at the first event; after that the behaviour is regular.

In order to better define the regression lines belonging to each data group, statistical analysis was carried out on the:

- Distribution of the regression lines' slope;
- Distribution of the difference between flight hours and flight cycles in consecutive engine shop visits;
- Distribution of the time between consecutive engine shop visits.

2.1.5.1 Distribution of slopes

The distribution of the regression lines slope is analysed here, considering all the engines with three, four, five and six shop visits. In the graph below (Figure 53), an overview of slopes' value, represented with respect to the engine flight hours and the engine flight cycles, is first shown. The fact that almost all points fall in a defined area, shown in the chart with black lines, is an evidence of the fact that the engines have a similar behaviour, in term of usage performance.

In Figure 54 and Figure 55, instead, the distribution and its attributes (mean, median and standard deviation) are depicted. All the slopes' values, except one, are in the range [3 – 6.3] for the flight hours, and [2,1 – 5,7] for the flight cycles; while the most frequent values fall in the bin [4,5 – 4,8] for the flight hours and in the bin [3,9 – 4,2] for the flight cycles, for both cases they collect 22% of total slope values.

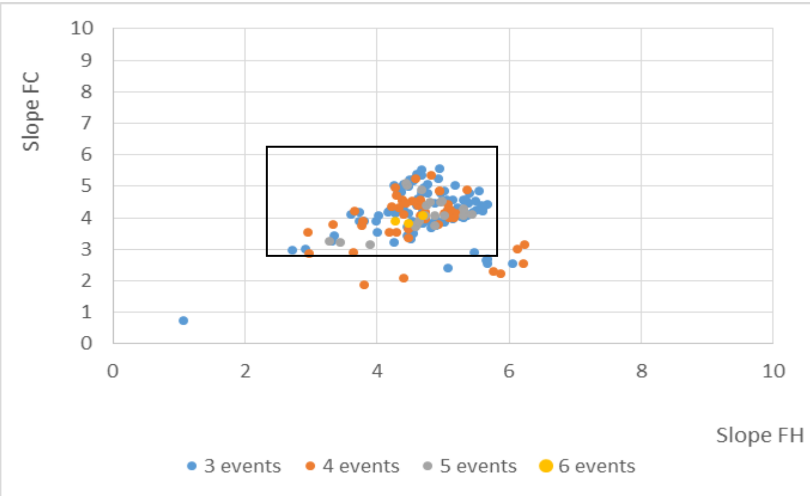

Figure 53. Slope cloud.

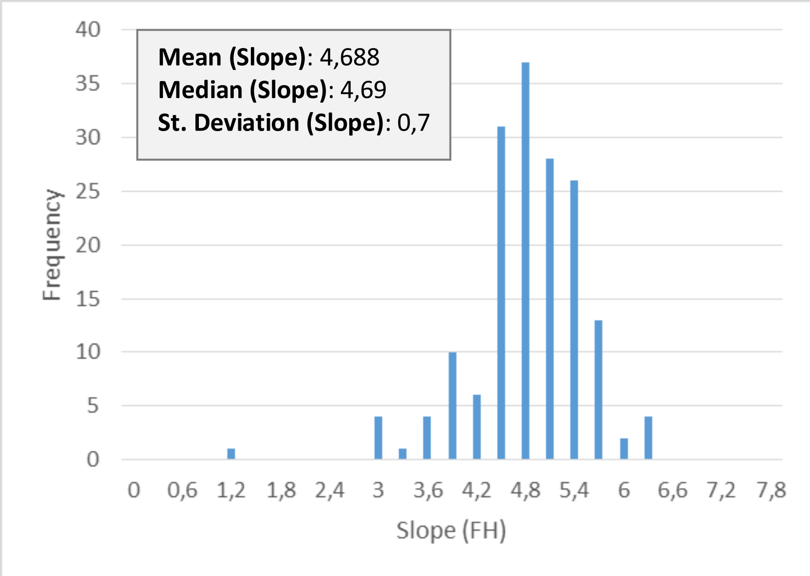

Figure 54. Slope distribution (TOTHOURS and DATEVE).

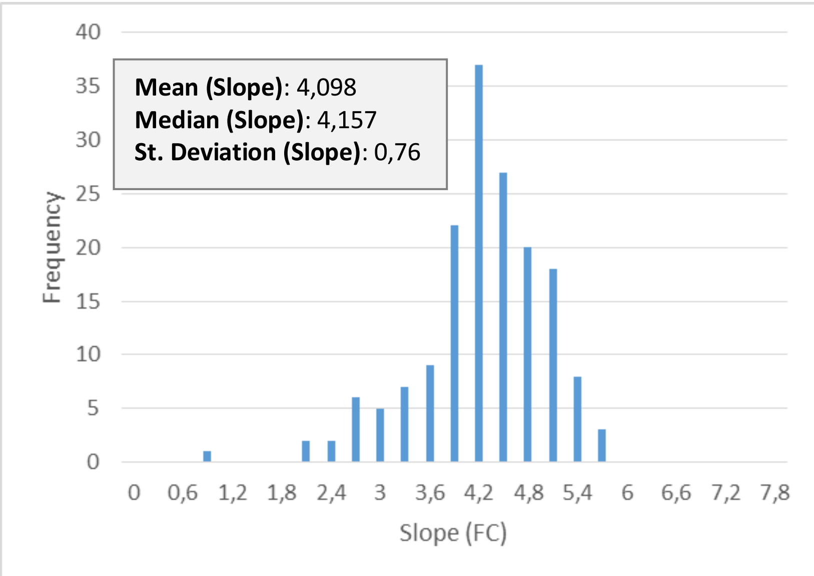

Figure 55. Slope distribution (TOTCYCLES and DATEVE).

2.1.5.2 Distribution of partial flight hours and cycles

In order to recognize which parameter is better suited to forecast the next MRO event, the flight hours and cycles between two consecutive MRO events were studied by analysing the distribution of frequencies (see Figure 56 and Figure 57). The values of mean, median and standard deviation are shown in the figures.

Regarding to the partial flight hours, all values are lower than 12.500 flight hours; whereas, in the case of partial flight cycles, all values are lower than 10,000 cycles, standard deviation values are quite high, 2.515 and 2.220 respectively. As a result, neither flight hours nor flight cycles are useful parameters to forecast MRO events; indeed, it is not possible to recognize any threshold value or any accumulation value.

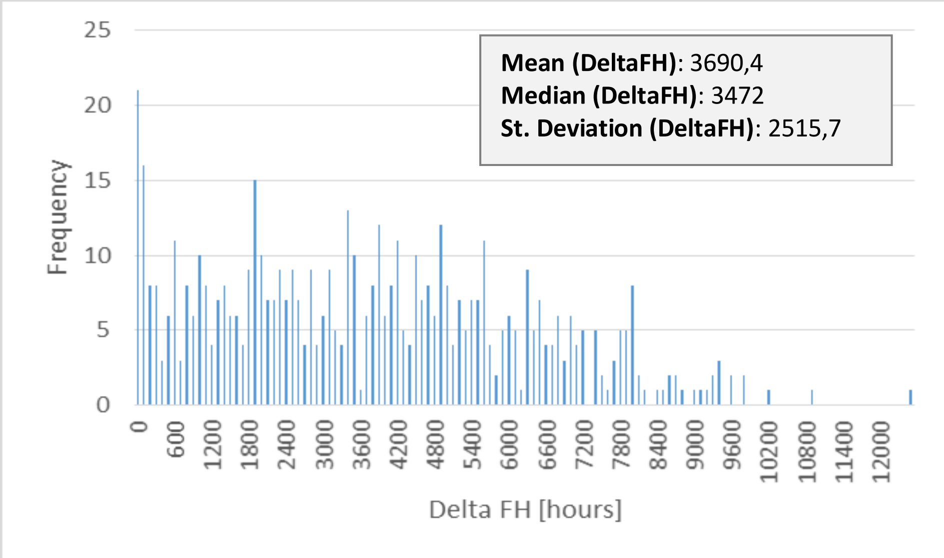

Figure 56. Delta FH distribution.

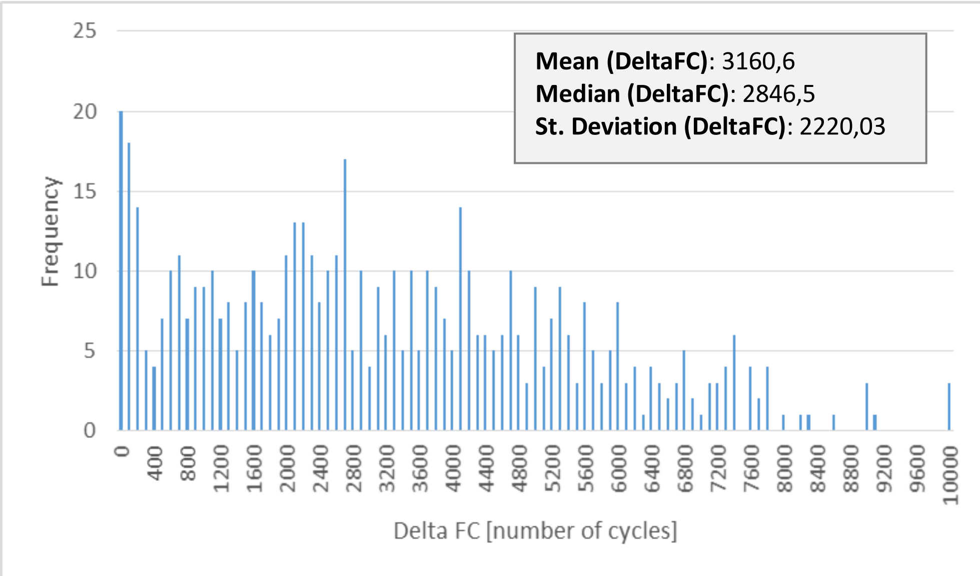

Figure 57. Delta FC distribution.

2.1.5.3 Distribution of time between shop visits

The analysis about the relation between total engine flight hours and cycles, and the date of the shop visit, concerns the distribution of Time Between Shop Visits (TBSV). The time unit is one day. In the Figure 58, the frequencies of TBSV, as well as the values of mean, median and standard deviation are shown. Moreover, in Figure 59 and Figure 61, the correlation between the difference of engine flight hours and cycles, and TBSV is depicted.

From the graphs analysis, it can be stated that the values of TBSV are quite random: the distribution is very broad and without a defined shape. All that mainly affects the spare parts inventory management. Indeed, since there isn't any threshold value for Delta TFH and/or Delta TFC, these data are not useful to forecast MRO services demand[10], so that it is often

[10] Actually, only the data available to authors.

necessary to increase the spare parts stock in order to respect the contract conditions (in terms of Turn Around Time).

Another approach could be to take into consideration the cumulative frequency of the events, respectively for increasing delta TFH and TFC (Figure 60 and Figure 62). The graph shows that quite all the events happen with values of TFH and TFC under a certain value, but it is not possible to recognize a specific threshold or accumulation value.

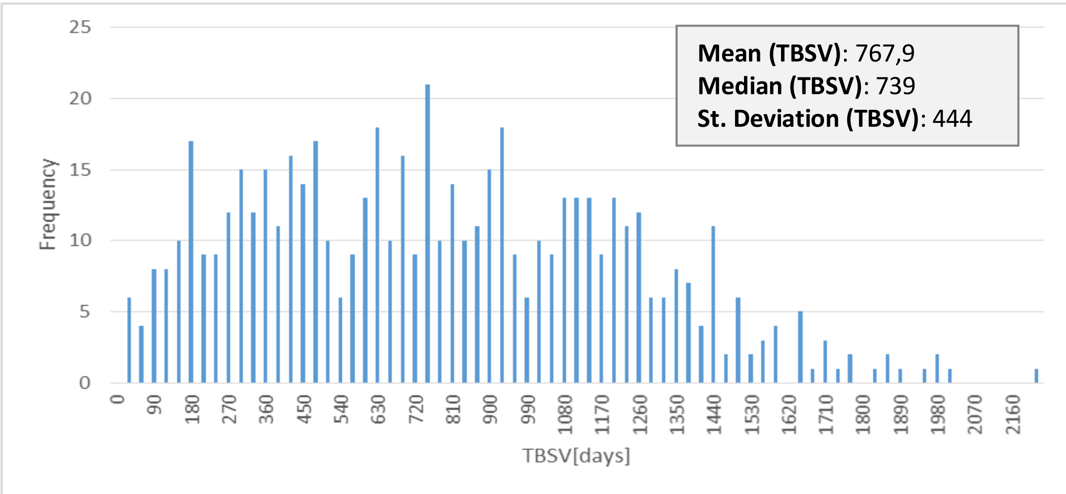

Figure 58. TBSV distribution.

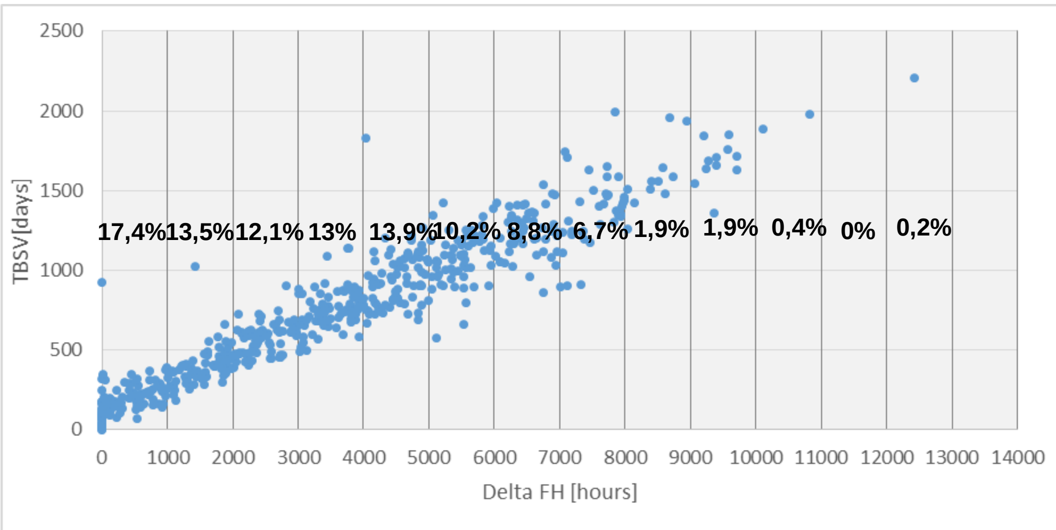

Figure 59. Correlation between TBSV and Delta TFH.

