An investigation of forecasting methods for a purchasing decision support system. A real-world case study of modelling, forecasting and decision support for purchasing decisions in the rental industry.

AN INVESTIGATION OF FORECASTING METHODS FOR A PURCHASING DECISION SUPPORT SYSTEM

A real-world case study of modelling, forecasting and decision support for purchasing decisions in the rental industry

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Abstract

Key words: Forecasting, Decision support system, Rental industry

This research designs a purchasing decision support system (PDSS) to assist real-world decision makings on whether to purchase or to sub-hire for equipment shortfalls problem, and to avoid shortage loss for rental business.

Research methodology includes an extensive literature review on decision support systems, rental industry, and forecasting methods. A case study was conducted in a rental company to learn the real world problem and to develop the research topics. A data converter is developed to recover the missing data and transform data sets to the accumulative usage data for the forecasting model.

Simulations on a number of forecasting methods was carried out to select the best method for the research data based on the lowest forecasting errors. A hybrid forecasting approach is proposed by adding company revenue data as a parameter, in addition to the selected regression model to further reduce the forecasting error. Using the forecasted equipment usage, a two stage PDSS model was constructed and integrated to the forecasting model and data converter.

This research fills the gap between decision support system and rental industry. The PDSS now assists the rental company on equipments buy or hire decisions. A hybrid forecasting method has been introduced to improve the forecasting accuracy significantly. A dada converter is designed to efficiently resolve data missing and data format problems, which is very common in real world.

Dedicated to my parents, husband and daughter!

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1. Introduction

1.1 General background

Operations research (OR) was developed in World War II as a scientific method for providing executive departments with a quantitative basis for decisions regarding the operating under their control (Goodeve, 1948). Decision support systems (DSSs) that use multiple operations research models, have been proven of great importance since the 1970s in various business and industrial areas (Little, 1970). Purchasing DSSs have been used to assist decision making on choosing suppliers based on cost and lead time, as well as on assess purchasing vs leasing problem with consideration on financial aspects (Ronen and Trietsch, 1988), (Neuhaus and Lusti, 1994). The equipment rental problem focuses on yield management, which has common objectives such as maximising capacity utilisation, maximising revenue, and minimising lost customer goodwill (Weatherford and Bodily, 1992). The problem in this thesis is raised by Universal AV services, an event solution company, which provides rental equipment and technical support all over the UK. It is essential to ensure that the equipment inventory level fulfils customer requirements and minimises holding of equipment stock. If a piece of equipment is only used for few jobs annually, it may be better to sub-hire than to purchase it. Related research problems in this area focus on hotel room booking and airline seat reservation (Weatherford and Kimes, 2003) (Gardner, 2006) with limited resources. In this research, a way of increasing the rental inventory is considered by “sub-hiring” from other suppliers.

1.2 Business background

The company, Universal AV Services, was started in early 1990s(Universal, 2012). It provides conference and presentation equipment to customers for dry hire or provides bespoke services for events. Dry hire means only equipment will be supplied to clients for hire, whereas in bespoke services the company arranges technicians to set up equipment and supports the events running (Bolton, 2007). As a small and medium sized company, the company is very successful on both local and national market with excellent customer reputations. A new information system is being implemented as a centralised database to help the equipment tracking as well as job management by recording job information.

The majority business covers any event that requires technicians to remain with the equipment and 'run the show' for the client. Types of events range from small meetings to conferences for 1000 people, from fashion shows to outdoor festivals, with budgets from around £500 to £1,000,000 (Horsfield, 2007).

1.3 Problem description / justification

In rental industry, it is essential to ensure that the rental inventory meets the customer requirement. However, for some infrequently used items, it would be less cost-effective to purchase rather than sub-hire from another supplier. A decision support system is then very helpful on the purchasing or sub-hire decision making.

This can be also extended to a SME in general. With limited resources to invest, the SMEs can also use a decision support system to decide the purchasing or hiring decisions on any piece of equipment or company vehicle. The rental company is a typical research case to build the research problems and models. Having an initial research on the DSS literature, there has been few research in this area.

Using Universal as the research case, the decisions are based on days of a certain type of equipment in use for a period (normally one year). The equipment *hire price charged per day*, *sub hire price per day*, *purchase price*, *depreciation scheme*. The depreciation scheme uses the present equipment book value after first year of purchase. For example, if the depreciation scheme in the current system is 30:20:20:20:10 in 5 years, it means the book value after first year is 70% of the purchase value. Other stock holding cost, insurance, maintenance cost, and warehouse space will be considered. Damaged and out-of-date equipment also need to be considered. The decisions are moved on to forecast sales volume of certain equipment categories for a decided period, which are normally one year. Previous year usage data will be the main parameters for forecasting. Other parameters considered in the forecasting will be the company revenue data.

It is expected that the company will gain more profits with the help of the purchase decision support system (PDSS). The directors can decide the number of equipment to be purchased by viewing the suggested output from the PDSS rather than from pure personal experiences. The perspective profits of the company could come from cutting off the unnecessary equipment purchase or sub-hire expenses (Horsfield, 2007). The tested results in chapter 6 will give an analytical result on business savings by using the proposed PDSS.

1.4 Research aims and objectives

The aim of this research is to investigate research and develop a decision support system to assist the company's decision on purchasing new equipment against sub-hiring from other suppliers. To achieve this solution, the following areas will be studied and relevant models will be developed:

1) Which equipment to be purchased or which to be sub-hired? If to purchase, how many of each type are required? This is the key question for the proposed decision support system.

2) What are the measurands to justify whether buy or sub-hire? The main measurand should be the total hire days. If the days on hire exceed the measurand, to purchase will be more cost-effective. A model will be built to calculate the minimum days on hire before purchase based on the parameters given (*hire price charged per day*, *sub hire price per day*, *purchase price*, *depreciation scheme*, stock holding cost and maintenance cost)

3) How to forecast the total number of days on hire for the objective equipment in a period (half year or one year)? This should be based on the previous years' hire records and company revenue data.

4) What are the relevant forecasting methods? Which ones will be more accurate for a long term prediction? A combination of different forecasting models will be suggested to improve the accuracy.

5) A literature review and systems analysis will be conducted to determine the most suitable form of decision support system for this application, and development work of this system is followed in later chapters.

1.5 Thesis structure

1) Literature review

The literature review includes two main parts. Chapter 2 focuses on the general background on decision support systems. The definitions, benefits and limitations, system structure, taxonomies and four relevant application examples on purchasing and customer enquiry are discussed. An overall understanding on decision support systems and the applications on purchasing are reviewed.

The purchase or sub-hire problem is then modelled as an equipment usage forecasting problem. Chapter 3 detailed the decision support systems using on forecasting context. Several popular forecasting methods are surveyed for a proper solution on this research project.

2) Simulation on selected forecasting methods

Chapter 4 introduces data collection methods and a conversion model to prepare the data for forecasting modelling and simulation. In chapter 5, a simulation study is carried out to selected appropriate forecasting methods. The equipment usage in year 2005 and 2006 will be used as main inputs to forecast the usage for year 2007. The simulation results will be compared with the actual data in year 2007. The simulation will focus on one or two categories first, and then spread to other categories. The selected forecasting methods will be compared to find out which is the most accurate for the real data. This method will be the core model for the proposed decision support system. Excel, Matlab, and Eviews are used for the simulation and building up the graphs.

3) The purchasing decision modelling

The purchasing decision measurand will be calculated in days, by comparing the sub-hire cost with the purchase price. Assumptions will be made for the proposed calculation model. The limitations will be discussed afterward.

4) Prototype system design, revising and full system implementation

C#.Net is used to build up the user interface for the decision support system. The prototype system will then be tested and refined as the final system. The 3) and 4) are illuminated in chapter 6.

5) Evaluation, recommendation on further research

The system is evaluated in chapter 7. Recommendations on further research are suggested in chapter 8.

1.6 Research contributions and publications

The outcome of this research will contribute to both decision support and forecasting areas. The three components of the purchasing decision support system, data converter, forecasting model, and purchasing model have been introduced to fill in the gaps between DSS research and practical rental industry problems.

The data converter has been developed to resolve data collection and transform problems. A number of forecasting methods has been tested for the particular research problem, with a new hybrid forecasting approach proposed for the usage demand forecasting. It also brings the idea on using half year data to build up more training periods for the forecasting model. The purchasing model has been designed using the forecasting result to suggest the answers for the problems in section 1.3.

The work has been presented by a poster at university research day, and at the knowledge transfer partnership seminars with formal KTP reports. The following papers have been published during the study:

R. Yang, P. Cowling, and K. Dahal, *A hybrid forecasting approach for a rental company's purchasing decisions*, 23rd European conference on operations research, Bonn, July 2009.

R. Yang, P. Cowling, K. Dahal, and V. Horsfield, A Purchasing Decision Support System with forecasting approach, OR 50 conference, York, September 2008.

R. Yang, P. Cowling, K. Dahal, and V. Horsfield, *A Purchasing Decision Support System for a Rental Company*, Springer Lecture Notes in Operations Research 8, Lijiang, November 2008.

2. Decision support systems

Generally speaking, decision support systems (DSSs) are tools commonly based on computer software that help users make decisions by presenting alternative options or other information (Anonymous, 2010). Nowadays, there are huge efforts of research and large numbers of successful commercial systems in this area (Power et al., 2011) (Kou et al., 2011). DSSs are applied in various business or technical areas, as described in section 1.1. This chapter describes a narrative on the definitions, benefits and limitations, frames, taxonomies in the first five sections. Three selected applications of DSSs are discussed: purchasing, marketing, enquiring, and web-based decision support systems. The last section further discusses the three selected cases on how it can contribute to the research in this thesis.

2.1 Definitions of decision support system

An early definition by Little on DSS is a “model-based set of procedures for processing data and judgments to assist a manager in his decision-making” (Little, 1970). In Keen and Morton’s book, DSS implies the use of computers to 1) assist managers in their decision processes in semi-structured tasks; 2) support, rather than replace, managerial judgment; 3) improve the effectiveness of decision making rather than its efficiency. Here efficiency was defined as performing a given task as well as possible in relation to some predefined performance criterion. Whereas effectiveness involves identifying what should be done and ensuring that the chosen criterion is the relevant one (Morton and Keen, 1978), Moore and Chang define DSS as “extendible systems capable of supporting ad hoc data analysis and decision modelling, oriented toward future planning, and used at irregular, unplanned intervals" (Moore and Chang, 1980). Alter defined DSS as "significant computer applications that help people perform management functions" (Alter, 1980).

DSS was defined by Mittra with four primary characteristics: to "help managers at the upper levels; to respond quickly to managers' questions; to provide what if scenarios; and to take into account the personal decision-making styles of managers" (Mittra, 1986).

Sauter defined Decision Support Systems as a "computer-based system that supports choice by assisting the decision maker in organizing information and modelling outcomes" (Sauter, 1997).

Rhodes descriptively defined DSS as "a methodology, embodied in an organised group of people and machines which is designed to assist, but only in a secondary role, one or more members of organisation to express a preference for one action amongst the many which could be taken where at least one of those actions involves embarking on a sequence of events whose outcome cannot be precisely determined. The preferred action is deemed to influence and be influenced by the actions of others within the organisation" (Rhodes, 1993). The main components of a DSS are described as 1) a computer-based system; 2) helping decision makers 3) confronting ill-structured problems 4) direct thought-interaction 5) built-in data and analysis modules (Sprague and Watson, 1996).

Though there is not a universal accepted definition on decision support system, from the above definitions, a conclusion of DSS can be summarised by its three parts of name. “Decision” suggests that the system is used to help managers to make decisions in various areas. From the current applications’ view, most of the DSSs are in use on the business and commercial contexts. “Support” specifies that the system only give suggestions on the decisions, not the full solutions for the final decisions. The users of the systems are responsible for the decisions, which can be the same as the systems suggested or may be different. “System” here generally means that the decisions are created by a sort of computer programs with some parameter inputs and algorithms.

2.2 Benefits and limitations

It is true that applying a decision support system costs time and money on purchasing system, human resources on training and system implementation. The reason to use a DSS is that a human decision maker has own cognitive, economic and time limits (Holsapple and Whinston, 1996).

The cognitive limits refer to the human mind’s ability on knowledge storage and processing, which means a person does not know everything all the time. However, decision making is a knowledge-intensive activity. Cognitive limits substantially restrict the efficiency and effectiveness of an individual’s decision making. DSS can play as a group of supporting participants, which could be in different levels, to share knowledge and extend the decision maker’s cognition (Holsapple and Whinston, 1996). Currently, with the great help of the Internet, knowledge issues are not as a big problem as before. From practical point of view, decision makers are able to procure a number of options from Internet and other sources. The main problems now focus on how to choose the best and validated solution from these (potentially trillion of) options.

Forming a large team might be a way of relaxing the cognitive limits. However, it can be expensive in terms of paying to staff and communication cost. It this case, a DSS is a cost-effective solution for decision makers.

The third limit encountered by decision maker is the time limit. DSS can greatly help on this since a computer can process much faster than human brain for some tasks (Holsapple and Whinston, 1996).

A computer program with the running equipment (e.g a PC) would be much less expensive than building a large team for decision making. The cost can be cut significantly without paying the staff salary or outsourcing consultants. Moreover, it is much faster than a human to “make” decisions. A decision can be calculated by a computer within several minutes that might need several days for a human decision maker. Therefore, a DSS can provide decision options, based on a wide knowledge of the decision makers inexpensively and effectively. The cost-benefit issue is one of the main advantages for DSSs.

On the other hand, there are limitations for the DSS themselves. DSSs are not yet designed to contain distinct human decision making talents, such as creativity, imagination, or intuition. The power of a DSS is limited upon the computer system's running, design, knowledge possession at the time of use (Marakas, 2003).

Marakas developed a framework for decision support based on Morton, Gorry and Marakas's model (Marakas, 2003; Morton and Gorry, 1971). This gives a picture on what DSSs can or cannot do on different classes of decisions. According to Morton and Gorry, the management activity has three types of decisions. The structured decisions are repetitive and routine. There are definite procedures to handle it once it occurs. An example is Management Information System (MIS) (Kadam, 2010). The unstructured decisions are novel. There is not cut - and - dried method to handle it since it never happened before. For example, making decision on a research topic is an unstructured decision, which will be still made by human intuition not a computer based system. The semi-structured problems normally have both characters. The system may form several different solutions, based on the structured information. The decision makers then need to choose one from the suggested solutions with their own intuition and experiences.

Another weakness of the DSS application is lacking of a codified integration into the administrative procedures (Petersson and Ostrowski, 2007). If the decision maker does not have a good practice on using the DSS, it will not help effectively on the decision making process.

2.3 Structures for decision support system

There is another definition of DSSs by Sprague and Little that indicates the structure. A DSS is an interactive system that provides the user with easy access to decision models and data in order to support semi-structured and unstructured decision-making tasks (Little, 1979; Sprague and Carlson, 1982).

A typical decision support system in general is illustrated by Sprague in Figure 2.1. It includes a database with database management software (DBMS), a model Base with model base software (MBSM), and the software for managing the Interface between the user and the system, which might be called the dialogue generation and management software (DGMS). These three major subsystems provide a convenient scheme for identifying the technical capability which a DSS must have (Sprague, 1980).

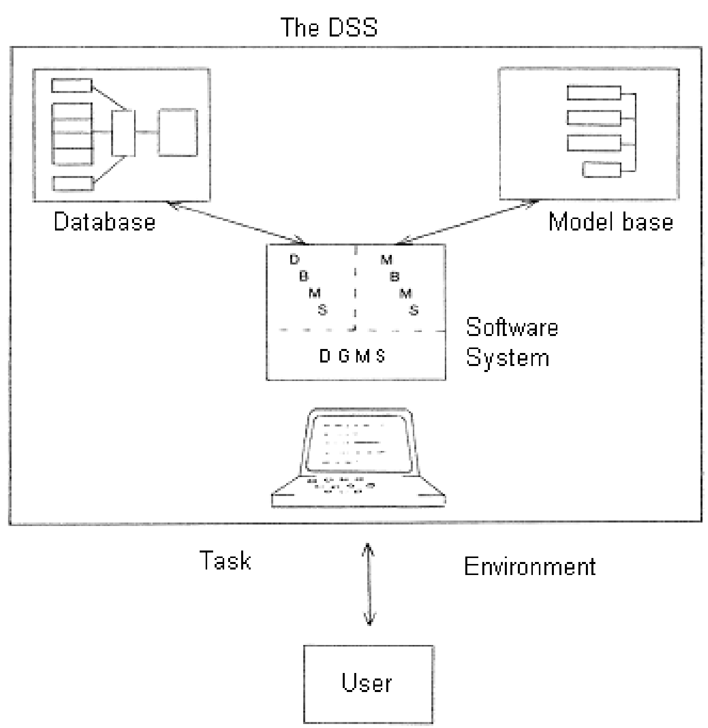


Figure 2.1 Structure of DSSs

In Sprague's paper, the database should be able to combine a variety of data sources through a data capture and extraction process. It should have a full range of data management functions to manage a wide variety of data (Sprague, 1980). The data place a significant role since the quality of data will directly affect the final decision making. In certain situations, a small mistake on a datum could make the final result totally different. Since the data might be processed by various data models and the small error might be increased at a geometric rate. For example, in this research, the accurate forecasting results will be very important to influence the final purchasing decisions.

It is essential to understand that why model base is in a DSS with a number of models. Nickerson defined three approaches to a Decision Maker's Problem, which are a set of alternatives, a set of outcomes, and a set of equivalent reference values. With modelling process the model-supplied distribution is used to update the decision maker's prior distribution to get the posterior distribution. In effect the decision maker's solution with modelling combines the other solutions in a logically consistent way to obtain the greatest equivalent reference value outcome (Nickerson and Boyd, 1980).

The models in the model base must be of sufficient quality as well to ensure that the output is valid and useful. Quality here is defined on user-oriented criteria rather than technical elegance. Systems with poor design will cause the input unable to provide or the output impossible to comprehend. Therefore, the logic of the model must have sufficient quality to facilitate the development of favourable attitudes (Lucas, 1978).

The user interface is the most flexible and variable part of a DSS. It can be designed with the user's performance. In Sprague's view, there are two languages to compose the user interface, which are Action Language and Presentation Language. The action language is used to accommodate user actions in a variety of media, whilst presentation language describes data in a variety of formats (Sprague, 1980). For example, "please enter the purchasing price for a piece of equipment" is an action language. Presentation language can be the output on screen for the final decision.

With proper design of the three parts, a decision support system is expected to exert the ability to supply the effective solution or option to the decision maker. The structure illustrated here is merely a standard model. More details of certain decision support systems will be reviewed in the application section.

2.4 Taxonomies

The classification of decision support systems was defined by Power based on the mode of assistance. The DSSs are differentiated as communication-driven DSS, data-driven DSS, document-driven DSS, knowledge-driven DSS, and model-driven DSS, whose characters was summarised by Power with the implementation technologies in Table 2.1 (Power, 2000):

	Technology	
DSS Types	LAN Based	Web-Based
Communications-Driven and GDSS	Narrow scope	Global scope
Data-Driven	Thick-client	Thin-Client
Document-Driven	Limited, .doc, .xls	HTML, Search engines
Knowledge-Driven	Stand – along PC	Shared rules
Model-Driven	Single user	Multiple users

Table 2.1 Classification of DSS (Power, 2000)

A Communications-Driven DSS supports more than one person working on a shared task, and examples include integrated tools like Microsoft's NetMeeting™. Communications-Driven DSS supports communication, collaboration, and coordination. A Group DSS (GDSS) includes decision models like rating or brainstorming and support for communication, collaboration, and coordination. Data-driven DSS or Data-oriented DSS emphasize access to and manipulation of a time-series of internal company data and sometimes external data (Power, 2000).

