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Demand forecasting

Models and solutions

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Technical Memorandum
DRDC Valcartier TM 2013-317
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Abstract

Canadian Armed Forces (CAF) are expected to evolve in adaptive dispersed operations characterized by Future Security Environments (FSE) and time-varying, hostile and uncertain contexts which involve major challenges to delivering effective and efficient In-Theatre logistics and sustainment. Accordingly, demand forecasting is perceived as a key research area in order to maximize service level, customer satisfaction, reduce logistic footprint, inventory and delivery costs, and increase system readiness. Demand forecasting is essential for efficient deployment, operations sustainment, and maintenance cycles. This document presents a survey of demand forecasting approaches applicable to the operational support and In-Theatre logistics domain. Customer demand is first characterized by introducing the forecasting problem and its pursued objectives in the military context, Then, existing statistical and causal demand forecast approaches, methodologies and technical procedures are presented. Strengths and weaknesses of the approaches are briefly discussed stating the main challenges lying ahead. Finally, commercial software and some military forecasting solutions are reported for a few nations.

Résumé

Les Forces Armées Canadiennes (FAC) sont appelées à évoluer en opérations dispersées adaptatives caractérisées par des environnements de sécurité futurs et des contextes dynamiques, hostiles et incertains lesquelles comportent des défis importants afin d'assurer une logistique et un soutien opérationnel et en Théâtre efficaces et efficients. En conséquence, la prévision de la demande est perçue comme un domaine de recherche clé pour maximiser le niveau de service, la satisfaction du client, de réduire l'empreinte logistique, les stocks et les coûts de livraison et accroître l'état de préparation des systèmes. La prévision de la demande est essentielle pour un déploiement efficace, le soutien aux opérations et les cycles de maintenance. Ce document présente un survol des approches de prévision de la demande applicable aux domaines du soutien opérationnel et de la logistique en Théâtre. Introduisant les problèmes de prévision et les objectifs poursuivis dans le contexte militaire, la demande des clients est d'abord caractérisée. Par la suite, les approches existantes de prévision de la demande statistiques et causales, les méthodologies et les procédures techniques sont présentées. Les forces et les faiblesses des approches sont brièvement discutées faisant état des principaux défis. Les outils logiciels commerciaux et quelques solutions de prévision de demande militaire sont finalement présentés pour quelques nations.

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Executive summary

Demand forecasting

J. Berger, A. Boukhtouta; DRDC Valcartier TM 2013-317; Defence R&D Canada – Valcartier; July 2013 .

Background: Canadian Army Forces (CAF) evolving in future security environments involves many challenges in delivering and operating effective and efficient In-Theatre logistics and sustainment supply chain management. As supply chain management efficiency traditionally induces significant cost for the CF in such contexts, improved demand forecasting is a relevant and promising area to be further investigated. Enhanced demand forecasting is believed to reduce the magnification of fluctuations associated with demand variability (bullwhip effect) over time, which will likely lead to significant cost-savings.

Results: This document presents a survey of demand forecasting approaches applicable to the operational support and In-Theatre logistics domain. It gives an overview of existing forecasting approaches, models, techniques and methods. It determines main forecasting techniques and framework currently available. Emphasis is on statistical and causal models. The former are often used for demand forecasting simulation purposes. When properly applied, such models may approximately determine future supply demands. From a causal approach, stochastic processes are often found successful in predicting (with certain probability distribution) expected demand by modeling conditional requirements. An assessment of the strengths and weaknesses of the respective approaches is reported. Customer demand distribution profiles are also characterized. Finally, commercial software tools and demand forecasting systems currently used in some allied countries are presented.

Significance: The document provides some guidance for selecting suitable forecasting methods given application domain customer demand characteristics or situations. It also identifies key challenges lying ahead and promising research directions. This paves the way to future forecasting technique investigation and comparative performance analysis for operational support and in-Theatre military logistics. More accurate demand forecasting is expected to provide significant cost reduction in inventory management, distribution, and maintenance over the supply chain network while enhancing readiness management.

Future Plans: Future work intends to develop new demand forecasting techniques applicable to operational and In-Theatre logistics aimed at closing the gap shown in the Canadian DND Distribution Resource Planning (DRP) tool suite. This forecasting capability shall be integrated with a sustainment management decision support capability component addressing supply network distribution for In-Theatre logistics and sustainment missions.

It shall enhance situation awareness and decision support, providing forecasting analysis while improving adaptive planning.

Sommaire

Demand forecasting

J. Berger, A. Boukhtouta ; DRDC Valcartier TM 2013-317 ; R & D pour la défense Canada – Valcartier ; juillet 2013.

Contexte : L'évolution des Forces Armées Canadiennes (FAC) dans des environnements de sécurité implique de nombreux défis dans la livraison et l'opération efficace et efficiente de la chaîne d'approvisionnement pour la gestion logistique en Théâtre et le soutien opérationnel. Comme l'efficacité de gestion de la chaîne logistique induit traditionnellement des coûts importants pour les FAC dans de tels contextes, l'amélioration de la prévision de la demande demeure un domaine pertinent et prometteur demandant davantage à être exploré. La mise en valeur accrue de la prévision de la demande est censée réduire l'amplitude des fluctuations liées à la variabilité de la demande (effet coup de fouet) au fil du temps, ce qui devrait conduire à des économies significatives.

Résultats : Ce document présente un survol des approches de prévision de la demande applicable au soutien opérationnel et au domaine logistique en Théâtre. Il donne un aperçu des méthodes de prévision existants, des modèles, des techniques et des méthodes. Il détermine les techniques de prévision et principaux cadres actuellement disponibles. L'accent est mis sur des modèles statistiques et causaux. Les premiers sont souvent utilisés à des fins de simulation de prévision de la demande. Lorsqu'ils sont correctement appliqués, ces modèles peuvent déterminer approximativement les demandes d'approvisionnement futures. Dans l'approche causale, les processus stochastiques sont souvent performants à prédire (avec une certaine distribution de probabilité) la demande prévue par la modélisation d'exigences conditionnelles. Une évaluation des forces et faiblesses de ces approches respectives est présentée. Les profils de distribution de demande de clients sont également caractérisés. Les outils logiciels commerciaux ainsi que les systèmes de prévision de la demande actuellement utilisés dans certains pays alliés, sont enfin présentées.

Importance : Le document donne des indications pour choisir convenablement les méthodes de prévision nécessaires pour une application étant donnée les caractéristiques du domaine demande des clients ou des situations. Il identifie également les principaux défis qui nous attendent et les orientations de recherche prometteuses méritant d'être poursuivie. Cela ouvre la voie à une investigation de techniques de prévision futures et de l'analyse comparative de performance pour le soutien opérationnel et la logistique militaire en Théâtre. Une prévision plus précise de la demande devrait permettre une réduction significative des coûts dans la gestion des stocks, la distribution et l'entretien (maintenance) du réseau d'approvisionnement tout en améliorant la gestion de la préparation.

Perspectives : Les travaux futurs visent à développer de nouvelles techniques de prévision de la demande applicables au soutien opérationnel et à la logistique en Théâtre réduisant les déficiences de la suite d'outils de Planification de Distribution des Ressources (PDR) du Ministère de la Défense Nationale canadien. Une telle capacité de prévision doit être intégrée à une composante d'aide à la décision de gestion de soutien abordant la distribution du réseau logistique pour la logistique en Théâtre et les missions de soutien opérationnel. Cette capacité rehaussera l'éveil situationnel et l'aide à la décision, offrant une analyse de prévision tout en améliorant la planification adaptative.

Table of contents

List of figures

List of tables

1 Introduction

The Canadian vision of 2021 force management [1] emphasizes the importance of the operating concept of force sustainment. This relates to efficient management of human resources, financial planning aspects and equipment movement within and outside theater of operations. Accordingly, interest has been shown in the investigation of efficient demand forecasting mechanisms for different spare parts and In-Theatre supply demand used in support of various missions. Based on knowledgeable Subject Matter Experts (SMEs), it becomes apparent that a state-of-the-art and well-integrated demand forecasting advisory system can play a key role in military planning, capability assessment, contingency evaluation and mission success. Consequently, the Canadian Armed Forces (CAF) is committed to meeting the need for superior technology-enabled demand sustainment underpinned by a renewed focus on information management applications for the future echelon systems. This, in turn, can also enhance situational awareness while providing appropriate information-sharing in intra-military, coalition environments and dispersed operations.

Inventory reduction is often critical to inventory planning. Insufficient stocks can lead to extended equipment down-time (or unavailability) whereas exceeding supply may unnecessarily induce higher costs. While an absolute demand forecasting method remains inherently elusive due to situation uncertainty, determining optimal stock levels is still very important for many industries in the military context as well as in civilian public and private sectors. As early as in 1968, Sherbrooke [1] published on this operational research problem in relation to the cost of recoverable spare parts in the United State Air Force (USAF). At that time, it amounted to ten billion dollars. This cost represented about 52% of the total cost of inventory for that year. In 2001, AMR Research, a Gartner, Inc. company [2] estimates that $700 billion were spent on service parts in the U.S., which represents 8% of the U.S. gross domestic product [2]. A study of the National Science Foundation (NSF) Group confirms the suitability of using forecasting models on 28,000 commercial data series of inventory items from nine companies in the U.S. and Europe, representing aviation, high tech, electronics components, marine equipment and other capital equipment industries [2]. In the industrial world, an annual cost of storing, depreciating, insuring, and moving service parts representing 25-35% percent of the inventory book value is very common. Patton Consultants, a specialist in field service and service parts management, estimates that the material (parts inventory) costs for service can reach as much as 60 percent of total service-related costs. For instance, in [3] it is described how Brake Parts, Inc., a manufacturer of automotive parts, improved its bottom line by $6 million per month after launching a company-wide effort to improve sales forecasting effectiveness [4]. The use of forecasting software tools based on methods such as Smart-Willemain [5] proved to bring significant benefits, as exemplified by a large telecommunications company, shown to save

1. Toward Land Operations 2021 Report, web link: `http://www.army.forces.gc.ca/DLCD-DCSFT/pubs/landops2021/Land\_Ops\_2021\_eng.pdf`
2. Advanced Market Research: `http://www.gartner.com/it/page.jsp?id=1379730`

$38 million more in inventory value than the estimate generated by a previous forecasting system[3]. Therefore, spare parts demand forecasting represents overall a multi-billion dollar problem affecting a variety of industries worldwide.

The document is outlined as follows. Chapter 1 introduces the forecasting problem and typical objectives to be pursued. In Chapter 2, we elaborate the context and the problem in terms of military logistic forecasting and provide the available classification of forecasting models to address the problem. Chapter 3 surveys and describes the main methodologies reported in literature. In chapter 4, we highlight theoretical and procedural challenges of demand forecasting in the context of inventory planning for spare parts and discuss a specific forecast diagnostics and a number of relevant software tools that can be used for demand forecasting. Chapter 5 describes some forecasting systems currently used by some military institutions. Finally, a summary is given in Chapter 6.

This work was conducted at DRDC Valcartier between April 2012 and March 2013 through DRDC-ARP DP project 12ss Decision Support Capability for In-Theatre Logistics Planning and Sustain Missions.

Below we discuss the forecasting problem and typical objectives to be pursued.

1.1 Problem Statement

It is important to understand what forecasting is and what it is not. The idea of typically accurate demand forecasting in supply management is elusive from various perspectives. It blurs the distinction between forecasts, plans, and goals [35]. More inclusively, it is a management process that also includes communication and collaboration beside the wise use of an automated prediction system.

In this report we will investigate the problem of the forecasting on time-series data of one type of item in the absence of any external information about the process that is generating data. The problem can be defined as follows. Given a hidden continuous process of demand generation, visible demand data is seen in a time-series. In this setting, we are required to verify the predictability and forecast the value of future demand over future time-scale $(t+f)$ with available demand values up to time t.

In future, we intend to extend this research as follows:
- Investigating the relationship among the demands of multiple items.
- Investigating stock inventory in order to minimize the probability of failure in sustaining future demand.
- Investigating the impact of demand forecasting.
- Investigating better forecasting in the presence of partial knowledge of the process of demand creation.

3. http://www.smartcorp.com/pdf/Intermittent_Demand_Forecasting_WhitePaper.pdf

In practice, better forecasting should also account for supply limitations along with specific goals of supplier and consumers. Just as mistrust and inadequate information must be dealt with, it is also understandable that an occasional high prediction of expected demand may exceed the supplier's ability or may incur elevated maintenance cost. On the other side, under-forecasting of demand may entail high transport cost that in effect may increase the cost of the overall supply chain process.

Demand forecasting is expected to play a vital role as the related military information systems will enable Command & Control (C2) to effectively handle force sustainment details in centralized and distributed settings. In military operation support, repair parts and components include kits, assemblies, and sub-assemblies (repairable or non-repairable) that are required for maintenance support of all equipment ranging from daily needs to complex weapon systems. While an accurate prediction mechanism will ensure the agility and productivity of the future defense force by proper inventory management, this kind of global mechanism is unlikely to exist.

Different uncertainty levels related to the demand for spare parts along with various objectives of prediction affect the choice of forecasting mechanism. Uncertainty is usually treated similarly to contingency by keeping additional spare parts, however, their accumulation raises delivery and maintenance costs. Therefore, this leads to an optimization problem constrained by the lumpy or intermittent nature of the demand. Ghobbar and Friend discuss the lumpy nature of the demand in the context of aircraft maintenance service parts [6] while Syntetos and Boylan address it in the context of the automotive industry [7].

1.2 Requirements

In the military context, demand forecasting informs decision makers about the reserves required to sustain stock supplies during mission execution or for upcoming missions. In this respect, necessary in the first instance to have an elaborated understanding of military forecasting needs. This understanding also entails developing robust models to predict the future needs of specific spare parts and equipments. Second, it is necessary to understand the main classical models for demand forecasting (qualitative, causal, time-series, etc.) and various approaches for handling the forecasting. Finally, these models have to be verified with respect to their suitability relative to various statistical criteria as well as historical data available.