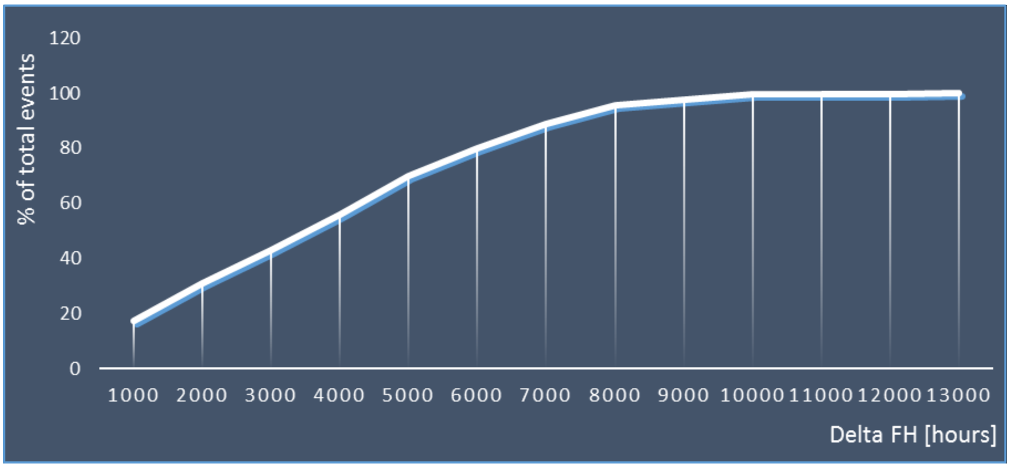

Figure 60. Cumulative frequency – Delta TFH.

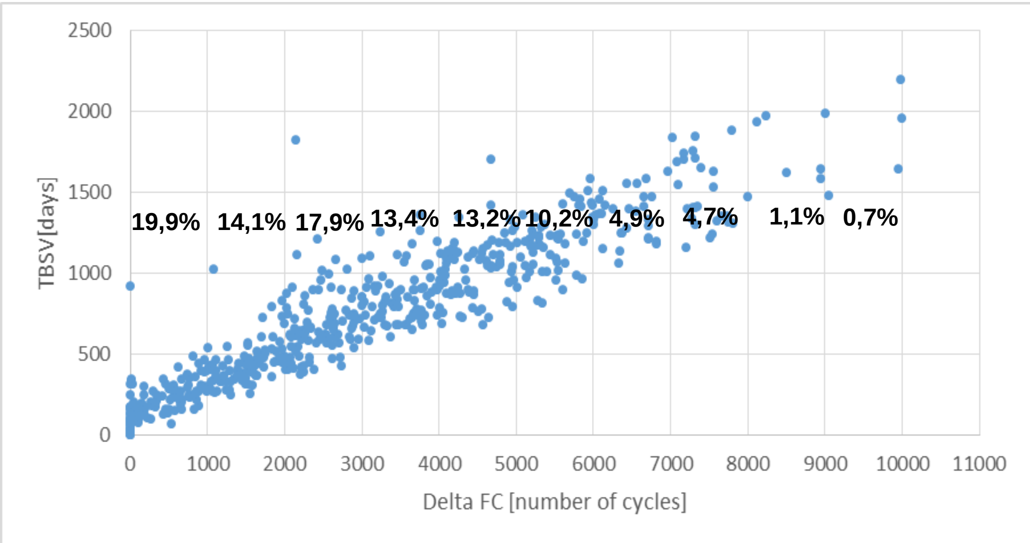

Figure 61. Correlation between TBSV and Delta TFC.

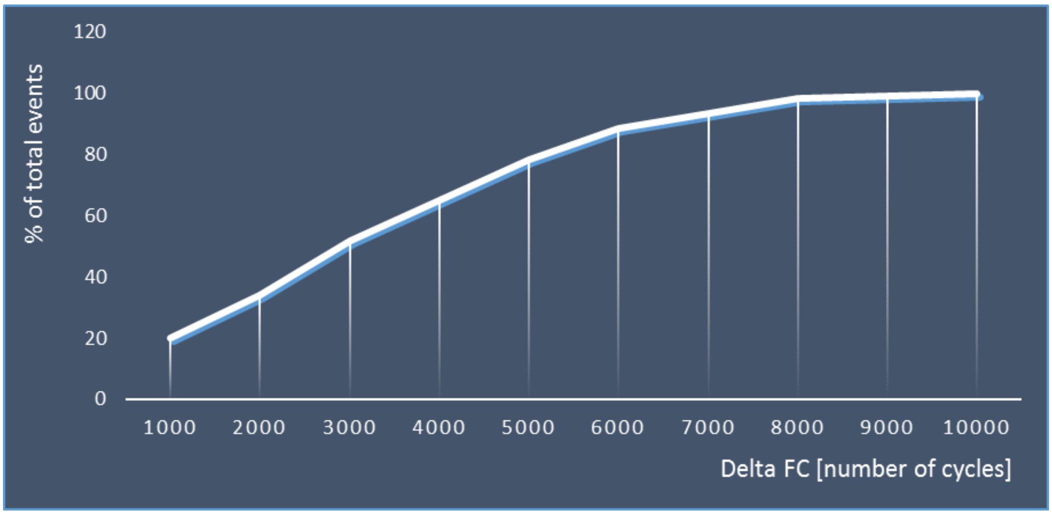

Figure 62. Cumulative frequency - Delta TFC.

2.1.6 Assessment of the engine MRO process

In this paragraph, the effectiveness of the aero engine MRO process will be evaluated, by applying some of KPIs discussed into the business assessment framework presented in D24.3 – Business modelling. In particular, the following KPIs, all belonging to the process impact area of the framework, can be computed on the dataset:

- Mean Turn Around Time (named P.1 in the assessment framework);
- Maintenance rate (P.3);
- Number of engines in WIP (P.5).

Mean Turn Around Time

This KPI evaluates Turn Around Time necessary to carry out repair and general inspection events, by measuring the average time taken from the engine receipt in the MRO plant (DATEVE attribute, in the dataset) until maintained engine is ready to be given back to the engine owner (DATOUTWOR attribute, in the dataset). In particular, the mean TAT was calculated for each year (considering the entire time span of the dataset, from 1998 to 2006), on the engines in arrival in that year. Figure 63 shows that, in total, the mean TAT decreased over time, going from about 250 days in 1998 to 123,5 days in 2006. Actually, the TAT is quite stable in the interval between 145 and 120 in the long period from the year 2000 and 2006; it can be argued that other improvements in the MRO service execution had not significant impacts on the TAT.

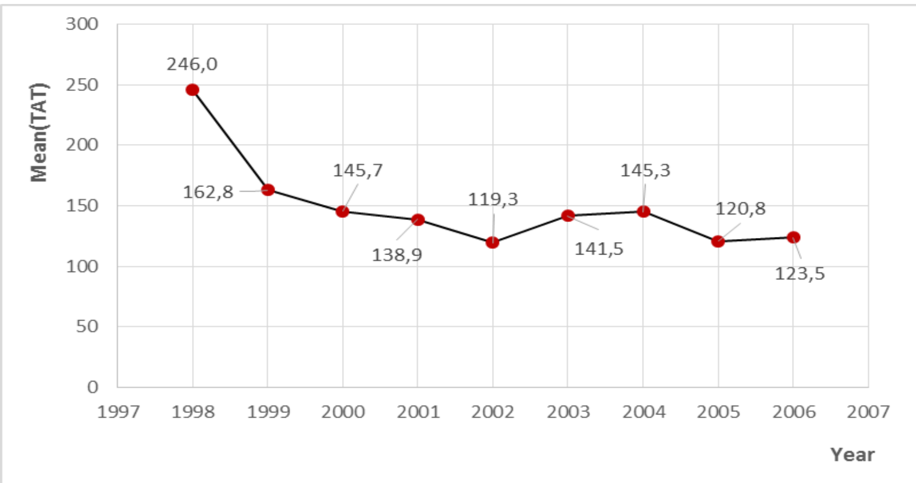

Figure 63. Mean Turn Around Time - P.1 KPI

Maintenance rate

The ‘maintenance rate’ KPI monitors the service capacity of the Company, by keeping track of the number of engines maintained for each year. In other words, Figure 64 depicts the number of engines, arrived in the MRO plant in order to be maintained in a certain year (DATEVE attribute, in the dataset) and exited, maintained, the same year (DATOUTWOR attribute, in the dataset). The trend of the maintenance rate is not stable over time. In particular, the graph shows that the service capacity could be about 100 engines per year (see the year 2001), but in the period from 2002 to 2006 the used capacity was always lower; this aspect could have had a positive impact on the TAT (that in the same period was lower).

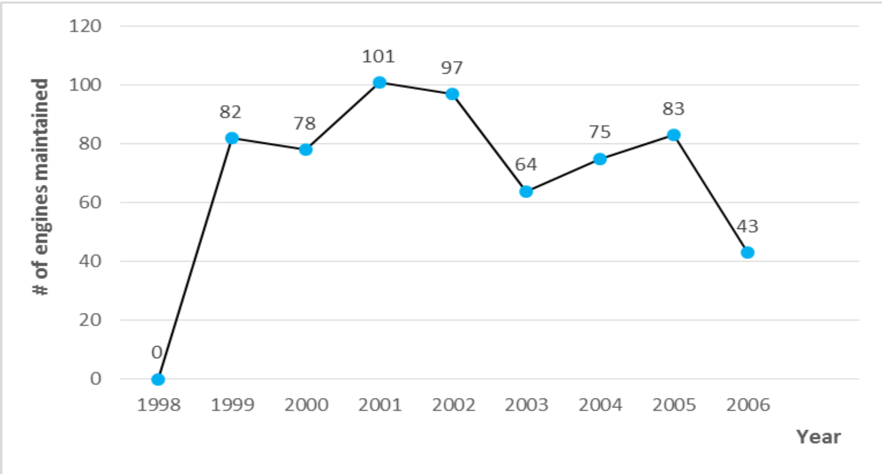

Figure 64. Maintenance rate - P.2 KPI

Number of engines in WIP

The last metric that can be measured on the dataset is the 'work in progress', which is here measured on monthly base. In the Figure 65 the WIP is represented: each bar represents the number of engine in the shop in that month. The shape of the WIP tells about a very steep increase of arrivals of engine in the first years (1998-1999), then a quite stable number of WIPs from 2000 to 2002, then it starts a series of quite irregular decreases and increases.

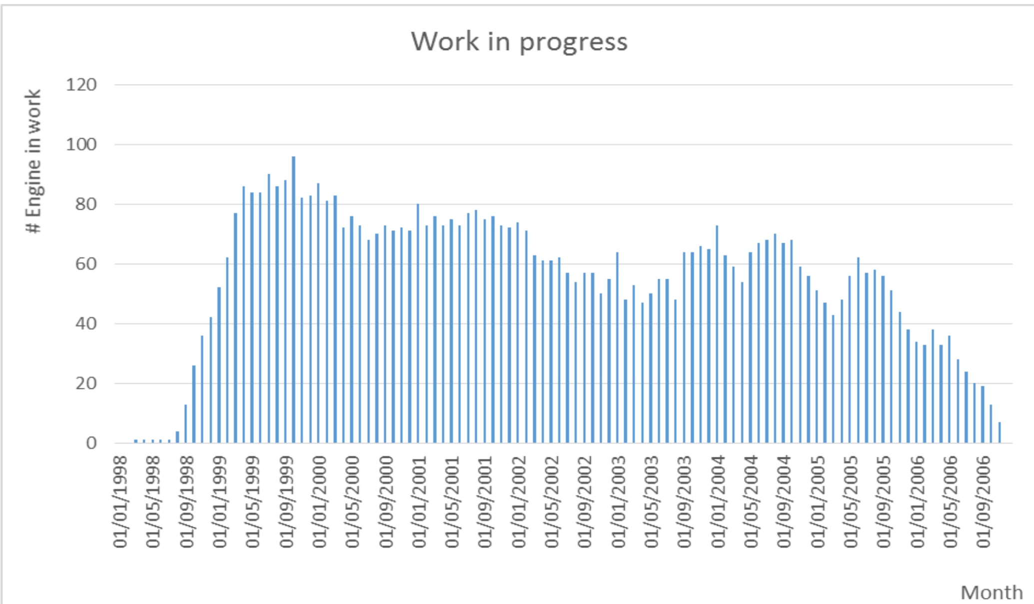

Figure 65. Work in Progress, number of engine in the factory in the selected months.

2.1.7 Conclusions

In conclusion, the entire analysis above, focused on the evaluation of the planning and the execution times of the MRO service, as well as on the process predictability, has put in evidence that performances of the MRO process, the Turn-Around-Time being the most important one in the framework of 'fleet management' business model, can improve if service demand and needs could be foreseen in sufficient advance.

The main features of the process recognized through the analysis are:

- TAT decreases in the first half of the period and reaches a stable value in the second half of the period; however, also in the plain part of the graphs, the value of TAT is quite high. It can be argued that in the second half of the period the process was optimized, so that further TAT reduction could be achieved only acting on supply chain factors (or increasing internal costs, in terms of resources and spare parts stocks, which is usually what a MRO company tries to reduce);
- Repair and general inspection events do not present valuable differences; this means both will benefit by improvements in the supply chain management and in the forecast capabilities;
- There are no significant differences in the service performance with respect to the customer,
- Flight hours and cycles (the health status data available for this study) are not right predictors of the engine service events; it is expected that processing data from sensors, valuable inputs to compute forecasts can be obtained[11].

The main source of improvements for this process is in supply chain management. A more frequent and updated data flow between customers and service provider will enable a smoother orchestration of process in the customer and service supplier nodes. In this case, a reduction of costs can be achieved thanks to a more effective resources management and to a less costly inventory management policies.

Actually, this business sector is a capital-intensive one, so inventory takes high costs. There are two main reasons for that:

1. the high number of spare parts required; the engines are composed of more than 1 thousand of parts (in this study were considered only the main structural modules[12]),
2. the cost of parts that can be as high as tens of thousands of euros.