Document-Driven DSSs manage, retrieve and manipulate unstructured information in a variety of electronic formats. This type of DSS assists in knowledge categorization, deployment, inquiry, discovery and communication. Knowledge-Driven DSSs have specialized problem-solving expertise stored as facts, rules, and procedures or in similar structures. The "expertise" consists of knowledge about a particular domain, understanding of problems within that domain, and "skill" at solving some specific problems (Power, 2000).

Model-Driven Decision Support Systems emphasize access to and manipulation of a statistical, financial, optimization or simulation model. Model-Driven DSSs use data and parameters provided by decision makers to aid decision makers in analysing a situation. However, they are not necessarily data intensive, which very large databases are not needed for many Model-Driven DSSs. Online analytical processing (OLAP) systems that provide complex analysis of data, were classified as hybrid DSSs providing both modelling and data retrieval and data summarisation functionality (Power, 2000).

By using the web technologies, the current application of decision support systems can be also classified as online or offline. Offline DSSs are mainly used on a single PC, with the internal data source from company. The customer enquiry DSS in 2.6.3 gives an example of this. The online or web-based DSSs allow users to access the system via Internet or other types of networks. Section 2.6.4 detailed an example of a web-based DSS for e-tourism.

2.5 Decision Support Systems versus Expert Systems

DSSs are often compared to Expert Systems (ESs). They are both widely in use and sometimes are easy to be confounded with each other. There are some functions that an Expert System can do but a DSS cannot. It is helpful here to discuss and declare the difference between them.

An Expert system is defined as a computer system with hardware and software, which captures the knowledge of human experts in a given area of specialisation (del Castillo, 1997). A comparison between the two systems has been illustrated in Turban's book with Table 2.2 (Turban, 1988).

Attributes	DSS	ES
Objectives	Assist human decision maker	Replicate a human adviser and replace him or her
Who makes the recommendations (decisions)?	The human and/or the system	The system
Major orientation	Decision making	Transfer of expertise (human-machine-human) and rendering of advice
Major query direction	Human queries the machine	Machine queries the human
Nature of support	Personal, groups, and institutional	Personal and groups
Data manipulation method	Numerical	Symbolic (mainly)
Characteristics of problem area	Complex, broad	Narrow domain
Type of problems treated	Ad hoc, unique	Repetitive
Content of database	Factual knowledge	Procedural and factual knowledge
Reasoning capability	No	Yes, limited
Explanation capability	Limited	Yes

Table 2.2 Comparison between DSS and ES (Turban, 1988)

It can be seen that the most significant distinction between the two systems is the final decision maker. In a DSS the system only gives suggestion and the human needs to decide either to follow it or not. In an ES, the system gives the final recommendation and replaces a human adviser as an expert (Turban, 1988).

When using an ES, the system will ask questions to the user one by one and then display the conclusion based on the user's answers. On the contrary, a DSS user will query the system for the suggestion. A DSS manipulate numerical data to calculate the decision, whereas ESs normally process logic data (Turban, 1988).

In ESs, the problems are limited and repetitive, and they have explanation capability to users. DSSs is used to treat unique problems, and have limited capability to explain the decisions (Turban, 1988).

There is plenty of current research that combines the two systems on both business and research areas (Kwiatkowska and Michalik, 2011) (Geng et al., 2011). This thesis mainly focuses on the Decision Support System solutions.

2.6 Application areas on decision support system

The application of decision support system can be in broad areas. It can be used on medical diagnosis with clinical decision support systems, health authority information systems, health system for public sectors, and planning in engineering areas for telecommunication networks (Cortes et al., 2001; Henderson and Schilling, 1985; Kaushal et al., 2003; Morgan, 1996). In this section, a number of the applications of DSSs on purchasing, marketing, and planning at the enquiry stage are studied and discussed for the model design of the proposed DSS.

2.6.1 Purchasing Decision Support System

There are a number of purchasing research discussions on the production decisions and vender selection (Chan and Ip, 2011). For manufacturing industry, the purchasing decisions focus on making decision on either buy or produce a product (Karpak et al., 1999). While in service industry, applications of purchasing decisions are mainly applied on purchasing of stock (Kuo et al., 2001).

The main decision points for a purchasing decision model are cost issues, technology capability, quality and delivery. If internal production costs, which means the cost of manufacturing a type of equipment or parts by the company itself, is higher than purchasing price, the buy decision will tend to be adopted more frequently. Humphreys and Lo proposed a strategic model for the formulation of an effective make or buy decision (Humphreys et al., 2000). There are four stages to evaluate the make or buy decision in the framework as Figure 2.2.

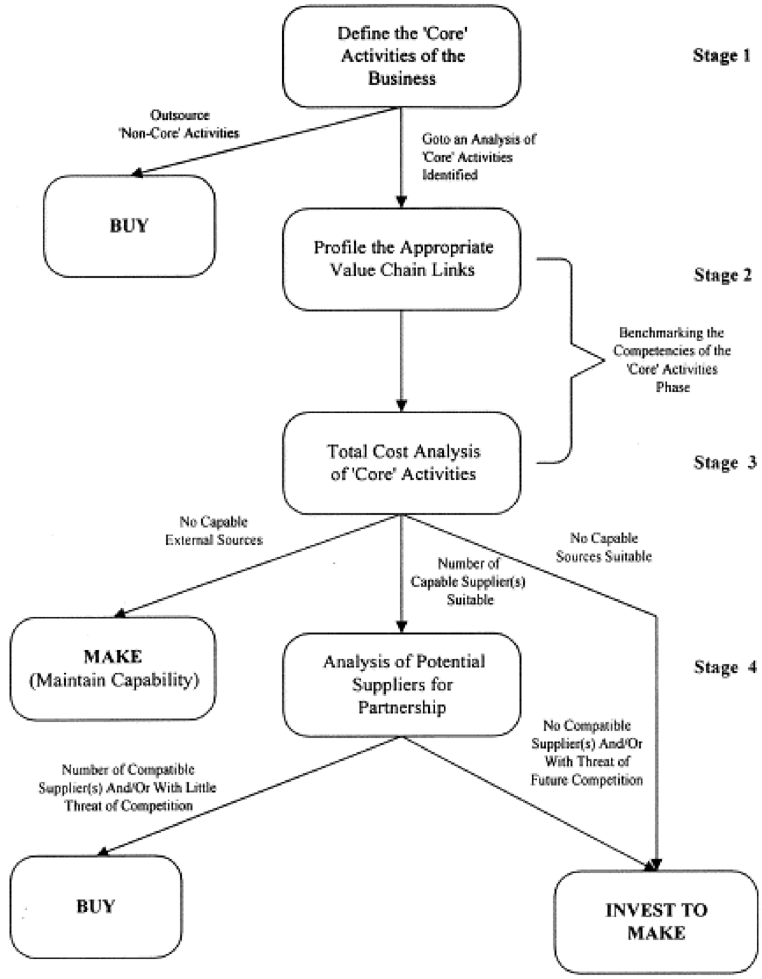


Figure 2.2 Framework of purchasing decision (Humphreys et al., 2000)

Stage 1 defines the core activities of the business. A core activity is the main products that the company serves their customers in each market. Non-Core activities can be outsourced by purchasing the product from another company.

Stage 2 profiles the appropriate value chain links. This analysis involves a structured benchmarking approach to assessing the company's competences in the range of core activities identified by top management in relation to the potential suppliers' and competitors' capacity to provide these activities (Humphreys et al., 2000). No decision is made in this stage.

Stage 3 gives total cost analysis. This involves measuring all the actual and potential costs involved in sourcing the activity both internally or externally. There are two types of costs identified at this stage:

1) Cost estimation of producing the component internally.

2) Cost estimation(s) associated with potential supplier(s) identified from the previous stages (Humphreys et al., 2000). If the cost 1) is less than the cost 2), the company should then make the product for more profit.

Stage 4 analyses the potential suppliers for partnership. If the company has found a suitable partner, purchasing from the supplier will keep the company's own capabilities and resources on its high value-added activities (Humphreys et al., 2000).

In both stage3 and stage 4, if there are no suppliers suitable, the company may need to invest strategy to produce the product.

This model gives a concise structure on how to make a purchase or produce decision for a manufacture organisation. In the given 4 steps, the decision can be made whenever enough information/analysis are obtain, which does not always require to go to the final stage. When making the decisions, there are two main considerations, which are cost and competition.

Learning from this model, Universal can also use benchmarking with cost analysis to decide their purchasing. As a service company, the decision is on either buy or sub-rental from a partner. Competition also needs to be considered as some of the sub-rental companies are also the rivals in the equipment rental market.

2.6.2 Marketing Decision Support System

Due to the huge and various information in marketing aspects, managers and marketers expect a system as DSSs to assist on high-quality decisions makings. For a marketing decision maker, high-quality decisions are those which can lead to high profit for its organisation. The Marketing DSS (MDSS) is then introduced in this particular area. In this section, studies on MDSSs are reviewed, with the design methodologies, tasks and results.

The MDSS containing simulation models to perform "what-if" analyses provides decision makers with the opportunity to integrate information and to simulate the outcomes of different values for the marketing mix (Bruggen et al., 1998). This makes possibility for the decision maker to simulate the marketplace and avoid loss on unconsidered factors which is important for the business.

In Bruggen's paper, an experiment was carried out based on a MDSS tool named MARKSTRAT environment. The environment tool can be found on a website (Larréché and Gatignon, 1990). MARKSTRAT is only an environment, which simulates as a real marketplace, and has nothing to do with decision makings. The aim of this experiment was to learn the effect of a MDSS on a marketing decision maker's final decisions. In this experiment, four participant decision groups were created, represent decision makers with an MDSS and low time pressure, with an MDSS and high time pressure, without an MDSS and low time pressure, and, without an MDSS and high time pressure.

The environment, MARKSTRAT is characterised as comprehensive, information-intensive, and dynamic and in which decisions have to be made on such diverse aspects as price, advertising, sales force, and production (Bruggen et al., 1998). The high level of its reality has been attested by several authors (Cook, 1987; Dodgson, 1987; Klammer and Kinnear, 1987). MARKSTRAT environment provides five companies to compete in markets with heterogeneous consumer preferences. The participants adopted the role of decision maker of the second company of MARKSTRAT. The other four competing companies were "phantom" companies that active in the same industry, and the decisions of these four companies were programmed by the experiment in advance (Bruggen et al., 1998; Gatignon, 1987; Larréché and Gatignon, 1990).

The experiment was run in four periods. In each period all decision makers received the standard MARKSTRAT computer output on net marking profits. The experiment results convinced the authors' original hypothesises, which were: 1) Marketing decision makers using an MDSS outperformed and made better decisions than unaided decision makers. 2) The use of an MDSS decreased the differences that existed between high-analytical and low-analytical decision makers with respect to performance, and decision quality. 3) Time pressure had a negative effect on decision quality and, consequently, on performance, since decision makers are not able to use all available information in their decision-making process (Bruggen et al., 1998).

This example gave a description on the using of a MDSS tool to assist marketing decision maker. It can be seen from the result that using MDSS could improve decision making on various marketing contexts. Moreover, it was able to support the low analytical decision makers to be more determinative and able to be less distinctive with the high analytical decision makers. This is considered as a key function of MDSS.

This tool introduced a method on running experiment to assist the decision making. It also suggested the four periods of the experiment, and compares the results with and without the MDSS. This can be learnt on the design and analysis of the performance of the purchasing decision system for Universal.

2.6.3 DSS at customer enquiry stage

Every business would like to reply and to fulfil all customer requests to obtain the profit and reputation. However, for Small and Medium-sized Enterprises (SMEs), it is not possible to take all order requests due to their limited capabilities on production and services. In this case, SMEs should select the optimised orders which can maximum their profits, and say ‘no’ to other orders.

In Xiong’s research, a decision support system framework to respond to customer enquires was first illustrated with available-to-promise (ATP) criterion, i.e. material availability and production capacity, at the customer enquiry stage (Xiong et al., 2006).

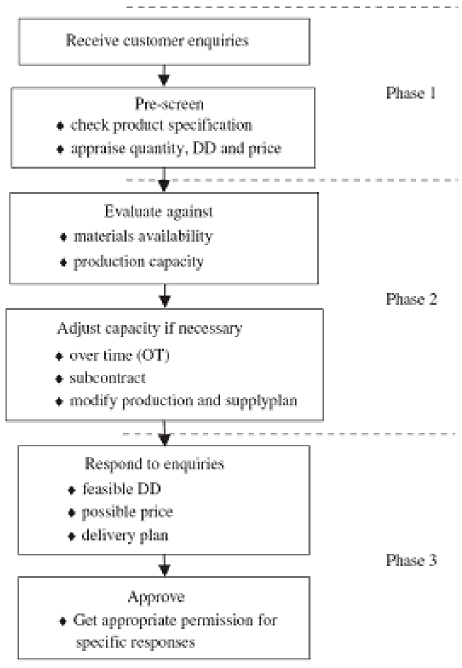


Figure 2.3 The workflow for processing enquiries at the customer enquiry stage (Xiong et al., 2006)

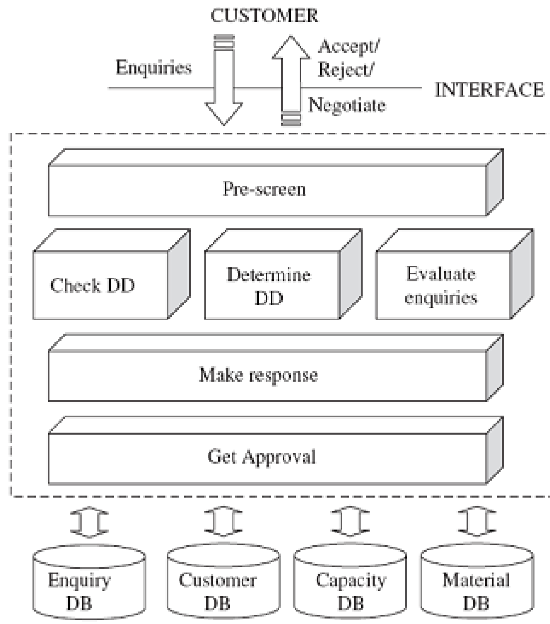


Figure 2.4 General DSS architecture for managing customer enquiries for SMEs (Xiong et al., 2006)

Xiong defined three phases in Figure 2.3 a customer enquire process, which are:

Phase 1: Receiving customer enquiries and Pre-screen: The product specification is checked and the delivery quantity, delivery dates (DD) and product price are appraised. The enquiries that are unsuitable to be produced by the company will be rejected in this phase. The remaining enquiries are then forwarded to Phase 2.

Phase 2: Two types of capacities — materials availability and production capacity are considered and evaluated in this phase. Capacity could be adjusted by planning for over-time (OT) and/or subcontracting to meet the production needs, as well as by modifying production and materials supply plan.

Phase 3: The feasibility of a specific DD, price and delivery plan are checked with regard to a specific customer enquiry. At the end of this phase, such responses are finalised and sent to key personnel in order to get appropriate permission (Xiong et al., 2006).

In Figure 2.4, the architecture of the DSS was drawn based on the left part's workflow. The structure of this DSS can be seen clearly, which includes four databases at the bottom, a model base in the central, and the customer interface at the top.

The traditional order fulfilment mechanism is not well compatible and poor on time delivery performance, as it quotes orders against finished product inventory and supply lead-time only (Stadtler and Kilger, 2000). To solve this shortcoming, a criterion ATP is used to measure the firm's capability to meet customer requirements. ATP is a time bucket quantity (typically on weekly basis) for a given type of product. It is computed based on the materials availability of all components (Xiong et al., 2006).

Xiong's model was based on several assumptions that only one product is considered with deterministic material availability and production capacity. The demand policy is either full or nothing will be fulfilled. The product structure and production routing are known, as well as inventory holding cost, manufacturing lead time, and unit processing time of every resource. The production capacity of work centres may neither be borrowed nor lent between different periods.

The material availability is accumulative, and product sales price are time dependent (Xiong et al., 2004).

The main learning point for this system is the structure of the DSS architecture, which including database, model base and customer interface. It is a similar model on a DSS design for Universal's purchasing. This model also suggests an assumption that only one product is considered at one time. This can be also applied on the DSS for Universal as for single equipment scenario.

2.7 Summary

This chapter discussed the definitions of decision support systems from the early age of this concept. There are various applications developed on decision support system recent years. However, the disagreements over definitions on decision support system remain. The pros and cons of DSSs are then explained as well as the structures of general DSSs. The taxonomies of DSS are also given based on Power's idea. For further understanding on DSS, a comparison between DSS and ES was produced based on their functions and objectives.

Three detailed application examples were then studied, which focus on the applications on purchasing, marketing, and customer relationship. The purchasing decision support system introduced the measurands concept on the decision making. In the cost view, if the purchasing cost is lower than the making cost, then it is higher profitable to outsource the production. This research gives a basic framework on buy or outsource scenario for production industry, which can be also extended to service industry.

The marketing decision support system introduces a tool “MARKSTRAT” to assist the decision making process. An experiment consists four periods of decision making process was also studied. This case gives a direction on how to process the decision making by a number of periods’ data.

The customer enquiry decision support system gives detailed architecture and process of decision making based on production capability. The assumption that only one product is considered at one time is similar to the research topic in this thesis. Learning from it, the equipment purchasing decision will be based on one equipment category.

3. Forecasting in rental industry

For a technical equipment rental business, it is essential to make decisions on how many equipment items should be owned or purchased for each type of equipment. To make the decisions on how many of new items for a type of equipment should be purchased for the company, it is important to estimate the usage (by number of days) of this type equipment and the peak number of items in use for the next year. The daily and monthly usage distributions are also considered in this chapter. To forecast these data source, the literatures on forecasting methods are reviewed in this chapter.

In the first section, rental industry and its characterises are discussed for a better understanding on the rental business background. Forecasting methods are then viewed for the theory basis of the modelling and simulation in the following research, followed by the discussion on measurements of the forecasting methods. A case study is then carried out to compare the different forecasting methods, which gives a guide of the modelling and simulation stage.

3.1 Nature of rental business

Rental business covers a wide range of business areas. Typical rental market includes car rental, property rental and films/video rental. The business principle of those rental types is not complex, since the customer just chooses the goods they want and pay for the rent. On the contrary, equipment rental needs to manage the group of equipment, as well as give technical support to some customers. There are also customers who just hire small amount of equipment without help of the technicians. This is called “dry hire” in this industry. However, the dry hire occupies no more than 5% of the company's business (Horsfield, 2007). In terms of customer category, the film/video rental is mainly for individual customers, whereas the equipment hire focuses on business or government. Their equipment includes laptop, projects, lens, speakers, stages and stands.

In the UK equipment rental market, there are two national companies. The national organisations have an advantage in that they have teams all over the country (Horsfield, 2007). Financially, they are more capable to invest novel equipment to draw customer attention. Other companies are local based with only one or two office.

The literature on rental business is not as much as the decision support system. Most of the literature focuses on the forecasting on hotel industry and airline seat reservation. In Weatherford's research on yield management (Weatherford and Bodily, 1992), some of the common management objectives of rental business are summarised as follows:

- Maximise profit
- Maximise capacity utilisation
- Maximise average revenue/customer
- Maximise revenue ignores cost side, when costs are essentially fixed
- Minimise lost customer good will
- Maximise the net present value of rental subject, i.e. equipment
- Extract each customer's maximum price

Savin described the rental business as company which invests in equipment for which there is a potential demand, and a stream of customers patronizes the company, renting its equipment (Savin, 2005). After each rental, the equipment is returned to the company. The rental durations are typically significantly shorter than the life of the equipment, so that each unit may be used repeatedly. The important managerial decisions for rental businesses focus on matching and pricing rental demand with the equipment supply. These decisions create a hierarchy of managerial controls in the company.

For the short term matching between supply and demand, capacity allocation decisions may be needed to determine which customers are served when rental capacity becomes scarce. For the long term decisions set the company's overall level of rental capacity and attempt to capture as much demand for rental services as is profitable with inventory management and investing new equipments (Savin, 2005).