1.3 Historical Data

Demand forecasting largely depends on the quality of available historical data and constant on-line sharing of logistics information within the network. The latter part depends on the availability of an infrastructure associated with the robust input of electronic data interchange (EDI) information such as point-of-sale (POS) demand and retail inventory levels. In this material, we detail the use of historical data. Demand related historical data is available as text files, Comma Separated Values (CSV) as well as data base query result set. Historical data can be used for training even if incomplete, erroneous/noisy, partially absent and/or anonymized (for various security reasons). Demand forecasting models are affected by the volume and accuracy of the training data. An example from NSK [4] (Nippon Seiko Kabushiki) corporation on anti-friction bearings and precision parts for automotive indus-tries reveals that two-thirds of a 7,000 sale history data corresponds to 50% of them having highly intermittent demand characteristic with zero value [2].

Historical data may exhibit functional linear or non-linear relationship with dependence on one or more variables. In practice, noise elimination and outliers (measurement error or heavy-tailed distribution) detection is also required before forecasting on raw data available from sensors or human input. In research article [8], the authors comment on the usefulness of the bootstrap technique to estimate the demand of spare parts with limited historical data. Poisson and binomial methods are also useful as their dependency on historical data is limited. In works such as [9], the use of artificial neural network (ANN) is emphasized as the means to capture nonlinear patterns in the data. Neural Network models can provide good approximations to just about any functional relationship. Also, ARIMA model [10, 11] can be applied in some cases where data shows evidence of non-stationarity, where an initial differencing step (corresponding to the “integrated” part of the model) can be applied to remove the n-stationarity. The S-ARIMA model can be applied to the seasonal data in the corresponding periods. Similarly, the Box-Jenkins model fits well if the residuals between the forecasting model and the historical data points are small, randomly distributed, and independent. Lanham Associates[5] emphasize various input techniques to improve the accuracy of historical data. One recommendation is to filter usage of data based on the expectation of reoccurrence. A one-time sale or unusual usage can be excluded from total usage for adjusting abnormalities. Such irregular usage can be automatically smoothed to improve usage patterns. The usage history from discontinued items can also be reassigned to new items. In addition, a percentage of historical usage can be duplicated from an existing item to a new item. This allows the forecasting of new items without waiting for historical usage to accumulate. Finally, the authors suggest gathering collaborative input from several customers in order to gather their expected buying patterns before forecasting.

1.4 Forecasting Objectives

It is important to understand what forecasting is and what it is not. The idea of typically accurate demand forecasting in supply management is illusive from various perspectives. It blurs the distinction between forecasts, plans, and goals [4]. More inclusively, it is a management process that also includes communication, and collaboration beside the wise use of an automated prediction system. In practice, better forecasting should also account for

4. http://www.nsk.com
5. http://www.lanhamassoc.com/downloads/global/AFP_Distribution_Global.pdf

supply limitations along with specific goals of supplier and consumers. Just as forecasting must deal with mistrust and inadequate information, it is also understandable that an occasional high prediction of expected demand may not meet the supplier's ability or may incur elevated maintenance cost. On the other side, under-forecasting of demand may entail high transport cost that in effect may increase the cost of the overall supply chain process.

The main objective of this study is to survey appropriate methods of demand forecasting for the supply chain that can be used in force sustainment. However, before a detailed discussion, it is important to understand the process of general military force sustainment prediction system and goals. Indeed, we will elaborate the context and problem of military logistic forecasting and provide the available models in the literature to address the problem. An extensive taxonomy of different forecasting techniques will be given alongside different demand forecast perspectives. We highlight theoretical and procedural challenges of demand forecasting in the context of inventory planning. A number of relevant software tools that can be used for demand forecasting will also be presented.

2 Forecasting Problems

Spare parts and materials are critical for maintenance systems, however, their respective demands may be different based on various factors such as wear and tear or established shelf life. This information can be characterized in various types of time-series data. In relation to military systems, two processes generate the demand for logistic resources in the theater of operations, namely attrition and consumption. Therefore, it is important to understand the relations (e.g. lead time) between the necessity and condition of resources that are needed to fulfill complex military campaigns [12]. The proper forecasting of future logistic operational requirements involves the factoring in of mission objectives and required resources in both time and space dimensions. Furthermore, the demand level is also related to uncertainties that are associated with processes of attrition and consumption.

2.1 Organizational Hierarchy

The envisioned demand forecasting system is required to fulfill different logistic requirements and allocations associated with different levels in the hierarchical chain of military command. These different levels include strategic, operational and tactical objectives. Each level has different forecasting requirements. Establishing a common hierarchy on various levels of demand forecasting by aggregating and composing different forecast is a challenging task.

2.1.1 Strategic Level

The top military commanders expect demand forecasting for their strategic requirements. It is often based on crude classification while the forecasting system has to use a predefined hierarchy to classify actual military logistics (ex. various weapon systems, transportation trucks, etc.) according to the strategic demand perspective. Therefore, at this level the estimated demand for logistics can be based on previous scenarios. To a strategist, supporting a military campaign objective may require certain air power, army and navy intervention without specifying specific planes, vehicles or ships. Therefore, the related demand fore-casting objectives are associated with the management of budget and overall inventory situation. In [12], the author mentions that the strategic goal is to determine demands for logistic resources by all combat forces in all reference scenarios. Such requirements can be predicted from historical data, war-games simulations and expert opinions by hierarchically summing up the anticipated demand of sub-scenarios.

Usually, strategic planning is performed far ahead of the execution time. Hence, an important feature of the forecast effort is that it is less concerned with the time dimension of forecasting. Also, the related demand forecasting objectives are long-term.

2.1.2 Operational Level

From an operational command perspective, the requirements for supporting a military campaign objective may require certain air power, army and navy intervention. The operational objectives of the demand forecasting are related to multi-item demand forecasting for related military logistic assets (ex. various weapon systems, transportation trucks, etc.). The goal of demand forecasting is to facilitate optimal combat readiness supported by proper inventory management.

2.1.3 Tactical Level

Tactical forecasting is often related to estimation of demand due to adversarial movements and unaccountable chance factors. At the tactical level, forecasting is required to be quick. Furthermore, as every combat situation is unique, the collection of historical data is significantly less and human judgment plays an important role. Therefore, demand forecasting is expected to have more errors at these levels than at the strategic level. Any forecasting effort that is being made at the tactical level is short-termed and usually limited to selected resources (e.g., medical services) in special circumstances [12].

2.2 Military Logistics Forecast Procedure

Moshe Kress mentioned in [12] that in theater, operational logisticians are concerned about forecasting to adjust the mix and quantity of resources that are requested from higher echelon. It also helps them to *a priori* measure the limitations that will be imposed by logistics. The process takes input from three factors: actual resources in the theater, potential resources in pipeline and demands.

Figure 1 depicts the details of forecasting procedure in military systems in three different domains based on the concepts provided in [12]. The logistic and information domain is shown to maintain a gap at every step of the flow diagram. This gap comes from the difference of perception and error that occurred while informing the forecast system. At every time phase (t), there is a gap between the actual logistical situation and its determination process because of the underlying gap between the factual amount and information available on actual consumption, actual supply and assessment of potential supply. In this respect, the decision problem emphasises narrowing the gap by inserting this difference/gap in a demand learning model. The model, in turn, forecasts the future demand that is additionally inserted in the resource of the echelon's inventory. After completion of the phase, previously (at time phase t) predicted demand for time phase $t+1$, is matched with actual demand generation to understand the error in forecast. An efficient model is expected to reduce this error.

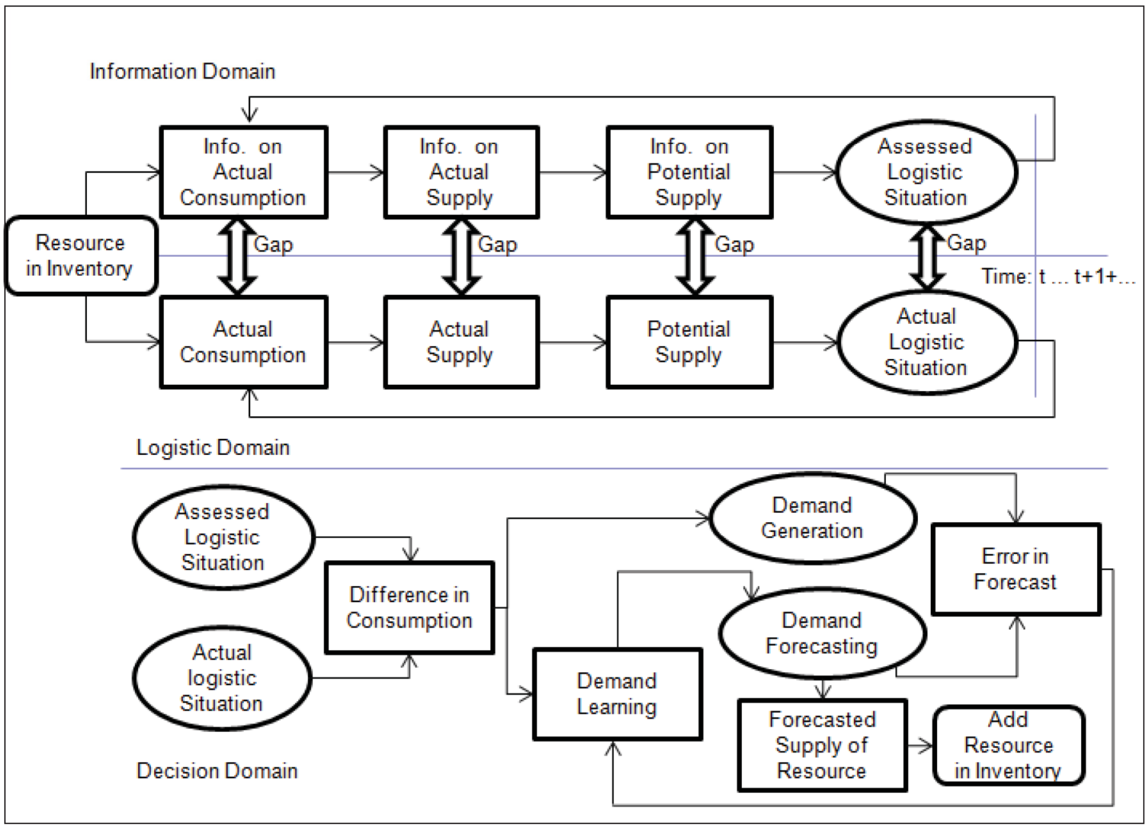


Figure 1: *Demand Forecasting Data Flow Diagram*

2.3 Forecast Characteristics

2.3.1 Horizon

In practice, there are three forecasting horizons that are commonly used:
– *Short* time horizon forecasting, which is valid from 1 to 30 days,
– *Medium*, ranging from 1 to 12 months and
– *Long*, where the time horizon corresponds to forecasting for more than a year.
Forecasting requires a set of demand observations for each given period t such that $D^t = \{D_t, D_{t-1}, \ldots\}$. The demand process D_t [13] is given by:

$D_t = \mu_t + \varepsilon_e$, where

$\mu_t = \mu_{t-1} + \nu_t$, with independent variables:

$\varepsilon_t \sim N(0, n^2)$

$\nu_t \sim N(0, c^2)$

There are two random components: temporary shock ε_t and long duration shock ν_t. The standard deviation c captures the change in the unobserved level μ that corresponds to long duration shocks persisting in the subsequent periods. The standard deviation n characterized the noise of the temporary shocks that last for a single period.

By changing the parameters n and c, the model can describe a wider range of environments from stable to highly unstable processes. For $n = 0$, this corresponds to a pure random and for $c = 0$, it corresponds to stationary white noise [6].

A forecast F_{t+1} can derived by means of a weighted average of the most recent demand observations along with the previous forecast:

$$F_{t+1} = \alpha D_t + (1 - \alpha) F_t = F_t + \alpha (D_t - F_t)$$

The latter part of the previous equation highlights that a forecast depends on an observed forecast error $(D_t - F_t)$ and the weight α coupled to the forecast error.

In theory, the optimal forecast revision from F_t to F_{t+1} based on new evidence D_t is a function of the strength of the new evidence D_t and its relative weight. The strength of the new evidence is given by the forecast error $D_t - F_t$. If everything else remains the same, the forecast should be more strongly revised the larger the forecast error. The evidence weight depends on the system parameters that generate the demand signals corresponding to the change (c) and the noise (n).

6. A random vector is said to be a white noise vector if its components each have a probability distribution with zero mean and finite variance, and are statistically independent.

In this context, we have the change to noise ratio W given by:

$W = c^2/n^2$, which is directly related to the optimal smoothing parameter.

All else staying the same, a forecast can be revised according to the change to noise ratio: lower values of W (variations in demand mostly from noise) indicate that forecast errors should be mostly discarded and should not have much influence on the new forecast. Conversely, for high values of W (variations in demand mostly due to level changes), the forecast error should be given greater influence on the forecast. This can be formally expressed as follows:

$$\alpha^*(W) = 2/(1+\sqrt{1+\frac{4}{W}})$$

This corresponds to having an optimal smoothing constant α^* depending only on the change to noise ratio W , while the demand time series is driven by absolute levels of c and n.