Improving forecasts accuracy will lead directly to the reduction of the inventory management costs via the decreasing the spare parts safety stock, the reduction of spare parts handling costs, the introduction of more effective inventory management policies and business relationships with suppliers. All that will be achieved without decreasing the quality of service, for example of TAT value, rather the contrary is true.

In the following, the impact of improvements in forecasts accuracy on the inventory management are studied, in order to estimate the economic benefits brought by the collaborative forecasts computation.

2.2 Impact of collaborative supply chain management

In this chapter we analyse what benefits we can expect from a roll-out of the prototype we described in the preceding subchapter. Since the MRO provides spare parts with very different properties – from cheap screws to complex combustion units - we also analyse for which part the application of an advanced forecasting technique, as provided via our secure collaborative platform, makes the most sense economically.

[11] Actually, global players are spending huge effort to study the relationship between engine performances, sensors values and service requirements.

[12] Applying the fleet management concept, service provider is required to consider the trade-off between the effort required to identify the parts to be replaced and the cost of replacing the whole module presenting troubles.

The profound data analysis reported in subchapter 2.1 implies that the implementation of the collaborative forecasting models need more data (engine health status data) than the actual ones need to be managed. It will be possible only after investments in additional IT infrastructure to collect and to store such data. The benefits analysis described hereafter supports supply chain manager in identifying which segmented of the supply chain should be involved in supply chain models (and in the IT system required to implement it) in order to achieve, in short time, the highest benefits.

2.2.1 Categorization of components

Our approach in this chapter is based on simulation of the economic benefits brought by improved forecasts. We model the cost structure of the MRO supply chain by various parameters, evaluate the costs that result if we just use a state-of-the art forecasting technique that doesn't benefit from any collaboration. Then we simulate improved forecasts and analyse the effects on the resulting costs. With this approach we can examine what (percental) cost reduction we can expect for a given average improvement of the forecast quality (by our secure collaborative approach) for a certain component. From this we can derive recommendations which is the most promising product category for a subsequent roll-out.

For the analysis in the MRO setting the experts from DTA propose 7 components that are interesting candidates for condition based forecasting since future engine generations will be able to track the necessary sensor data. The goal of our analysis is to identify the components for which improved forecasting promises the highest benefits. The two main criteria that drive the economical impact of making good inventory decisions is the irregularity in demand and the value of a component, respectively the costs that occur if a component is not available if needed. Demand for a component is irregular if variations in demand are high and/or if there are many periods with zero demand while facing high demand in others. According to these two criteria we derive four categories depicted in Figure 66 to classify the components.

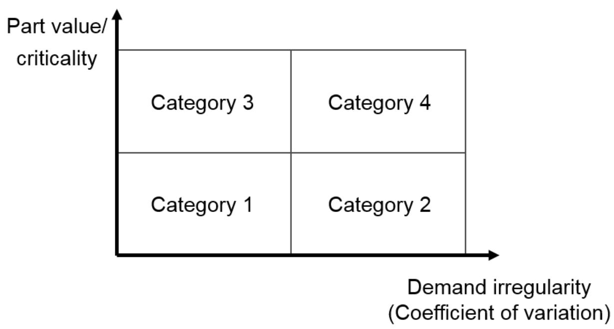

Figure 66. The four categories components can belong to depending on their demand irregularity and purchasing criticality.

In the aerospace setting the two criteria for component categorization (irregularity and criticality) are driven by multiple factors that are the columns in Figure 67. Probability of damage for wear and incident probability drive the Demand irregularity while purchasing cost, Handling and Lead time drive the part value/criticality. Those determine the final Category.

Module	Probability of damage for wear	Incidents probability	product	Demand irregularity	Purchasing cost	Handling	Lead time	product	part value/ criticality	Category
Fan	2	3	6	1	1	2	1	2	1	1
Low pressure compressor	3	2	6	1	2	3	2	12	1	1
High pressure compressor	3	2	6	1	2	3	2	12	1	1
Combustor	1	1	1	2	3	3	3	27	2	4
High pressure turbine	2	1	2	2	2	3	2	12	1	2
Low pressure turbine	2	1	2	2	2	3	2	12	1	2
Accessory drive	3	2	6	1	3	2	3	18	2	3

values meaning	
1=	low
2=	medium
3=	high

Figure 67. Categorization of components.

2.2.2 Benefit Simulation for representative components

For each of the four categories we choose one component as representative for further detailed analysis: Low pressure compressor (Cat. 1), High pressure turbine (Cat 2), Accessory drive (Cat. 3) and Combustor (Cat. 4).

2.2.2.1 Low pressure compressor

The low pressure compressor is a representative of the first category and characterized by low demand irregularity and little part value. Table 4 shows the parameters we used in the simulation.

Table 4. Simulation parameters for low pressure compressor

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	200	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	20000	Purchasing costs per unit.
HOLDING-COSTS	0.05	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	500	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.02	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	5	The expected mean demand per period in units.
DEMAND-SD	2.2	The standard-deviation of our demand per period in units.
LEAD-TIME	2	The lead-time tells us how many periods we have to wait until our order arrives.

SERVICE-LEVEL	0.9	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

We note that the main parameter is the FC-IMPROVEMENT-MEAN: that is the average percentage improvement of the new forecast (as provided by our secure collaborative forecasting system) compared to the one obtained by a standard forecasting approach (e.g. just taking the mean over past demand realizations). Since we are not sure that we obtain always exactly a – say 10% – better forecast, we simulate this improvement. I.e., for each period we take the predicted value from the standard approach and the actual demand, and calculate the improved value by drawing from a normal distribution with mean 10% closer to the actual value and standard deviation given by the parameter FC-IMPROVEMENT-SD. By this we also allow for worse forecasts in individual periods which leads to more realistic results.

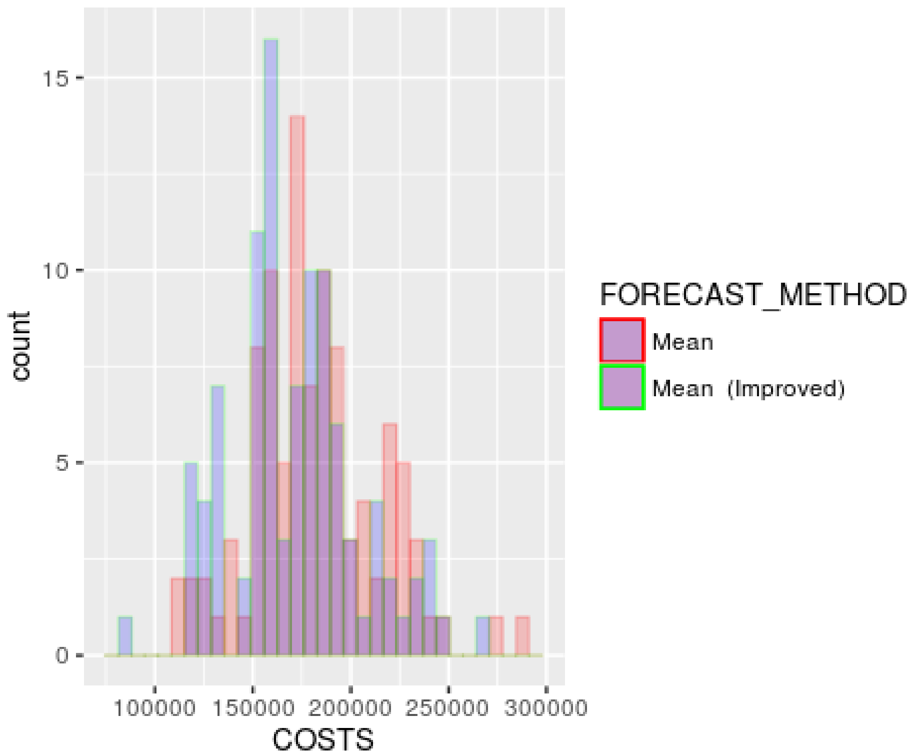

Figure 68. Histogram of Costs for Low pressure compressor.

We run the simulation 100 times, each over 24 months (this is constant for all subsequent simulations). The main results are the overall costs including unit costs, holding costs, order costs and penalty costs. The results from the simulation runs is displayed in Figure 68. We see that the histogram of the improved method (blue) is shifted to the left. We have much less realizations with costs of more than 200000. The boxplot in Figure 69 shows the reduction in the mean cost to below 175000 and also a lower spread of results.

In detail we obtain:

Total costs normal – total costs improved: 18165800 - 17204400 = 961400
Percentage of cost reduction: 5.29
Service level normal: 93.1248
Service level improved: 93.2501

For the low pressure compressor a 10% improved forecast therefore results in a mean cost reduction of 5.29% while the service level is increased by 0.12 percentage points.

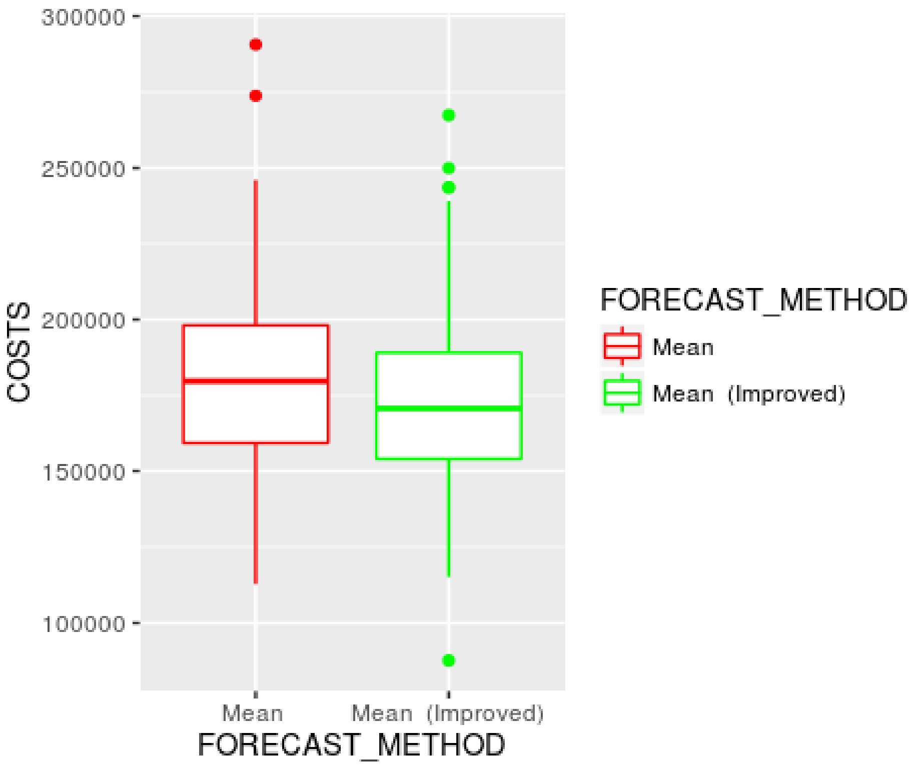

Figure 69. Boxplot for overall costs

2.2.2.2 High pressure turbine

The high pressure turbine is a representative of the second category and characterized by high demand irregularity and little part value. Table 5 shows the parameters we used in the simulation:

Table 5. Simulation parameters for the high pressure turbine

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	200	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	20000	Purchasing costs per unit.
HOLDING-COSTS	0.05	Holding costs per unit and period, if a unit is stored in our warehouse.

ORDER-COSTS	500	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.05	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	3	The expected mean demand per period in units.
DEMAND-SD	1.8	The standard-deviation of our demand per period in units.
LEAD-TIME	2	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.9	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

Compared to the low pressure compressor (Cat. 1) we now have higher demand irregularity modeled via higher ratio of periods with zero demand (RATE-ZERO-FORECAST is 0.05 instead of 0.02) and an increased coefficient of variation defined as DEMAND-SD / EXPECTED-MEAN-DEMAND (1.8/3 =0.6 instead of 2.2/5=0.44).

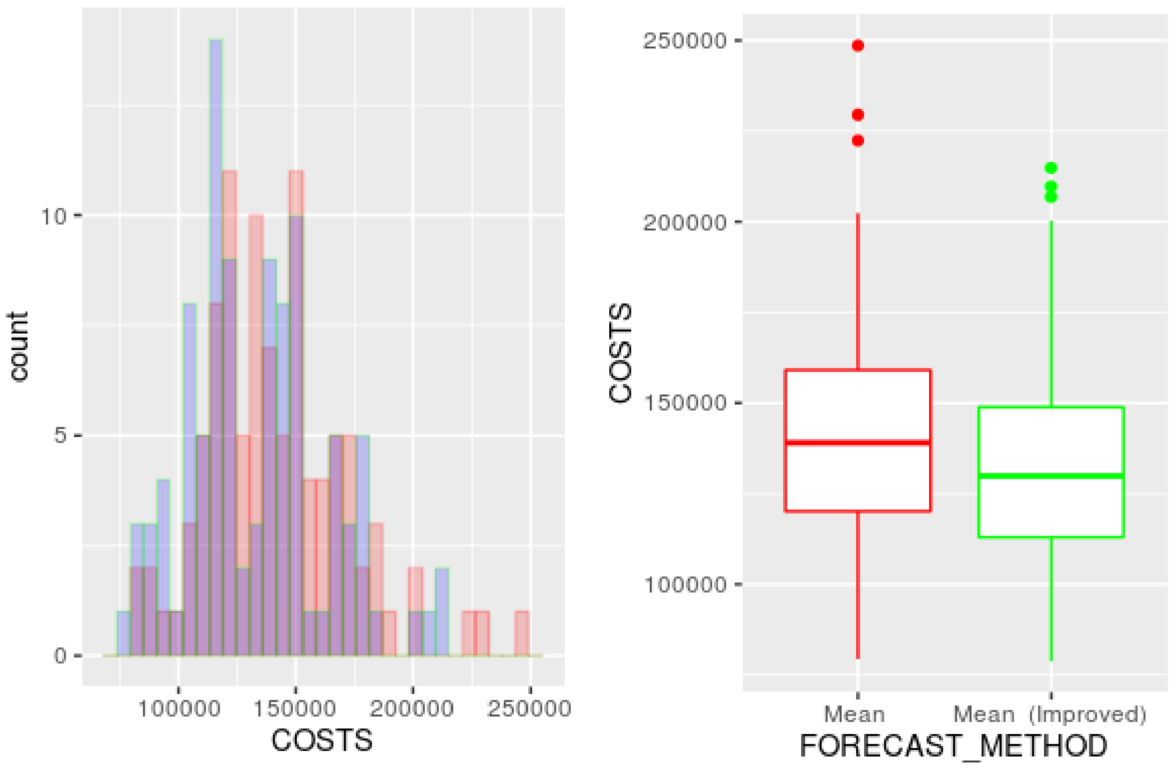

Figure 70. Output plots for the high pressure turbine

The main results are the overall costs from each simulation run. They include unit costs, holding costs, order costs and penalty costs. The results from the simulation runs is displayed in Figure 70. We see that the histogram of the improved method (blue) is shifted to the left. We have much less realizations with costs of more than 200000.