The company aims to improve their overall level of rental capacity by decisions on the equipment purchasing. Moreover, the equipment purchasing must be cost-benefit for the capital invested. For instance, if a piece of equipment is only used for one or two jobs in a year, it would be better to sub-hire it from another supplier rather than buy one. Therefore, the main problem focuses on the forecasting of the overall hire period for equipment during a long period, as well as the peak and average number of equipment required during this period.

3.2 Introduction of forecasting methods

Forecasting is a process that predicts or estimates unknown situations. It has been used in various application areas which include supply chain planning (Stadtler and Fleischmann, 2012), weather forecasting (Grell and Baklanov, 2011), and transport planning (Li et al., 2011), stock market (Umstead, 1977) and individual securities (EUBANK and ZUMWALT, 1979). In business context, forecasting is used on purchasing, sales and marketing and manufacturing planning. Ideally, people would like to obtain the precise data and facts that what are going to happen before making decisions. However, it is not possible for anybody to obtain one hundred percent accurate prediction.

A number of forecasting tools have been introduced and developed to help on the prediction and estimation (Baltagi and Boozer, 1997). The data used for forecasting can be time series or cross-sectional data. Time series data come from the previous or historical data that consist a sequence of observations over time. For the company's situation, it can be the monthly or annually usage of a certain equipment category. The forecasting method observes how the sequence of observations will continue into the future. Most forecasting methods assume that the times of observations are equally spaced, so it can observe the data in a regular base. Cross-sectional data are observed at the same time. It looks at the data from different companies at the same time for forecasting. For example, during a period, the number of certain equipment types used by each customer respectively. There could be period that no equipment was in stock and available to hire. The sub-rental data are used to avoid missing of these types of data.

The techniques used may be quantitative or qualitative. Qualitative forecasting methods are based on educated opinions of appropriate persons. Quantitative forecasting models may be classified into causal models in which independent variables are used to forecast dependent variables, and time series models, which produce forecasts by extrapolating the historical values of the variables of interest (Lancaster and Lomas, 1985). Two of the typical quantitative forecasting models will be introduced in the following two sections.

3.3 Exponential smoothing

Exponential smoothing is a very common time series forecasting methods. It is a time series method that uses historical data as the basis for estimating future outcomes, which fits for the equipment usage forecasting case. In this section, a variety of the exponential smoothing methods are discussed, considering level, trend and seasonal factors.

3.3.1 Single exponential smoothing

Single exponential smoothing only considers the level of forecasting. The current value of time series Y_t is to be observed, the forecast for it is denoted by F_t. Once the observation Y_t becomes available, the forecast error is found to be Y_t - F_t. The single exponential forecasting takes the forecast for the previous period and adjusts it using the forecast error. Then the forecast for the next period is:

$$F_{t+1} = F_t + \alpha\,(Y_t - F_t) \qquad (3.1)$$

It can be written in another way:

$$F_{t+1} = \alpha\ Y_t + (1 - \alpha)\ F_t \qquad (3.2)$$

Here α is a constant between 0 and 1. It can be seen here that the new forecast is the old forecast plus an adjustment for the error that occurred in the last forecast. When α has a value close to 1, the new forecast will include a substantial adjustment for the error in the previous forecast. Conversely, when α is close to 0, the new forecast will include very little adjustment. Thus, the effect of α is completely analogous to the effect of observations when computing a moving average (Makridakis et al., 1998).

In this method, the past forecast error is used to correct the next forecast in a direction opposite to that of the error. There will be an adjustment until the error is corrected. It is the same principle that the deviation (error) has taken place. This principle plays an extremely important role in forecasting. It can be used to develop a self-adjusting process that corrects for forecasting error automatically (Makridakis et al., 1998).

The equation (3.2) is the general form for exponential smoothing methods. It substantially reduces the necessity of obtaining all the historical data or a subset of them. Rather, only the most recent observation, forecast and a value of α must be stored. The implications of exponential smoothing can be better seen if equation (3.2) is expanded by replacing F_t with its components as follows (Makridakis et al., 1998):

$$F_{t+1} = \alpha\ Y_t + (1 - \alpha)\ [\alpha\ Y_{t-1} + (1 - \alpha)\ F_{t-1}]$$

$$= \alpha\, Y_t + \alpha\,(1 - \alpha)\; Y_{t-1} + (1 - \alpha)^2\, F_{t-1} \qquad (3.3)$$

The substitution process can be repeated several times by replacing F_{t-1} by its components, F_{t-2} by its components, and so on. Therefore, the F_{t+1} then represents a weighted moving average of all past observations. Giving α = 0.2, 0.4, 0.6 or 0.8, the weight assigned to past observations will be in the following table:

Past observations' weight to F_{t+1}	α weight assigned			
	α = 0.2	α = 0.4	α = 0.6	α = 0.8
Y_t	0.2	0.4	0.6	0.8
Y_{t-1}	0.16	0.24	0.24	0.16
Y_{t-2}	0.128	0.144	0.096	0.032
Y_{t-3}	0.1024	0.0864	0.0384	0.0064
Y_{t-4}	0.08192	0.05184	0.01536	0. 00128

Table 3.1 Weight assignment

From Table 3.1, it can be seen clearly that the earlier the data recorded, the smaller the weight will be. These data indicate that the most recent observation is more important for the forecast than early observations. This technique has only one parameter on weight. Therefore, it does not works with data that with no trend or seasonal characters.

3.3.2 Holt's linear method

The Holt's linear method extends single exponential smoothing to linear exponential smoothing, which allows forecasting of data with trends. The Holt's linear method uses two smoothing constants, α and β (with values between 0 and 1), and three equations (Makridakis et al., 1998):

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + b_{t-1}) \qquad (3.4)$$

$$b_t = \beta(L_t - L_{t-1}) + (1- \beta)\, b_{t-1} \qquad (3.5)$$

$$F_{t+m} = L_t + b_t\, m \qquad (3.6)$$

The level of series L_t for the trend of the previous period adjusted in equation (3.4), by adding b_{t-1} to the last smoothed value L_{t-1}. This method eliminates the lag and brings L_t to the approximate level of the current data value. The trend or slope is the difference between the last two smoothed values, which is calculated in equation (3.5). If there is a trend in the data, new values should be higher or lower than the previous ones. The trend is modified by smoothing with β multipling the trend in the last period (L_t - L_{t-1}), and adding that to the previous estimate of the trend multiplied by (1 - β). This is due to some randomness remaining. Similar to the basic form of single smoothing given by equation (3.2), the equation (3.5) applies to the updating of the trend. Finally, equation (3.6) is used to forecast ahead. The trend b_t is multiplied by the number of periods ahead to be forecast, m, and added to the base value, L_t (Makridakis et al., 1998). The Holt's method adds trend factors into the SES and aims to improve the forecasting accuracy for data that has this kind of character.

3.3.3 Holt-Winter's seasonality method

The single exponential smoothing methods are appropriate for no trend or seasonal pattern data. The Holt's linear method is appropriate for linear trend data. The Holt-Winter's method extended Holt's linear method to capture seasonality. Based on the two Holt's equations, this method adds one more equation to deal with seasonality. The basic equations for Holt-Winter's multiplicative method are as follows:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1 - \alpha)(L_{t-1} + b_{t-1}) \qquad (3.7)$$

$$b_t = \beta(L_t - L_{t-1}) + (1- \beta)\, b_{t-1} \qquad (3.8)$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1- \gamma)\, S_{t-s} \qquad (3.9)$$

$$F_{t+m} = (L_t + b_t\, m)\, S_{t-s+m} \qquad (3.10)$$

Here s is the length of seasonality. It can be a number of months or quarters in a year. L_t is the level of the series, b_t denotes the trend; S_t is the seasonal component; and F_{t+m} is the forecast for m period ahead. The L_t is a smoothed value of the series that does not include seasonality, whereas the data values Y_t do contain seasonality (Makridakis et al., 1998).

To initialise the Holt-Winter's forecasting method, the value L_s, b_s and S_s are set using the equation (3.11) - (3.13). At least one season's data are required to determine initial estimates of the seasonal indices. The level is initialised by taking the average of the first season:

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \ldots + Y_s) \qquad (3.11)$$

To initialise trend, it is convenient to use two complete seasons (2s periods):

$$b_s = \frac{1}{s}\left(\frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_2}{s} + \ldots + \frac{Y_{s+s} - Y_s}{s}\right) \qquad (3.12)$$

Finally, the seasonal indices are initialised using the ratio of the first few data values to the mean of the first year:

$$S_1 = \frac{Y_1}{L_s},\ S_2 = \frac{Y_2}{L_s},\ \ldots,\ S_s = \frac{Y_s}{L_s} \qquad (3.13)$$

The parameters α, β, γ can be chosen to minimise the errors with non linear optimisation algorithm.

Compared the three exponential smoothing methods, the single exponential smoothing only considers the errors with adjustments between the forecasted data and observed data. The next forecasted data is corrected by the past errors. In the Holt's linear method, the trends are developed by introducing the level and slope of the series data. These extend the single exponential method by considering the randomness remaining. The last method adds the seasonality to the Holt's linear method.

From the review, exponential smoothing methods are mainly used on forecasting for the situations that have strong link with historical data. It can be level, trend and seasonal characters. The more characters added, the more parameters are required to test models. Considering the nature of Universal's equipment usage, the next year's usage data could be forecasted based on the previous year's data using exponential smoothing method. All of these three methods can be tested to compare the performance in this thesis.

3.4 Regression

Unlike the exponential smoothing methods, regression methods are a kind of causal / econometric methods. They use the assumption that it is possible to identify the underlying factors that might influence the variable that is being forecasted. For example, sales of umbrellas might be associated with weather conditions. If the causes are understood, projections of the influencing variables can be made and used in the forecast.

3.4.1 Simple regression and *F*-test

A simple regression has only one predictor variable. Simple linear regression is a basic form of multiple regression. Simple linear regression is used in situations to evaluate the linear relationship between two variables. The forecast object Y is only affected by one explanatory / independent variable X. A linear relationship between X and Y fall into a function that can be plotted as a straight line (Hays, 1969):

$$Y = a + bX + e \qquad (3.14)$$

where a is the intercept, b is the slope of the line, and e denotes the error that is the deviation of the observation from the linear relationship. The objective is to find values of a and b so the line $\hat{Y} = a + bX$ presents the “best fit” to the data.

The error e is the vertical deviation on the Y axis:

$$e_i = Y_i - \hat{Y}_i \qquad (3.15)$$

To obtain an overall measure of “goodness of fit”, the sum of squared error is introduced as:

$$SSE = e_1^2 + e_2^2 + \ldots + e_n^2 = \sum_{i=1}^{n} e_i^2 \qquad (3.16)$$

When X and Y are given by at least two pairs of data, the intercept a and slop b can be then calculated.

Before using the simple regression method, it is necessary to test whether there is a real relationship between X and Y. F-test is then introduced to aid the decision on the significance of the relationship. The F statistic is defined as follows:

$$F = \frac{\sum(\hat{Y}_i - \overline{Y})^2/(m-1)}{\sum(Y_i - \hat{Y}_i)^2/(n-m)} \tag{3.17}$$

where m is the number of parameters in the regression equation, and n is the total pairs of previous data. In regression, the correlation between Y and $\hat{Y}$ is usually designated R. R^2 is then defined as:

$$R^2 = \frac{\sum(\hat{Y}_i - \overline{Y})^2}{\sum(Y_i - \overline{Y})^2} \tag{3.18}$$

Then the (3.11) can be developed as:

$$F = \frac{R^2/(m-1)}{(1-R^2)/(n-m)} \tag{3.19}$$

If the slope is significantly different from zero, the regression will explain a substantial proportion of the variance, so the F statistic will be large.

Nonlinear regression is the problem of inference for a model based on multidimensional x,y data (Seber and Wild, 1989). Non-linear simple regression is also used in forecasting. This includes exponential ($Y = e^{\alpha+\beta X}$), quadratic ($Y = \alpha + \beta_1 X + \beta_2 X^2$) and cubic ($Y = \alpha + \beta_1 X + \beta_2 X^2 + \beta_3 X^3$). The exponential model can be linearised by taking a logarithm of both sides: $ln\ Y = \alpha + \beta X$. The regression methods give another way on forecasting, which will be used in chapter 5 to compare the results with the ES methods.

3.4.2 Multiple regression

In simple regression, there is only one explanatory variable for the variable to be predicted. In the multiple regression, there are two or more explanatory variables ($X_1, X_2, \ldots, X_k$). A general form for multiple regression can be as follow:

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_kX_k + e \quad (3.20)$$

Although simple regression is considered as an econometric method, in multiple regression, the time series can be combined by creating new explanatory variables to allow various time-related features of data to be included in the model.

If a linear time trend is required in the regression model, an independent variable X_j can be created to take the values that equal to the times of observation. To deal with seasonality, dummy variables can be used to assume that the seasonal component is unchanging from year to year. An example is given in (Makridakis et al., 1998) on monthly data with a collection of monthly variables.

Looking into the regression method, it is suitable to track the data which needs fast response. If Universal's equipment requirement grows rapidly, this can be a good model to fit the situation. Moreover, regression methods allow external parameters on the relationship between the forecasted data and other factors which can influence the result. For Universal's situation, the sale revenue could be an important factor for the forecasting results.

3.5 Box-Jenkins methodology

Box-Jenkins methodology is one of the most popular methods used in forecasting. It is named after the statisticians George Box and Gwilym Jenkins, who suggested this method in early 1970s. Box-Jenkins applies autoregressive moving average (ARMA) or autoregressive moving integrated average (ARIMA) models to find the best fit of a time series to past values of this time series. The ARMA can be only used when the data are stationary. A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. For non-stationary data, the ARIMA models were then introduced to deal with this problem (Vandaele, 1983).

Original ARIMA model uses an iterative three-stage modelling approach:

1) Model identification and selection:

Identifying seasonality in the dependent series (seasonally differencing it if necessary), and using plots of the autocorrelation and partial autocorrelation (Brockwell and Davis, 2002) functions of the dependent time series to decide which (if any) autoregressive or moving average component should be used in the model. An example of strong autocorrelation is given in the engineering and statistics book (NIST and SEMATECH, 2012).

2) Parameter estimation

Using econometric computation algorithms to generate at coefficients (p, d, q) which best fit the selected ARIMA model.

3) Model checking

Testing whether the estimated model conforms to the specifications of a stationary univariate process. In particular, the residuals (errors) should be independent from each other (which also means they are random) and constant in mean and variance over time. Computing the autocorrelations of the residuals can tell the level of the residuals that relates to each other. If no autocorrelations are significantly different from zero, the model identified is adequate. Otherwise, the estimation is inadequate. It has to return to step one and attempt to build a better model (Box and Jenkins, 1970) (Pankratz, 1983).

The general non-seasonal model is known as ARIMA (*p*, *d*, *q*):

AR: *p* = order of the autoregressive part

I: *d* = degree of first differencing involved

MA: *q* = order of the moving average part

There are several exceptive situations in this model. A white noise is classified as ARIMA (0,0,0), and a random walk model is classified as ARIMA (0,1,0). When the coefficients are (1,0,0), the ARIMA is called an autoregressive model and can be written as AR (1) for short. The basic form of an AR(1) model is:

$$Y_t = c + \varphi_1 Y_{t-1} + e_t \qquad (3.21)$$

where φ_1 is the autoregressive coefficient that is restricted between –1 and +1. When the coefficients are (0, 0, 1), the ARIMA (0, 0, 1) is called a moving average model and can be written as MA (1) for short. The basic form of an MA (1) model is in equation (3.22). The coefficient $-\theta_1$ is restricted between –1 and +1.

$$Y_t = c + e_t - \theta_1 e_{t-1} \qquad (3.22)$$

When the seasonality is added into the model, the ARIMA can be written as:

$$\text{ARIMA}\ (p, d, q)\ (P, D, Q)_s \qquad (3.23)$$

where (p, d, q) is the non-seasonal part of the model, s is the number of periods per season, and $(P, D, Q)_s$ is the seasonal part of the model (Makridakis et al., 1998) (Vandaele, 1983).

The applications on ARIMA models are various. It can be used in engineering areas for temperature forecasting (Babu, 2012). For the business applications, an example was introduced using Box-Jenkins methodology on retail sales forecasting of printing and writing papers (Makridakis and Wheelwright, 1989). Monthly data was used for a seasonal pattern of 12 month data. Considering the similarity of the sales data and hire data the Box-Jenkins method can also be selected as one of the forecasting methods on the hire volume prediction in this thesis.

3.6 Measurements on forecasting methods

Accuracy is the most important concern of a forecasting method. In most situations, it is treaded as the overriding criterion for the method selection (Athanasopoulos et al., 2011). This section will discuss a variety of the measurements.

3.6.1 Standard measures

If Y_t is the actual observation for time period t and F_t is the forecast for the same period, the error is defined as:

$$e_t = Y_t - F_t \qquad (3.24)$$

The e_t here is a one-step forecast error since the F_t is calculated by using data $Y_1, \ldots, Y_{t-1}$, which is forecasting one period ahead of the last observation. If there are observations and forecasts for n time periods, then there will be n error terms. The following standard statistical measures are then defined (Makridakis et al., 1998):

$$\mathrm{ME} = \frac{1}{n}\sum_{t=1}^{n} e_t \qquad (3.25)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |e_t| \qquad (3.26)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \qquad (3.27)$$

It can be easily seen that the ME is likely to be small since the positive and negative errors can offset one another. Therefore, the MAE is introduced to eliminate this disadvantage. MAE is firstly making each error positive by taking its absolute value, and then averaging the result. The MSE idea is similar as the MAE, where the errors are made positive by squaring each of them. The squared errors are then averaged (Makridakis et al., 1998). The MSE is often used in statistical optimisation, since it has the advantage of showing the difference by using squared error that gives bigger difference for values above 1. Moreover, from the view of computer programming, squaring is easier to be handled than taking absolute value. Taking absolute value requires two steps, which are 1) comparing the parameter with zero and deciding the sign (positive or negative); and 2) transferring the negative parameter to the opposite positive one. Whereas, squaring a parameter is one step.

The above statistics only deal with measures of accuracy having same time series. They do not compare across different time series for different time intervals. The error is very different when forecasting the monthly usage of an equipment or the annually usage. Therefore, the relative/ percentage error (PE) was introduced:

$$\mathrm{PE}_t = \left(\frac{Y_t - F_t}{Y_t}\right) \times 100 \qquad (3.28)$$

Then there are two more frequently used measures defined:

$$\text{MPE} = \frac{1}{n}\sum_{t=1}^{n} PE_t \qquad (3.29)$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} |PE_t| \qquad (3.30)$$

Similar as ME, the MPE is likely to be small since the positive and negative errors tend to offset one another. Hence the MAPE becomes a more popular measure in many literatures. From the forecasting user's point of view, knowing that the MAPE of a method is 5% is more meaningful than simply knowing that the MSE is 183. However, the MAPE depends on a good origin. It is not in use for assessing the temperature forecasting accuracy, since the common temperature scales have fairly zero points. When the time series contains zeros, the PE cannot be computed. Moreover, if the time series values are very close to zero, the computation involving PE can be meaningless (Makridakis et al., 1998).