By combining optimal structure of the forecasting mechanism with optimal parameters we can provide optimal forecast for the demand environment:

$$F_{t+1} = F_t + \alpha^*(W)(D_t - F_t)$$

2.3.2 Data Characteristics

Demand forecasting also depends on the specific subject of forecasting. In works such as [9], the spare parts features are analyzed based on the importance during need (often called down-time). A commodity in demand can be general purpose and it may require the procurement of different equipment, historically supported by data from each equipment. On the other hand, it can be specific to a single equipment. Spare parts are usually treated as the latter. While the former may be more predictable (combination of large number of history time-series follows a bell-curve distribution) the latter may exhibit serious intermittent characteristics. In [9], spare parts are also seen to have high unit value with high purchase and maintenance costs. In the same work, the corresponding demands are also classified into four categories:

- Slow-moving: Traditional smooth behavior,
- Strictly intermittent: Extremely sporadic demand without accentuated variability in the quantity of single demand,
- Erratic: Great variability of the requested, quantity, but the demand is approximately constant as distribution in the time
- Lumpy: A lot of intervals with zero-demand and a great variability in the quantity.

With respect to the supply-chain demand, it has specific characteristics such as taking place at irregular intervals while involving either reduced or very variable quantities. Two widely recognized parameters are used to characterize the demand of spare parts:

- The coefficient of variation: $CV = (\sqrt{\frac{\sum_{i=1}^{N}(Dt_i - Dt)^2}{N}})/Dt$

– The average inter demand interval: $ADI = (\sum_{i=1}^{N} t_i)/N$

For both parameters, $Dt = (\sum_{i=1}^{N} Dt_i)/N$

Dt_i is the consumption of spare parts and N is the number of periods for CV while in the case of ADI it represents the number of periods with non zero demand. In this context [6], there are so called "cut values" that can more accurately describe the intermittent demand of spare parts. The cutoff values are respectively 0.49 for CV and 1.32 for ADI. This corresponds to the following demand characteristics:

1. $0 \leq CV \leq 0.49$ and $0 \leq ADI \leq 1.32$: slow moving demand
2. $CV > 0.49$ and $0 \leq ADI \leq 1.32$: erratic demand
3. $0 \leq CV \leq 0.49$ and $ADI > 1.32$: intermittent demand
4. $CV > 0.49$ and $ADI > 1.32$: lumpy demand

In forecasting, one needs to decide whether an observed variation in the time-series data provides a reason to modify a previous forecast for the next period [13]. If the variation represents a change in the underlying level of the time series, recent demand observations contain more information about the future than past observations do. Thus, recent observations should be given more weight. Also if one concludes that the variation is indicative of a trend, then one would project the variation to not only shift the level once, but also to continue doing so in future periods. In practice, these options are not seen as mutually exclusive. It may be considered that variation is in some part due to noise and in other part due to level change.

2.4 Modeling Limitations

Single exponential smoothing can be viewed as a plausible model for describing human forecasting behavior. Essentially, exponential smoothing corresponds to the mental process of error detection and adaptation involving a form of trial-and-error learning. This way, a person performing a forecast can observe an error and then adjusts the next forecast factoring that error.

In addition, exponential smoothing has the important characteristics of a bounded rational decision heuristic as it requires a small amount of memory resources since the most recent forecast and demand contain all the information necessary to make the next forecast. Also, there are compelling behavioral reasons to assume that forecasters follow the error response logic of exponential smoothing. The important question is about the behavioral error-response parameter $\alpha(W)$ relative to the optimal $\alpha^*(W)$. We can assume that decision makers will update the forecasts based on new evidence (observations) and that they will incorporate both the strength of the evidence (the magnitude of the observed variation in demand signal) as well as its related statistical weight ($W = c^2/n^2$). In this respect, the standard deviation c relates to the real but unobserved demand level changes while the standard deviation n captures the noise related to the demand level for a single forecasting period.

One hypothesis is that forecasts conducted by decision makers may sub-optimally incorporate the demand signal strength and weight [13]. This might suggest that decision makers may assign more weight to forecast errors at the expense of the system parameters (c,n) that are behind such errors. The primary indication for this situation stems from the fact that demand signals and associated forecast errors are rather salient, whereas the system parameters are not. Moreover, in many cases, the system parameters n and c are unknown or it may not be feasible to derive them. Even in the case where decision makers know the exact system parameters, the parameters are likely to remain latent in the background in relation to the signals produced. Thus, one may expect that for the optimal benchmark, the behavioral $\alpha(W)$ would be less responsive to W than $\alpha^*(W)$ as given by the relation: $\frac{d\alpha(W)}{dW} < \frac{d\alpha^*}{dW}$.

This corresponds to the hypothesis of system neglect whereby decision makers are likely to show relatively more over-reaction for low values of W and relative more under-reaction for high values of W.

2.5 Classification of Forecasting Models

Spare parts and material are critical for maintenance systems, however, their respective demands may vary differently based on several factors and chance occurrences. Such information can be characterized in various types of time-series data. In literature, there exist different models/techniques to address the forecasting issues on the data. In the following, we briefly describe these models. We elaborate more on specific techniques of interest in Section 3.

Figure 2 depicts various types of forecasting approaches and their relationship based on underlying methodologies [14]. At a very high level, these methods share two different analysis paradigms: judgmental analysis in the absence of sufficient objective data and quantitative or statistical analysis otherwise. The dotted blue lines in the figure represent the potential use of a method as part of another method. In addition, the stakeholders can assume player roles depending on situation (e.g. producer/consumer) and improvise realistic interactions until a decision can be reached.

2.5.1 Judgment-Based Analysis

Judgment-based analysis entails qualitative assessment. Qualitative models incorporate judgmental and subjective factors into demand forecast. Human judgment in forecast-

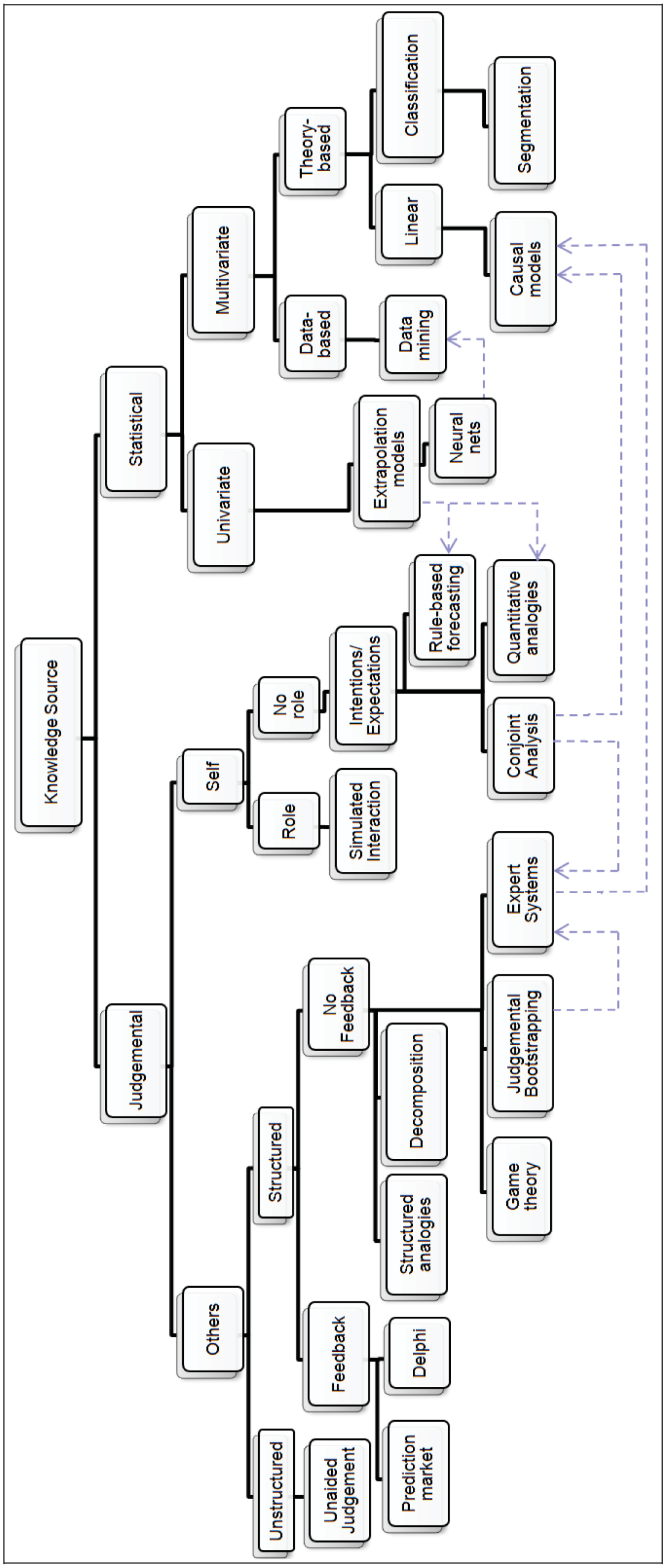


Figure 2: *Methodology Tree for Forecasting*

ing is important for attenuating errors in higher-order decisions such as purchasing, inventory, and capacity. Extensive literature on human judgment in time-series forecasting is avail-able on-line [13]. It involves anchoring and adjustment, as well as the influence of feedback and task decomposition on forecasting performance. It also offers detection of patterns in a time series, such as trends or seasonality. Some of the useful qualitative methods include the Delphi method, jury of executive opinion, sales force and consumer market surveys. These methods require subject matter experts or a group of experts to make forecasts.

Some examples of Judgment-based analysis are given below:

- *Unaided Judgment:* Mainly based on expert advice. It is assumed that the experts are unbiased, large data changes are unlikely, relationships are well understood by experts, experts possess privileged information, experts receive accurate and well-summarized feedback about their forecasts.
- *The Delphi technique:* Delphi involves recruiting five to twenty experts and polling them for their forecasts and reasons. The experts are provided with anonymous summary statistics on the forecasts. The process is repeated until there is little change in forecasts between rounds - usually two or three rounds are enough.
- *Structured Analogies:* The outcomes of similar past situations may help to forecast the outcome of a new situation. The structured-analogies method uses a specific process to overcome biased and inefficient use of information from similar situations by preparing a description of the target situation and selecting experts knowledgeable of analogous situations, preferably by direct experience.
- *Game Theory:* Game theory may provide the means to obtain better forecasts in situations involving negotiations or conflicts. However, the potential use of game theory for accurate forecasts is not conclusive.
- *Judgmental Decomposition:* Involves the division of the forecasting problem into parts that are easier to forecast individually by appropriate methods. Then, the parts are combined to obtain the forecast. One approach is to break the problem into multiplicative components. Decomposition is accurate where there is much uncertainty about the aggregate forecast and where large numbers are involved.
- *Judgmental Bootstrapping:* In this process, the experts are given the information needed to make predictions about a class of situations and then they are asked to make predictions for diverse real or hypothetical cases. The results are converted to a model by estimating a regression equation relating the judgmental forecasts to the information used. It is based on the fact that a model can apply the derived rules more consistently then humans can.
- *Expert Systems:* Structured rule representations are used by experts for predicting. Rules are often created from protocols, whereby forecasters talk about what they do while making forecasts. Expert opinion, conjoint analysis, and bootstrapping also aid to develop expert systems. Expert systems forecasting involves identifying forecasting rules used by experts and the rules learned from empirical research.
- *Simulated Interaction:* Simulated interaction is especially useful when the situation in-

volves conflict. To use simulated interaction, an administrator prepares a description of the target situation (scenario), describes the main roles, and provides a list of possible decisions. Players adopt a role and read about the situation and then improvise realistic interactions with other role players until a decision is reached.

- *Intentions and Expectations:* Involves inquiry into intended behavior in specified situations. Expectations differ from intentions because decision makers realize that unintended events may happen. Expectations and intentions can be obtained using probability scales with descriptions such as 0 = "No chance", or almost no chance (1 in 100), up to 10 = "Certain, or practically certain (99 in 100)". Bias in responses should be assessed if possible and the data adjusted accordingly. Useful methods were developed for selecting samples, obtaining high response rates, compensating for non-response bias, and reducing response error.
- *Conjoint analysis:* The method is similar to bootstrapping, and is called "conjoint analysis" because respondents consider the features jointly. The accuracy of forecasts from conjoint analysis is likely to increase with increasing realism of the choices presented to respondents. The method is based on sound principles, such as using experimental design and soliciting independent intentions.

2.5.2 Statistical Analysis

Statistical analysis is performed in various ways. Statistical modeling techniques are mainly used to predict future demand by using historical data from the past. Examples include moving average, weighted moving average, exponential smoothing, trend analysis, seasonality analysis, multiplicative decomposition, etc.

Statistical methods can be classical time-series analyses such as: auto-regression, moving average, ARMA, ARIMA, S-ARMA, etc. They can also be econometric or finance models, such as: GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model, or machine learning techniques such as: neural networks, data mining, etc. Hybrid methods like empirical mode decomposition, other techniques, such as bootstrapping and simulations are also available. Statistical analysis also involves understanding the hidden model which incorporates factors that may influence the quantity being predicted into the model. Examples include Bayesian networks, simple regression analysis, multiple regression analysis.

Examples of statistical analysis include:

- *Extrapolation:* Extrapolation uses historical data. Exponential smoothing is the most popular and cost effective tool based on historical data. It exploits the principle that recent data should be weighted more heavily and "smooths" out cyclical fluctuations to forecast the trend. Statistical extrapolations are cost effective when forecasts are needed for each of hundreds of inventory items. Seasonality adjustments leads to substantial gains in accuracy in the large-scale study of time series.