In detail we obtain:

Total costs normal – total costs improved:	14130800 – 13292100 = 838700
Percentage of cost reduction:	5.94
Service level normal:	92.7508
Service level improved:	93.2501

We have a similar percental cost reduction compared to the low pressure compressor. Also the slight changes in the achieved service level are similar. That means that solely the increase in demand irregularity does not make a big difference on the impact of improved forecasts.

2.2.2.3 Accessory drive

The accessory drive is a representative of the third category and characterized by low demand irregularity and high part value. Table 6 shows the parameters we used in the simulation:

Table 6. Simulation parameters for accessory drive.

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	200	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	40000	Purchasing costs per unit.
HOLDING-COSTS	0.02	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	500	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.02	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	2	The expected mean demand per period in units.
DEMAND-SD	1.1	The standard-deviation of our demand per period in units.
LEAD-TIME	3	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.98	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

The main differences are now the increased UNIT-COSTS (40000 instead of 20000) modeling part value and the increased SERVICE-LEVEL (0.98 instead of 0.9) modeling part criticality.

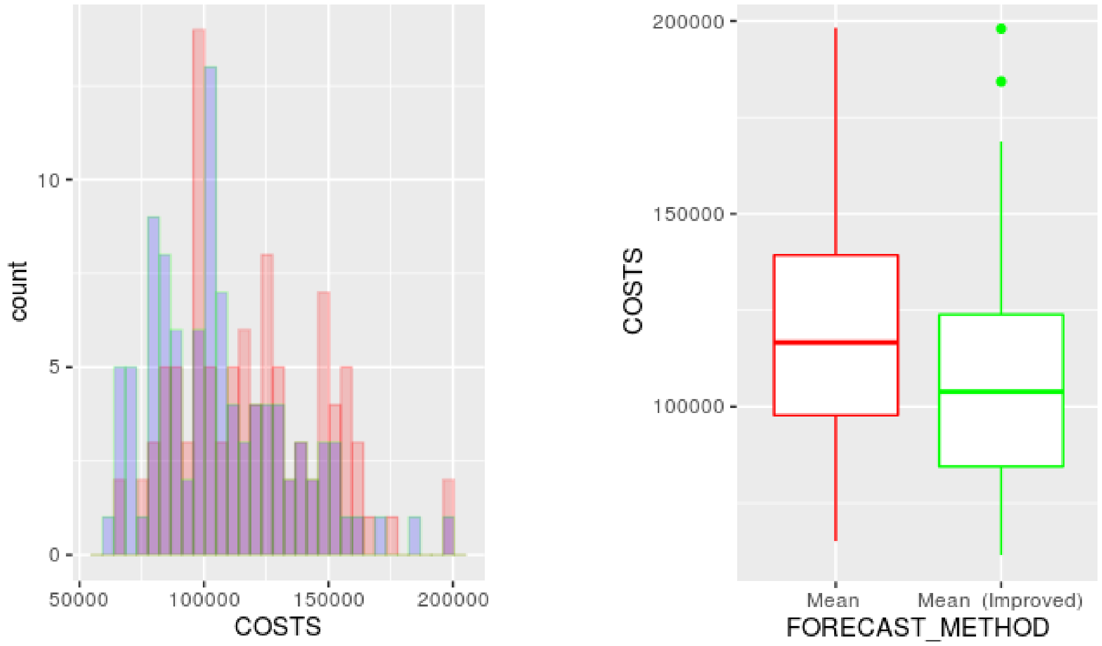

Figure 71. Output plots of the accessory drive

The main result are the overall costs from each simulation run. They include unit costs, holding costs, order costs and penalty costs. The results from the simulation runs is displayed in Figure 71. We see that the histogram of the improved method (blue) is shifted to the left. We have much more realizations with costs of less than 100000.

In detail we obtain:

Total costs normal – total costs improved:	11899000 - 10652500 = 1246500
Percentage of cost reduction:	10.48
Service level normal:	90.7932
Service level improved:	90.7932

We have a much higher percental cost reduction compared to the components from categories 1 and 2 (both with low part value/criticality). That means that for parts with high part value/criticality the improved forecasts promises significantly higher cost improvements.

We note that for this component we don't achieve an improved service level. However this was not a task of the optimization – there we only set a minimum service level that had to be achieved (90 in this case).

2.2.2.4 Combustor

The accessory drive is a representative of the fourth category and characterized by high demand irregularity and high part value. Table 7 shows the parameters we used in the simulation:

Table 7. Simulation parameters for combustor

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	200	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	40000	Purchasing costs per unit.
HOLDING-COSTS	0.04	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	500	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.05	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	1.1	The expected mean demand per period in units.
DEMAND-SD	1	The standard-deviation of our demand per period in units.
LEAD-TIME	3	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.98	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

For the accessory drive we now have increased value/criticality as for the accessory drive modeled via higher UNIT-COSTS and higher SERVICE-LEVEL compared to the components from category 1 and 2. In addition we also have higher demand irregularity compared to the accessory drive, modeled via higher coefficient of variation as for the high pressure turbine (Cat. 2).

Figure 72. Output plots for Combustor

The combination of a very high service level and the high costs results in more extreme cost realizations. The shift to the left is less obvious in the histogram on the left of Figure 72. However the boxplot shows that the improved forecasts leads to no extreme results with costs of more than 500000.

In detail we obtain:

Total costs normal – total costs improved:	12947500 – 11751800 = 1195700
Percentage of cost reduction:	9.23
Service level normal:	92.0444
Service level improved:	91.8777

Similarly to category 3 we have a much higher percental cost reduction compared to the components from categories 1 and 2 (both with low part value/criticality). That means for parts with high part value/criticality the improved forecasts promises significantly higher cost improvements. However, the additional increase in demand irregularity does not add up to this effect. It seems to even work in the opposite direction since we see a lower percental cost reduction along with slight reduction in mean realized service level.

2.2.3 Conclusion and component prioritization

As final conclusion for the aerospace setting, we state that the potential impact of improved forecasting on spare part inventory costs is significant for all of the analyzed categories of components. However, the components from categories 3 and 4 which are characterized by high part value/criticality would benefit most from improved forecasting. The results are summarized in Figure 73. For products from category 4 such as the combustor we can expect an average cost reduction of 9.23%. The most promising category is the third (including the accessory drive) with an expected average cost improvement of 10.48%.

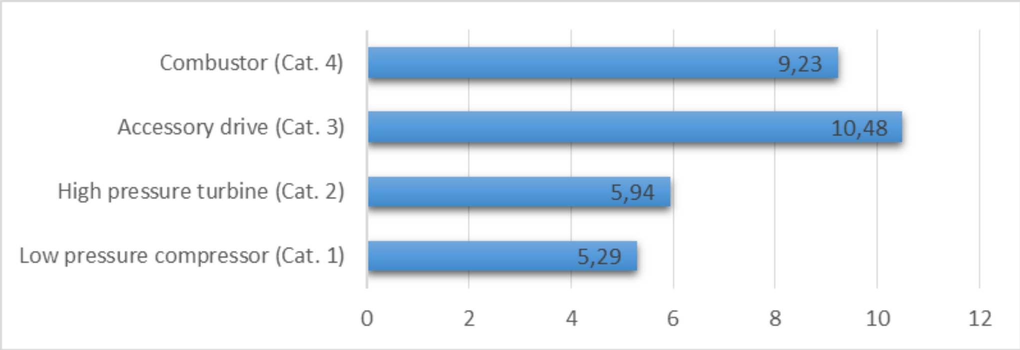

Figure 73. Potential percental cost reductions per category

As suggestion for future implementations of secure collaborative forecasting, components from categories 3 and 4 should be prioritized.

Chapter 3 Vendor Managed Inventory

3.1 Description of the case study (products and customers)

First of all, it is necessary to provide a brief overview of Arçelik's supply chain network to give an idea about the characteristics of the household appliances supply chain network.

As it is seen in Figure 74, Arçelik's supply chain network basically deals with the intelligent management of inbound materials to one or more production site(s) and the smart distribution of finished goods to customers. Basically, the orders from customers initiates the management of the inbound transportation of raw materials or semi-finished components from the most suitable suppliers to the most suitable Arcelik facility. After the delivery and consumption of raw materials and/or semi-finished components at related Arçelik facility, they will be transformed into finished goods that in turn will be exported as household appliances to the customers initiating the orders. By taking in consideration that Arçelik manages more than one washing machines and refrigerators plants, it is understandable that operational planning of logistics activity, purchasing/planning of logistics operations and the execution of the transport activities, focusing on inbound production logistics and including deviation management, has a strong impact on the final production cost.

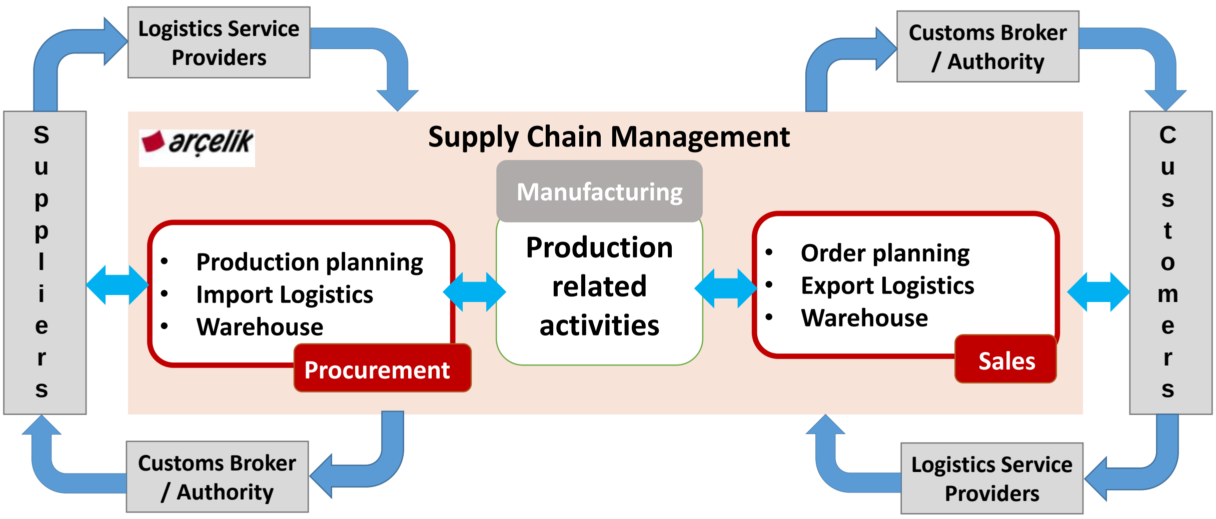

Figure 74. Overview of Arçelik's Supply Chain Management.

The household appliances have a supply chain network which can be differentiated by several dimensions:

- the nature of the markets, i.e. consumer expectations in the markets,
- the product ranges, relative importance i.e. priority of a product in that specific market,
- sourcing types, production or trading and also by the agreements and the content of the business done in collaboration with transport service providers and their capabilities. (The international transport part of the supply chain network will not be included in the scope of this use case)

It is also necessary to provide some details about the import and export of goods to show the data and info exchange and the complexity of the day to day operations. Arçelik's supply chain management has Import and Export logistics groups dealing with the import of materials and/or semi-finished goods and export of household appliances.

Import logistics group works with over 1800 suppliers in 49 countries and uses 51 logistics service providers to handle over 32,000 shipments per year covering over 40,000 SKUs.

Export logistics group works with over 544 customers and 1760 end customers in 132 countries and uses 101 logistics service providers to handle over 74,000 shipments per year covering over 10,000 different products (or SKUs).

Arçelik supply chain management mainly has internal and external communication and data flow during import and export operations. The documents and/or data flows through either related portals (logistics, purchasing etc.) or using phone, fax, e-mail during operations. The documents and/or data exchanged between partners are not encrypted but the ERP system and the portal usage is possible with valid user-id and passwords. The documents/data flow among partners are explained shortly in the following sections.

3.1.1 Supply chain internal communication and data flow

Figure 75. Supply Chain of **Internal** Communication Stakeholders, they communicate through ARC' ICT systems, ERP and Logistical Portal, mainly.

Order management uses related app in ERP (SAP) for creating sales orders. Warehouse management uses ERP system for warehouse management and uses Arçelik Logistics Portal for capacity planning, loading & unloading activities and shipment detail entries. Logistics uses ERP system to provide input for production planning, order management, warehouse management and uses logistics portal for logistics planning and order creation. Purchasing uses ERP system for recording purchasing agreements with material suppliers.

Production Planning uses ERP system for purchase order creation and for production planning.

3.1.2 Supply chain external communication and data flow

Subsidiaries and other end-customers can use purchasing portal or phone, email, fax for procurement from Arcelik. Material suppliers can use supplier portal or use phone, fax, email for material sales. Logistics service providers use logistics portal and phone, fax, email for transport order confirmation and document transfer as well as informing shipment status. Logistics Controller uses logistics portal for transport order creation and shipment tracking using phone, fax, e-mail for document transfer and communication. Customs Broker / Authorities uses government system (ex: BILGE, ATLAS) for customs clearance and uses logistics portal for informing customs status using phone, fax, e-mail for document transfer.