3.6.2 Theil's U-statistic

The U-statistic was developed by Theil in 1966. It was suggested to measure both disproportionate cost of large errors to provide a relative basis for comparison with naïve methods. Naïve methods is to regard the different method results for the same analysis as being repeated estimates of a single true mean. It computes the consensus mean as the unweighted mean of the different group means (Neter et al., 1996). The U-Statistic allows a relative comparison of formal forecasting methods with naïve approaches and also squares the errors involved. Hence large errors are given much more weight than small errors. The U-statistic is defined as the following equation (Makridakis et al., 1998):

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}(FPE_{t+1} - APE_{t+1})^2}{\sum_{t=1}^{n-1} APE_{t+1}^{\;2}}} \qquad (3.31)$$

where $\quad FPE_{t+1} = (\frac{F_{t+1} - Y_t}{Y_t})$

and $\quad APE_{t+1} = (\frac{Y_{t+1} - Y_t}{Y_t})$

When substituted the FPE_{t+1} and APE_{t+1} into equation (3.31), the result is:

$$U = \sqrt{\frac{\sum_{t=1}^{n-1}(\frac{F_{t+1} - Y_{t+1}}{Y_t})^2}{\sum_{t=1}^{n-1}(\frac{Y_{t+1} - Y_t}{Y_t})^2}} \qquad (3.32)$$

The value of the equation of (3.25) will be 0 if FPE_{t+1} = APE_{t+1}, which means that the forecast has no error. This is easy to be seen from the equation (3.32) as well, where F_{t+1} = Y_{t+1}. Alternatively, when U = 1, $(FPE_{t+1} - APE_{t+1})^2$ = $(APE_{t+1})^2$ means the FPE_{t+1} = 0, that is, $F_{t+1} = Y_t$. This means the errors in the forecasting method were the same as the errors that would be obtained by forecasting no change at all in the actual values.

There are more measures developed on the forecasting accuracy, such as Root Mean Square Error (RMSE) and Root Mean Square Percentage Error (RMSPE). The RMSE will be the main error measurement used in this thesis.

3.7 Case study – forecasting on hotel revenue management

Most literatures mentioned the forecasting on rental industry are on airplane seat reservation. In recent years, the research extended to the hotel room booking forecast based on the seat booking forecast research. Hence, a hotel revenue management system was reviewed as a case study. The equipment rental has similar nature as the hotel room booking market, which the forecast is laid on the usage of objects room or equipment.

There are three models considered in revenue management forecasting, which are historical booking models, advanced booking models and combined models. Historical booking models only consider the final number of rooms or arrivals on a particular stay night. Advanced booking models only include the build-up of reservations over time for a particular stay night. Combined models use either regression or a weighted average of historical and advanced booking models to develop forecasts (Lee, 1990).

For advanced booking models, a classical "pickup" method is widely used in airline reservations. Pickup is defined as the number of reservations picked up from a given point in time to a different point in time over the booking process.

The classical pickup method determines the average (or weighted average) of reservations picked up between different reading days (e.g., between 120 days out and 90 days out) for departed flights for a particular day of week to forecast the future pickup between the same reading days for the same flight number on the same day of week in the future. The advanced pickup method is similar to the classical pickup method, with the extension that it includes relevant data from all flights, even those that have not yet departed (L'Heureux, 1986) (Weatherford and Kimes, 2003).

Two combined Methods were produced, which were weighted average of the advanced booking models, and a full information model that viewed the booking process as a time series of historical bookings. Lee found that the later one outperformed the early one by reducing the MAE 31% (Lee, 1990).

In a forecast competition across industries, Makridakis found that the single exponential smoothing, Holt's double exponential smoothing, and Holt–Winters' triple exponential smoothing worked well on their 1001 time series data sets. However, the regression methods and Bayesian methods were not as robust as the methods above. The results were measured by MAPE, Median APE and MSE measurements. Makridakis also found that complex or statistically sophisticated methods like ARIMA did not outperform simple ones in general (Makridakis and Andersen, 1982). This could be caused by the trend and seasonal characteristics of the data that fit the double or triple exponential smoothing methods.

3.7.1 Data in use

There are two dimensions of data in use in Weatherford's hotel forecasting research, which are when the reservation was booked and when the room was consumed. The first one gives the manager additional details to update the forecast. Therefore, the user does not need to rely solely on the historical information on the daily number of arrivals or rooms sold. In Weatherford's research, the main forecast objects were the number of guests on a certain stay night, and the length of stay. Two data approaches were selected which are: A) the forecaster was only allowed to access the data from stay nights that had already occurred. For example, for forecasts made on Monday July 13, only information from previous Monday night stays (July 6 and earlier) was used; B) the forecaster was allowed to access to all relevant data, even from stay nights that had not yet occurred. For example, on Monday July 13, it not only have the data available in approach A, but also have data from all the reading days from 84 days out down to 7 days out for next Monday's stay night on July 20 (Weatherford and Kimes, 2003).

This research did not mention the situation that when the hotel were fully booked, and cannot accept any more guests. It can because the hotel was never fully book. However, if it did occur and were not recorded, the actual data could not be precise. In the equipment usage forecast, this point has been considered by adding sub-hire equipment usage.

3.7.2 Methodology and Results discussion

Seven methods were tested in Weatherford's research, which are:

1) **Simple exponential smoothing**, using *α* values between 0.05 and 0.95. The single parameter α is determined based on the value that minimises the MAE in the training set and is then held constant as forecasts are generated in the holdout sample.

2) **Moving average methods** with the number of periods in the average varying between 2 and 8. The single parameter *n* is determined based on the value that minimises the MAE in the training set and is then held constant as forecasts are generated in the holdout sample.

3) **Linear regression methods** assume that there is a correlation between the number of reservations on hand currently (day *n*) and final number of reservations (day 0). e.g., $\text{Forecast}_{\text{Day 0}} = a + b \times \text{Bookings}_{\text{Day n}}$.

4) **Logarithmic linear regression methods** can be explained by

$\log(\text{Forecast}_{\text{Day 0}}) = a + b \times \log(\text{Bookings}_{\text{Day n}})$. For method 3) and 4), the two parameter *a* and *b* are determined based on the value that minimises the MSE in the training set and is then held constant as forecasts are generated in the holdout sample.

5) **Additive, or 'pickup', method** adds the current bookings to the average historical pickup in bookings from the current reading day to the actual stay night. e.g., $\text{Forecast}_{\text{Day 0}} = \text{Bookings}_{\text{Day n}}$ + Average Pickup (Day *n* to Day 0). No parameter needs to be set here, only a calculation of the historical average

pickup. This is done by simply taking the arithmetic average of the pickup values found in all of the available historical data.

6) **Multiplicative method** multiplies the current bookings by the average historical pickup ratio in bookings from the current reading day to the actual stay night, e.g., $\text{Forecast}_{\text{Day 0}} = \text{Bookings}_{\text{Day n}} \times$ Average Pickup Ratio (Day *n* to Day 0). There is no parameter to set here as well, only a calculation of the historical average pickup ratio. This is done by simply taking the arithmetic average of the pickup ratio values found in all of the available historical data.

7) **Holt's Double Exponential smoothing** uses α values between 0.05 and 0.95, β values between 0.05 and 0.95. The two parameter α and β are determined based on the value that minimises the MAE in the training set and is then held constant as forecasts are generated in the holdout sample (Weatherford and Kimes, 2003).

By matching the two data sets and seven methods, Weatherford and Kimes did 14 tests in their research. It was found that the forecasting methods which minimised the MAE across all data sets was the method 1) *exponential smoothing method using only completed stay night data*. The method that minimized the MAPE was the method 5) *pickup method using only completed stay night data*.

The most robust methods (as measured by the percentage of the cases that they had the lowest MAE) were exponential smoothing (1) and pickup (5) methods with 33.3 and 25.1%, respectively. Next most robust were the moving average (2), Holt's method (7) and linear regression (3) methods with 15.4, 12.9 and 10.9%, respectively. Log linear methods (4) and multiplicative methods (6) performed poorly. Whether the methods used only completed stay night data or all available stay nights did not seem to matter. There were 52.5% of the cases did better with approach A) that only completed stay night data, and 47.5% did better with approach B) that using all relevant data. These results are consistent with the Makridakis et al. (1982) competition which found that moving averages and exponential smoothing methods were among the most robust.

The principle of the hotel room usage forecast is similar to the equipment usage. This is shown in two questions for each of them.

In the hotel room booking problem, the questions focus on:

1) How many rooms are in use for a night?

2) What's the length of the rooms in use?

In the equipment usage forecasting, the problems are:

1) How many equipment are in use for a day?

2) How many days each equipment has been used for a period?

Therefore, the case study gives a good suggestion on the forecasting method choosing for this kind of problem.

3.8 Summary

This chapter reviews forecasting methods that are relevant to this thesis's research problems. In section 3.1, the nature of rental business was reviewed. It helps to define the forecasting aims on rental industrial. Section 3.2 - 3.5 studied a number of quantitative forecasting models and methods. One or more from the studied models will be selected and simulated to build up the forecasting model in this thesis.

Section 3.6 discussed the measurements of forecasting errors. From the view of computing modelling, MSE (Mean Squared Error) is the most popular method in the reference. The power of the result is easier to be programmed than the absolute value. There is no difference on the accuracy between MSE and MAE, although the results are different. MSE can also show more difference if the error values are not closed to 1.

Section 3.7 gives a case study on a hotel room booking forecasting problem. As no research on equipment rental was found, this case is the most relevant one to be studied. The problem, the data and modules in use, and the results were discussed. At the end of the section, the forecasting objectives were suggested for the problem of this thesis.

4. Data converter for forecasting model

Data inputs are important for the accuracy, no matter which forecasting method is applied. This chapter introduces a method to process the raw collected data, which mainly focuses on the data converting from the daily series to the yearly usage.

The collected data are on all items' daily usage format for one equipment type in a period. However, the proposed forecasting model needs equipment usage data for the purchasing decisions on later stage. To prepare the data inputs for the forecasting model, a data conversion model is developed to transfer the daily number of items into each items' number of days in use for a period.

4.1 Data collection, recovery, and format

The collected data are daily usages on a type of equipment. The collected data comes from organisation's historical data on sales or production that stored in a variety of sources, i.e. spreadsheets or database (Snydera et al., 2002). This research's data are collected from the company's previous years' jobs records. One of the most common equipment, laptop, is selected for the simulation. There are three methods used for the data collection, namely equipment logbook, Job records, and usage history from an information system, which will be explained in the following paragraphs.

The earliest data record can be found in the company since April 2006, when a paper "logbook" for laptops was introduce to record all the laptop out and in dates (UniversalLive, 2006). An example of the usage is shown in Figure 4.1. To collect these data, daily data were entered into a spreadsheet from the logbook by marking “1” for an item in use and “0” for an idle item.

From March 2007, an information system was introduced to record all jobs, when the logbook was abandoned as a management fault. However, no equipment usage had been recorded until September 2007. To recover the data in this period, all jobs’ start and end dates were searched in the system. The Job handlers were asked to reference the number of laptops that have been used on each job. A data set was then manually added into a spreadsheet on laptop usage similar as the laptop logbook for the last period.

Miles discussed a data recovery method for purchasing decisions on expenditure information which summed the food and beverage commodities in a week and cloth commodities in a month to obtain the total expenditure on a single commodity (Miles, 2001). Compared with Miles’s data recovery method, the data recovery method introduced in this thesis takes more time, but expected to be more accurate. This is due to the same period’s actual job data were used to obtain the equipment used for each job, rather than prediction methods.

From Oct 2007, equipment usage was recorded by the implemented system as mentioned in paragraph 3. A report can be generated from the system for all equipment usage. Data can be easily entered into Excel from the report. By the time of the forecasting experiments, there were 656 daily usages collected in spreadsheet which cover 21 months. Data can be output in a yearly distribution format. An example is shown in figure 4.1.

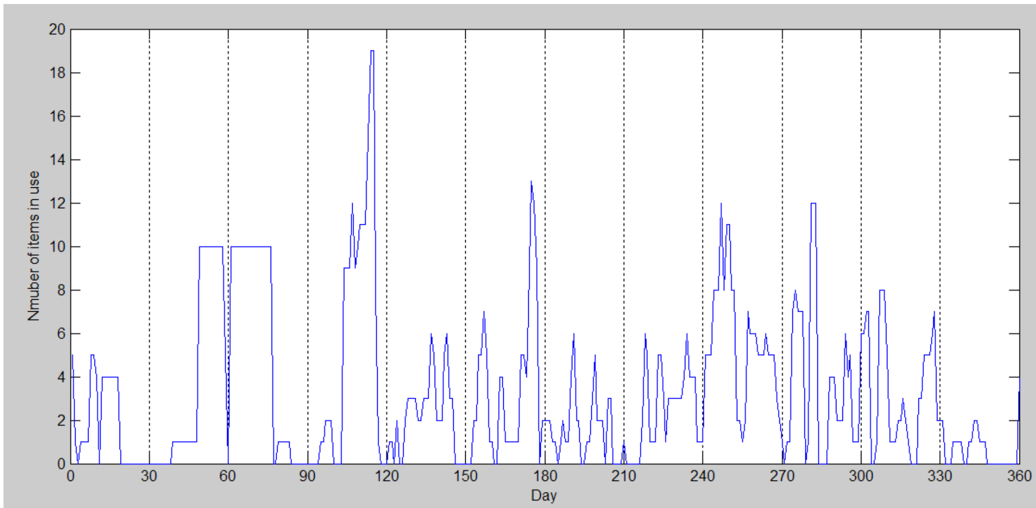


Figure 4.1 Daily equipment usage for year 2007

However, the decision needs to be made based on the next year's equipment usage. In the purchasing model, decisions will be made on a yearly usage.

There are two sets of data input required for the purchasing decision, which are 1) The maximum number of items in use $Item_{max}$; and 2) The number of days in one year that for each level (number) of item and above in use. "Above" here means when calculating the number of days that n items in use, the result should include n items, n+1 items, n+2 items, …, till $Item_{max}$ items situation. An example of the laptop data distribution (year 2007) is plotted in Figure 4.2. It illustrates the number of days that on each number of laptops has been in used during a given period (one year in this example). This curve is the forecasting objective of this research, which will be detailed in section 5.5.

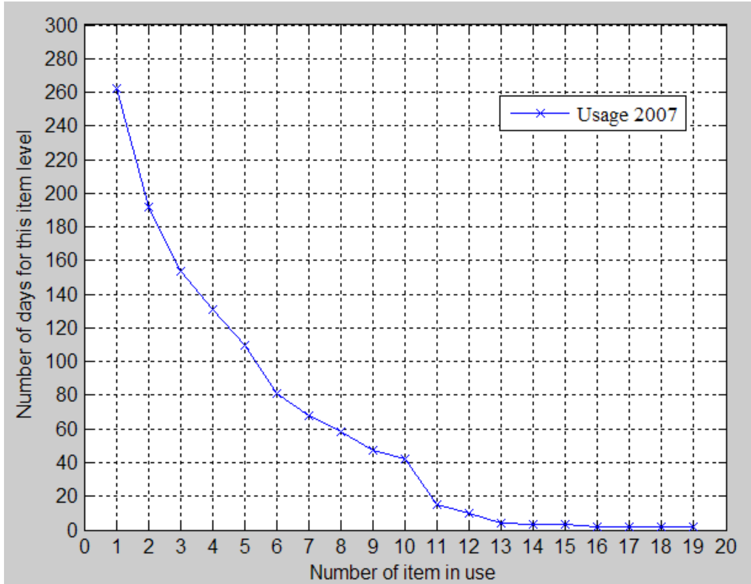


Figure 4.2 Equipment yearly usage

From the above two figures, it can be seen that there is a gap between the original data and required input data. To solve this problem and integrate the system, this chapter proposes a data conversion model to transfer the daily number of items into each items' number of days in use for a year.

4.2 Data converter module

Since the collected data are based on daily series, a data conversion model is developed to transform the daily number of items into each items' number of days in use for a period (a year or half year), using an aggregate forecasting method that forecasts the usage for a period by number of days. This idea comes from a wireless usage forecasting research that aggregates the mobile phone call duration usage based on phone number, date, hour, and dialled number (Tan et al., 2000). To meet the requirements described at the beginning of this section, the data converter consists of two parts. The first one calculates maximum number of items in use $Item_{max}$. The second part produces the number of days for each level of equipment.

In the first part, the maximum number of items, $Item_{max}$, in use is calculated in a simple counting program. The flowchart for this program is detailed in Figure 4.3 below, as the initial step of the further converting process. It uses 360 for a year's number of days, and 180 for half year. This avoids changing parameter for the loop year problem.

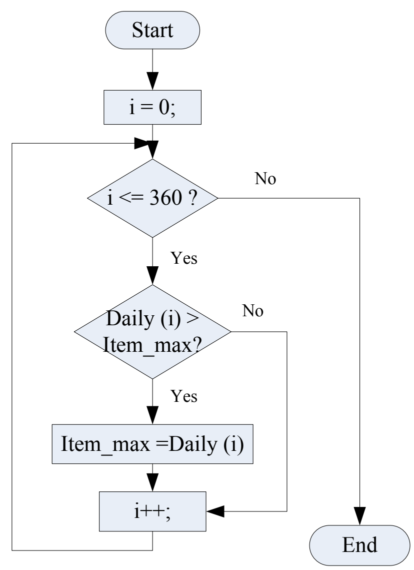


Figure 4.3 Calculation for maximum number of items in use

The second part is to calculate number of days for each level of equipment. The flowchart is illustrated in Figure 4.4.

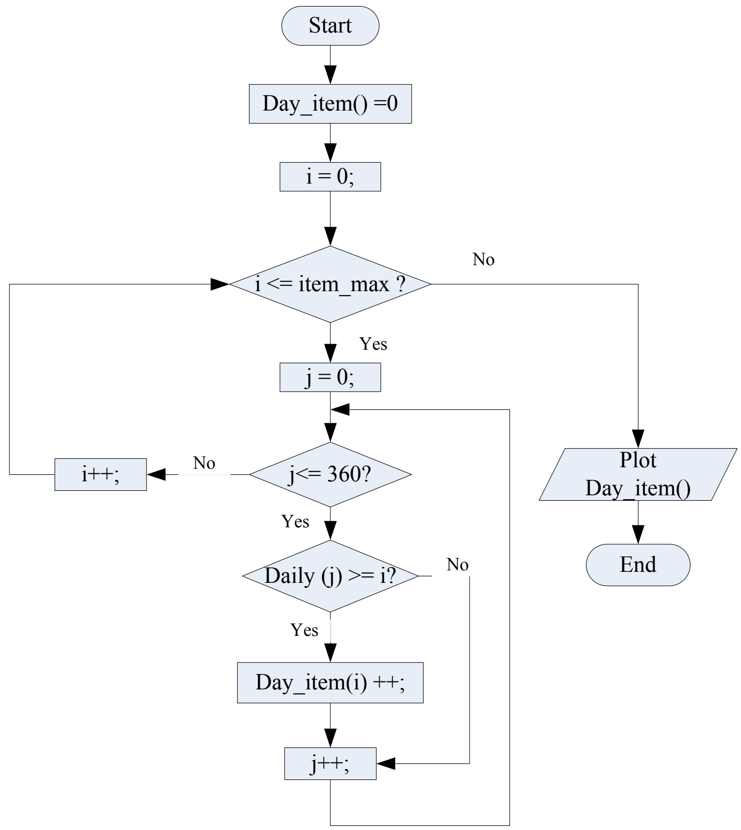


Figure 4.4 Converter for item usage by days

In the second part program, the parameter *i* is used to control the number of items in use, and the parameter *j* is used to control the number of days from 0 to 360. The Daily( ) array is the input, which is the daily number of items in use as plotted in Figure 4.1. The Day_item( ) array is the output/final result for the equipment usage by days.

4.3 Model development and evaluation

Since the forecasting model was originally developed in MatLab, the data converter is developed in MatLab to fit the forecasting model. Using MatLab for the converter also makes the data plotting easier than transferring the result from another program.

The model has been tested on the year 2007's daily usage. The result from this model is shown in Figure 4.2. This gives an overview on equipment usage. The result can be saved in an Excel spreadsheet, which is easy to be entered into the purchasing decision module. Further development on this model can be improved on system integration. For example, a data interface can be designed to transfer the result from this model into the purchasing model in C#.NET. Moreover, when the system is finally issued to public users, the forecasting model and data converter can be rewritten in C#.NET.

Using the data converter described in section 4.2, the daily series can be transferred into periodical usage. The final forecasting model will use previous period's usage to forecast the next period's usage. The final yearly usage data will be calculated as an input for the purchasing model.