- *Quantitative Analogies:* Experts can identify previously encountered situations analogous to a given situation. These can be used to extrapolate the outcome of a target situation. Forecast using quantitative analogies involves asking experts to identify situations that are analogous to the target situation and for which data is available. If the analogous data provides information about the future of the target situation, one can forecast by calculating averages. Otherwise, one can construct a model using target situation data, another one using analogous data and combine the parameters of these models in order to forecast with the combined model.
- *Rule-based Forecasting:* Allows the integration of knowledge about the domain with time-series data in a structured and cost effective manner. To apply rule based forecasting, the decision maker must first identify features of the series using statistical analysis, inspection, and domain knowledge. The rules are then used to adjust data, and to estimate short and long range models. Many expert system use rules combining forecasts from simple extrapolation methods such as linear regression, simple exponential smoothing, Winters methods and the like. In this sense, rule base forecasting is a knowledge based system that successfully combines domain knowledge with statistical techniques.
- *Neuronal Nets:* Neuronal Nets are computing intensive methods that use decision processes analogous to those of biological brains. They are capable of learning changes in the data patterns and support updated parameter estimates. Large volumes of data are needed to train neural network models and to reduce the risk of over-fitting.
- *Data Mining:* Data mining uses sophisticated statistical analysis to identify relationships. Data mining analyzes the supplied data and ignores theory and prior knowledge in the search for patterns.
- *Causal models:* In practice, causal models use statistical methods based on prior knowledge and theory. Time-series regression is commonly used for estimating model parameters or coefficients. To develop causal models, one needs to select causal variables by using theory and prior knowledge. The key is to identify important variables, the direction of their effects, and related constraints.
- *Segmentation:* Segmentation is the process of breaking a problem down into independent parts. The decision makers forecast on smaller parts using historical data for each part and then combine the effects to predict on the whole problem. However, in this process, one should first identify important causal variables that can be used to define the segments and their respective importance. They are derived relative to each segment and finally the segment forecasts are summed.

The common goal of time series analysis is to be able to extrapolate past behavior into the future. However, various forecasting procedures may provide different expected futures based on the same sample pool of historical data. Thus, an important challenge is the issues of reliable predictability. In this context, one can use predictability metrics such as η-metric [23] which is largely affected by the length of the time series. Another generic way to assess predictability is provided by the Detrended Fluctuation Analysis (DFA) [24] which is used for determining statistical self-affinity. In this respect, self-similarity requires the points on the log-log graph to be sufficiently collinear across a very wide range of window sizes [7].

2.6 Measures and Benchmarks

In Table 1 we show some of the essential measurement terms usually considered as benchmarks for measuring the deviation of actual situation from the predicted one.

7. http://www.ltrr.arizona.edu/d̃meko/notes_7.pdf

Table 1: *Measurement Benchmarks*

Measure	Description
Forecast Error ($fcsterror$)	Forecast Error is the deviation of actual situation and the predicted situation. $fcsterr = A_t - F_t$, where A_t is the actual value at time t F_t is the forecast value for time t.
Mean Square Error (MSE)	It is similar to simple sample variance (adjusted for degrees of freedom). $MSE = \sum_{t=1}^{T} \|fcsterr\|^2/T = \sum_{t=1}^{T}(A_t - F_t)^2/T$
Mean Absolute Deviation (MAD)	Mean of absolute deviations in a data series relative to data mean. Gives the average distance of data from its mean. $MAD = \sum_{t=1}^{T} \|fcsterr\|/T = \sum_{t=1}^{T} \|A_t - F_t\|/T$
Mean Absolute Percentage Error (MAPE):	It is an extension of MAD that provides percentage reference results. $MAPE = 100\sum_{t=1}^{T}[\|A_t - F_t\|/A_t]/T$
Root Mean Square Deviation (RMSD)	Established measure of the difference in the predicted and actual observed values. $RMSD = \frac{1}{N}\sum_{t=1}^{N}\sqrt{(A_t - F_t)^2}$
Relative Geometric Root Mean Square Error (RGRMSE)	This accuracy measures is given by: $RGRMSE = \frac{(\Pi_{t=1}^{N}(A_{a,t}-F_{a,t})^2)^{1/2n}}{(\Pi_{t=1}^{N}(A_{b,t}-F_{b,t})^2)^{1/2n}}$ $A_{k,t}$ is the actual demand at the end of interval t when using method k $F_{k,t}$ is the forecast demand at the end of interval t when using method k The interpretation of the $RGRMSE$ value [15] is that method a performs better than method b if $RGRMSE < 1$.
Coefficient of Variation (CV)	$CV = (\sqrt{\frac{\sum_{i=1}^{N}(Dt_i - Dt)^2}{N}})/Dt,\ Dt = (\sum_{i=1}^{N} Dt_i)/N$ Dt_i represents the spare parts consumption N is the number of periods
Average Inter demand Interval (ADI)	$ADI = (\sum_{i=1}^{N} t_i)/N,\ Dt = (\sum_{i=1}^{N} Dt_i)/N$, Dt_i represents the spare parts consumption N is the number of periods

2.7 Forecasting and Predictability Issues

Predictability can be viewed as the ability to draw conclusions about future situations with a high degree of certainty. Decision theory can be used based on reliable or well-calibrated probabilities, to indicate how to make rational decisions even if the dispersion of the underlying probability distribution is large [16]. The problem of low predictability arises when well calibrated probabilities are not available and in the case where it is not possible to measure calibration and to assess the level of confidence that one should attribute to probabilities [17]. Thus, unpredictability is a major concern especially with respect to rare event occurrences which in the case of demand forecasting correspond to a higher degree of lumpiness. In this context, there is the potential to underestimate probabilities of such occurrences. Moreover, in the cases where past data is unavailable, the reliability of the corresponding probabilities cannot be assessed. Consequently, any associated biases will be very hard to detect.

However, traditional demand forecasting relies on time series techniques based on historical data usually spanning over several years in order to provide insights into predictable patterns. The volume, frequency and required small processing window require automation and the application of models and techniques in a structured way. There is however, a defined ceiling for time series forecast accuracy. This ceiling is governed by fundamental limitations stemming from information theory along with the decoupling between historical and current conditions. More specifically, reliable forecasting becomes elusive in the presence of emergent behavior where the underlying dynamics results form complex interactions that escape meaningful characterization based on mathematical modeling and related techniques. A classical example is the emergent behavior of cellular automatons, which although governed by very simple rules at the local level of each cell, exhibit nevertheless highly complex overall dynamics. The behavior of such a system is essentially computationally irreducible [18], meaning that the only way to know its future evolution is let the system run. In other words, no simple set of equations can be devised to look into its future.

Such interactions are prevalent in economic activities which usually involve complex demand/supply players interacting in a dynamic environment. In this context, the equations employed in mathematical models use abstractions to describe approximations of real world processes. Such models are often very sensitive to small changes in the parameter values such that they can be made to fit past data, but this cannot guarantee a good prediction for the future.

With respect to the value of historical data, forecasting in the field of economics tends to use very large amounts of data that are available up to millisecond timescales. In addition, commercial organizations can use computers and programs that are comparable to those of weather forecasters in terms of capability and sophistication. Nevertheless, even with large amounts of available data and the increased power and sophistication of computer analysis constantly improving over decades, there has not been any significant increase in forecast accuracy, as recently demonstrated by the credit crunch of 2007 - 2008, where the demand for credit was largely miscalculated by economic forecasters. In this setting, industry figures show that despite developing and applying highly-tuned models, forecast-ing reliability remains a challenge. Even in the presence of high-volume, and established seasonality patterns, important near-term forecast errors are to be expected. [8]

8. http://www.terratechnology.com/forecast-error/index.html.

2.8 Summary

In this section, we portray a high level description of military forecasting problems from three different perspectives: Organizational hierarchy, forecasting procedures and forecast characteristics in terms of time-line and data type.

Demand forecasting of military logistics and their spare parts is critical for maintenance systems, however, their respective demands may be different based on various factors such as wear and tear or established shelf life. This information can be characterized in various types of time-series data. In relation to the military systems, two processes generate the demand for logistic resources in the theater of operations, namely attrition and consumption. Therefore, it is important to understand the relations (e.g. lead time) between the necessity and condition of resources that are needed to fulfill complex military campaigns [12]. The proper forecasting of future logistic operational requirements involves the factoring of mission objectives and required resources in both time and space dimensions. Furthermore, the demand level is also related to the uncertainties that are associated with processes of attrition and consumption.

3 Survey of Statistical Methods

An interest in knowing future demands is very important for production planning and for inventory management in general. For spare parts, fairly accurate forecasts are instrumental in cost effectiveness. In the manufacturing sector, the issues of uncertainty in the demand for spare parts has led to the development of many forecasting techniques. Classical statistical methods (e.g., regression analysis or exponential smoothing) have been applied for a very long time. However, traditional time-series methods may not account for nonlinearities in the data patterns [19].

Uncertainty reduction methods have also been devised to cope with demand uncertainty in manufacturing and control systems [20]. However, such methods general perform poorly when demand for an item is lumpy or intermittent [19]. Lumpiness is a known issue in the automotive industry with respect to replacement parts [21] and can also be observed in the area of aircraft maintenance parts [6] and other industries as well. Single exponential smoothing was traditionally used in inventory control systems. In this context, lumpiness generally leads to stock levels that are inappropriate since it places most weight on the most recent demand leading to higher demand estimates after a demand occurrence and lower before such a demand occurrence as shown in [22]. The research work mentioned proposes an alternate forecasting method for lumpiness using the average size of nonzero demand occurrences and the average interval between such occurrences. Subsequently, this method was revised [21] to address a bias that was noticed by simulating estimates of demand. This modification, known as the Syntetos-Boylan approximation (SBA), yields an approximately unbiased estimator and it is superior to simple moving average and single exponential smoothing. With respect to methods based on Poisson distribution, an investigation for spare parts supply is in [23]. In this area, there are also specific long term forecasting methods such as Grey prediction [24].

In this section, we illustrate the statistical models/methods, followed by a group of procedures commonly used to address forecasting at industrial scale.

3.1 Single Exponential Smoothing (SES)

A method based on time series that is particularly suited for low period forecast. The forecast of spare parts demand results from applying a series of weights that decrease exponentially relative to the historical data (see [25]).

The formula is as follows:

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t$$

Where:

X_t is the actual observed value of the demand at moment t;

F_{t+1} is the forecast for instant $t+1$; α is the smoothing parameter. It can have different values, in general between 0.1 and 0.4, based on demand features (unstable demand go with higher values).

3.2 Croston Method (CR)

The Croston method takes into account both demand size and inter-arrival time between demands (see [26]). Croston's original method (CR) forecasts separately the time between consecutive demands P_t and the magnitude Z_t.

If a demand occurs such that $X_t > 0$, then the estimates are updated by:

$Z_t = X_t + (1-\alpha)Z_{t-1}$

$P_t = G_t + (1-\alpha)P_{t-1}$

where:

X_t is the actual observed value of demand at instant t;

G_t is the actual value of the time between consecutive demands at instant t;

α is the smoothing parameter between 0 and 1.

The forecast of demand per period at time t is:

$F_{t+1} = Z_t/P_t$.

3.3 Syntetos - Boylan Approximation (SBA)

There are different variations applied to Croston's method. SBA is considered one that performs quite well. The proposed estimator is calculated as follows [27]:

$F_{t+1} = (1-\alpha/2)(Z_t/P_t)$

3.4 Auto Regression (AR)

Auto regression is part of a group of linear prediction methods attempting to predict the output of a system based on previous outputs [28].

The autoregressive model of order p is as follows:

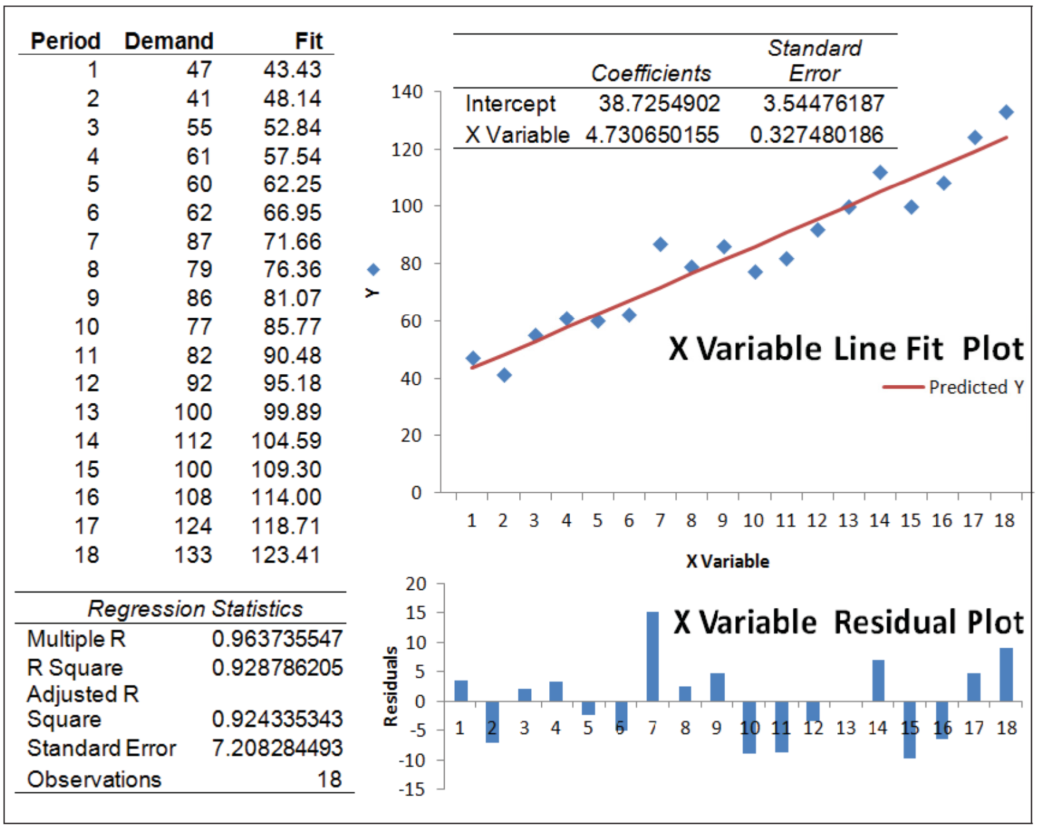
$F_{t+1} = \rho_1 u_t + \rho_2 u_{t-1} + \ldots + \rho_p u_{t-p+1} + \varepsilon_t$ where

u_i is the sampled value in the period i

ρ_i represents a coefficient

ε_t is a residual representing random events not accounted in the model.