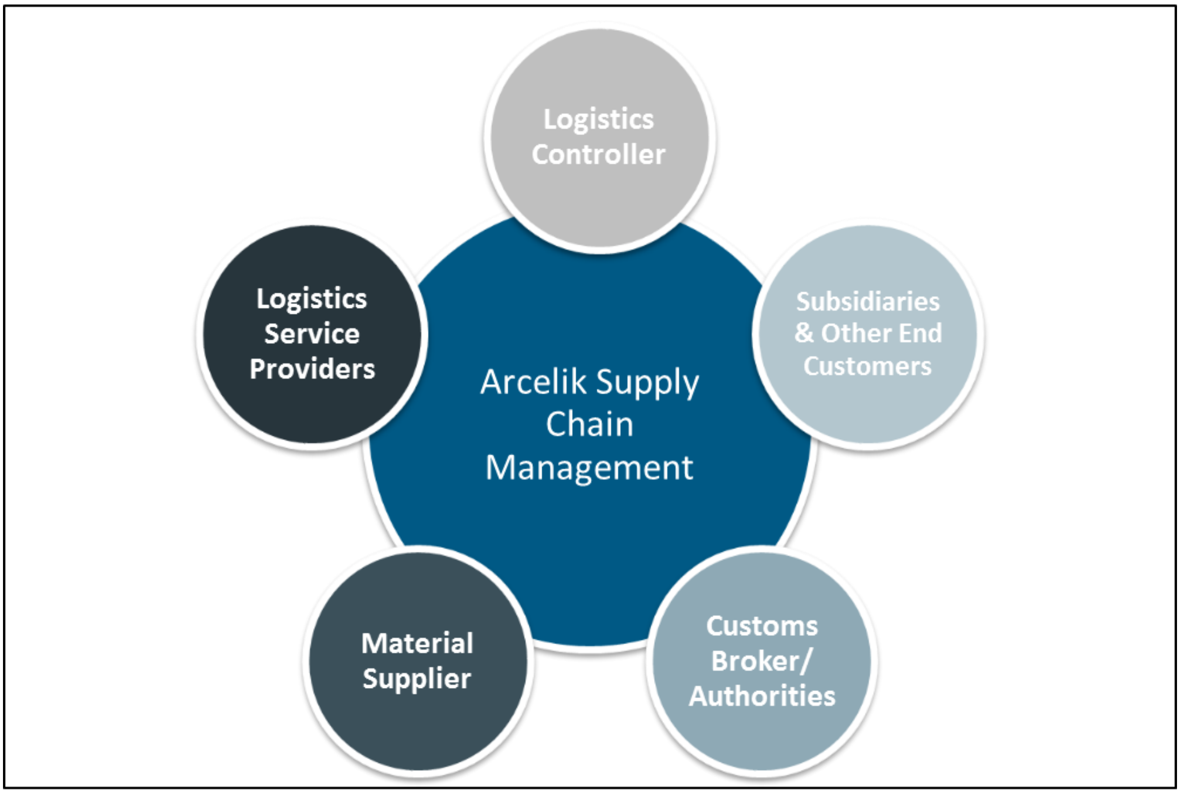

Figure 76. Supply Chain of **External** Communication Stakeholders, multiple communication systems convey their communication.

3.2 Household appliances use case

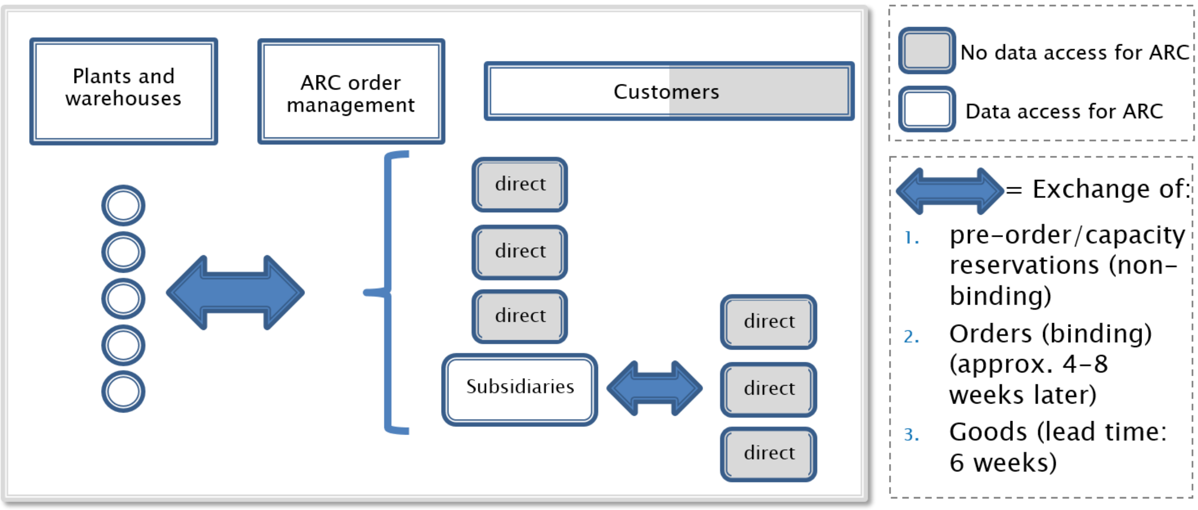

Figure 77. Arçelik Supply Chain Stakeholders

As summarized in above section the stakeholders in Arçelik's supply chain network are exchanging information through the portals or with other medium as e-mails, phones or facsimile messages during the import and export of materials, semi-finished components and products.

As depicted in Figure 77 the customers of Arçelik are either subsidiaries or direct customers. The subsidiaries are part of the Arcelik group of companies and thus the inventory and point of sales data are fully available for the Arçelik order management in supply chain department. The direct customers are large retail stores; e.g. Satürn or Media Markt; in many countries. They are not a part of Arçelik group of companies and thus Arçelik has no access to any information besides the incoming (pre-) orders.

The customers; direct customers or subsidiaries, can select and order required number of products from the available catalogue of 10,000 products. Arçelik has selected a dataset of 1800 products out of 10,000 products for the use case. The four products are selected to make analysis of the present situation and to calculate the potential optimization when using secure vendor managed inventory approach.

The selected four products monthly demand and actual sales figures for fourteen months are depicted in following figures. The blue bars are showing monthly demand and red bars are showing the monthly sales data.

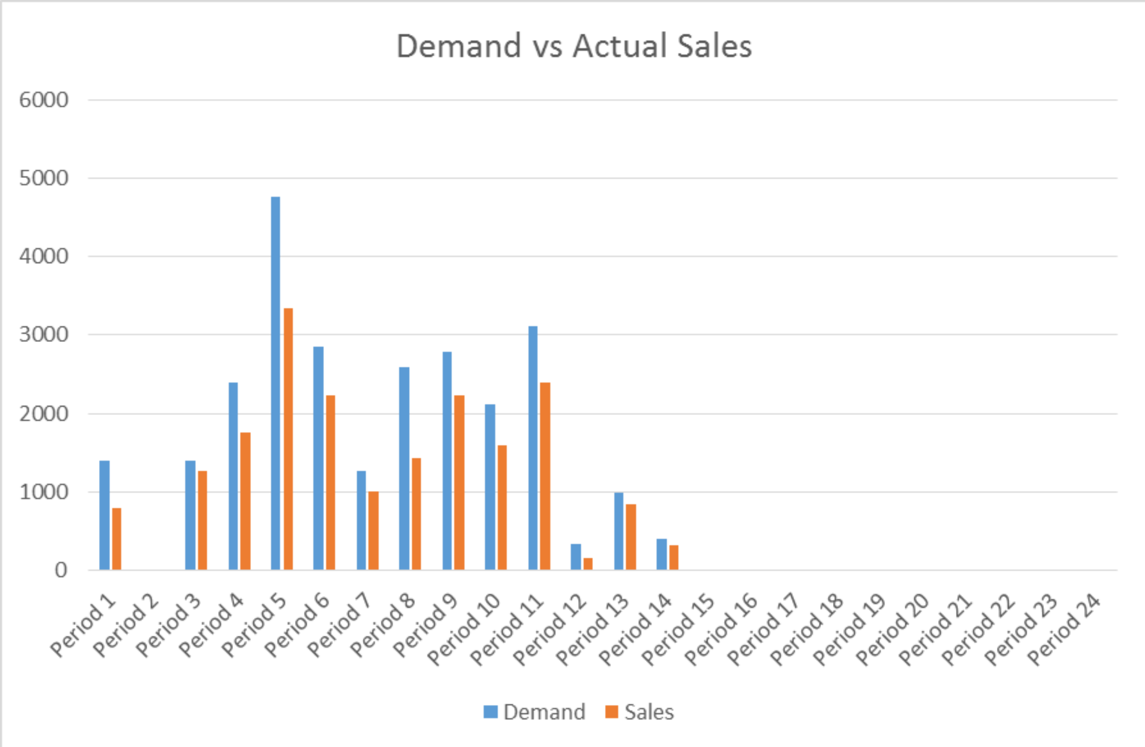

Figure 78. Demand vs Actual Sales of Washing Machine 7146041500

This washing machine represents a product group with low demand irregularity in terms of the coefficient of variation but a relatively high margin while the demand volume is rather low.

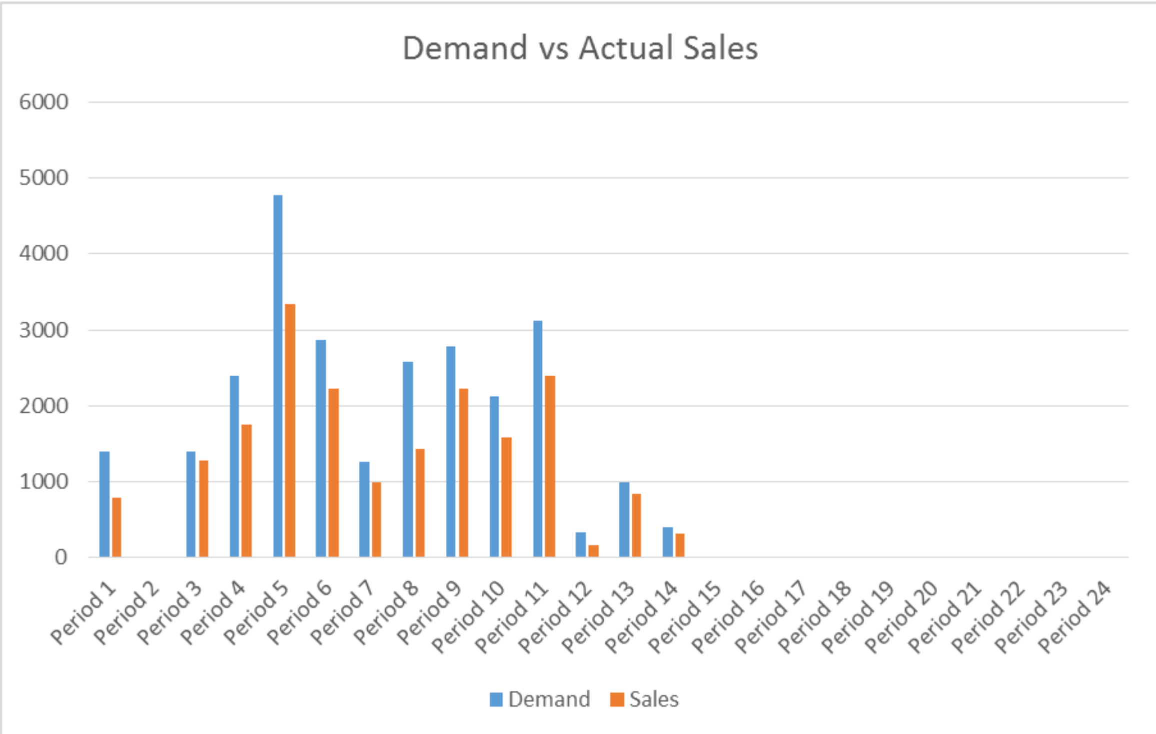

Figure 79. Demand vs Actual Sales of Washing Machine 7129441100

This washing machine represents a product group with medium coefficient of variation and low margin.

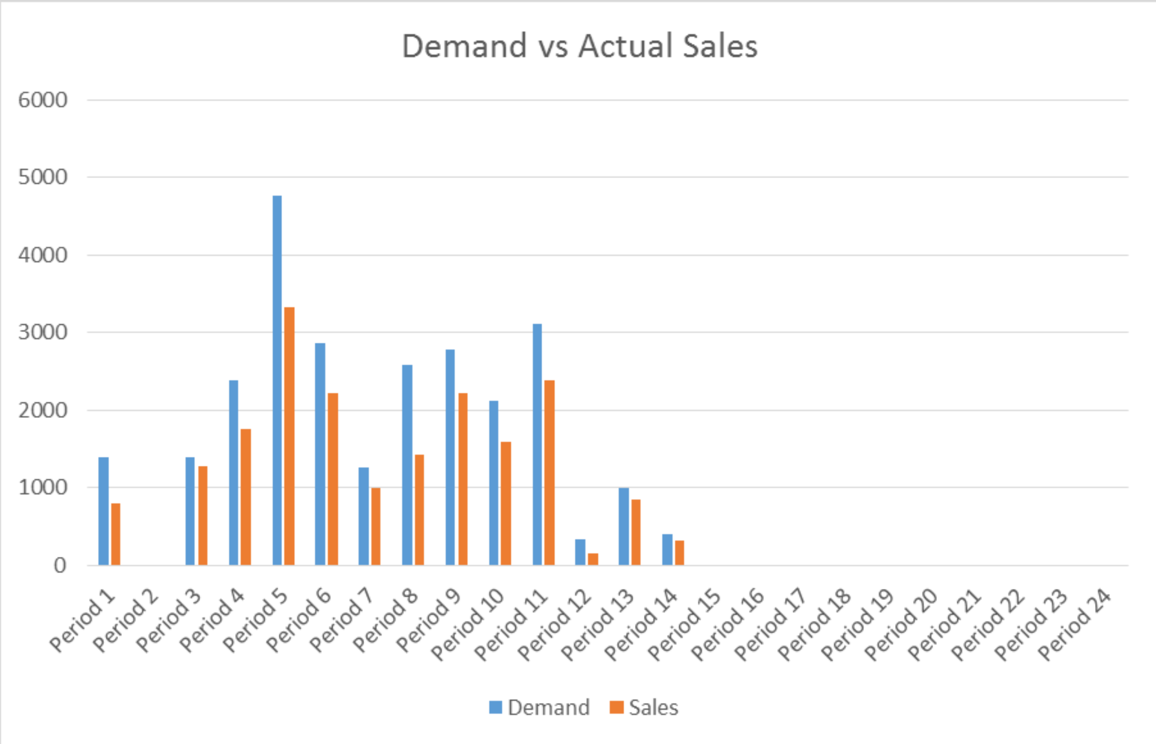

Figure 80. Demand vs Actual Sales of Refrigerator 7291540682

This refrigerator represents a product group with high margin, high ratio of zero demands and low volume.