The $Item_{max}$ for the next period could be more than $Item_{max}$ in the current period, which will affect the accuracy on forecasting result. However, it will not be a major problem, as most important required data, the measurand days, is less likely to be on or near the days on $Item_{max}$ level.

4.4 Summary

This chapter propose a data converting model for the further forecasting simulation and modelling. Section 4.1 reviews data collection and recovery methods. According to the company's data storage situation, three different data collections are applied to obtain the maximum available data. Although some data are not properly stored, a recovery method is used to ensure the data accuracy.

Section 4.2 illustrates the data converter module with flowcharts. All flowcharts are presented in the section to keep the integrity of the calculation model. The data converter module has been developed under C#.NET environment. Section 4.3 discusses and evaluates the designed module.

5. Forecasting Methods Simulation

In this chapter, a number of exponential smoothing (ES) methods are applied initially on the daily and monthly equipment usage data, to find out the "best" method for these data, and to learn the methods' characters. The ES methods are then applied on the laptop usage data, generated by the data converter described in chapter 4, for an in-depth comparison on error performance.

For each method, this chapter aims to find the optimal parameter(s) to minimise the error for different data inputs. The mathematical expressions and parameter definition of the main forecasting methods are described in Chapter 3. The minimised errors are then compared to find out the most accurate method to forecast the equipment usage for the purchase decision system that described in Chapter 6.

5.1 Forecasting methods selection

By reviewing forecasting work similar to this research in Chapter 3, such as Electric utility (Huss, 1985) and demands (Taylor, 2003), call centre volume (Bianchi et al., 1998), and supermarket sales (Taylor, 2004), various forecasting methods are used, including exponential smoothing methods, regression, and ARMA. Gardner (Gardner, 2006) found that the exponential smoothing methods were optimal for a very general class of state space models and broader than the ARIMA class. The hotel reservation case study in Chapter 3 also shows that exponential smoothing methods outweigh other methods.

There are a number of research papers discussing the best methods. The "best methods" here means the method that has lowest error between the observed and forecasted data (Foster and Vohra, 1993).

There are various classic forecasting methods, such as exponential smoothing, regression and Box-Jenkins (ARIMA) method (Makridakis et al., 1998). ARIMA has been selected on supply chain demand forecasting (Huynh Trung Luong, 2008). Methods bared on exponential smoothing have been referred to be successful on daily demand forecast (Gardner, 2006). Since equipment daily usage forecasting was no mentioned in previous research, in this research, experiments are designed on exponential smoothing, regression, and ARIMA methods to find out the best one for the equipment usage case.

The input data of the proposed purchasing decision support system is a forecasted equipment usage in the coming year. As there are no more than two year's data available, the data are simulated on daily and monthly basis first to learn the characteristics of these forecasting methods. The accumulated daily data are then converted into a half yearly usage that to forecast the next half year's usage, using the model explained in Chapter 4.

5.2 Daily series forecasting

This method uses the daily equipment usage data to forecast day by day. As mentioned in Chapter 4, there are 656 series data in use. A software EViews (Eviews, 2012) is used for the forecasting simulation in this section. Three exponential smoothing models are selected to use this software. By importing the time series from Excel, EViews can give forecasting results as well as RMSE.

5.2.1 Single exponential smoothing

The data are forecasted based on the single exponential smoothing (SES) equation (3.1) and (3.2) introduced by Makridakis (Makridakis et al., 1998). The parameter α mainly affects the accuracy of the forecasted result. It can be seen that choosing α between 0 and 1 will adjust the ratio of actual data (Y_t) and forecasted data (F_t) in the forecasting result (F_{t+1}). When $\alpha = 0$, $F_{t+1} = F_t$, which means the actual data Y_t has no influence on the F_{t+1}. Whereas $\alpha = 1$, $F_{t+1} = Y_t$, which means Y_t has been totally copied to F_{t+1}. In this simulation, α is set to 0.2, 0.4, 0.6 and 0.8 for the 656 series.

	RMSE-day by day
$\alpha = 0.2$	2.703
$\alpha = 0.4$	2.363
$\alpha = 0.6$	2.183
$\alpha = 0.8$	**2.084**

Table 5.1 Mean RMSE for 656 data series using SES and comparison

The calculated RMSEs are summarised in Table 5.1. It can be seen that when $\alpha = 0.8$, the minimum RMSE for this data set is obtained.

5.2.2 Holt's linear method

As described in Makridakis's book (Makridakis et al., 1998), Holt's linear method contains three equations as described in (3.4) - (3.6)

There are two sets of data required to initialise, which are the estimate level of series L_0 and estimate slope of series b_0. In the simulation for forecasting here, the two values are set as $L_0 = Y_0$, $b_0 = Y_1 – Y_0$. The m is set to 1 for the next day, which makes the last equation to the below from: $F_{t+1} = L_t + b_t$.

In this section both α and β are set in 0.2, 0.4, 0.6, and 0.8 to decide the best combination. To compare the result with section 5.3.2, α=0.5 is added. The error results are detailed in Table 5.2.

RMSE	β=0.2	β=0.4	β=0.6	β=0.8
α=0.2	3.048	3.329	3.489	3.538
α=0.4	2.592	2.720	2.926	2.358
α=0.5	2.456	2.576	2.682	2.784
α=0.6	2.358	2.474	2.757	2.659
α=0.8	**2.237**	2.350	2.447	2.535

Table 5.2 Mean RMSE for 656 data series using Holt's

Generally speaking, it can be seen from Table 5.2 that:

1) The minimum error for Holt's occurs when α=0.8 and β=0.2.

2) When α is fixed, the error increases with of the rise of β.

3) When β is fixed, the error decreases with the rise of α.

4) The minimum RMSE occurs when α=0.8, which is the same as the α=0.8 setting in SES for these data.

By comparing the errors between SES and Holt's, it can be seen that for the daily usage data, Holt's doesn't perform better than the SES. The next section will test the seasonal method's character.

5.2.3 Holt–Winter's linear method

The mathematical expression of this method is described in chapter 3. In this method, a seasonal character is included. As required by Holt–Winter method, there are three parameters in use, which are α, β and γ for the level, trend and seasonal factors respectively. By using EViews, the three parameters are set from 0.2 to 0.8 to obtain a combination. As seasonal factor is considered in this simulation, the "Cycle for Seasonal" is default to 7 for daily series.

RMSE	γ =0.2	γ =0.4	γ =0.6	γ =0.8
α=0.2, β=0.2	3.11	3.22	3.36	3.53
α=0.4, β=0.2	2.64	2.76	2.92	3.11
α=0.6, β=0.2	2.38	2.44	2.55	2.70
α=0.8, β=0.2	**2.25**	2.28	2.29	2.32
α=0.2, β=0.4	3.40	3.54	3.71	3.93
α=0.4, β=0.4	2.80	2.99	3.26	3.64
α=0.6, β=0.4	2.51	2.60	2.80	3.14
α=0.8, β=0.4	2.40	2.45	2.42	2.49
α=0.2, β=0.6	3.58	3.75	3.98	4.30
α=0.4, β=0.6	2.94	3.29	3.85	4.84
α=0.6, β=0.6	2.63	2.78	3.22	8.24
α=0.8, β=0.6	2.57	2.85	3.63	4.69
α=0.2, β=0.8	3.66	3.90	4.23	4.71
α=0.4, β=0.8	3.13	3.82	5.25	19.78
α=0.6, β=0.8	2.71	5.00	46.45	2559.46
α=0.8, β=0.8	2.73	4.46	8.55	35.62

Table 5.3 Mean RMSE for 656 data series using Holt-Winter's

Generally speaking, it can be seen from Table 5.3 that:

1) The smallest RMSE occurs when α=0.8, β=0.2, and γ =0.2.

2) The minimum RMSE occurs when α=0.8 which is the same as the α=0.8 setting in SES, and Holt's.

3) When β and γ are fixed, error decreases with the drop of α.

4) When α and β are fixed, error increases with the rise of γ.

5) When α and γ are fixed, error increases with the rise of β.

6) The error reaches the peak when α=0.6, β=0.8, and γ =0.8. It is also much higher than other results when α=0.6, β=0.8, and γ =0.6; and α=0.8, β=0.8, and γ =0.8. As this situation does not occur in Holt's model, it is most likely caused by the seasonal parameters when the value of β and γ rise.

To further analyse the trend of RMSE, the errors are plotted. Figure 5.1 illustrates the trends of the errors. There are some exceptions. For example, α =0.8 β =0.4 has a decrease from γ = 0.4 to 0.6.

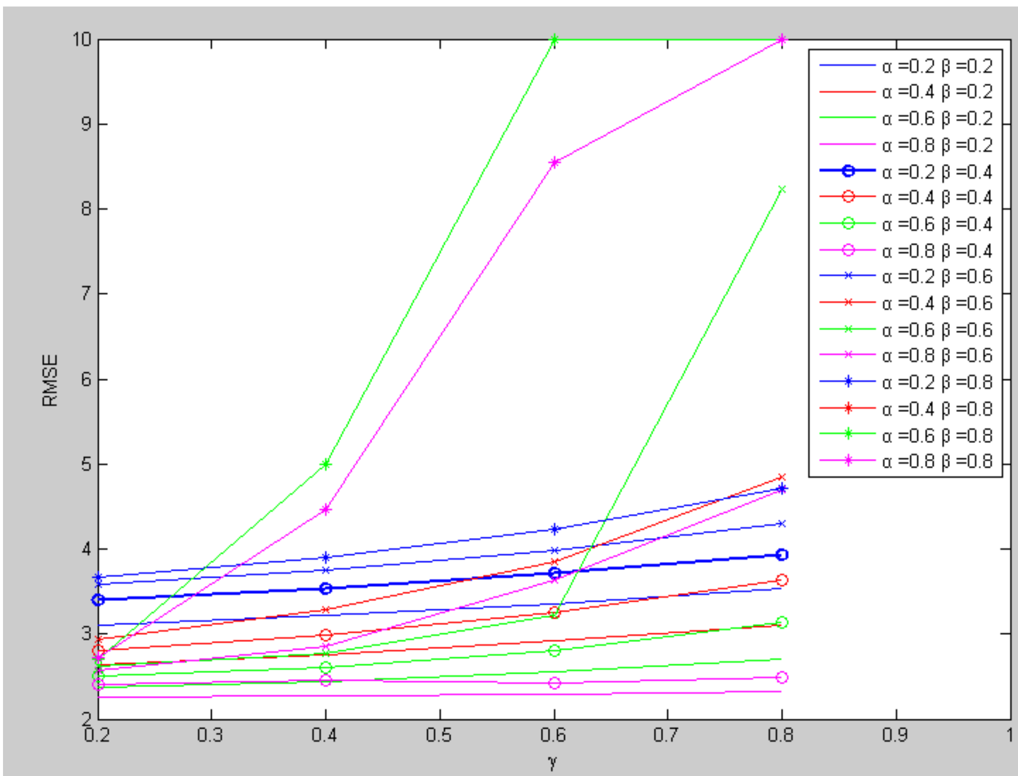


Figure 5.1 Forecasted errors Comparison – Holt-Winter

By comparing the errors between SES, Holt's and Holt - winter, it concludes that for the daily usage data, Holt's and Holt - winter doesn't perform better than the SES. Selection of Holt – winter method is not applied for short of training data.

5.2.4 Forecasting on cash machine series

A set of 111 cash machine transaction data series were downloaded from NN5 forecasting competition website (NN5, 2008). The three exponential smoothing (ES) forecasting simulations are applied in this set of data to compare with the equipment usage daily series. Results on RMSE are shown in Table 5.4 and 5.5.

RMSE	SES	Holt's			
		β=0.2	β=0.4	β=0.6	β=0.8
α=0.2	**3.98**	**4.36**	4.55	4.71	4.93
α=0.4	4.06	4.38	4.66	4.96	5.24
α=0.6	4.20	4.54	4.86	5.16	5.46
α=0.8	4.41	4.79	5.18	5.57	5.99

Table 5.4 Mean RMSE for 111 data series using SES and Holt's

RMSE	γ =0.2	γ =0.4	γ =0.6	γ =0.8
α=0.2, β=0.2	**4.46**	4.64	5.24	5.26
α=0.4, β=0.2	4.50	4.68	4.92	5.23
α=0.6, β=0.2	4.63	4.74	4.88	5.07
α=0.8, β=0.2	4.83	4.89	4.95	5.01
α=0.2, β=0.4	4.69	4.91	5.24	5.69
α=0.4, β=0.4	4.83	5.06	5.38	5.79
α=0.6, β=0.4	4.98	5.10	5.30	5.56
α=0.8, β=0.4	5.23	5.30	5.38	5.45
α=0.2, β=0.6	4.91	5.20	5.62	6.19
α=0.4, β=0.6	5.18	5.47	5.88	6.43
α=0.6, β=0.6	5.31	5.47	5.74	6.09
α=0.8, β=0.6	5.63	5.74	5.84	5.92
α=0.2, β=0.8	5.20	5.57	6.11	6.88
α=0.4, β=0.8	5.50	5.87	6.40	7.19
α=0.6, β=0.8	5.63	5.83	6.25	6.81
α=0.8, β=0.8	6.07	6.22	6.38	6.50

Table 5.5 Mean RMSE for 111 data series using Holt-Winter's

The simulation results show that smallest RMSE obtained for each method are: SES 3.98 (α=0.2); Holt's 4.36 (α=0.2, β=0.2); Winter 4.46 (α=0.2, β=0.2, γ =0.2). Compared with the equipment usage series, the RMSEs for this cash machine series are higher, which means ES methods are more suitable for the equipment usage simulation. A same conclusion as the equipment usage is that the minimum RMSEs for the three methods occur in the same α setting (α = 0.2). Moreover, the cash machine series using SES performs lowest RMSE among the three methods, which is the same as the equipment usage series. During the simulations for the cash machine series, there was no negative (below 0) result found.

5.3 Monthly data set forecasting

This method uses daily data in a monthly way to test the monthly seasonal character on the series. Single Exponential Smoothing (SES) and Holt's method are used in this experiment. The experiment is designed to forecast the next month's daily data based on this month same day's data. For example, it uses 1st April's data to forecast 1st May's data and then 1st Jun, 2nd April for 2nd May and then 2nd Jun, etc. As the number of days in each month is not same, the following correction methods are used to make all months with a 30 days data. The usages on 31st Jan and 31st Mar are added to 29th and 30th Feb. The 31st of May, Jul, Aug, Oct, and Dec are added into the 30th of each month. Reason of using this correction is that in the purchasing decision for this thesis is required for laptop's usage for a period of at least half year. The result needs to be more accurate on a yearly usage basis, but not very necessary for a single day at the end of month.

5.3.1 Single exponential smoothing

Similar as described in section 4.2.1, α is set by 0.2, 0.4, 0.6, and 0.8 to obtain various results for error comparison. As F_t is requested to calculate F_{t+1}, the F_0

needs to be initialised to start the simulation. In this section, F_0 is set as Y_1, which means the first forecasted data equals the actual data.

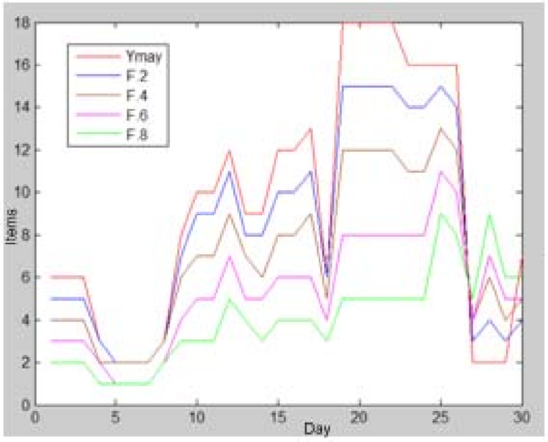


Figure 5.2 Forecasted and actual data in May 06

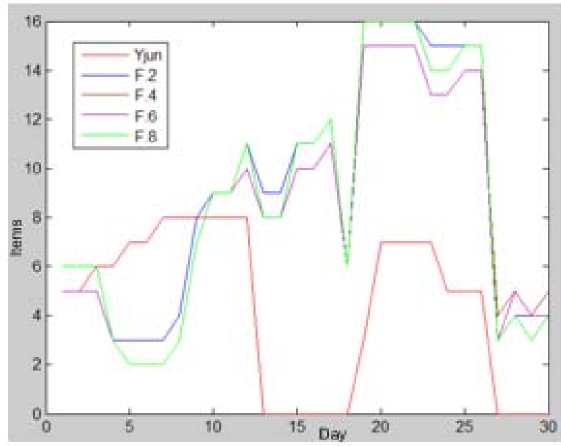


Figure 5.3 Forecasted and actual data in Jun 06

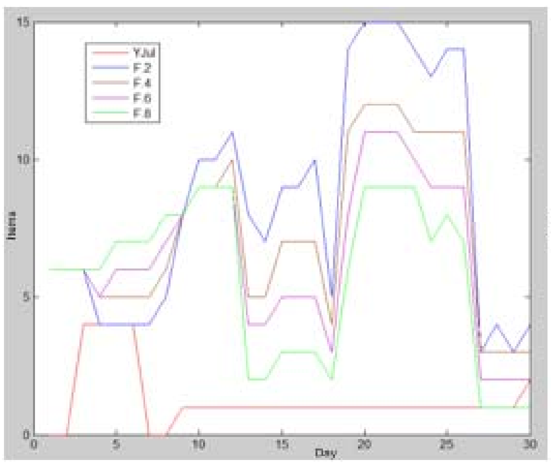


Figure 5.4 Forecasted and actual data in Jul 06

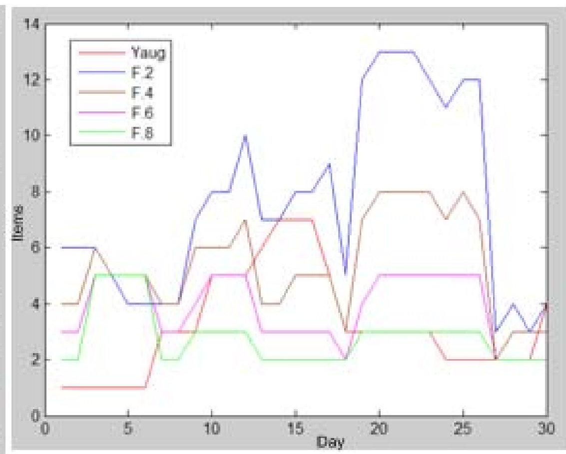


Figure 5.5 Forecasted and actual data in Aug 06

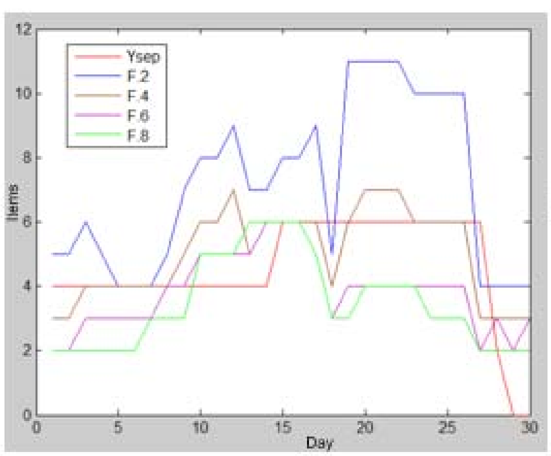


Figure 5.6 Forecasted and actual data in Sep 06

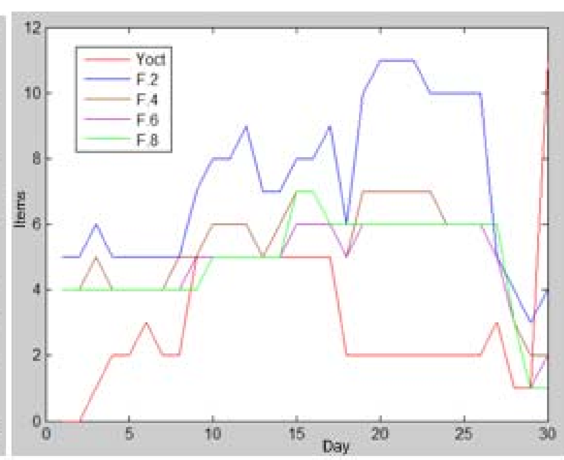


Figure 5.7 Forecasted and actual data in Oct 06

There are seven months data in use from April 06 to Oct 06. The data on Apr 06 are used as entry data. Therefore, there are six months forecasted data from May 06 to Oct 06, as shown in the Figure 5.2 to 5.7.