In Figure 3, we have an example of regression trend-line based on a time series of 18 demand observations. We can notice in the figure the observation data and the parameters obtained after the regression analysis. Moreover, the residuals are also shown for each data point.



Period	Demand	Fit
1	47	43.43
2	41	48.14
3	55	52.84
4	61	57.54
5	60	62.25
6	62	66.95
7	87	71.66
8	79	76.36
9	86	81.07
10	77	85.77
11	82	90.48
12	92	95.18
13	100	99.89
14	112	104.59
15	100	109.30
16	108	114.00
17	124	118.71
18	133	123.41

Regression Statistics	
Multiple R	0.963735547
R Square	0.928786205
Adjusted R Square	0.924335343
Standard Error	7.208284493
Observations	18

	Coefficients	*Standard Error*
Intercept	38.7254902	3.54476187
X Variable	4.730650155	0.327480186

Figure 3: *Example of Regression Trend-line*

3.5 Moving Average (MA)

The moving average is calculated using the mean of the previous n data values. The forecast formula is [28]:

$$F_{t+1} = MA(n) = (X_t + X_{t-1} + \ldots + X_{t-n+1})/n$$

where:

$X_t, X_{t-1}, \ldots$ represent the actual observed values of demand at instant t, $t-1$, ...;

This method is applicable only in case of slow moving demand.

3.6 Weighted Moving Average (WMA)

The weighted moving average uses multiplying factors to give different weights to different data points. The moving average represents the convolution of data points with a moving average function. Typically, the weights decrease arithmetically. Thus, for n-period WMA, the latest period weight is n, the second latest $n-1$, and so on (see [28]):

$$F_{t+1} = [n\ p_t + (n-1)p_{t-1} + (n-2)p_{t-2} + \ldots + p_{(t-n)+1}]/(n + (n-1) + (n-2) + \ldots + 1)$$

3.7 X11 Procedure

The X11 procedure [29] relates to the seasonal adjustment of time series based on the U.S. Bureau of Census X-11 seasonal adjustment program and the X-11 ARIMA method developed by Statistics Canada.

The X11 procedure takes a series of monthly observations x_t and applies a filtering operation y_t corresponding to seasonally adjusted values with respect to x_t. In essence, this involves a sequence of moving averages with the overall effect of a single set of moving averages, assuming a sufficient amount of historical data. In this setting, the historical adjusted value $y_t^{(m)}$ is obtained from a symmetric filter $a_m(L)$, where L is called the lag operator:

$$y_t^{(m)} = a_m(L)x_t$$

L represent the lag operator with $a_{m,j} = a_{m,-j}$ such that

$$a_m(L)x_t = \sum_{j=-m}^{m} a_{m,j}x_{t-j}$$

This filter is commonly known as $(2m+1)$-term moving average (symmetric filter of half-length m)

For current and recent data, the used filters are asymmetric and truncated:

$$y_t^{(i)} = a_i(L)x_t = \sum_{j=-i}^{m} a_{i,j}x_{t-j}$$

For the filter $a_i(L), i \in \{0, 1, \ldots m\}$, i stands for the number of future values of x entering in the moving average.

At times $t+i$ and $t+k$, two seasonally adjusted values $y_t^{(i)}$ and $y_t^{(k)}$ are calculated with respect to the unadjusted value x_t, with the revision defined by:

$r_t^{(i,k)} = y_t^{(k)} - y_t^{(i)}$, where $0 < i < k \leq m$

This can serve to capture the new data $x_{t+i+1}, x_{t+i+2}, \ldots, x_{t+i+k}$. The overall revision relative to a particular point in time $t+i$ is $r_t^{(i,m)}$. In this context, seasonality adjustments are usually applied on a yearly basis corresponding to $r_t^{(i,i+12)}$ with the first revision $r_t^{(0,12)}$.

3.8 Box-Jenkins Models

The Box-Jenkins method provides the means to employ three forecasting models, namely ARMA, ARIMA and S-ARIMA. It does not assume any particular pattern in the historical data and it is based on an iterative approach to identifying a possible useful model from a general class of models. ARMA, ARIMA and S-ARIMA represent a class of methods that combine the use of autoregressive and moving average [28].

The use of a moving average in the forecasting model involves the tracking of lagged forecast values in relation to the error ε such as to improve the current forecast. The first order moving average terms use the most recent forecast error while a second order term uses the forecast error from the two most recent periods and likewise for the third, fourth and so forth. For the order q, we have:

$F_{t+1} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q+1}$ where

ε_i represents the residual for the period i

θ_i is a coefficient.

The selected model is checked against the historical data for accuracy. The model is deemed to fit well if the residuals of the historical data and forecast data are small, independent and distributed randomly. If the selected model does not fit well, the process is repeated with another model to improve on the previous one. The repetition continues until the best fitting model is identified.

The method can be described by the following algorithm:

Algorithm 1 Box-Jenkins algorithm

Step 1: Initialize *modelList* as a list of candidate models
Step 2: Initialize *bestFitModel* as NULL
Step 3:
for each candidate model *candModel* in *modelList* **do**
  Estimate parameters for *candModel*
  if *candModel* fits well **then**
    bestFitModel = *candModel*;
    goto Step 4;
  end if
end for
Step 4:
if *bestFitModel* is NULL **then**
  goto Step 5;
else
  use model *bestFitModel* to forecast;
end if
Step 5: End

3.8.1 ARMA(p,q)

The autoregressive moving average (ARMA) method is used when the time series is stationary in nature such that it has an approximately constant average over time. The corre-sponding forecasting is given by [28]:

$$F_{t+1} = \rho_1 u_t + \ldots + \rho_p u_{t-p+1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q+1}$$

such that the auto-regression is combined with the moving average. The degrees p and q are selected by analyzing the global and partial autocorrelation. The global autocorrelation measures (varying k) the relation between u_t and u_{t-k} not considering other variables. The partial autocorrelation measures the relation between u_t and u_{t-k} not considering other variables. These two types of autocorrelation can be analyzed by so called correlograms and the degrees p and q are tied to the distribution shown by the correlograms [30].

3.8.2 ARIMA(p,d,q)

The autoregressive integrated moving average (ARIMA) model represents a generalization of ARMA that can be applied in the case where the data is non-stationary, where an initial differencing step (the integrated part of the model) can be applied to counter the non- stationarity. When the non-stationarity is removed, ARIMA is the same as ARMA [28].

The model uses the p, d and q integer values grater or equal to 0 referring respectively to the order of the autoregressive, integrated and moving average aspects of the model. Thus, is offers the capabilities of each of the models (e.g. MA is given by ARIMA(0,0,1));

3.8.3 S-ARIMA(p,d,q)(P,D,Q)s

This method is suitable for seasonality of the order s. The procedure is similar to ARIMA but with 3 other degrees: P, D and Q that have the same meaning as p, d, q but are only applied to the seasonal data corresponding to the periods t, $t-n$, $t-2n$, ... where n is the number of periods in the year divided by s (see [28]).

3.9 Winters Methods

The additive winter (AW) and multiplicative winter (MW) methods have been devised in order to address seasonal effects [31]. One way to consider the seasonal effects is by the introduction of a drift D which modifies the level values according to time depending variables. The drift function represents the trend:

$$F_{t+k} = L_t + D_t K$$

where:

$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + D_{t-1})$ is the weighted average of the observed value y_t and the forecast calculated at the previous period;

$D_t = \beta(L_t - L_{t-1}) + (1-\beta)D_{t-1}$ is the weighted average of the difference between the forecasts calculated at period t and $t-1$ and the drift calculated at period $t-1$. A unity weight β means a linear trend or constant drift.

The AW and MW represent an extension that is considering seasonality.

For AW, we have:

$$L_t = \alpha(y_t - S_{t-p}) + (1-\alpha)(L_{t-1} + D_{t-1})$$

$$D_t = \beta(L_t - L_{t-1}) + (1-\beta)D_{t-1}$$

$$S_t = \gamma(y_t - L_{t+1}) - (1-\gamma)S_{t-p}$$

where S_t is a factor of seasonality and p its periodicity (e.g. 12 for monthly data). The demand forecast for the period t is then:

$$F_{t+k} = L_t + D_t k + S_{t+k-p}$$

For MW, we have the following relations:

$$L_t = \alpha(y_t / S_{t-p}) + (1-\alpha)(L_{t-1} + D_{t-1})$$

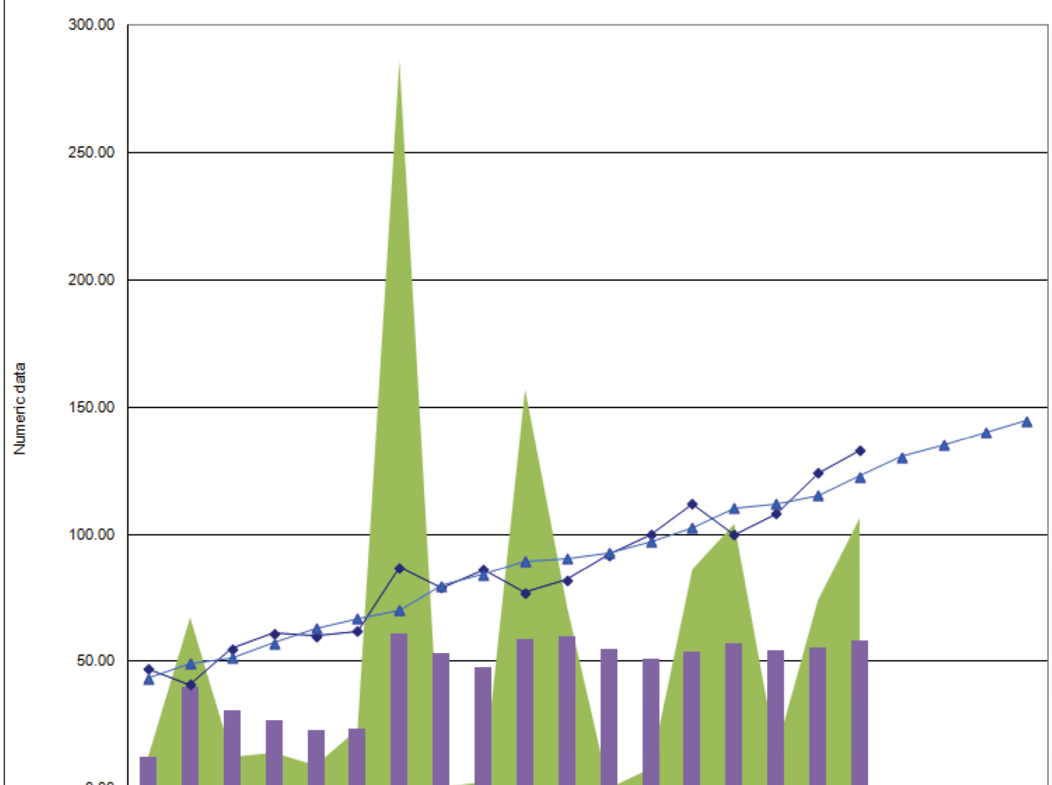
$$D_t = \beta(L_t - L_{t-1}) + (1-\beta)D_{t-1}$$

$S_t = \gamma(y_t/L_t) + (1-\gamma)S_{t-p}$

with the demand forecast for the period t:

$F_{t+k} = (L_t + D_t k)S_{t+k-p}$

The AW and MW are flexible as they can consider non-polynomial trends and dissimilar seasonality patterns. Regarding the parameters, α represents the data smoothing factor $(0 < \alpha < 1)$, β stands for the trend smoothing factor $(0 < \beta < 1)$ while γ is the seasonality change smoothing factor $(0 < \gamma < 1)$. The selection of the α, β and γ weight values can be done for instance such as to minimize the squares of the gaps.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
E^2	12.74	67.34	12.61	14.29	9.35	23.48	285.7	0.76	2.84	156.9	71.79	0.40	8.12	86.31	104.0	14.79	74.01	106.4				
MSE	12.74	40.04	30.90	26.75	23.27	23.30	60.79	53.29	47.68	58.60	59.80	54.85	51.26	53.76	57.12	54.47	55.62	58.44				
Demand	47	41	55	61	60	62	87	79	86	77	82	92	100	112	100	108	124	133				
Forecast	43.43	49.21	51.45	57.22	63.06	66.85	70.10	79.87	84.32	89.53	90.47	92.64	97.15	102.7	110.2	111.8	115.4	122.6	130.4	135.1	139.8	144.6

Figure 4: *Example of Forecasting Using Exponential Smoothing (Additive Winter)*

In Figure 4, we have an example of forecasting using the Additive Winter Method based on the parameters obtained in the regression analysis depicted in Figure 3. Moreover, Figure 4 depicts the squared error (E^2) and the mean square error (MSE) along with the observed and forecast values. Note how E^2 shows the marked discrepancy between the forecast and the observation, while in contrast, the MSE is gradually stabilizing such that it shows only slight changes corresponding to an approximately steady average error.

3.10 Bootstrap Method

The bootstrap method is useful for estimating the demand for spare parts when historical data is limited [8]. Bootstrap is superior to the normal approximation of spare parts demand estimation for independent data [32]. It is also effective in dealing with smooth demand [33]. For intermittent demand related to service parts inventories [5], the approach is to distribute the sum of intermittent demands over a fixed lead time.

Bootstrapping represents a more recent general purpose and computational intensive approach to statistical inference, being part of a larger array of re-sampling methods. Bootstrapping uses an estimator (such as variance) by measuring properties when sampling from an approximating distribution. A usual choice for an approximating distribution is to use the distribution of the observed data. When a set of observations are assumed to be from an independent and uniformly distributed population, it consists in constructing a number of re-samples of the observed dataset (equal size to the observed dataset), each of which is obtained by random sampling with replacement from the original dataset.