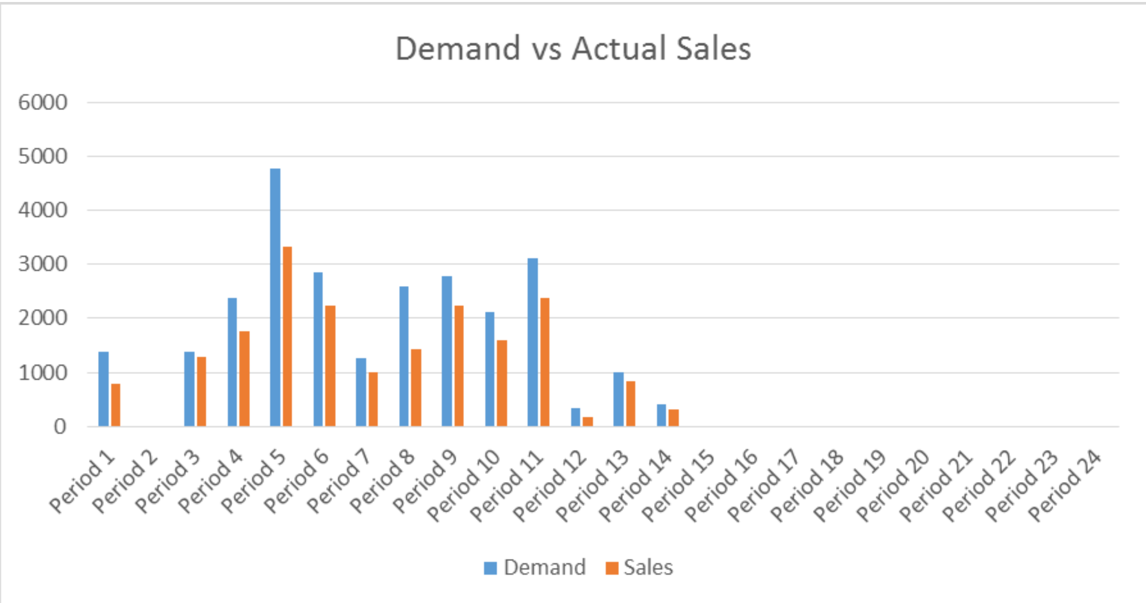

Figure 81. Demand vs Actual Sales of Dishwasher 7615033853

This dishwasher represents a product group with high coefficient of variation, low margin and high volume.

As it is seen from all above figures the demand values are higher in contrast to lower sales figures. This will cause Arçelik extra production, transport and warehouse costs.

Thus, it is worth to introduce secure VMI approach that allows Arçelik to manage the inventories of its customers without getting to know their real-time private data. Actually, it would not be necessary for the customers to give up full control over their inventories, since the actual order process would still be under customer control. But the pre-ordering will be controlled by Arçelik. So, Arçelik will manage the inventories of its customers. Arçelik has broad database of historic data and experience with many customer in different markets so it can provide better forecasts at least at an aggregated level.

3.3 Impact of collaborative supply chain management

In this chapter we analyse what benefits we can expect from roll-out of the prototype we described in the preceding subchapter. Since Arcelik sells products with very different properties even within the considered product group of white goods – from cheaper microwave ovens to high-end fridge freezers - we also analyse for which product the application of an advanced forecasting technique as provided via our secure collaborative platform makes the most sense economically. Since only Arcelik would directly benefit from improved forecasts, we will probably need to create incentives for its customers so that they join the collaboration and are willing to invest in necessary interfaces. Therefore we estimate the potential benefits we can expect from improved forecasts from different product categories.

3.3.1 Categorization of products

Arcelik provided data for over 1800 different products, i.e., stock keeping units (SKUs). The data includes on a monthly basis inventory levels and sales numbers. We filtered the list of SKUs for products that are sold to two or more customers, since only for those products we can apply our secure collaboration logic. From the remaining SKUs we picked four with typical characteristics in terms of margin, demand volume, demand irregularity, cost structure.

SKU	Characteristics
7146041500 Washing machine	Low coefficient of variation, high margin
7129441100 Washing machine	Medium coefficient of variation; Low margin
7291540682 Refrigerator	High margin; high ratio of zero demands; low volume
7615033853 Dishwasher	High coefficient of variation; Low margin; high volume

We note that there seems to be a positive correlation between these two dimensions. As depicted in Figure 82 a higher ratio of zeros can be observed with products with a higher margin.

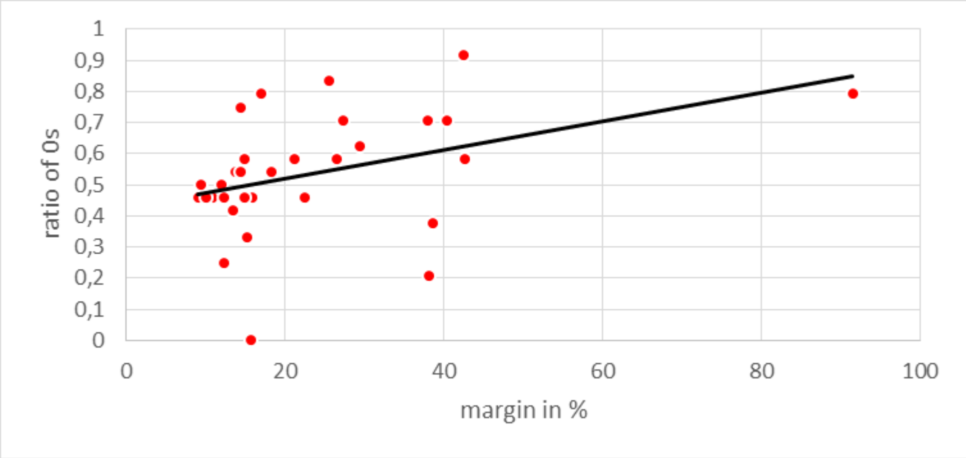

Figure 82. Correlation between margin and demand irregularity

3.3.2 *Benefit simulation for representative products*

For each of the four products we simulate the inventory performance over 24 months in 100 runs. Order costs and lead-time are fixed. As well as the simulated mean forecast improvement of 10%. The optimal service levels are derived from the overage and underage costs for each SKU. However, in the simulation they serve only as a lower bound not as an actual target value.

3.3.2.1 7146041500 Washing machine

The 7146041500 Washing machine represents SKUs with low demand irregularity in terms of the coefficient of variation but a relatively high margin while the demand volume is rather low. Table 8 shows the parameters we derived from Arcelik's data and used in the simulation:

Table 8. Simulation parameters for washing machine (7146041500)

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	111.86	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	223.72	Purchasing costs per unit.
HOLDING-COSTS	0.04	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	4000	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.58	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	62.2	The expected mean demand per period in units.
DEMAND-SD	56.3702049	The standard-deviation of our demand per period in units.

LEAD-TIME	1	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.78	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

The main result from the simulation are displayed in the following Figure 83.

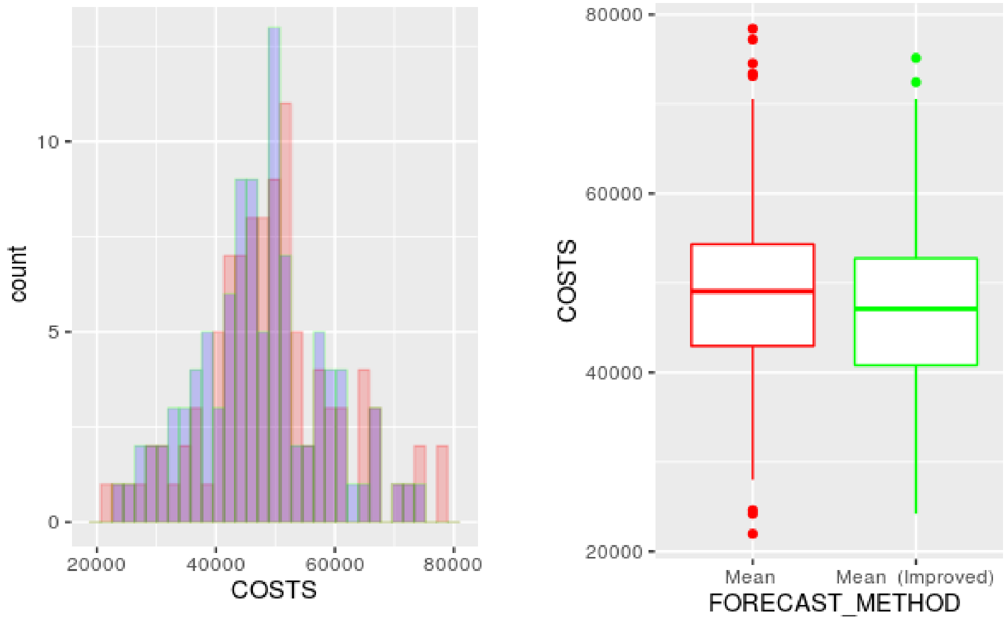

Figure 83. Output of simulation for 7146041500 Washing machine

In detail we obtain:

Total costs normal – total costs improved: 4920929.73 – 4741922.69 = 179007.04
Percentage of cost reduction: 3.64
Service level improved: 95.9155

Hence the forecast improvement of 10% leads only to a cost reduction of 3.64% for this product. This is mainly due to the low coefficient of variation, which limits the costs that result from poor forecast performance.

3.3.2.2 7129441100 Washing machine

The 7129441100 Washing machine represents SKUs with medium coefficient of variation and low margin. Table 9 shows the parameters we derived from Arcelik's data and used in the simulation:

Table 9. Simulation parameter for washing machine (7129441100)

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	65.805	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	131.61	Purchasing costs per unit.
HOLDING-COSTS	0.04	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	4000	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.5	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	323.3333333	The expected mean demand per period in units.
DEMAND-SD	530.0421367	The standard-deviation of our demand per period in units.
LEAD-TIME	1	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.94	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

The main difference compared to the washing machine in the previous section is the higher coefficient of variation: 530/323=1.64 now instead of 56/62=0.9 before.

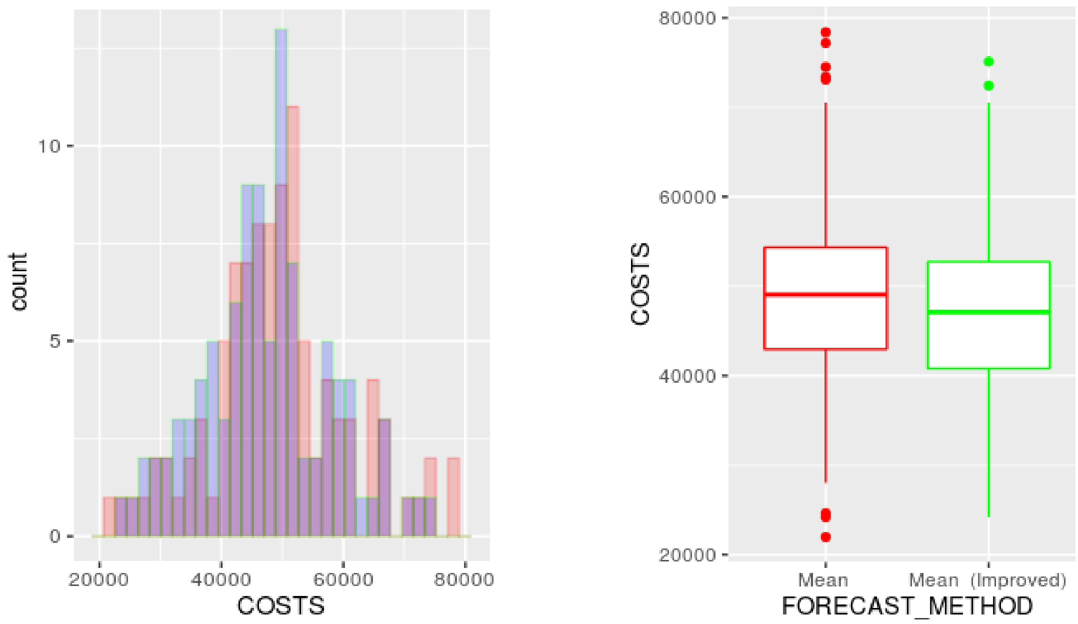

Figure 84. Output of simulation for 7129441100 Washing machine

In detail we obtain:

Total costs normal – total costs improved:	17681146 – 16594220 = 1086926
Percentage of cost reduction:	6.15
Service level improved:	96.24

Hence the forecast improvement of 10% leads to a cost reduction of 6.15% for this product. This in comparison with the results for the other washing machine with higher margin but lower coefficient of variation shows us that the coefficient of variation is the more important driver compared to the margin.

3.3.2.3 7291540682 Refrigerator

The 7291540682 Refrigerator represents SKUs with high margin, high ratio of zero demands and low volume. The following table shows the parameters we derived from Arcelik's data and used in the simulation:

Table 10. Simulation parameters for Refrigerator (7291540682)

input-key	value	description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	265.98	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	531.96	Purchasing costs per unit.
HOLDING-COSTS	0.22	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	4000	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.79	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	115.2	The expected mean demand per period in units.
DEMAND-SD	187.1384514	The standard-deviation of our demand per period in units.
LEAD-TIME	1	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.62	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

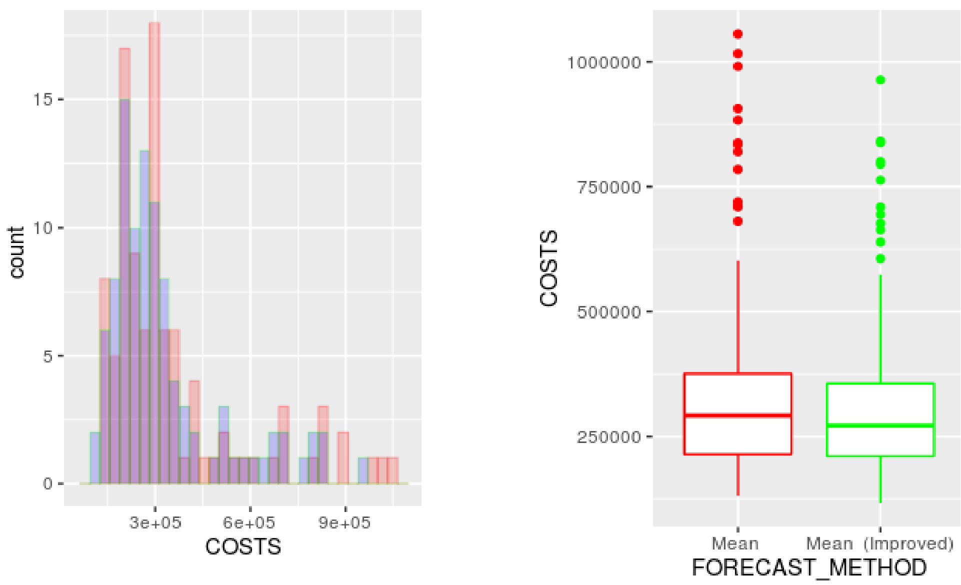

Figure 85. Output of simulation for 7291540682 Refrigerator

Figure 85 shows that the mean costs are reduced almost down to 250000 and that the spread of the results with the improved forecast is lower. In detail we achieve:

Total costs normal – total costs improved: 35507090 - 32839397 = 2667692
Percentage of cost reduction: 7.51
Service level improved: 91.00

Hence the forecast improvement of 10% leads to a cost reduction of 7.15% for this product. In spite of the low volume the high margin and the high demand irregularity make this product an interesting candidate for forecast improvements.