In each figure, the red line shows the actual (observed) data for that month, while others are the forecasted data with different α settings. The actual and forecasted data for one month are plotted into one figure to give a clear comparison. X axis represents each day in the month, and Y axis represents the number of item in use on each day.

Form the forecasted results figures, a first impression can be seen that forecasted lines are more contiguous to the actual data. To give a comprehensive comparison on all the results, errors are calculated. In this thesis, all errors are measured by RMSE (root mean square error). This will allow compare the errors on same entry data for different forecasting methods. The errors using single exponential smoothing method are concluded in Table 5.6. As there are 30 groups of data sets (for 30 days per month), a mean of the 1st, 15th, and 25th day's RMSE are calculated for later comparison.

RMSE	1st day	15th day	25th day	Mean
α=0.2	3.18	3.57	5.55	4.10
α=0.4	3.50	3.79	5.91	4.40
α=0.6	3.88	4.05	6.39	4.77
α=0.8	4.36	4.37	7.08	5.27

Table 5.6 Mean RMSE for 22 data series using SES

From the error data, it can be seen that the lowest RMSE occurs when α=0.2. This means the forecasted data are more likely to approach the last time's forecasted data. The daily and monthly forecasting errors using SES on RMSEs are compared in Table 5.7.

	RMSE-day by day	RMSE-month by month
α=0.2	2.703	**4.10**
α=0.4	2.363	4.40
α=0.6	2.183	4.77
α=0.8	**2.084**	5.27

Table 5.7 Comparison on daily and monthly forecasting errors using SES

It can be seen that daily forecasting significantly reduces the error. As the error standard using here is the root of MSE, two times in RMSE means 4 times in MSE. Compared with the mean RMSE result in section 5.2.1, using data day by day significantly reduces the errors in these data sets.

5.3.2 Holt's linear method

The mathematic expression for this method is described in section 3.3.2. Simulations are designed to select α and β to minimise the errors (RMSE). Learning from the single exponential smoothing method, the minimum RMSE occurred in three ES in the same α setting. In section 5.3.1, from SES daily forecasting, the minimum RMSE occurs when α=0.5. Therefore, α is set to 0.5 for the forecasting, while β is chosen between 0.2 and 0.8 to plot the results.

In these simulations, input data are the actual daily usage from April 06 to Oct 06, which are the same as the single exponential smoothing. As the initialisation of Holt's method requires the past two month data (L_{t-1}, L_t) to forecast the next month data (F_t), totally 5 months usage data, from Jun 06 to Oct 06 can be forecasted. Red lines are used for observed (actual) data, and other colours are for the forecasted data. F_{month1} is the result for β = 0.2, F_{month2} is the result for β = 0.4, etc. The forecasted data for June are all same for different α and β settings, shown in Green line in figure 5.8. Figure 5.9 - 5.12 give the results from July to October.

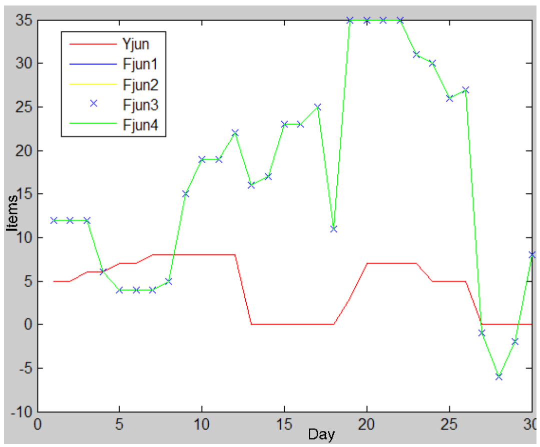


Figure 5.8 Forecasted actual data in Jun 06

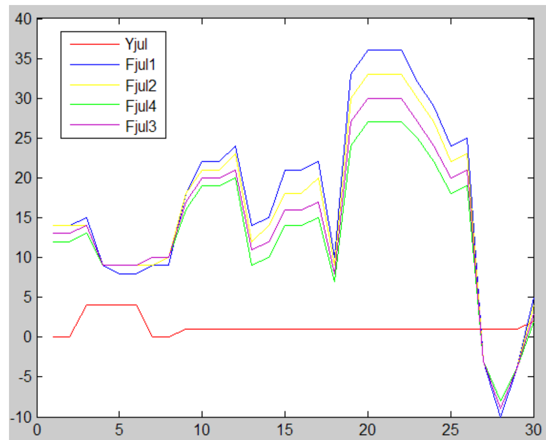


Figure 5.9 Forecasted and actual data in Jul 06

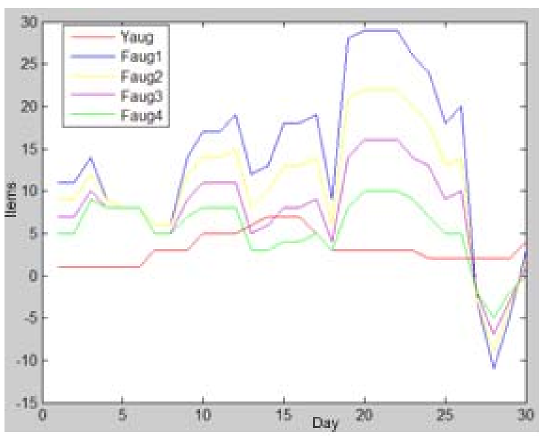


Figure 5.10 Forecasted actual data in Aug 06

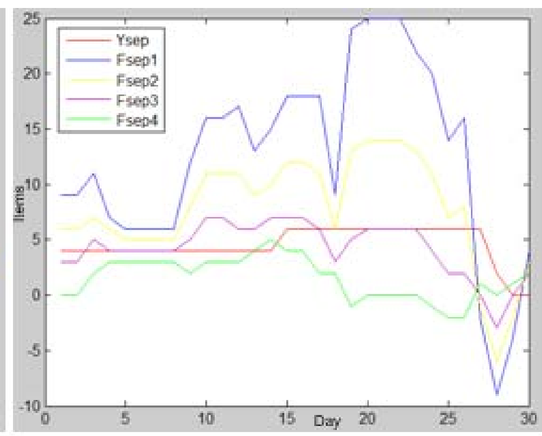


Figure 5.11 Forecasted and actual data in Sep 06

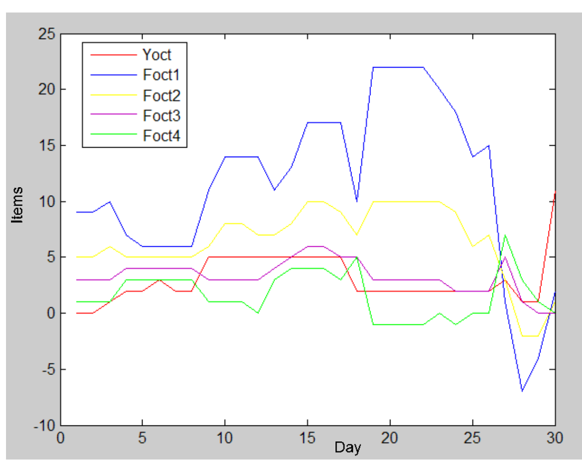


Figure 5.12 Forecasted and actual data in Oct 06

Using the same method in section 5.2.2, a mean of the 1st, 15th, and 25th day's RMSE are calculated in Table 5.8. Learning from Section 5.3.1, the lowest RMSE for the whole period occurs when α=0.2.

Holt's		1st day	15th day	25th day	Mean
α=0.2	β=0.2	2.48	3.90	5.92	4.10
α=0.2	β=0.4	3.50	3.90	6.31	4.57
α=0.2	β=0.6	3.58	3.97	6.67	4.74
α=0.2	β=0.8	3.65	4.10	6.88	4.87

Table 5.8 Mean RMSE for 22 data series using Holt's

Comparing Table 5.7 with Table 5.8, it can be concluded that the two methods have no significant difference on forecasting daily series in monthly cycle for this data set. Further comparisons are discussed in section 5.3.3 and 5.4.

5.3.3 Comparison between SES and Holt's in monthly forecast

Figure 5.13 compares the forecasting results by using single exponential smoothing method and Holt's smoothing method with monthly input data. From the overview of the error table, SES method generally has lower error level than Holt's method. This is also displayed in Table 5.7 and 5.8. From the point of view on forecasting errors, Holt's method does not outweigh SES.

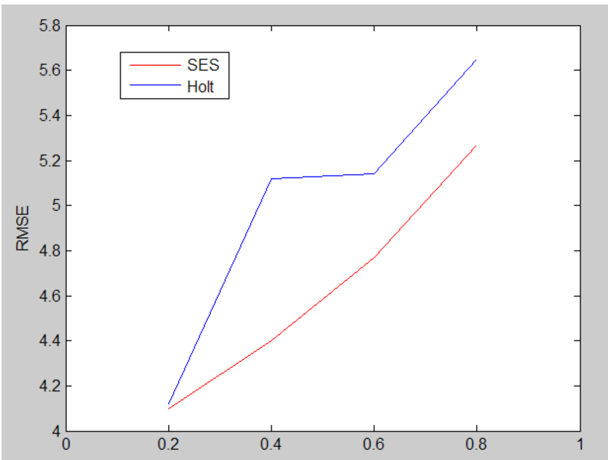


Figure 5.13 Forecasted errors Comparison (x axis: α for SES, β for Holt)

Comparing the forecasting results, SES obtains all results above zero. Holt's obtains negative results (below 0) at the end of each month. This is caused by the function:

$$b_t = \beta\ (L_t - L_{t\text{-}1}) + (1\text{-}\ \beta)\ b_{t\ \text{-}1}$$

when $L_t < L_{t\text{-}1}$, $\beta\ (L_t - L_{t\text{-}1})$ is negative. If $(1\text{-}\ \beta)\ b_{t\ \text{-}1}$ is not greater than $-\ \beta\ (L_t - L_{t\text{-}1})$, b_t is negative. The negative F_{t+1} in daily usage is not realistic for the real world application.

5.4 Comparison of the daily and monthly forecasting methods

Comparing the daily series forecast results and monthly forecast results using SES method, it can be seen that the daily forecasting method obtains half RMSE (2.084 min) than the monthly (4.10 min). As the error criteria is the root of MSE, two times in RMSE means 4 times in MSE. Therefore, the monthly seasonal character is not significant for this research data. Daily series forecasting performs better than monthly forecast in this research problem.

The second set of comparison lays on the daily series using SES, Holt's, and Winter's methods. Winkler found that the "best" forecasting methods for various forecasting case are different (Winkler, 1992). Therefore, it does not mean that the more complex the method, the better its performance. Comparing the lowest RMSE in single exponential smoothing 2.084 (α=0.8), Holt's linear 2.237 (α=0.8, β=0.2), and Holt-Winter 2.25 (α=0.8, β=0.2, γ=0.2) in Table 5.1, 5.2, and 5.3 the lowest RMSE for this problem is obtained by using single exponential smoothing method. In Gardner's telecommunications forecasting, it is also found that using drift SES obtained 7.10 in MSE (2.66 in RMSE) which is better performed than Holt's 7.92 in MSE (2.81 in RMSE) using 261 series (Gardner and Joaquin, 2008).

From the forecasting result view, there are negative results occurred when by using Holt's and Holt-Winter methods, which is explored and discussed in Section 5.3.3. The negative daily usage is not realistic for the real world application for this research problem, since the company cannot have negative number of items on hire in a period. Moreover, since the daily data will need to be added together for yearly usage, the negative results will counteract positive data and make final result inaccurate.

From the implementation view, more parameters will increase design complicacy of a model. Moreover, at the initialisation stage, having more parameters also means more series are required for the initialisation.

In conclusion, from the view of the error comparison, forecasting results, and implementation, the single exponential smoothing method using daily series is found the "best" method on the collected usage data.

5.5 Forecasting on accumulated usage

5.5.1 Data in use

In Trueman's paper on Internet firm revenue forecasting (Trueman et al., 2001), a solution was introduced to obtain internet access usage by the sum of actual data and forecasted data, and the accumulated actual daily usage was used as the forecasting objective. Learning from Trueman's research idea, the converted accumulated usage data are used in this section.

Considering the usage peak values and distributions, the laptop data from May 2006 to Apr 2008 were divided into four half-year periods, namely May-Oct 2006 (06-01), Nov 2006-Apr 2007 (06-02), May-Oct 2007 (07-01), and Nov 2007-Apr 2008 (07-02) as shown in Figure 5.14. One year's usage is split into two periods with a balance of peak values and distributions, since annual peaks generally occur after Easter and summer holidays. By using the data converter introduced in chapter 4, the four usage curves were obtained, as shown in Figure 5.14. From the past half year's usage, the designed model forecasts the next half year's usage for each item's daily usage level.

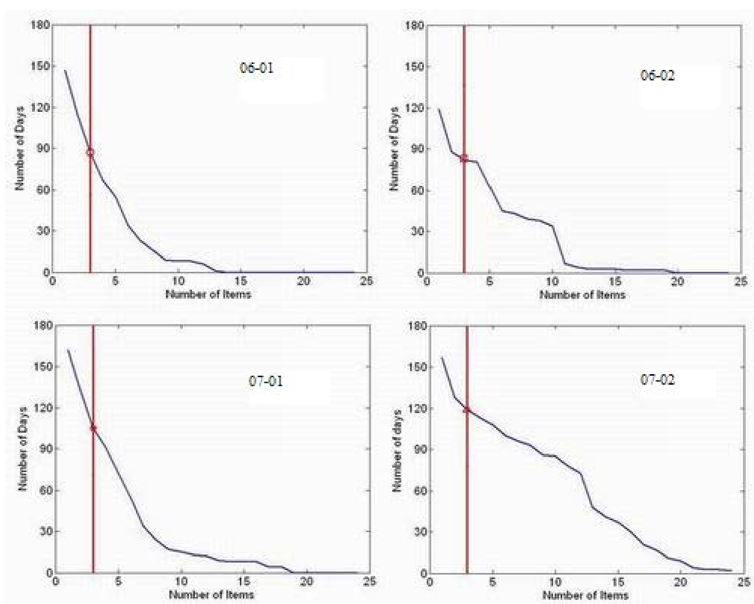


Figure 5.14 Half year usage curves

A 3 laptops' usage historical data can be obtained from the usage levels shown in Figure 5.14, with the four markers shared with Figure 5.15. The 3 laptops' usage has been chosen because it represents the middle of the usage curve, which is neither too high nor to low.

From Figure 5.15, it can be seen that the usage has a positive trend of growth, though there is a slight drop in 06-2. Year 2008's first half year usage of 3 laptops can then be forecasted based on the data in the past periods. The annual usage data for the previous 1½ years will be used to forecast the next half year's usage. To compare the forecasting method's performance, Root Mean Square Error (RMSE) is used to compare the forecasting results by different forecasting methods.

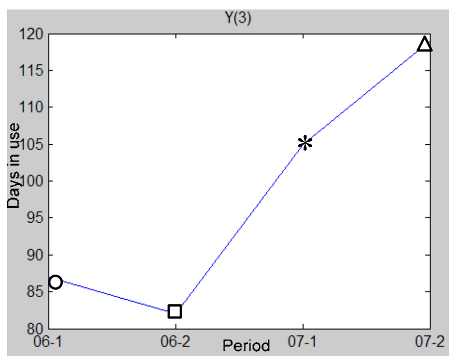


Figure 5.15 Three laptops' usage obversed data for forecasting

5.5.2 Forecasting with observed data

ES methods was applied in section 5.2 and 5.3, and have been successful in demand forecasting (Gardner, 2006). Regression is another class of methods that have been used on hotel and network usage forecasting (Tan et al., 2000). Two ES methods, Single Exponential Smoothing (SES) for level (α) and Holt's double ES for trend (β) (Makridakis et al., 1998) are used from the time series class forecasting methods. These two ES methods are selected due to their satisfactory performance on error results performance illustrated in section 5.2 and 5.3.

A set of forecasting simulations are carried out to identify the forecasting method for 4 sets of laptop half year usage in the two year's periods. The input data are 3 half year usage (06-01, 06-02, 07-01), curves as shown in Figure 5.14. The usage curve 07-02 will be used to compare with the forecasting results.

The model is developed and implemented in MatLab. The lowest RMSE by using ES method occurs by using Holt's method when α = 0.6 and β = 0.4. The RMSEs by using Holt's are significantly lower than SES's. This means that the data have trend characterisation. This forecasted results and actual data on the second half of year 2007 are compared in Table 5.9. From Figure 5.14 it can be seen that the business has a fast growth in second half of 2007, which ES methods are not suitable to catch up with this trend very well.

	RMSE				
	SES	Holt's			
		β = 0.2	β = 0.4	β = 0.6	β = 0.8
α = 0.2	40.989	35.602	35.073	34.57	34.094
α = 0.4	39.833	32.824	32.164	31.622	31.223
α = 0.6	38.827	31.223	**30.903**	30.926	31.291
α = 0.8	**38.186**	30.926	31.488	32.625	34.282

Table 5.9 Mean RMSE for yearly usage using SES and Holt's

Regression methods are explored on the sets of usage data. There are two regression methods considered in this thesis, which are linear regression and Logarithmic Regression as described in section 3.4, and suggested in

Weatherford's hotel room usage forecasting paper (Weatherford and Kimes, 2003).

In linear regression, each level of items usage has a set of coefficients calculated in Matlab function to obtain the minimum RMSE on this method, which is 9.937. The forecasted results and actual data on the second half of year 2007 are compared in Figure 5.17.

In the logarithmic regression model, the nonlinear functions are transformed into linear functions for the calculation of coefficients. There are a number of ways doing this. The method used in this paper is taken from (Weatherford and Kimes, 2003), which has similar inputs. The minimum RMSE on this method is 23.454 and the forecasted results and actual data on the second half of year 2007 are compared in Figure 5.18.

From the result view of the two regression methods, it can be seen that the linear regression performs better than the logarithmic regression.

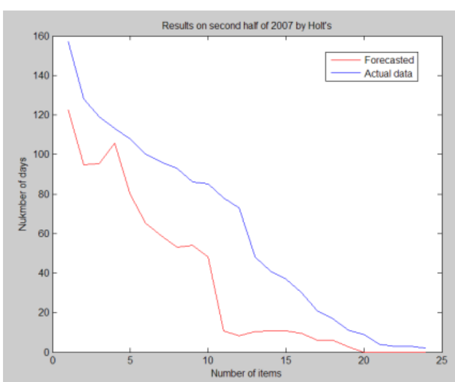


Figure 5.16 Usage 07-2 by Holt's

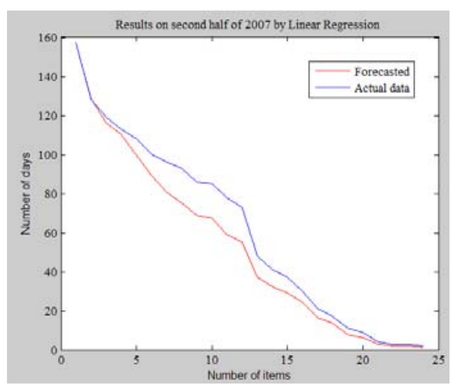


Figure 5.17 Usage 07-2 by Linear Regression

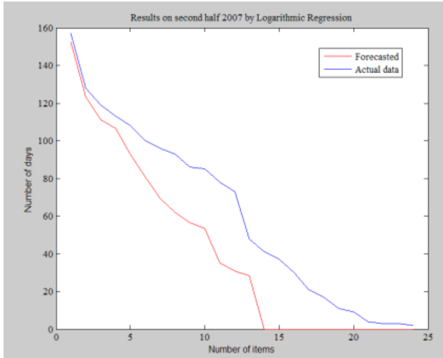


Figure 5.18 Usage 07-2 by Logarithmic Regression

Figure 5.16, 5.17, and 5.18 are forecasted results for the same period (07-2). Comparing the regression and ES methods, it can be seen that regression results are much closer to the actual curve than ES method. Using the lowest RMSE = 38.186 in SES as a measurand, the RMSE from Holt's method reduces by 19.08%. Regression methods further reduce the RMSE. The logarithmic regression reduces the RMSE by 38.58%, which doubles the Holt's error performance. Furthermore, the linear regression reduces RMSE by 73.98%, which doubles the logarithmic regression's error performance, and is four times less than the Holt's one. Since the observed data has a high growth trend, the historical data are all important to extract this growth rate, for which linear regression is better than ES methods. Whereas the ES methods treat the nearer observed data more important, which influences the accuracy of the calculated growth rate. Considering the business situation in the research case, the growth rate in the current years is high. Linear regression is an appropriate method for the current forecasting model.