The procedure involves the following steps:

1. take an observed sample (e.g. historical spare parts demand) of n elements, called $X = (x_1, x_2, \ldots, x_n)$;
2. from X, re-sample m other samples of number equal to n obtaining $X_1, X_2, \ldots, X_m$ (in every bootstrap extraction, the data of the observed sample can be extracted more then one time and every data has the probability $1/n$ to be extracted);
3. given T as estimator of Θ parameter of interest (e.g. the average demand), calculate T for every bootstrap sample. In this way we have m estimates of Θ;
4. from these estimates calculate the desired value: the average of T_1,..., T_m as the demand forecast. This method can be applied not only to find the average demand (that can be the demand forecast) but also the intervals between non zero-demand or other desired values.

3.11 Poisson Method

This method is typically used to forecast the probability of a rare event happening [23]. It precludes a direct calculation of the variable to forecast, but arrives at an estimate of the probability that assumes a determined value.

The start point is the valuation of the average value of the variable to forecast. For spare parts, given the average consumption in an interval time T, equal to d, the probability of having a demand equal to x (i.e. x requires of components) in the interval time T is:

$$P_{d,T,x} = \frac{(dT)^x e^{-(dT)}}{x!}$$

Hence, the cumulative probability (measure that not more than x components are required) can be expressed as:

$$P_{CUMd,T,x} = \sum_{k=0}^{x} \frac{(dT)^k e^{-(dT)}}{k!}$$

3.12 Binomial Method

The binomial method represents an application of Poisson formula. It uses two additive terms and has as point of departure the average consumption of the product. This method can also consider the simultaneous use of a certain type of spare parts in several applications, trough the parameter n. The forecast is given by:

$$F = x_1 + x_2$$

where (using $\lfloor\ \rfloor$ as the flooring notation), we have:

$$x_1 = \lfloor T/(\tfrac{1}{d})\rfloor n;$$

F: is the demand forecast

d: is the historical average consumption

T: is the interval time considered for the estimation of requirements

x_2 is defined relative to the accepted probability that exactly x_2 breakdowns happen in the interval time T, defining $T_{residual}$ as the time that is "not covered" by the mean term x_1: $T_{residual} = T - \lfloor T/(1/d)\rfloor(1/d)$

In the period $T_{residual}$, the cumulative probability of consumption p is introduced assuming an exponential function: $func(T_{residual}) = 1 - e^{-(1/(1/d))T_{residual}} = p$

Using the properties of the binomial distribution and an iterative procedure, the x_2 value for spare parts that allows to achieve the desired level of stock (LS) can be found. Specifically, the x_2 value of interest is that for which:

$$P(x_2) = \sum_{i=0}^{x_2} \binom{n}{i}(1-p)^{n-i} p^i \geq LS.$$

3.13 Grey Prediction Model

Focuses on model uncertainty and information insufficiency and aims at understanding the system evolution by conditional analysis and prediction based decision [34]. Unlike conventional regression which is based on probability theory, Grey forecasting relies upon the Grey generating function such as the GM(1,1) model, which is the most used Grey prediction method. In this context, the first 1 in GM(1,1) means there is only one variable of interest while the next 1 means that the first order Grey differential equation is employed in the model. The Grey prediction model has the ability to predict with a small amount of historical data.

The function uses the variation within the system to find the relations of sequential data and to establish the prediction model.

GM(1,1) prediction model can be summarized as follows:

1. Form the initial sequence of observations:
   $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ where
   $x^{(0)}(i)$ is the base line (initial state, 0) data with respect to time i.
2. Generate the first order accumulated generating operation (AGO) sequence
   $x^{(1)}$ based on initial sequence $x^{(0)}$
   $x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$ where
   $x^{(1)}(k) = \sum_{i=1}^{k} x^{(1)}(i)$
3. Compute the mean value of first-order AGO sequence:
   $Z^{(1)}(k) = \frac{1}{2}\, x^{(1)}(k) + \frac{1}{2}\, x^{(1)}(k-1)$
4. Derive a first-order differential equation of the sequence $x^{(1)}$:
   $\frac{dx^{(1)}(k)}{dk} + ax^{(1)}(k) = b$ where
   a and b are estimated parameters of grey forecasting model.
5. Use least squares method to define the estimated first-order sequence $x^{(1)}(k+1)$ and the inverse estimate sequence $x^{(0)}(k+1)$ representing the forecast:
   $x^{(1)}(k+1) = (x^{(0)}(k) - (b/a))\, e^{-ak} + (b/a)$
   $x^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k)$

The parameters a and b are derived from:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T y$$

$$B = \begin{bmatrix} -0.5(x^{(1)}(1)+x^{(1)}(2)) & 1 \\ -0.5(x^{(1)}(2)+x^{(1)}(3)) & 1 \\ \ldots & \ldots \\ -0.5(x^{(1)}(n-1)+x^{(1)}(n)) & 1 \end{bmatrix}$$

$$y = [x^{(0)}(2), x^{(0)}(3), x^{(0)}(n)]^T.$$

3.14 Neuronal Networks

Neuronal networks represent massively parallel and distributed structures made up of simple processing units (neurons) with the property of storing and using experiential knowledge. The concept is inspired from the working of neurons in biological brains in that the knowledge is acquired through a learning process and the inter-neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge. In this setting, the artificial neurons can be linear or nonlinear. Neuronal networks have the ability to learn and generalize. Generalization relates to producing reasonable appropriate outputs for inputs not encountered during the training on which the learning is based.

Learning is achieved through the modification of the connection weights. Statistically, the value of the connections can be interpreted as parameters (e.g., like the values of the regression parameters a and b in a regression equation $y = ax + b$).

The information processing abilities of neuronal networks can be harnessed to obtain competitive solutions to large-scale complex problems that are analytically intractable. The architecture of neuronal networks is suitable for pattern recognition or classification, signal processing, and adaptive control applications. Neural networks have several noteworthy properties [35] such as:

- *Nonlinearity*: A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Also, nonlinearity is distributed throughout the network and it represents a highly important property, particularly when the input signals are inherently nonlinear.
- *Input-Output Mapping*: This relates to supervised learning which involves the modification of the synaptic weights by applying labeled training examples. Each example is a unique input signal corresponding to a desired output response. The network is presented with a random example picked from the set, and the synaptic weights (parameters) are modified to minimize the difference between desired and actual response based on a statistical criterion. Training is repeated on many examples up to a steady state where no further significant synaptic weight changes are occurring.
- *Nonparametric Statistical Inference*: Learning from examples by constructing an input-output mapping for the problem relates to nonparametric statistical inference, which is a branch of statistics dealing with model-free estimation. The nonparametric aspect

signifies that no prior assumptions are made with respect to a statistical model for the input data.
– *Adaptivity*: This is a built-in capability to adapt synaptic weights to changes in the environment (based on the inputs). A neuronal network trained in a given environment can be easily retrained to accommodate small level of changes in the operating environment conditions. Also, in a non-stationary environment where the statistical properties change with time, the synaptic weights can be updated in real time.
– *Evidential Response*: Neuronal networks can be designed to provide information about the confidence in the decision choice relative to a particular selected pattern. This may be used to reject ambiguous patterns and thus improve the classification performance.
– *Fault Tolerance*: When implemented in hardware, neuronal networks are inherently fault tolerant since their performance degrades gracefully under adverse operating conditions. More precisely, in case that a neuron or some links are damaged, the use of a stored pattern degrades. However, given the distributed nature of storing information, only an extensive damage would lead to an overall seriously degraded response.

The use of neuronal networks for spare parts demand forecast is generally satisfactory but the results obtained are not always better than those of other methods [36].

3.15 Data Mining

Data mining techniques aim at identifying patterns in a collection of data usually contained in a relational database. In the field of demand forecasting, a multi-relational data mining approach is usually employed in order to analyze data from a multiple relation perspective.

Two important types of such data mining models [37] are the Pure Classification (PC) model and the Hybrid Clustering Classification (HCC) model. The former uses k-Nearest Neighbor Classification technique while the latter uses k-Mean Mode Clustering to define clusters and then employs k-Nearest Neighbor classification.

The k-Nearest Neighbor (k-NN) Classification is based on selecting the closest training examples. In this respect, k-NN is a type of instance-based learning, where the related function is only approximated locally. In the k-nearest neighbor algorithm, an object is classified by majority vote of its neighbors, with the object being assigned to the class most common among ts its k nearest neighbors, where k represent a positive integer, usually of small value. In particular, for k = 1, the object to be classified is simply assigned to the class of its nearest neighbor. The procedure can likewise be used for regression, by assigning the property value for the object as the average of the values of its k nearest neighbors. This can be useful in order to assess the weight contributions of the neighbors. Hence, the neighbors that are near would contribute more to the average than the ones more distant.

The k-mean clustering aims to partition a set of n observations into k clusters in which each observation belongs to the cluster with the nearest mean. One important limitation of the k-mean clustering relates to its clustering model which is based on separable spherical clusters such that the mean value converges toward the cluster center. In this setting, the clusters are expected to be similar in size, so that an assignment on the nearest cluster center would be appropriate.

The HCC model combines traditional k-Nearest Neighbor Classification data mining techniques with k-Mean Mode Clustering in the context of multi-relational data sets. In this respect, the experimental results provided in [37] show that HCC provides a promising avenue to using data mining for demand forecasting in relation to supply chain management [38].

3.16 Summary

In this section, we have summarized the statistical techniques along with a brief overview of related characteristics and areas of use. Table 2 presents the taxonomy of the most commonly used statistical methods.

Table 2: *Commonly used Forecasting Methods*

Name	Characteristics
SINGLE EXPONENTIAL SMOOTHING (SES)	Uses a smoothing constant of the real demands; Adapt for low period forecasts; Easy to compute; Has few fields of application.
CROSTON METHOD (CM)	Improvement of the SES method; Takes into account intervals of zero demand; It is deterministic.
SYNTETOS-BOYLAN APPROXIMATION (SBA)	Enhancement of Croston method to decrease error of expected demand per time period; Useful to handle lumpiness; It is deterministic.
AUTO REGRESSION (AR)	Modeling natural phenomenon using maximum entropy model; Applicable for less historical data; It is deterministic.
MOVING AVERAGE (MA)	Uses the arithmetic mean of the past demands; Adapted for constant demands; Has lightweight computation; Strictly deterministic and moderately accurate.
WEIGHTED MOVING AVERAGE (WMA)	Uses arithmetic mean of past demands with decreasing weights; Applicable to distant demands (higher weights on recent demands); Has lightweight computation and strictly deterministic; Has good accuracy only in the absence of lumpiness.
BOX-JENKINS METHODS (ARMA, ARIMA, S-ARIMA)	Uses auto-regression and weighted residual average; Combination of autoregressive and MA models in iterative way; Allows the possibility of using non-stationarity and seasonality; Requires extensive historical data.
ADDITIVE WINTER (AW)	Evolution of the SES method that introduces additive terms on prediction components; It is deterministic; Can handle seasonality (in an additive manner).
MULTIPLICATIVE WINTER (MW):	Evolution of the SES method that introduces multiplicative terms on prediction components; It is deterministic; Can handle seasonality (in multiplicative manner).
BOOTSTRAP METHOD (BS)	Uses statistical inference; Represents a wider class of re-sampling methods that value demand in a probabilistic manner; Adapts to limited availability of historical data; May lead to highly biased forecast.
POISSON METHOD (PM)	Evaluates the demand probabilistically; Adapted for rare demand but it can overestimate in the cases of erratic/lumpy demands.
BINOMIAL METHOD (BM)	Probabilistic model that uses binomial distribution; Estimates the forecast demand as sum of two terms associated to the probability of happening; Guarantees a certain level of service.
GREY METHOD (GM)	Uses accumulative generating operation and least squares; Uses cumulative demand while minimizing the error. Does not perform well for medium and long term
NEURAL NETWORKS (NN)	Learning procedure from training data; Forecast using connection between inputs and outputs; Computationally expensive; Requires large amounts of historical data.
DATA MINING (DM)	Requires training from historical data; Accuracy is high for coarse grained categorical data between inputs and outputs; Computationally inexpensive classification but expensive training. Requires large amounts of historical data.

4 Diagnostics and Software tools

4.1 Forecasting Method Selection

A number of basic recommendations [39] for the selection of the appropriate forecasting method consider seasonality, trend, cycle, and randomness of the time series. In the following, we describe some of the main criteria for method selection according to the recommendations of previous research work.

4.1.1 Randomness

The degree of randomness along with the trend and cycle behavior represent key elements for selecting the appropriate forecasting method. In this respect, given that for spare parts the demand may be large, the larger the randomness the more it is appropriate to select simpler methods such as single exponential smoothing, if randomness is dominant over the trend-cycles. Conversely, if there is little randomness and the trend dominates cyclical fluctuations, the Winter method is better suited. Nevertheless, when the cyclical component dominates the trend, a damped exponential smoothing is more beneficial as it can limit the trend extrapolation.

4.1.2 Lumpiness

Another important aspect is the presence of lumpy demand patterns. In [9], it is noted that if single exponential smoothing is used for inventory control forecasting, the presence of lumpiness is likely to lead to inappropriate stock levels. This relates to a bias toward placing the most weight on the most recent demand, leading to situations where the demand estimates that tend to be highest just after a demand occurrence and likewise, lowest just before receiving a demand. In this respect, the Croston method for forecasting lumpy demand is applicable, using both the average size of nonzero demand occurrences and the average interval between such occurrences.

4.1.3 Intermittent Demand

In [2], a bootstrapping approach is proposed for forecasting intermittent demand and it has been shown as giving better forecast accuracy in compare to Croston's method. In another work [6], several methods are evaluated in relation to forecasting intermittent demands of aircraft spare parts. In the results, the weighted moving average method outperformed other forecasting methods for intermittent demand.