3.3.2.4 7615033853 Dishwasher

The 7615033853 Dishwasher represents SKUs with high coefficient of variation, low margin and high volume The following table shows the parameters we derived from Arcelik's data and used in the simulation:

Table 11. Simulation parameters for Dishwasher (7615033853)

input-key	value	Description
SIMULATION-PERIODS	24	Number of simulated periods. E.g. 12 if you want to run a simulation over 12 months.
PENALTY-COSTS	45.035	Costs per unit and period, if an order could not be fulfilled in this period.
UNIT-COSTS	90.07	Purchasing costs per unit.
HOLDING-COSTS	0.04	Holding costs per unit and period, if a unit is stored in our warehouse.
ORDER-COSTS	4000	Order costs e.g. shipping-costs for one order (independent of units in the order).
RATE-ZERO-FORECAST	0.45	Percentage of zero-periods (average number of periods without customer demand) divided through 100.
EXPECTED-MEAN-DEMAND	2030.384615	The expected mean demand per period in units.
DEMAND-SD	4288.542768	The standard-deviation of our demand per period in units.
LEAD-TIME	1	The lead-time tells us how many periods we have to wait until our order arrives.
SERVICE-LEVEL	0.94	The alpha service-level shows us how many orders could be fulfilled within the official deadline.
FC-IMPROVEMENT-MEAN	10	Mean of improvement of the better forecast.
FC-IMPROVEMENT-SD	10	Standard-deviation of improvement of the better forecast.

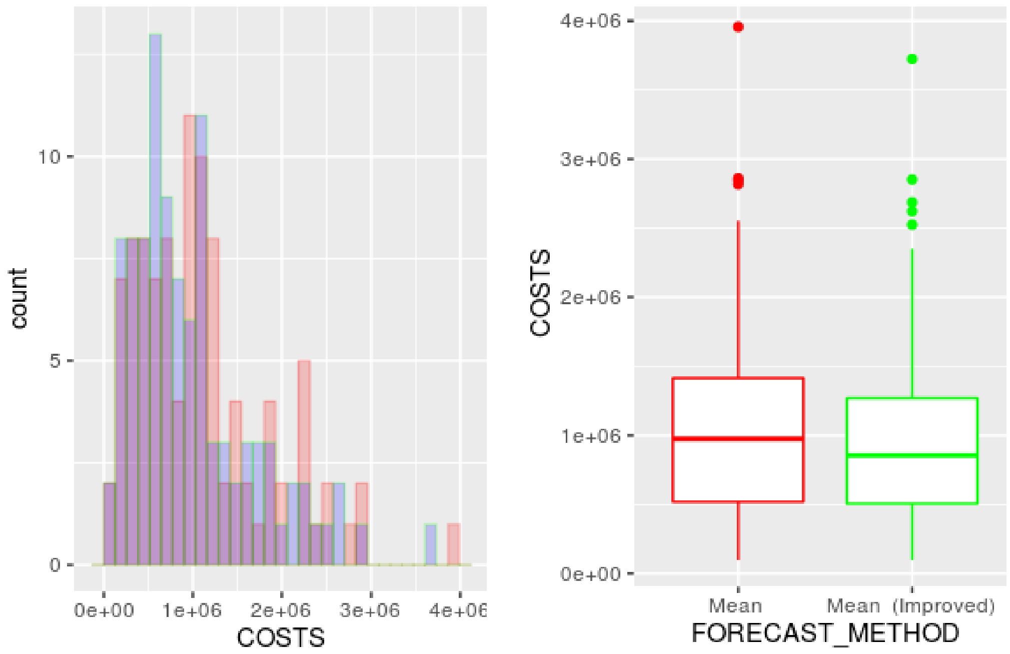

Figure 86. Output of simulation for 7615033853 Dishwasher

In Figure 86 we see a clear shift of the histogram to the left. In detail we obtain the following results:

Total costs normal – total costs improved:	108769281 - 99353538 = 9415742
Percentage of cost reduction:	8.66
Service level improved:	96.04

Hence the forecast improvement of 10% leads to a cost reduction of 8.66% for this product. The high volume combined with the high demand irregularity make this product the most interesting candidate for investments in forecast improvements.

3.3.3 Conclusion and product prioritization

As final conclusion for the Arcelik retail setting we state that the potential impact of improved forecasting on inventory costs is significant for all of the analyzed SKUs. However, SKUs which are characterized by high demand irregularity would benefit most from improved forecasting. The results are summarized in the following table and can be used for prioritizing SKUs in subsequent deployment phase.

SKU	Potential cost reduction in %	Service Level
7146041500 Washing machine	3.64	95.9155
7129441100 Washing machine	6.14	96.2485
7291540682 Refrigerator	7.51	91.0004
7615033853 Dishwasher	8.66	96.04

Table 12. Potential cost reduction and service levels for selected household appliances

Top candidates are SKUs with similar feature as the 7615033853 Dishwasher, i.e., SKUs with high coefficient of variation, low margin and high volume. For this category, we can expect a cost reduction of 8.66% along with a service level increase from 94 to 96%. These parts should be in the focus for further industrialization of secure collaboration solution in the Arcelik supply chain.

Chapter 4 Innovation of the Secure Cloud Supply Chain Management

4.1 Collaboration among customers and suppliers

Our approach towards secure VMI enables collaboration throughout Arcelik's supply chain. The main idea is that Arcelik manages inventories at the customers' sites. Arcelik therefore has better information about what is going on at the customers' side. This enables Arcelik to smooth out demand variability. Arcelik's supplier will therefore also face less unexpected demand fluctuations.

The sensitive demand information from the customers is stored securely in the cloud – an optimization algorithm determines future deliveries to customers' inventories. Therefore, while maintaining contractually defined service levels, Arcelik can optimally plan production and stock levels to minimize total cost.

Via an additional benefit sharing mechanism that distributes cost savings between collaborators Arcelik's customers are incented for to participate in secure VMI.

For the implementation we propose a two-step approach: The first step is the secure aggregation of forecasts from the customers' ERP systems. This is implemented in our prototype and will allow Arcelik to obtain more accurate aggregate mid-term forecasts. The second step would be the actual secure vendor managed inventory (sVMI) that allows Arcelik a better short-term planning since customers' real-time inventory levels and sales numbers are used as input in addition to the mid-term forecasts. The secure aggregation protocol can be reused for computing the real-time aggregate inventory levels in this setting.

4.2 Prototype computation performance

In this section we evaluate our two prototypes with respect to the actual computation time. We simulate typical tasks (e.g. adding new data to the encrypted database, analysing the data) that are supported by our prototypical implementation developed in the previous periods. For this evaluation we do not access the prototype via the web user interface described in the previous Deliverable D24.4 but access it directly via the backend API. We assume this methodology to model real world deployment since the analysis over encrypted data will extend existing tools that are modified to fit the individual environment. We emphasize that our web interface has been developed for a demonstrational purpose of our prototype for privacy-preserving data analytics in the cloud computing environment.

For both use cases the setting was as follows: the client application was executed on a Lenovo X230 Laptop with 8GB main memory and an i5-3320M CPU with two cores with a clock speed of 2.60GHz. As database system we used SAP's HANA and a custom cloud application. These ran on a HP Z820 workstation with 256GB main memory and four XEON E2670 CPUs with 8 cores each with a clock speed of 2.60GHz.

4.2.1 Evaluation of the Prototype for Fleet Management

In this section, we present evaluation results of the prototype for the Fleet Management use case. Due to privacy and legal issues with respect to real world sensor data of airlines' actual vehicles evaluation is based on artificial, simulated data. In more detail, this data is labelled with 16 different attributes from V_1 to V_{16}. Each simulated airplane is then defined by its set of attribute values that have been sampled randomly. As described in the previous deliverable, these values are then encrypted with order-preserving encryption and transferred to the cloud. We summarized both operations in our benchmarks for insertion where the time needed to insert 1000 to 5000 rows of data is plotted in Figure 87 and ranges from 500 to roughly 800 seconds.

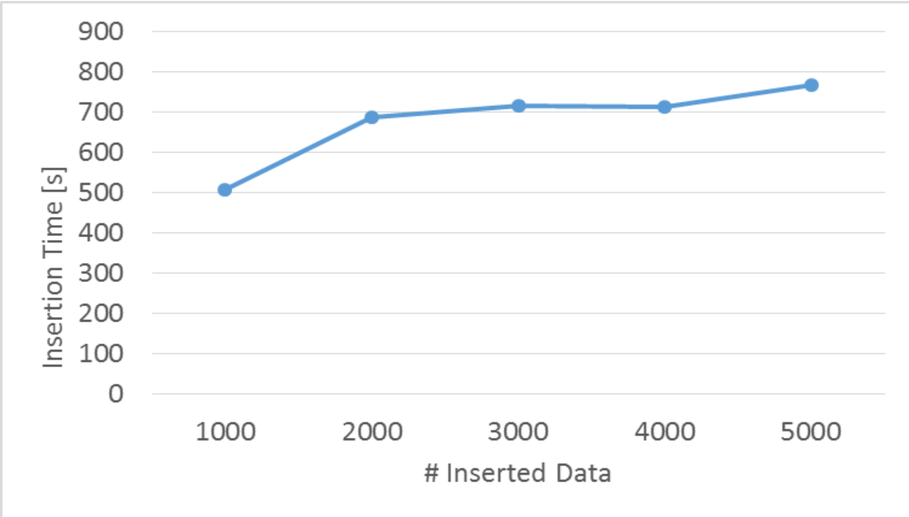

Figure 87. Insertion time for data rows.

To simulate the evaluation (i.e. the classification of fictional data) we created trees that fit to the artificially generated data[13]. One example for such a decision tree is depicted in Figure 88 where c_1 to c_3 are comparison values used in the classification process.

[13] The tree represents the way in which sensors' values (from a specific engine type) are used to classify an engine's need for MRO service.

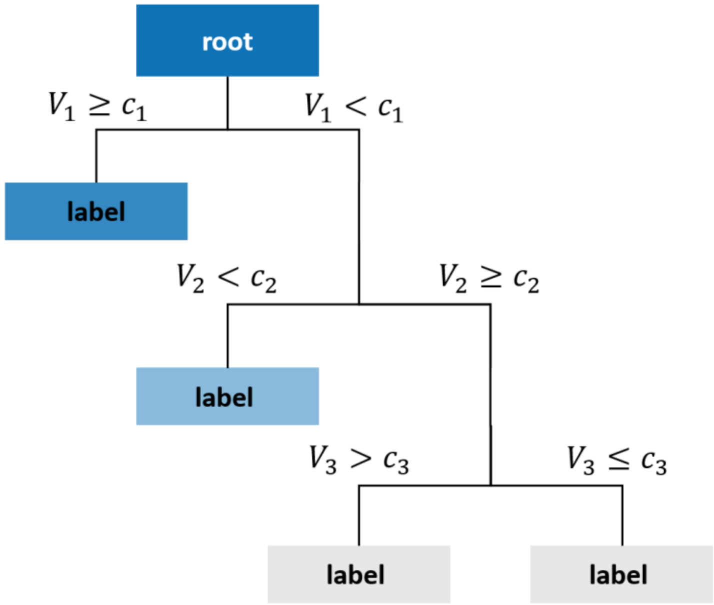

Figure 88. Example for decision tree.

We created different trees with varying characteristics[14], namely the number of leafs. Hence, the number of attributes from the root node to a leaf node vary for each tree. As expected the evaluation time increases with the number of attributes that are used for classification. For example, the evaluation of 2000 rows for different leaf nodes consisting of different numbers of attributes is presented in Figure 89.

Figure 89. Evaluation time for 3 to 9 attributes on 2000 rows.

Furthermore, we analyzed the evaluation for different database sizes in Figure 90. More particular, complete (artificially generated) trees – with up to tree size 16 – are evaluated for

[14] As knowledge on the relationship between sensors' values and MRO needs increases the tree can be updated.

database of different size. As we can see, the evaluation time is barely effected by the dabase size but increasing evaluation time is dominated by the number of attributes that need to be evaluated for classification. This effect appears due to internal optimizations and dictionaries by SAP's HANA.