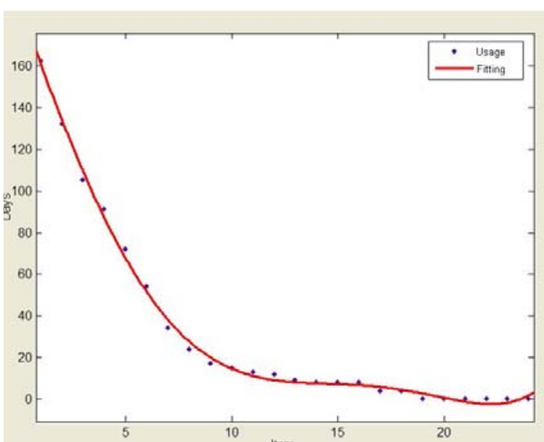
5.5.3 Generate past usage with revenue

Knight introduced a method to generate data from monthly average weather data to the hourly data (Knight et al., 1991). Similar research has been focused on weather and climate impacts (Hunt et al., 2011). Learned from this, the idea of this section is to generate the usage curve based on the revenue in the same period. This is to generate more usage curve in the previous period by the revenue data, and to add them together with the observed data for the forecasting simulations.

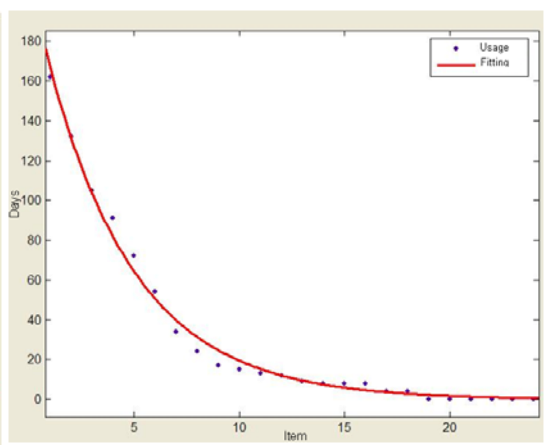
Looking at the trend of data set, polynomial and exponential were selected for the best fitting by Matlab (Hanselman and Littlefield, 1997). The errors are compared in Table 5.10, curve examples for the period 07-01 are given on the fitting curves in Figure 5.19 a and b.

RMSE	Polynomial 5th	Exponential simple
Period 06-01	2.049	3.083
Period 06-02	6.196	7.349
Period 07-01	2.841	4.219
Period 07-02	3.71	13.22

Table 5.10 RMSE for fitting with Polynomial and Exponential methods



5.19 a Fitting with 5th Polynomial curve



5.19 b Fitting with Exponential curve

Figure 5.19 Fitting curves for period 07-01

In Table 5.10, the 5th Polynomial looks better on the error performance. Comparing Figure 5.19 a and b, the polynomial function also passes through more data points than the exponential fitting. However, the 5th Polynomial have large oscillations at the ends, which is not showing a decreasing trend. This can be seen on the figure 5.19 a when items above 20. The equipment usage curve should be a monotonic decreasing curve. Therefore, exponential fitting is selected for the equipment usage fitting.

The four periods usage curves were generated by the exponential method:

$$f(x) = a \times e^{bx}$$

To help decide the two parameters *a* and *b* from the revenue data, the level 1 usage (1 item in use) U_1 is picked up as the input. The relationship between the half year period's revenue $R_{(i)}$ and the level 1 usage U_1 is found :

$$U_{1(i)} = 7.196\ R_{(i)}^3 - 65.73\ R_{(i)}^2 + 208.6 \times R_{(i)} - 45.29$$

The unit for revenue is million pounds. The coefficients are with 95% confidence bounds. *i* indicates the i^{th} period. The parameter *b* is calculated by the average *b* value of observed four periods. The parameter *a* is calculated by:

$$U_{1(i)} = a_{(i)} \times e^{b}$$

Using this method, the four past periods' usage curves, which are 04-01, 04-02, 05-01, or 05-02, were generated from the same periods' revenue data. Putting the generated and observed usage curves together, there are 8 periods of usage data for the forecasting method trails. Forecast the generated and observed data with different methods, the errors for each method are given in Table 5.11.

	Mean FPE	RMSE
SES (α = 0.8)	n/a	38.241
Holt's (α = 0.6 , β = 0.8)	n/a	33.479
Linear Regression	n/a	20.564
AR(1)	424.6822	n/a
MA(1)	1870.286	n/a
ARMA(1,1)	259.5866	56.55

Table 5.11 Errors for different forecasting methods

The equations on ARMA model were already introduced in section 3.5. The ARMA model's error measure FPE (Final Prediction Error) (MathWorks, 2008) was standard output from MatLab, which can be easily compared to find the smallest error in ARMA model initially. It is shown that the ARMA(1,1) obtained smallest error among the three ARMA methods. This also mean that the RMSE for the ARMA(1,1) method is smallest. The ARMA(1,1)'s RMSE was calculated to be compared with other methods, which is still higher than the biggest RMSE among the ES and regression methods as shown in Table 5.11.

5.5.4 Sales revenue forecasting

Pardo introduced another forecasting method that use daily average temperature to forecast the daily electricity demand (Angel Pardo et al., 2002). This means that external parameters also affect the forecast apart from previous period's data. Applying this thought to the equipment usage forecast, another way to forecast the usage curve is to forecast the next period's revenue first, and then use the method in last sub-section to generate the usage curve.

The company's ten periods of revenue data (unit: million pounds) were forecasted with the AR(1), MA(1) and ARMA(1,1) models in MatLab. The forecasting errors FPE are compared in Table 5.12.

	AR(1) (φ = 1.359)	MA(1) (θ = 1.01)	ARMA(1,1) (φ = 1.373, θ = 0.04155)
FPE	0.1655	1.0388	0.213957

Table 5.12 Errors for ARMA methods

From the error performance, it can be seen that the AR(1) obtains the minimum error among the three ARMA methods. Using the given parameters, the last period 07-02's forecasted revenue result by AR(1) is then calculated.

The period 07-02's usage can be generated by the Exponential method discussed in section 5.5.3.

$$U_{1(07\text{-}02)} = 7.196\, F_{07\text{-}02}{}^{3} - 65.73\, F_{07\text{-}02}{}^{2} + 208.6\, F_{07\text{-}02} - 45.29$$

$$= 179.7678 \approx 180$$

$U_{1(07\text{-}02)} = a_{(07\text{-}02)} \times e^{b\times x},\ b$ = -0.225257 therefore

$a_{(07\text{-}02)}$ = 225.476

Usage 07-02 curve can be then obtained. The RMSE for the period is 33.22, which is only smaller than SES in the observed data forecasting. The forecasting errors in 5.5.2, 5.5.3 and 5.5.4 are compared in the next section to discuss the best way of using the forecasting data.

5.5.5 Conclusion on forecasting simulations

In this section, three sets of forecasting methods have been considered to compare the forecasting errors. The first one described in 5.5.2 considers observed data only, using ES and regression methods. The second one described 5.5.3 considers generated and observed data, using ES, regression and ARMA methods. The last one, described in 5.5.4 forecasts the revenue with

ARMA methods, and then generates the usage curves from the forecasted revenue data. For the generated final curve results in section 5.5.3 and 5.5.4, heuristics and biases methods were used for adjustments. The overall error comparison is concluded in Table 5.13.

Method	1. Observed data	2. Combined data		3. Revenue data	
Error measure	RMSE	RMSE	FPE	RMSE	Rev FPE
SES	38.186	38.241	n/a	n/a	n/a
Holt's	30.903	33.479	n/a	n/a	n/a
Linear Regression	**9.937**	20.564	n/a	34.42	n/a
Logarithmic regression	23.454	n/a	n/a	n/a	n/a
AR(1)	n/a	n/a	424.6822	41.87	0.1655
MA(1)	n/a	n/a	1870.286	n/a	1.0388
ARMA(1,1)	n/a	56.55	259.5866	n/a	0.2139

Table 5.13 Overall errors comparison

The conclusions of the various forecasting methods are:

1) The smallest RMSE is obtained by using Linear Regression method with observed data only. It is then suggested for the forecasting model.

2) Comparing the combined and observed data, the later one obtained smaller errors. This is due to the fast growth of the business that the long past data have less effects, which means the observed data is less uncertain.

3) Comparing the combined data forecast in column 2 and revenue data forecast in column 3, the combined data is more accurate. This means generate previous usage curves from revenue performs better than forecast the next period's revenue first, then generate the usage curve from the forecasted revenue.

4) Comparing the various forecasting methods on the combined data in column 2, the linear regression method performs best on the RMSE, whereas ARMA model obtains highest RMSE. This is due to a main characteristic of ARMA that more training data gives better forecasting performance (Chang et al., 2000). In this research, 4 periods observed data or 8 periods combined trail data may not be enough to obtain a good performance using ARMA method. Moreover, for the observed data in column 1, there are only 3 periods' data for trail, which is not suitable for ARMA model parameter trail.

As the fast growth of the business, the usage and revenue climb fast as well. The ES methods judge the result from last period's forecasted and observed data, which cannot catch up with the growth trend. The linear regression method can track the trends much faster than exponential smoothing methods.

5.6 A hybrid forecasting approach

5.6.1 Problems on single forecasting approach

The current best method learnt from the forecasting simulations (section 5.5) is the linear regression method on observed data according to Table 5.13 among the forecasting methods.

However, a regression model along itself is not adequate for precise usage forecasting, as it considers the past periods usage data only. In this research, the forecasting period is every half year, which means there may be more factors that affect the forecasting accuracy. Therefore, this section seeks for a new approach to add on the regression method to reduce the forecasting errors.

In Figure 5.17, the forecasting result from regression method and the observed data have a large deviation the middle part of usage data. In the purchasing decision model, the middle part of data are more important than the beginning, which is due to the decision point selection. In Figure 5.17, the main stock level that the company should watch is from five items to the peak. Four items and less are less likely to influence the decision point due to the higher number of days (more than 120 days in half year) on hire.

Therefore， it is important to reduce the middle part of error to ensure the accuracy of purchasing decisions. In the hotel room booking research, (Weatherford and Kimes, 2003) a pickup method was suggested to add new booking data into the next period’s forecasting results. However, it is not the case for the equipment usage in this research, as the forecasting period is half a year. The new booking data obtained on today’s date could be the 1st or last day of the next period, which gives a great difference to the forecasting result as well as parameter trail.

5.6.2 A hybrid approach to reduce error

Learning from section 5.5.3 and 5.5.4, it is proven that there is a relationship between the equipment usage and company's total revenue in the period. Therefore the value of half year revenue data is added into the regression model to improve the forecasting accuracy.

The forecasted revenue (R_f) data (unit: million pounds) in use is the forecasted result of the period, based on previous periods' revenue data. This forecast uses quadratic regression. The regression model is:

$$R_f(x) = p_1 x^2 + p_2 x + p_3$$

where x is the number of items on hire

The coefficients (with 95% confidence bounds) are:

p_1 = 0. 3192

p_2 = -0.957

p_3= 1.903

By investigating the error distributions by Linear Regression method (Figure 5.17), it is found that it has the character of Gauss (normal) distribution. Figure 5.20 gives the error plot in blue dots and the best fitted normal distribution curve by Matlab (Hanselman and Littlefield, 1997). Best here means the setting of parameters that minimised the fitting errors.

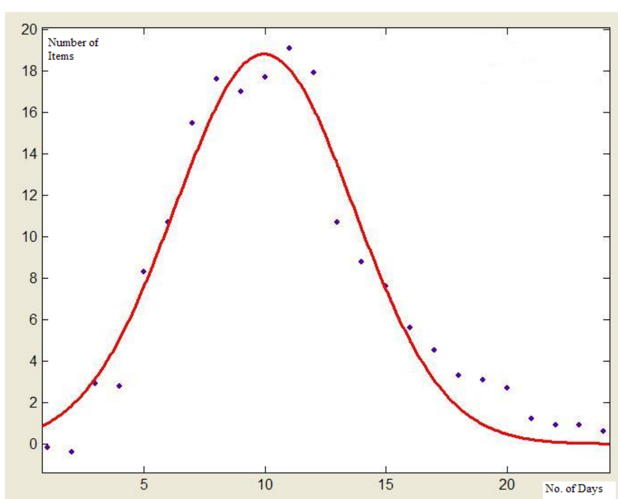


Figure 5.20 Normal distribution for regression error adjustment

The model of the error adjustment curve is:

$$EA(x) = \frac{FR}{a} \times \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

where x is the number of days on hire

FR is the forecasted revenue to the usage period.

The model coefficients are:

$\alpha = 1826$

The normal distribution coefficients are:

$\sigma^2 = 13.645636$

$\mu = 9.968$

Adding the error adjustment curve onto the regression forecasting result, the final forecasted semi-annual usage curve in year 07's second period ($F_{072final}$) is then:

$F_{072final} = F_{072} + EA(x)$

With the adding error adjustment, the final result's RMSE by the hybrid forecasting method can be calculated as 1.459, which significantly reduces by 85.3% of the 9.937 RMSE by using a single forecasting method. The errors in the RMSE are in absolute value, due to the nature of RMSE calculation. It is shown that the regression forecasting method with revenue adjustment gives a significant improvement than using sole forecasting method.

5.6.3 Application on other forecasting case

In this section, the developed hybrid forecasting model is tested on another set of data to see whether it can be a versatile model for other forecasting problems.

The data was daily cash machine transaction data over two year period. The data was converted into four half year accumulated curves with the data converter developed in Chapter 4. The meaning of the curve is the number of days that has each level (and above this level) of transactions during this period. The forecasted result may be helpful to assess the future transaction volumes (total cash volume in the machine) for cash machines.

The linear regression model was applied to the cash machine data without the error adjustment. The observed (in blue) and forecasted (red) fourth period data are plotted in Figure 5.21, with RMSE 12.644. Compared with the forecasting result on usage, the RMSE is 27% higher than the 9.937 on the equipment usage forecasting. This is due to the different nature of data. Looking at the RMSE results on equipment usage and cash machine transactions, it can be concluded that the regression method works accurately on the accumulated data forecasting.

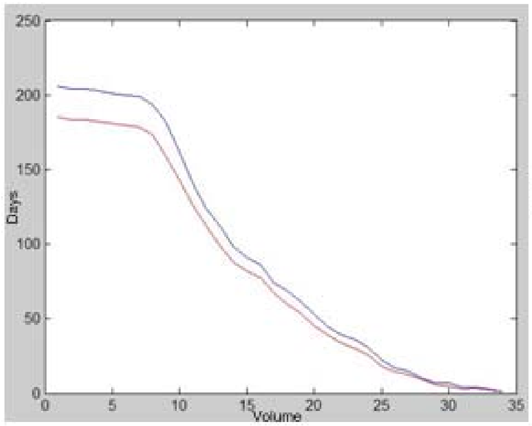


Figure 5.21 Fourth period data by linear regression

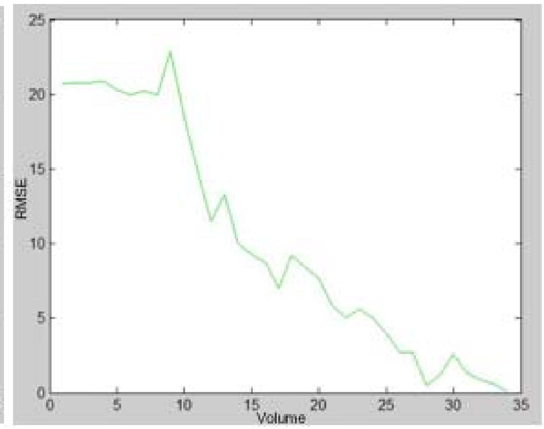


Figure 5.22 Fourth period forecasting error

The error deviation between the forecasting and observed cash machine data is plotted in Figure 5.22. Unlike the equipment usage forecast, it can be seen from the graph that the error curve does not follow normal distribution, but most like a half distribution. The errors keep high on volume from 1 to 10 and reduce significantly thereafter, whereas in the equipment usage errors, the highest errors occurred between 5-15 volumes. This is mainly due to the nature of the two different set of data. The equipment usage has more changes and unsure factors in the middle part and the cash machine data are more unstable at the starting part. As the additional data that can affect the cash machine data is not available, the error corrections are not discussed here. From the simulation results in this section, it can be seen that although the error adjustment methods vary on the different nature of data, the hybrid forecasting approach have generality on demand forecasting. It can be extended into broader area on demand forecasting issues.

5.7 Summary

Section 5.1 describes data collection and processing methods. In section 5.2, the daily usages are forecasted day by day in Single Exponential Smoothing (SES) for level (α), Holt's double exponential smoothing for trend (β), and Holt-Winter's triple exponential smoothing for seasonal (γ) (Makridakis et al., 1998). In section 5.3, the Holt-Winter method is replaced by a new method that tests the seasonal character by forecasting data month after month to learn whether there is a monthly cycle existed. Section 5.4 compares the daily and monthly series forecasting results with evaluation. The characters of each forecasting model are analysed to suggest their potential applications.

Section 5.5 describes forecasting on accumulative usage data, with exponential smoothing methods, regression, and ARMA methods. Three sets of data are in used in this section. In sub-section 5.5.1, forecasting simulations are carried out on 4 periods of observed usage data, each period covering half a year. In sub section 5.5.2, a relationship between the department revenue and the laptop usage is explored to generate another 4 periods' usage data from revenue data. The combined 8 periods' observed and generated data are then processed with various forecasting methods. In sub-section 5.5.3, the revenue data on each half year are simulated to forecast the next half year's revenue, which is used to generate the usage curve with the method described on 5.5.2. The last section 5.5.5 compares and discusses error results for each method in section 5.5. Errors in this thesis are all measured by RMSE (root mean squired error) for comparison. FPE (final prediction error) is also used on some methods, in which RMSE is also calculated for comparison. The simulation result, errors, findings, and suggestions are discussed in each section initially. Section 5.4 and 5.5.5 compares and evaluates the methods comprehensively.

To further improve the forecasting accuracy, section 5.6 introduced a new hybrid forecasting model for the accumulative usage situation. The company revenue data are brought in to adjust the forecasting result. By using the new method, the error has been reduced by 85.3%. Therefore, this model is proposed for the purchasing decision support system in this thesis. The hybrid model is also applied to another forecasting application, that is, cash machine transaction data. It is concluded that this model is versatile and can be applied in other areas.

6. Purchase decision modelling

In this chapter, the decision models are built for the model base of the proposed decision support system, using the forested result discussed in chapter 5. The decision model developed in this thesis uses a rental company as prototype. However, it is not only for rental business, it can assist other types of companies to make buy-or-hire decisions. For example, a company may use this model to decide whether need to buy a small van or just hire it from another company.