4.1.4 Method Complexity

A noteworthy albeit multi decade old study [40] investigated the relative accuracy of complex versus simple forecasting methods. In this context, exponential smoothing is considered more complex than moving averages and following this line, the Box Jenkins method resides at the apex of sophistication. Based on numerous experiments, roughly half supported the conclusion that there are negligible differences between simple to more complex methods. From the other half that showed differences, a preference for complexity was found on exponential smoothing over moving averages, leaving a small faction of studies favoring even more complex methods. Extensive empirical studies [41] known as M-studies, have compared the performance of a large number of major time series forecasting methods. The conclusions are that:

- statistically sophisticated or complex methods do not necessarily produce more accurate forecasts compared to more simpler ones. However, this does not preclude the possibility that some sophisticated methods might do better in certain situations
- the accuracy of combined forecasting methods outperforms on average each of the specific methods being combined
- the performance ranking of the forecasting methods depends on the accuracy measure that is used
- the forecasting performance depends on the depth of the forecasting horizon

According to [41], the conclusion that more sophisticated methods do not necessarily produce more accurate forecasts relates to the fact that in many cases, time series are characterized by strong cycles of varying duration, whose turning points are unpredictable. Thus, simple methods such as exponential smoothing that do not extrapolate a trend, can outperform statistically more sophisticated methods that use trend extrapolation and other data patterns. In [42], various forecasting methods available in the US Army's ERP are evaluated. The evaluation takes into account various parts ranging over different commodities, volatility, levels of dollar demand and monthly demands. The findings are that 12 and 24 month moving averages outperform more complex methods irrespective of the commodity area or demand characteristics. Similarly, from [43], it is apparent that a simple 24 month moving average typically outperforms other conventional forecasting techniques after weighting by inventory and supply performance expenses. However, the same study points out that certain unconventional models could be beneficial when limited to high cost value performance driver spare parts. In this setting, the GARCH method is shown to have good potential for reduction in safety level investment based on conditional variance adjusted forecasts coupled with lower percent errors in order quantity.

4.1.5 Nonlinearity

In the situations where there are important non linear patterns in the data, traditional methods cannot account for the necessary data transformations. In contrast, neuronal networks

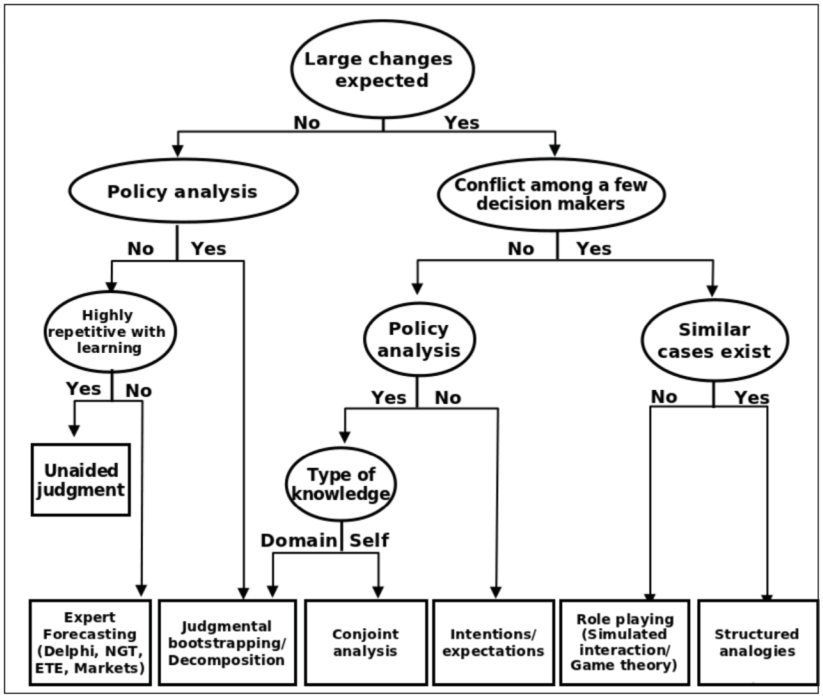


Figure 5: *Decision Tree for Judgmental Analysis*

overcome these limitations. In [44], it is found that neuronal networks can provide superior forecasts to traditional time series models when dealing with lumpy demand. Furthermore, in [45], a comparison is performed between traditional statistical time series and neuronal networks. The conclusion is that neuronal networks perform better when forecasting quarterly and monthly data. However, both type of techniques were similar in performance when forecasting annual data. Notably, the variance of the neuronal networks forecast errors was in almost every case smaller than that of traditional models, corresponding to a reduction in extreme error likelihood.

4.1.6 Decision Trees for Method Selection

The decision trees [9] for judgmental analysis and for quantitative analysis are depicted respectively in Figure 5 and Figure 6.

9. More details on decision trees for forecasting can be found at: `forecastingprinciples.com`

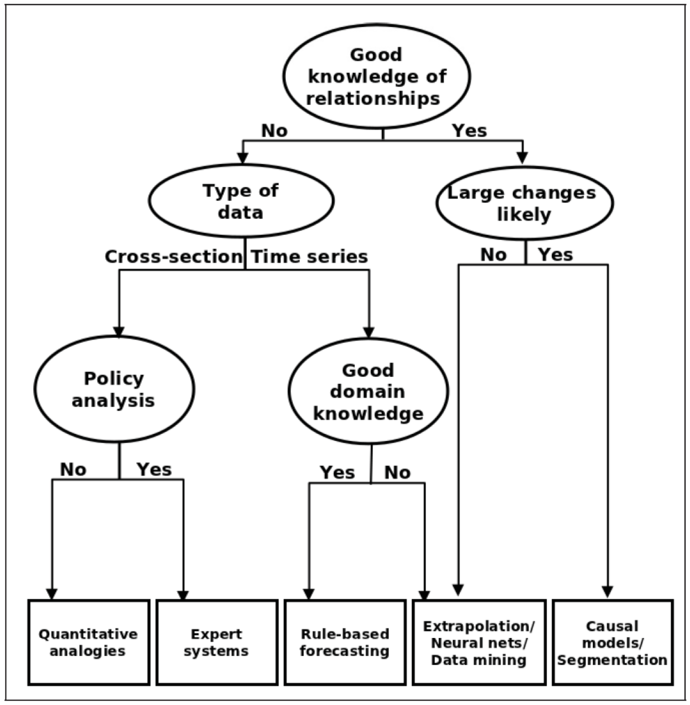


Figure 6: *Decision Tree for Quantitative/Statistical Analysis*

4.2 Commonly Used Forecasting Diagnostic Procedures

Here we discuss some of the commonly used forecasting diagnostic procedures that may help in making the appropriate choice among various candidate models. We also briefly comment on a number of commonly used forecasting diagnostic procedures.

4.2.1 Diagnostic Rationale

In order to assess the degree of confidence in selecting from different candidate forecasting models, one usually looks for a diagnostic of the most appropriate (highest confidence degree) model among a set of candidate models relative to a particular data set. It is quite difficult to immediately understand the suitability of a particular forecasting method. Experienced forecasters often fail to reliably choose the appropriate technique based on intuition. Furthermore, the diagnostic tools can also indicate shortage of historical data in relation to the chosen method.

4.2.2 Diagnostic Statistics for ARIMA

The ARIMA (Autoregressive Integrated Moving Average) procedure relates to identification and parameter estimation and it is used in forecasting based on autoregressive integrated moving average (Box-Jenkins) models, seasonal ARIMA models, transfer function models, and intervention models. Estimation can be done by exact maximum likelihood, conditional least squares, or unconditional least squares. ARIMA can be subjected to model diagnostic statistics such as:

- *Akaike's information criterion (AIC)*: measures the relative fitting appropriateness of a statistical model. Initially developed by Hirotsugu Akaike as "an information criterion" (AIC), it is based on the concept of information entropy, in effect offering a relative measure of the information lost when a given model is used to describe reality. It characterizes the trade-off between bias and variance in model construction. AIC does not provide a test of a model in regard to a null hypothesis (cannot tell how well a model fits the data in absolute sense). If all candidate models fit poorly, then AIC can provide no hint on that.
- *Schwarz's Bayesian criterion (SBC or BIC)*: a criterion for model selection among a finite set of models. It is partly based on the likelihood function and it relates closely to Akaike information criterion (AIC). When fitting models, it is possible to increase the likelihood by adding parameters, but it may result in over-fitting. BIC addresses this problem by introducing a penalty term for the number of parameters.
- *Ljung-Box chi-square test*: statistics for white noise residuals: statistical test of whether any of a group of autocorrelations of a time series are different from zero. Instead of testing randomness at each distinct lag, the "overall" randomness is tested based on a number of lags.

4.2.3 Auto Regression

The auto-regression procedure provides regression analysis and forecasting of linear models with autocorrelated or conditional heteroscedastic errors. It allows estimations and predictions based on linear regression models with autoregressive errors. It supports testing of linear hypotheses and estimate as well as heteroscedasticity. Moreover, it involves potential restrictions on the regression estimates along with a choice of different estimation methods:

- exact maximum likelihood,
- exact nonlinear least squares,
- forecasts with confidence limits.

The auto-regression relates to estimation and forecasting of autoregressive conditional heteroscedasticity (ARCH), generalized autoregressive conditional heteroscedasticity (GARCH), integrated GARCH (I-GARCH), exponential GARCH (E-GARCH), and GARCH-in-mean

(GARCH-M) models. In relation to forecasting demand for spare parts, a noteworthy study on the benefits of using GARCH is presented in [43], especially in relation to high value de-mand items. Auto-regression can support model diagnostic information including, among others, autocorrelation plots, partial autocorrelation plots, statistic and significance level, marginal probability for the autoregressive model, AIC tests for ARCH, Lagrange multi-plier test for serial correlation, Lagrange multiplier test for heteroscedasticity.

4.2.4 X11 Diagnostics

The X11 procedure [10] and the related X12 procedure [11] involve the decomposition of monthly or quarterly series into seasonal, trend, trading day, and irregular components. This allows for multiplicative and additive forms of the decomposition processes for variables with the ability to project seasonal component one year ahead, enabling reintroduction of seasonal factors for an extrapolated series. The X11 procedure incorporates Sliding Spans Analysis [12].

This type of analysis is used as a diagnostic for determining the suitability of seasonal adjustment for economic series.

4.2.5 Entropy

The entropy procedure [46] relates to a parametric method of linear estimation based on generalized maximum entropy. It is mostly suitable in the following cases: a) when there are outliers in the data and robustness is required, b) when the model is under-determined for available observations or for regressions that involve small datasets. The related characteristics include:

- estimation of simultaneous systems of linear regression models,
- estimation of Markov models,
- estimation of seemingly unrelated regression models,
- performance of tests on parameters.

10. http://www2.stat.unibo.it/manualisas/ets/chap21.pdf
11. http://www.fcsm.gov/03papers/Burck.pdf
12. http://www.census.gov/ts/papers/rr86-18.pdf

4.3 Software Tools

In this section, we comment on some of the commonly known software tools providing forecasting capabilities, many of which are evaluated in more depth by the following reviews widely circulated within forecasting communities: [13]

- Jesus Flores-Cerrillo, *State-of-the-art software for automatic time series analysis* pp. 64-69. February 2010)
- Jack Yurkiewicz, *Forecasting at Steady State?*, June 2008 - OR/MS Today website.
- Bruce D. McCullough,*The Unreliability of Excel's Statistical Procedures*, Foresight, Issue 3, February, 44-45, 2006.
- Robert S. Rycroft, *Microcomputer Software of Interest to Forecasters in Comparative Review: Updated Again* Published Reviews of Software Programs, 2002
- Armstrong, *Assessment of the use of forecasting principles in commercial software*, Surveys of Software Programs (Characteristics), 2001
- Dr.Ulrich Küsters and Michael Bell; *The Forecasting Report: A Comparative Review of Commercial Forecasting Systems*, 1999

4.3.1 Microsoft Dynamics NAV

The advanced forecasting and procurement system built inside Microsoft Dynamics NAV[14] offers a variety of techniques for demand forecasting and replenishment. This soft-ware tool uses a 'Best Fit Formula' approach over refined forecasting input. Such methods use statistical formulas and collaborative techniques to predict future demands. The latter can be used to improve forecast accuracy as sometimes it is more accurate than the statistical forecast. The Dynamics NAV environment promotes certain techniques based on suitability and allows for human intervention and adjustment. Finally, the tool also offers alert support management and can generate alerts in anticipation of exceptional future demands.

4.3.2 IBM Cognos TM1

The IBM Cognos TM115 Enterprise Resource Planning (ERP) solution provides key capabilities for managing materials, production and supply chains. Primarily, it is attached to a data orchestration tool to collect data on enterprise scale. Its business intelligence modules allow data to be consolidated, tracked, and analyzed. These advanced analytics allow the user to anticipate trends and predict future situations.

Moreover, it supports a proactive identification of events, trends and various conditions of interest including demand quantity. The use of predictive models allows the maintenance of adequate inventory levels.

13. http://www.forecastingprinciples.com/index.php?option=com_content&view=article&id=9&Itemid=19
14. http://www.lanhamassoc.com/downloads/global/AFP_Distribution_Global.pdf
15. http://www-01.ibm.com/software/analytics/cognos/products/tm1/features-and-benefits.html

Moreover, one can receive notifications on various events in a collaborative environment. Other notable features relate to global optimization support that is based on gaining insights into cause-and-effect relationships, allowing understanding of the impact of pending decisions over various hierarchical levels.

4.3.3 Smart Software SmartForecasts

Smart Software SmartForecasts [16] uses the Smart-Willemain [5] method for more accurately forecasting intermittent demand based on historical data. Smart Software SmartForecasts integrated this new technology into its flagship product SmartForecasts Enterprise, which provides enterprise-wide demand forecasting, planning and inventory optimization system.