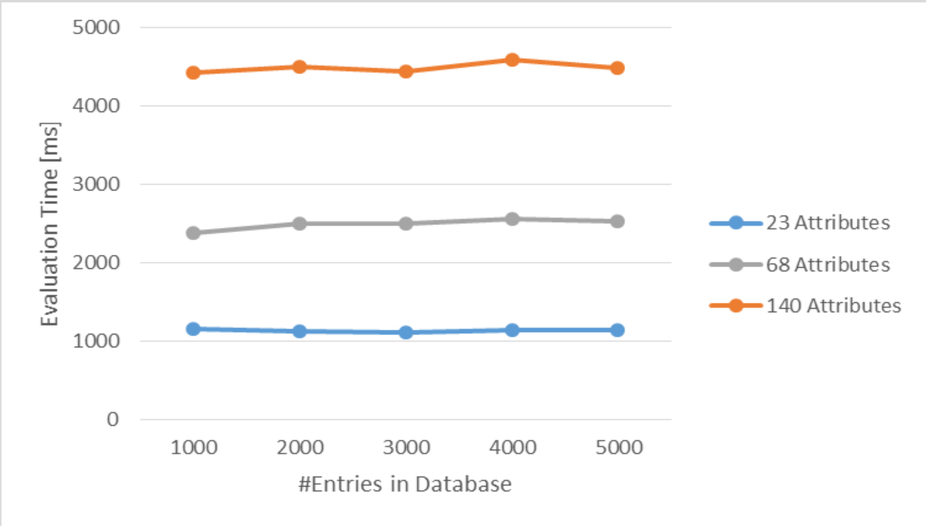

Figure 90. Evaluation time for different database sizes

4.2.2 Evaluation of the Prototype for Vendor Managed Inventory

In this section we present evaluation results of the prototype for Vendor Managed Inventory developed in the previous periods. This evaluation is performed using real world data provided by Arçelik and Arçelik's customers. The data is structured as follows:

`CUSTOMER;SKU;PRODUCT_HIERARCHY;DEMAND;DATE`

The `CUSTOMER` field identifies the party who submits orders. `SKU` is the stock keeping unit and defines the actual product that is ordered. Furthermore, `PRODUCT_HIERARCHY` defines the product hierarchy, for example `PRODUCT_HIEARCHY` with value 0 represents the following: WHITE GOODS – Refrigerator – Cooling. The `DEMAND` field defines the actual amount of ordered products and `DATE` the preferred delivery date. As described in the previous deliverables of this work package, information about the ordered product (e.g. product ID, product hierarchy) and the planned delivery date is encrypted deterministically to enable GROUP BY operations. The actual amount of orders is encrypted using additive homomorphic encryption to enable secure aggregation of the individual orders.

For evaluation of the insertion time (i.e. encryption time at the client and insertion time into the database), we insert data from a one year period. We inserted the data of each customer individually and benchmarked the insertion time as depicted in Figure 91. Note, that different customers hold different amounts of orders, e.g. the customer in the first iteration ordered 8376 different products, while the last customer only ordered 972 different products.

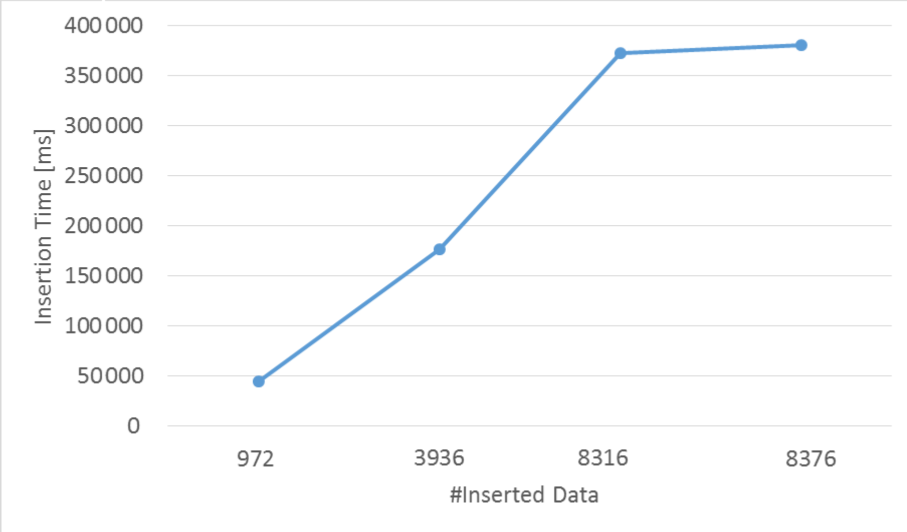

Figure 91. Insertion time for different customers.

We evaluated this secure aggregation for varying amounts of data after the insertion of each customer as shown in Figure 92. Note, that aggregation time does not increase linearly with the amount of data as one could assume. This is due to internal optimizations of the used database which are performed transparently, i.e. SEEED has no optimizations regarding increasing data volume but relies on the database optimizations.

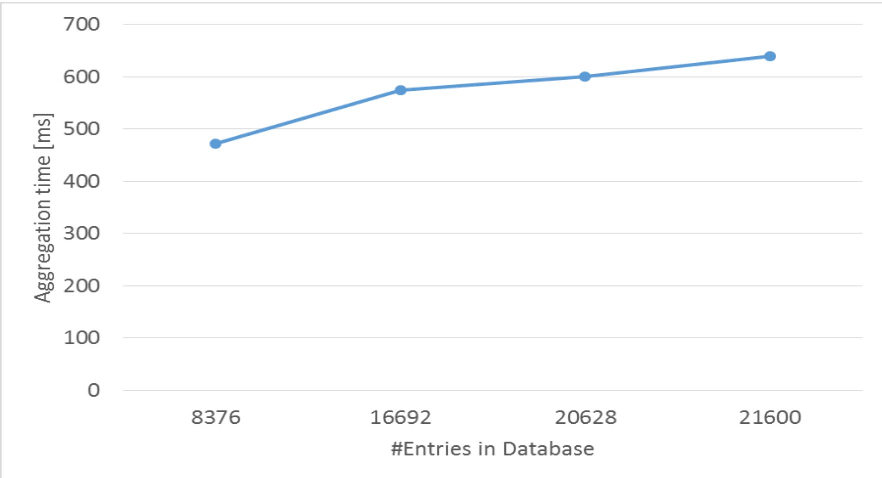

Figure 92. Aggregation time for different database sizes.

4.2.3 Conclusion

The initial encryption in the Fleet Management prototype with order-preserving encryption takes between 500 to roughly 800 seconds for 1000 to 5000 records as shown in Figure 87. The time for encryption followed by database insertion for Vendor Managed Inventory takes between approximately 50 and 400 seconds for 1000 to 8000 records.

However, this is an initial cost that can be easily parallelized. Furthermore, it only needs to be performed at certain times (e.g. once per week) or in small increments (i.e. when new data becomes available) and can be scheduled to run during times when computation resources are available and energy consumption is cheap (e.g. during the night).

The important benchmark is the sum aggregation which is two to three orders of magnitude smaller than the initial encryption, i.e. around 500 to 650ms for Vendor Managed Inventory (Figure 92) and around 150 to 300ms for Fleet Management (Figure 89). The aggregation only requires milliseconds instead of seconds like the initial encryption.

Chapter 5 Conclusions

The WP24 – Supply chain prototype contributed to the PRACTICE project with a number of results, here the list of the main ones:

1. **Innovative supply chain business models and collaborative supply chain management processes**; in particular, a collaborative demand forecasting process was designed for the aeronautic aftersales business segment, and a vendor managed inventory process was tailored to the consumer goods industry represented by ARC. Moreover, a service planning processes were also modelled for the aeronautic applications; these innovative business and process models are based on the availability of sensitive data to a collaborative supply chain management system. Such data is not available to avoid the intrinsic data leakage risks of collaborative ICT systems.
2. **Algorithms** implementing the modelled innovative supply chain management processes; the developed algorithms automate, or support, some decision making processes in supply chains, providing to the local decision makers more objective, real and updated information;
3. **Business risks implied by data leakage** due to the use of collaborative cloud-based supply chain management systems. In particular, risks depend on the specific combination of three factors, which are the data owner, the leaked data, and the recipient of the data leakage event;
4. **The data protection level required by industrial players** in order to apply collaborative cloud supply chain management systems in their daily practices to grasp the expected economic benefits. A survey was conducted measuring the data protection level on the base of the recipient of a data leakage event and of how much the public is informed about that data;
5. **Two prototype secure cloud supply chain management applications** were developed by leveraging architecture and tools from WP21 and 22. The two prototype applications implement specific algorithms and business processes developed to satisfy aeronautic and consumer goods industries, so they present different business functionalities, which can be offered as part of the secure PRACTICE cloud infrastructure, but the same security performance being it on tools;
6. **Validation of the prototype applications.** The two prototype applications were applied to two industrial scenarios, representing the aeronautic and the consumer goods case respectively, and it was verified that the functionalities comply with the business and security requirements.
7. **The economic benefits brought to the supply chain applying a collaborative forecasts system**. Collaborative forecast models are expected to deliver economic benefits to the whole supply chain system, in terms of reduced costs and better process quality. A methodology was developed to assess the economic impacts of accuracy of demand forecasts by taking into consideration the inventory setting and the product characteristics.

The last two results were achieved in the last semester of the project and were discussed deeply in this deliverable.

Those results show that Work Package 24 achieved its goal. It was the customization of a prototype secure cloud collaborative supply chain management system on the base of the actual business and security requirements. Such a system will contribute to the diffusion of more effective innovative supply chain business models and supply chain management processes, able to reduce costs and deliver higher quality services and products to the end users.

In the following, the results are represented from the two industrial points of view.

5.1 Results for the aeronautic industry

In the aeronautical industry, the challenge for the MRO supply chain to move towards performance-based contract models (where the service provider is paid for the actual hours flown by the engine, rather than for time and materials spent during the MRO shop visits) should be associated with that of stable, and as short as possible, TAT in the completion of the Maintenance, Repair and Overhaul service (first WP24 result). On the contrary, the analysis of the process data provided by an aeronautic company involved in the MRO segment, highlighted that not only the service demand seems not to have any stable trend (depending on the specific routes on which the aircrafts operate and to the entering into force of new contracts), but also that TAT values are higher than the expected ones. The real data do not regard the status of the spare parts inventory, however scientific literature demonstrated that spare parts shortage is one of the most frequent motivation of service delays.

In general, Turn Around Time depends on three main factors: demand of MRO services; resources necessary to the execution of the MRO activities; spare parts availability when they are required by the MRO process. Whether the service provider was able to forecast, in a more accurate way than now, the MRO demand and thus to plan the service activities and to adapt inventory management policy, significant performance improvements would be achieved, in terms of reduced costs and service times (these would be the direct consequence of a better usage of resource and a more effective inventory management).

The fleet management process model, designed in previous deliverables, shows that more accurate forecasts of the demand generated by all customers of a MRO service provider could be computed if private data coming from aircraft owners (such as data related to the engine health status) was processed simultaneously. Furthermore, in order to plan the service in the MRO service node, private engine health status data should be processed in connection with confidential data belonging to service provider (service capacity, inventory status, …). That is the second WP24 result: the development of models for data management and algorithms for demand forecast computing in the fleet management perspective.

The data management model, the forecast computing algorithms and the data protection levels (the fourth results of the WP24), measured through a field survey, were all input to the development of a prototype secure cloud supply chain management system (the fifth main result of the project).

The secure cloud supply chain management prototype, able to process and compute on private data while they remain encrypted, was developed and tested (in this last semester) in the specific aeronautic aftersales service. Due to privacy and legal issues, with respect to real world sensor data of airlines' actual vehicles, the prototype evaluation is based on artificial, simulated data. Anyway, data was simulated by leveraging the data model developed for the fleet management case and discussed in the previous deliverable.

Several cases were tested, differing with respect to the specific sensors' data analysis carried out. Indeed, the way in which sensors' data are processed to signal a service need is represented in the specific protocol implementation.

The results of the prototype test can be summarized as follows:

1. The secure cloud supply chain management system is able to protect data through encryption during all phases of data management, from the data entering to the computation results, to results delivering;
2. The secure cloud collaborative supply chain management system is able to compute on encrypted data and provides demand forecasts for specific future time slots, this is generally used by inventory manager staff to decide about spare parts purchase;
3. The (secure) computation time is well acceptable with respect to the business conditions of the fleet management process, being in the order of minutes;
4. The system is simply scalable to take advantage of new knowledge about the service requirements (which repair activities, or which parts are to be replaced) that will be developed in the future by aeronautic companies; indeed, it will be enough to update the computing algorithms, while the data management system will remain substantially unchanged;
5. As the data management of prototype is based on SAP HANA, the prototype system is able to manage the 'big data' that aero fleet is going to send to MRO service providers.

As supply chain collaborative applications need huge effort to be effectively deployed, it was recognized that a step-by-step approach would be the most suitable. The first task is to make evident the economic benefits brought to the supply chain by improved forecast accuracy and capability (obtained by applying the secure cloud supply chain management system).
In order to identify which sector of the supply chain (which engine modules/parts) will provide the highest economic benefits, a methodology to simulate the effects on the supply chain was prepared (the seventh project result). It is based on the categorization of engine parts with respect to their criticality (price, lead time, …) and demand variability, as well as to the model of inventory settings and the demand process (modelled in the two cases: current practices and collaborative demand forecasts). By simulating the impact of specific spare parts management costs, it is possible to rank the parts with respect to the economic benefits they can bring to the supply chain. The higher the economic benefits, the higher the urgency for moving toward collaborative demand computation. The simulation shows that improving forecast accuracy for parts characterized by higher criticality by 10%, the inventory costs can on average be reduced by close to 10% which can lead to an even higher impact in terms of profit. Focusing the deployment on that supply chain sector the highest economic benefits can be achieved by the MRO service provider, and shared with customers in terms of reduced service costs and increased service quality.

As a conclusion, the prototype application satisfies the business and security requirements for deploying a fleet management process in the MRO segment of the aeronautic industry (sixth result). The prototype application is designed and implemented to integrate the innovation expected in the next few years, mainly coming from big data technologies and from new knowledge on the MRO needs.

In the near future, it is expected that the collaborative demand forecast computation will be associated with a collaborative service planning. In this case, in addition to the improved spare parts management, also the resource management planning will be improved and other benefits can be delivered to end users. Specifically, the improvements will regard a more efficient usage of staff and repair machines, and a more effective service capacity planning.

5.2 Results for the consumer goods industry

As it is seen from the secure vendor managed inventory prototype the impact of improved forecasting on inventory costs are significant for all selected and analyzed SKUs. However, SKUs which are characterized by high demand irregularity would benefit most from improved forecasting.

The results are summarized in Table 12 and will be used for prioritizing SKUs in subsequent deployment phase. As it can be seen from the Table 12 the potential cost reduction is possible from 3.6% to 8.6% depending on the product group. The service level increases for these product groups to 95.91% to 96.04% as well. Thus, the higher cost reduction and higher service level increase products will be in the focus for further industrialization of secure collaboration solution in the Arcelik supply chain.

As a result, the secure vendor managed inventory approach in household appliances industry ensures effective planning of related activities resulting in improved coordination, loss minimization, efficient use of resources and high customer satisfaction level.