4.3.4 ClickForecast

ClickForecast [17] is an enterprise solution software package enabling organizations to more accurately predict future demand over short and long term horizons based on work type, and geographical context. It supports collaborative environments and provides results quickly.

ClickForecast uses historical data to automatically analyze and identify trends, seasonality, anomalies, and other indicators from the past in order to indicate the levels of demand expected for the future. Whereas typical forecasting applications provide complex forecasting models that are developed for products, ClickForecast provides greater value specifically to service provisioning. It identifies historical patterns and enables the integration of other information including new product rollouts requiring a change in skill set and temporarily longer job durations, sales and marketing campaigns which increase demand for a finite period, and strategic decisions which bring the business into a new market or geography.

ClickForecast can capture forecasting assumptions allowing stakeholders to build and maintain a business knowledge repository. Moreover, ClickForecast can feed demand scenarios into plans for staffing based on resource availability and qualifications.

4.3.5 Forecast Pro

Forecast Pro [18] is a fast, relatively easy to use and fairly accurate forecasting software for business and professionals. It has a shallow learning curve and can provide better results than those obtained with forecasting based on spreadsheets or guesstimating.

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16. http://www.smartcorp.com/
17. http://www.clicksoftware.com/solutions-demand-forecasting-software-\
clickforecast-features.htm
18. http://www.forecastpro.com/products/overview/method.htm

One can provide the historical data for the items that need to be analyzed for forecasting purposes. Based on the historical data, Forecast Pro does the rest. The built-in expert selection mode analyzes the data, selects the appropriate forecasting technique and calculates the forecasts using established statistical methods. Furthermore, it supports collaborative environments and allows adjustments to the statistical forecasts and easy documenting and saving changes. Forecast Pro can generate customizable reports and graphs of interest. It also automates forecasting and integrates the forecast results with other planning systems.

The models used by Forecast Pro take into consideration important forecasting aspects such as seasonal demand, product hierarchies, promotions, slow-moving items, causal variables as well as outliers based on the following tailored methods:

- Exponential Smoothing: Twelve different Holt-Winters exponential smoothing models are available to accommodate a wide range of data characteristics. The robustness of exponential smoothing makes it ideal when there are no leading indicators, and when the historical data is limited or volatile for a Box-Jenkins approach.
- Box-Jenkins: Useful for stable data sets. Forecast Pro supports a multiplicative seasonal Box-Jenkins model which can be built automatically or interactively.
- Dynamic regression: Applicable when there are important leading indicators. One can include independent variables, lagged or transformed variables in order to build generalized Cochrane-Orcutt models.
- Event models: Event models extend exponential smoothing by allowing adjustments for the case of special events such as promotions, strikes or other irregular occurrences.
- Multiple-level models: Suitable for aggregating data into groups that can be reconciled using a top-down or bottom-up approach to produce consistent forecasts at all levels of aggregation. Seasonal and event indexes can also be extracted from higher-level aggregates in order to be applied to lower-level data.
- Seasonal Simplification: A useful technique when forecasting based on data sets with more than 12 observations per year. Seasonal Simplification reduces the number of seasonal indexes used to model the data and can often improve notably the forecast accuracy.
- Low Volume Models: Based on Croston's intermittent demand model and discrete data models to accommodate low volume and intermittently (sparse) data where the demand is often null (absent).
- Curve Fitting: Offers a quick and easy way to identify the general form of the curve which the data is following such as straight line, quadratic, exponential and sigmoid (S-curve).
- Simple Methods: Moving average, percentage growth and fixed forecast models.

4.3.6 Statistical Analysis System (SAS)

SAS [19] provides a wide array of techniques suitable for optimization, simulation, forecasting and project scheduling. It allows the user to explore and tuneup various parameters that can improve statistical indicators and expected outcomes while operating within resource lim-itations and constraints.

SAS can analyze and forecast processes that take place over time. One can identify previously unseen trends and anticipate fluctuations. It can be helpful to understand past trends, forecast future ones or better understand functions by employing a wide range of analytical tools.

The SAS/ETS (Econometrics and Time Series) package provides analysis based on time series and forecasting techniques that enable modeling and simulation for strategic and tactical planning. It can automatically select the best-fitting time series based forecasting model and provides a full range of forecasting and related time series methods such as:
- Trend extrapolation and exponential smoothing;
- Winters' method (additive and multiplicative); ARIMA (Box-Jenkins).
- Dynamic regression;
- Joint forecasting of multiple time series using vector time series analysis;
- Automatic outliers and event detection.
- Time series decomposition and seasonal adjustment.
- Spectral and cross-spectral analysis for finding periodicities or cyclical patterns.
- Singular spectrum analysis.
- Similarity analysis for sets of time series.
- Regression with correction for autocorrelated errors.
- Custom time intervals.

4.3.7 Forecast Package for R

Freeware tool package [20] for forecasting using time-series data in Language R for Windows. It contains: 24 exponential methods (smoothing in the state space modeling framework) from Hyndman, Koehler, Snyder and Grose, International Journal of Forecasting, 2002, 18, 439-454). automatic selection of model ARIMA graphical methods to show time series sets of data from Makridakis, Wheelwright and Hyndman (1998), Forecasting: methods and applications, Wiley & Sons: New York. See review. ESCI ("ESS-key", Exploratory Software for Confidence Intervals) is a freeware [21] that accompanies the book "Understanding The New Statistics" [47]. ESCI runs under Microsoft Excel, on Windows or Mac. ESCI provides interactive simulations designed to help understanding

19. http://www.sas.com
20. http://cran.r-project.org/web/packages/forecast/index.html
21. http://www.thenewstatistics.com

of sampling, confidence intervals, estimation, replication, and meta-analysis. It also calculates and graphs confidence intervals for a useful range of measures and designs.

4.3.8 PEERForecaster Add-in for Excel

This is a univariate time series forecasting package [22]. It provides an implementation of the state-space models from [48]. It includes all the well-known techniques from simple smoothing, Holt trending, Holt-Winters seasonal models, and damped trend exponential smoothing models to the Box Jenkins ARIMA models. These would be useful to practitioners for benchmarking and validating comparable models found in expensive demand planning systems. The algorithms and model interpretations are documented in [49].

22. http://www.peerforecaster.com/

5 Forecasting Tools used by Military Institutions

In Canada, the Distribution Resource Planning (DRP) tool is the CAF/DND department-wide demand forecasting application that provides: some planning capabilities, excess inventory analysis, inventory rationalization, and reporting. DRP has been developed with the objective of providing missing forecasting capability and reducing CAF/DND operating costs via improving planners and management effectiveness. The statistical forecasting methods implemented within DRP are: Moving Average, Weighted Average, Single Exponential Smoothing, Linear Regression, Seasonality Winter's Method, Seasonality Adaptive Smoothing and Intermittent Croston's method. DRP analyses demand history and automatically choose the best statistical forecasting method for each spare part (stock code) and forecasts requirements 6 years in the future. It also offers the possibility to select one of the statistical forecasting methods mentioned above. DRP is a relatively new application (introduced only in the last 3 years within CAF/DND baseline) within DND and it has been implemented using Servigistics (IT company) tools. DRP is now used by some CAF units (more than 800 users) and some DND institutions should be assessed for this functionality. DRP is not currently used in CJOC.

The main tools and models in use by the Australian Defence Force for demand forecasting are: Military Integrated Logistics Information System (MILIS) and the Advanced Inventory Management System (AIMS). MILIS is an Enterprise Resource Planning (ERP) system that implements six forecasting algorithms including Moving Average, Single Exponential Smoothing (SES), and Adaptive Smoothing. AIMS is a militarized version of a Com-mercial Off-The-Shelf (COTS) ERP. Thirty four forecasting algorithms are implemented. AIMS selects the most appropriate algorithm in use based on forecasting performance.

The United Kingdom (UK) Army, UK Royal Air Force (RAF) and UK Navy are using different approaches to forecast demands. The UK Land Forces use exponential smoothing but this has been found to be not sufficiently responsive although adequate for steady-state demand forecasting. Woolford and Rutherford [50] addressed the problem of *one size fits all* for the UK services where the UK Army and the UK RAF use exponential smoothing and the Royal Navy employs Croston's method. They found that bootstrapping provides a good technique for different demand patterns.

The Logistics Modernization Program (LMP) is a single Army Logistics ERP that has been implemented by the US Army for inventory management. The LMP is based on an enterprise business architecture that enables vertical and horizontal integration at all levels of logistics across the Army. LMP provides a set of standard forecasting techniques similar to those we can find in commercial ERPs. US Army research has shown that 12 or 24 month moving average forecasts outperform other commonly used techniques (see [42] and [51]).

6 Conclusion

Demand forecasting is a key element impacting multi-level supply chain management optimality. This document presented a survey of demand forecasting approaches and techniques applicable to the operational support and In-Theater logistics domain (e.g. spare parts). Customer demand has been characterized along various dimensions (e.g. lumpy, random, erratic/sporadic). Current forecasting models, methods and assumptions have been described, and strengths and weaknesses briefly discussed. It turns out that careful judgment must be exercised when increasing model sophistication to determine the best fit model since this may reach a point of decreasing return. Despite this inconvenience, the pursuit of better forecasts remains relevant from practical perspectives as it can directly translate into significant operating cost savings. Commercial software tools and some national military forecasting solutions were finally reported.

Future work will consist in developing a new approach combining multiple methods and building on respective procedure strengths (e.g. neural network variants) to enhance predictability performance. For instance, a combination of data mining, risk analysis and time series forecasting techniques might be considered in which a tailored set of features for time series given known limitations might be exploited.

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List of Acronyms & Abbreviations

ADI	Average Demand Interval
AIMS	Advanced Inventory Management System
ARIMA	AutoRegressive Integrated Moving Average
AR	Auto Regression
ARMA	AutoRegressive Moving Average
AW	Additive Winter
C2	Command and Control
C4ISR	Command, Control, Communications, Computing, Intelligence Surveillance and Reconnaissance
CAF	Canadian Armed Forces
CANOSCOM	Canadian Operational Support Command
CEFCOM	Canadian Expeditionary Force Command
CJOC	Canadian Joint Operational Command
COMFEC	Commandement de la Force expéditionnaire du Canada
COP	Common Operating Picture
CORA	Centre for Operational Research & Analysis
COTS	Commercial Off The Shelf
CR	Croston Method
CSV	Comma Separated Values
CV	Coefficient of Variation
DND	Department of National Defence
DRDC	Defence Research and Development Canada
EDI	Electronic Data Interchange
DRP	Distribution Resource Planning
ERP	Enterprise Resource Planning
FAC	Forces Armées Canadiennes
FSE	Future Security Environments
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GMAE	Geometric Mean Absolute Error
HCC	Hybric Clustering Classification
LMP	Logistics Modernization Program
MAD	Mean Absolute Deviation

MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MILIS	Military Integrated Logistics Information System
MMAE	Minimum Mean Aabsolute Error
MMAPE	Minimum Mean Absolute Percent Error
MME	Multi-Model Ensemble
MMPE	Minimum Mean Prediction Error
MMSE	Minimum Mean Square Eerror
MSE	Mean Square Error
MW	Muliplicative Winter
NATO	North Atlantic Treaty Organization
Op	Operation
POS	Point-of-Sale
RGRMSE	Relative Geometric Root Mean Square Error
SBA	Syntetos-Boylan Approximation
SES	Simple Exponential Smoothing
SME	Subject Matter Expert
TTCP	The Technical Cooperation Program
US	United States (of America)
VAR	Vector Autoregression

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Canadian Armed Forces (CAF) are expected to evolve in adaptive dispersed operations characterized by Future Security Environments (FSE) and time-varying, hostile and uncertain contexts which involve major challenges to delivering effective and efficient In-Theatre logistics and sustainment. Accordingly, demand forecasting is perceived as a key research area in order to maximize service level, customer satisfaction, reduce logistic footprint, inventory and delivery costs, and increase system readiness. Demand forecasting is essential for efficient deployment, operations sustainment, and maintenance cycles. This document presents a survey of demand forecasting approaches applicable to the operational support and In-Theatre logistics domain. Customer demand is first characterized by introducing the forecasting problem and its pursued objectives in the military context, Then, existing statistical and causal demand forecast approaches, methodologies and tech-nical procedures are presented. Strengths and weaknesses of the approaches are briefly discussed stating the main challenges lying ahead. Finally, commercial software and some military forecasting solutions are reported for a few nations.

Les Forces Armées Canadiennes (FAC) sont appelées à évoluer en opérations dispersées adaptatives caractérisées par des environnements de sécurité futurs et des contextes dynamiques, hostiles et incertains lesquelles comportent des défis importants afin d'assurer une logistique et un soutien opérationnel et en Théâtre efficaces et efficients. En conséquence, la prévision de la demande est perçue comme un domaine de recherche clé pour maximiser le niveau de service, la satisfaction du client, de réduire l'empreinte logistique, les stocks et les coûts de livraison et accroître l'état de préparation des systèmes. La prévision de la demande est essentielle pour un déploiement efficace, le soutien aux opérations et les cycles de maintenance. Ce document présente un survol des approches de prévision de la demande applicable aux domaines du soutien opérationnel et de la logistique en Théâtre. Introduisant les problèmes de prévision et les objectifs poursuivis dans le contexte militaire, la demande des clients est d'abord caractérisée. Par la suite, les approches existantes de prévision de la demande statistiques et causales, les méthodologies et les procédures techniques sont présentées. Les forces et les faiblesses des approches sont brièvement discutées faisant état des principaux défis. Les outils logiciels commerciaux et quelques solutions de prévision de demande militaire sont finalement présentés pour quelques nations.

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Demand forecasting models, statistical analysis, force sustainment, military logistics

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