The purchasing decisions in this thesis focus on two problems, which are:

1) To own or to sub-hire one item of a certain type equipment;

2) The quantity of this type of equipment to be owned. If the quantity to be owned is exceeds the current stock level, the additional number needs to be purchased.

The models for question 1) and 2) are elaborated in section 6.1 and 6.2 respectively. The main inputs for the two models are generated from forecasted data based on previous year's usages. Section 6.3 discussed the test results for the developed purchasing model. It also compares the purchasing decision model with other purchasing decision system.

Before introducing the formulas, it is necessary to describe the symbols using in this chapter. A list of symbols is concluded in Table 6.1. There are two types of inputs, constant inputs and variable inputs.

Constant inputs	P_h	Hire price per day (charged by company)
	P_s	Sub hire price per day (charged by Supplier)
	P_{pur}	Equipment's purchase price
	dep	First year depreciation percentage
	C_m	Maintenance cost per year
	N_{own}	Number currently owned by company
Variable inputs	N_{peak}	Peak number of this equipment in use
	D_f	Forecasted number of total hire days on an item
Outputs	D_{min}	Minimum days on hire for own this item
	N_{pur}	Number to be purchased

Table 6.1 Symbol of input and output data

The detailed explanation of Table 6.1 are as follows:

Constant inputs are extracted from the company's hire, account, and marketing data.

1) P_h Hire price charged per day (charged by the company, no need to consider too much on this)

2) P_s Sub hire price per day (charged by the supplier/competitor)

3) P_{pur} An equipment item's purchasing price (market price)

4) *dep* Depreciation scheme (use the first year depreciation. The depreciation schemes are various for different categories of equipment)

5) C_m Maintenance cost per year, including stock holding cost – warehouse space etc.

6) N_{own} The number of an equipment type that is owned by the company.

Variable inputs:

1) N_{peak} The peak number of an equipment that was used in the past period (year). Since the inventory pool can be instantly filled by sub-hiring items, N_{peak} may be greater than N_{own}, that is, $N_{peak} = N_{own}$+ peak number of sub-hires.

2) D_f Forecasted total number of days on hire for one item.

Outputs:

1) D_{min} Minimum days on hire for own this item, above which to own costs less than to sub-hire.

2) N_{pur} Suggested number of items to be purchased for company inventory. If the number is negative, it means the company may own more than required items for this equipment type.

In the revenue business, the day hire price for an item is fixed for simplifying total price calculation. However, the customers do obtain discounts for a long term hire. Therefore, most companies use a *x* days per week methods to set the discount. This means if an item is on hire for more than *x* days but no more than a week, the price will be capped on the *x* days' total hire price.

For example, an item's daily rate is £10 and the price scheme is 3 days per week. If it is requested for a 2 day's hire, the total hire price is £10 $\times$ 2 days = £20. If it is requested for a 6 day's hire, the total hire price will be £10 $\times$ 3 days = £30.

Assumptions: There are a number of assumptions made in this research.

Assumption 1: Only the next year data is considered (days on hire, depreciation rate in percentage, maintenance cost). The data output is for the next year. The data inputs are this year's and the previous year's data.

Assumption 2: Only one type of equipment is considered at one time, and its usage is considered to be independent of other equipment's usage.

Assumption 3: The sub-hire price (P_s) herein is set as a constant value (market price). In a real situation, suppliers may change the price depending on how urgent the equipment is required. Sub-hires from a competitor may be charged two or three times more than an ordinary price. Therefore the calculation of P_s uses non-uniform weighted mean average on various suppliers' prices:

$$P_s = \frac{\sum_{i=1}^{N} iP_{si}.}{\sum_{i=1}^{N} i}$$

where weight i is the number of times sub-hire from each supplier in the past year. P_{si} is the sub-hire price from each supplier.

Assumption 4: The purchase price is set as a constant value. It is assumed no change from the decision making point to the purchasing date.

Assumption 5: The *x* days per week situation is not considered in this research.

The assumption simplified the research problem from the real word case. They will be a little difference from the real world data. However, considering the data used in the purchasing model, it should not affect the final result significantly.

6.1 Item level purchase or sub-hire decision

This section focuses on a single item's usage in one year's period. The company's expenditure on this item by own or sub-hire are compared based on the designed functions below:

If the company own the equipment,

the company's expenditure at the first year:

$$C_{exp,o} = P_{pur} \times dep + C_m \tag{6.1}$$

the company's revenue at the first year:

$$C_{rev,o} = D_f \times P_h \tag{6.2}$$

The net cost to own the equipment:

$$C_{net,o} = C_{exp,o} - C_{rev,o} \tag{6.3}$$

If sub-hire from a supplier (competitor),

the company's expenditure at the first year:

$$C_{exp,s} = D_f \times P_s \tag{6.4}$$

the company's revenue at the first year:

$$C_{rev,s} = D_f \times P_h \tag{6.5}$$

The net cost to sub-hire the equipment:

$$C_{net,s} = C_{exp,s} - C_{rev,s} \tag{6.6}$$

Therefore, if $C_{net,o} \leq C_{net,s}$, it costs the company less to own the equipment in stock rather than sub-hire, which is:

$$C_{net,s} - C_{net,o} \geq 0 \tag{6.7}$$

that is:

$$D_f \times P_s - P_{pur} \times dep - C_m \geq 0 \qquad (6.8)$$

It can be seen clearly from (6.1.8) that the hire price P_h is not in use for the final result. That means that the model can be used not only for the rental business, but for any company to make buy-or-hire decisions.

The problem focuses on the minimum days D_{min} on hire for the first year, as a measurand.

$$D_f \geq \frac{P_{pur} \times dep + C_m}{P_s} = D_{min} \qquad (6.9)$$

When D_f for this item's next year usage is obtained from the forecasting result, the decision can be suggested: when $D_f \geq D_{min}$, it costs the company less to own the equipment in stock than to sub-hire. The "=" here means that the cost of owning and sub-hiring are same. In this case, the system will advise to own the item. All inputs will have two digit decimals. The result D_{min} is roundup to integer as it is number of days.

6.2 The equipment purchasing quantity decision

In the last section, only one item's annual usage is considered from a type of equipment. If the usage is predicted to be more than the measurand D_{min}, the company is suggested to own this item. The method in 6.1 can be applied to each item to decide whether a single item should be purchased for the company. Now the consideration is extended to a type of equipment, which is a group of identical items. "Identical" here means that each item in this equipment type has the same function. Learning from the single item situation, the requirement is to obtain how many items that have their $D_f \geq D_{min}$ by comparing each item's D_f and the D_{min} for this type of equipment.

A simple example is given in Table 6.2. For the owned laptop 1, the forecasted number of days is 8 days, which is less than the 9 days D_{min}. This means the owned laptop 1 is not required to be owned. The forecasted number of days for owned laptop 2 is more than the 9 days D_{min}, which means it should be kept in stock. The forecasted number of days for owned laptop 3 equals to the 9 days D_{min}, which means it should be kept in stock as well. Following this rule, it calculates the total number of laptops that should be owned.

	D_{min}	D_f	Comparison
Owned Laptop 1	9 days	8 days	<
Owned Laptop 2		260 days	>
Owned Laptop 3		9 days	=
Owned Laptop 4		80 days	>
Owned Laptop 5		8 days	<
……		……	……
Sub-hired Laptop 1		5 days	<
Sub-hired Laptop 2		2 days	<
……		……	……

Table 6.2 Comparison in item D_f and D_{min}

In the purchasing decision making process, the decision maker needs to know totally how many items of a type of equipment would be required for the next year. If the number to be required outweighs the current owned number, the decision support system will suggest a number of new items to be brought. If the number of items to be required is less than the current owned number, then the system will suggest a number of redundant items to be sold out to increase the cash flow. The decision support system suggested in this thesis considers both of the two situations.

For the purchasing decision, two parameters need to be focused, which are the peak number of equipment items in use N_{peak}, and the suggested number of equipment items to be purchased N_{pur}. Since the inventory pool can be instantly filled by sub-hired items, N_{peak} may be greater than N_{own}. In the data converter described in chapter 4, N_{peak} is also known as $Item_{max}$. The D_f for each level of equipment in use during a year's period is represented by an vector *DaysInUse*[*i*], in which *i* indicates the number of items in use. The plot of the D_f is similar to Figure 4.2. It aims to find out on which level (number) of items that the D_f is less and just less than D_{min}. Then this level is the number of items that should be owned in stock. The following flowchart and steps explain how to calculate N_{pur} based on given D_f, D_{min} and N_{peak}.

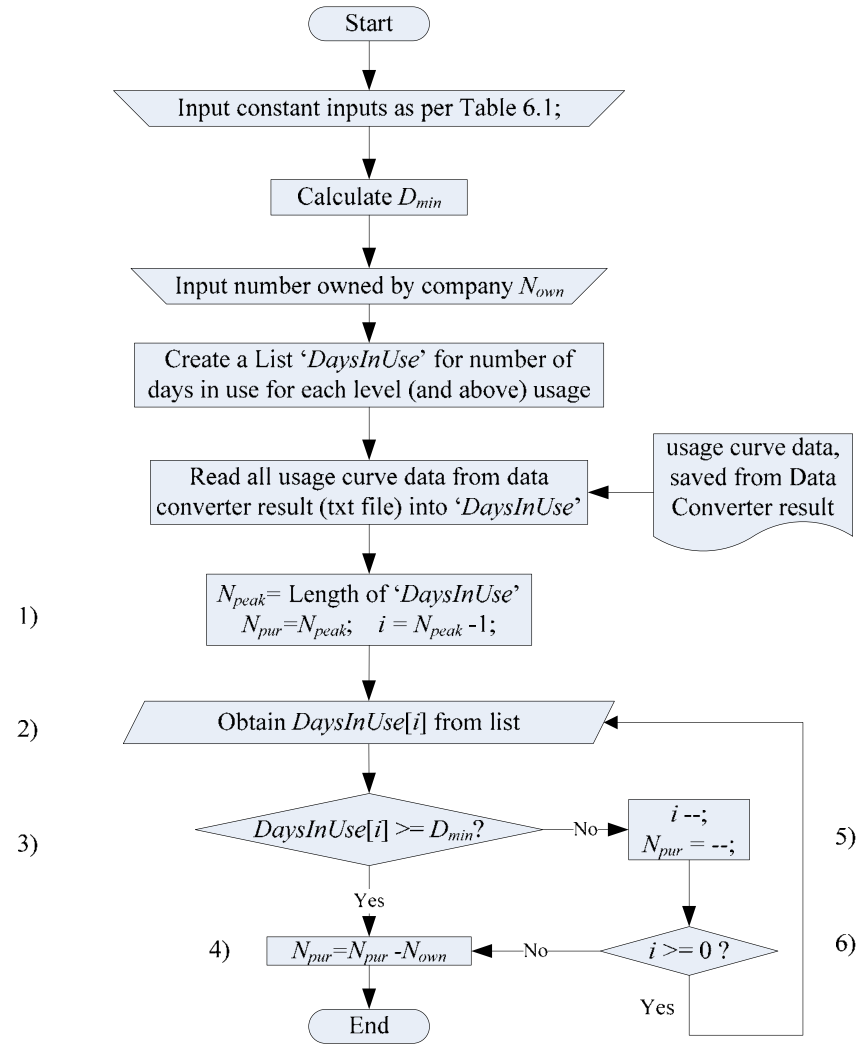


Figure 6.1 N_{pur} calculation flowchart

The flowchart in Figure 6.1 illustrates the process of calculating the N_{pur}. The following steps details how the suggested number of purchasing (N_{pur}) are calculated:

1) Obtain the peak usage number N_{peak},

Initialise N_{pur} = N_{peak}, Initialise the loop indicator i = N_{peak} -1.

2) Obtaining the i level of usage days *DaysInUse*[i] read from data converter output.

3) Comparing *DaysInUse*[i] with D_{min},

3.1) If Yes, ($DaysInUse[i] \geq D_{min}$),

It means that the current N_{pur} is the number of items that are required.

4) Subtract the N_{own} from N_{pur}

Return the final output N_{pur} which is the suggest number of items should be bought, end.

3.2) If No, ($D_f < D_{min}$),

It means that the current N_{pur} is still more than the number of items that need to own. Further reducing of N_{pur} is required.

5) The loop indicator i should be reduced by 1, and the N_{pur} is decreased by 1.

6) Check whether loop indicator $i >= 0$,

If Yes, go back to step 2)

If No, it means this is the level 1 usage, go to step 4)

The final output N_{pur} is from step 4), which is the suggested number of item(s) that need to be purchased for this type of equipment. The process will be applied in C#.NET, and the system testing and validation are discussed in chapter 7.

6.3 Model evaluation and result analysis

Based on the flowchart in 6.2, a model is developed to calculate the number of equipment items that need to be purchased / owned for an equipment type. The model is a versatile one which can be used in purchasing decisions for either rental companies or other business.

The input data are the owned volume plus the sub-hired volume forecasted for the next year usage. The output is the number suggested to be purchased or to be reduced. If the result is positive, it suggests the number of items that the company should purchase. If the result is negative, it suggests the number of items that is not necessary to be kept in inventory.

The model is developed in C#.NET (code attached in the appendix 1). The system inputs include two main parts. The first part is marketing data for the item, including purchasing price, first year depreciation rate (using decimal fraction), first year maintenance cost, and sub-hire price. The other part is the forecasting data for the item usage. Using the second situation in the above paragraph, the forecasted data are the annual usage under each number of items in use. The output also includes two parts of data. The first part is D_{min}, the measurand of minimum days on hire, based on equation 6.1.9. The result is converted to the nearest integer that is no less than it. The second part of the output is the suggested number of items that should be purchased for the inventory. A number of tests were carried out on the designed purchasing model. Test results are attached in the appendix 2. Comparison between system output and the manually calculated result using the functions showed same results. One example of the test is carried out on the company's actual data and market data for the P_{pur} and P_s. The list of inputs, system outputs and manually calculated results are shown in Table 6.3 and Figure 6.2.

Inputs			
P_s	£65	N_{own}	25 (items)
P_{pur}	£1350	N_{peak}	24 (items)
Dep	50%	D_f	Listed
C_m	£50		

Outputs	System outputs	Manually outputs
D_{min}	12 (days)	12 (days)
N_{pur}	-6 (items)	-6 (items)

Table 6.3 System test Results

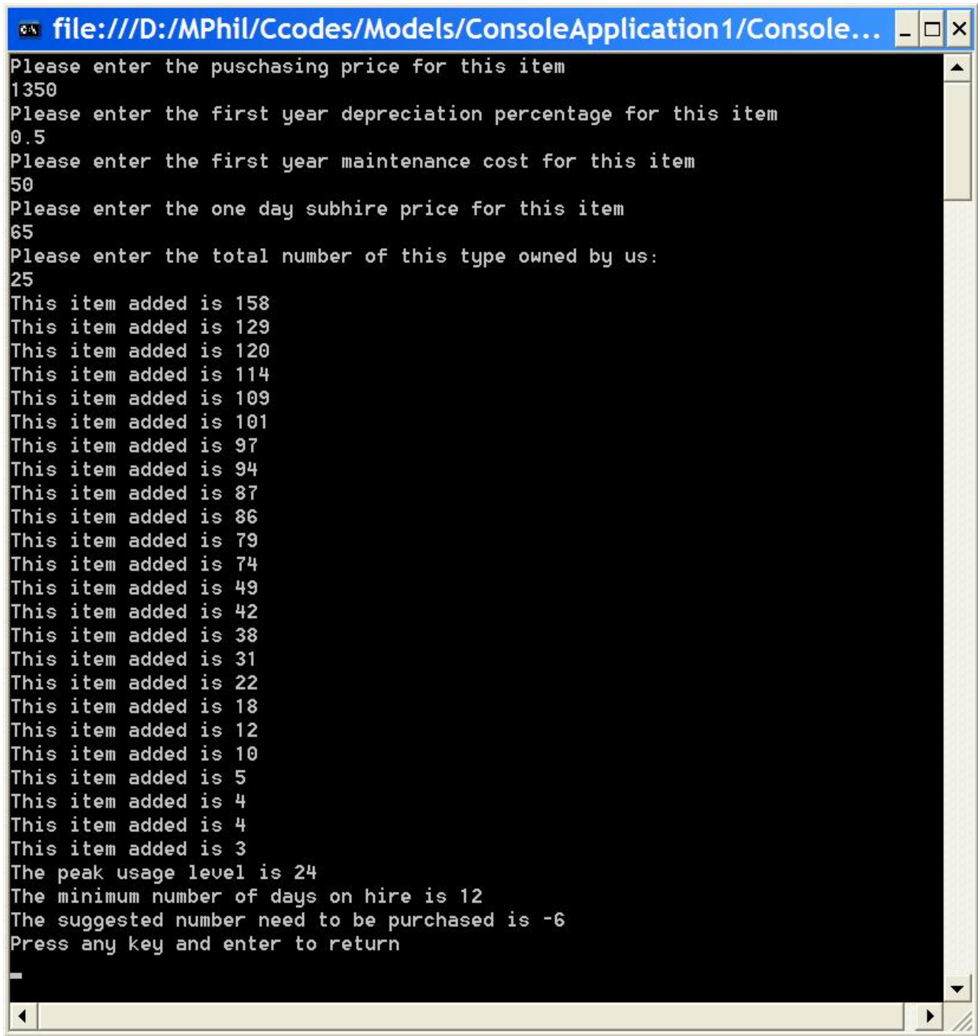


Figure 6.2 C# purchasing model running results

The results show that the peak usage during the year is 24 laptops, while there are 25 owned in stock. The suggested number of purchase is -6, which means 6 of the owned items are not frequently used and not required to be kept in stock. In Neuhaus's asset PDSS, the system was based on an Expert System which gives Yes or No for asset purchasing or leasing decisions, based on analysis results. The PDSS proposed in this paper extend the system output into a quantitative result which can give a required number on purchasing decisions (Neuhaus and Lusti, 1994).

6.4 Summary

This chapter illustrates the decision model for this thesis. The parameters, required results, and assumptions were discussed initially. Section 6.1 described the decision on single item level. Section 6.2 detailed the decision on the final purchasing requirements. The flowchart for the purchasing model is given in this section. In section 6.3, the full purchasing module was developed in C#.Net. It was tested and evaluated with a number of results.

7. Module integration and evaluation

The three components of the purchasing decision support system, Data converter, Forecasting model, and Purchasing model have been introduced in chapter 4, chapter 5 and chapter 6 respectively. This chapter discusses how to integrate these three models into the final purchasing decision support system.

7.1 Forecasting integration into purchasing decisions

In this section, the integration of the forecasting model into the purchasing model with the data conversion is designed and discussed. Figure 7.1 shows the full system framework. The core system is composed of three models discussed in previous chapters. The user interface includes data inputs and system outputs which have been described in section 6.3.

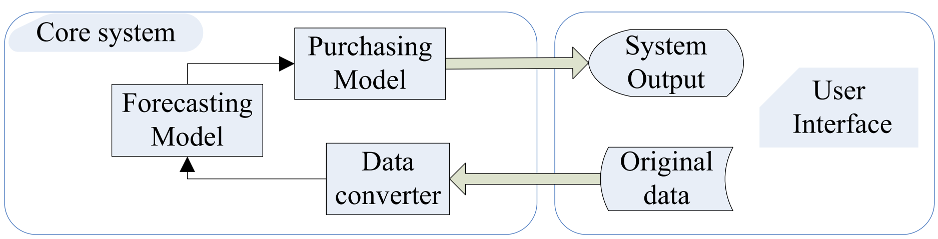


Figure 7.1 Structure of the proposed PDSS

A data flow diagram has been designed, followed by the explanation of the data interface, and a process evaluation.

7.1.1 Data flow diagram and data interfaces

The data flow for the purchasing decision support system is detailed in Figure 7.2. Rectangles represent process and parallelograms represent data.

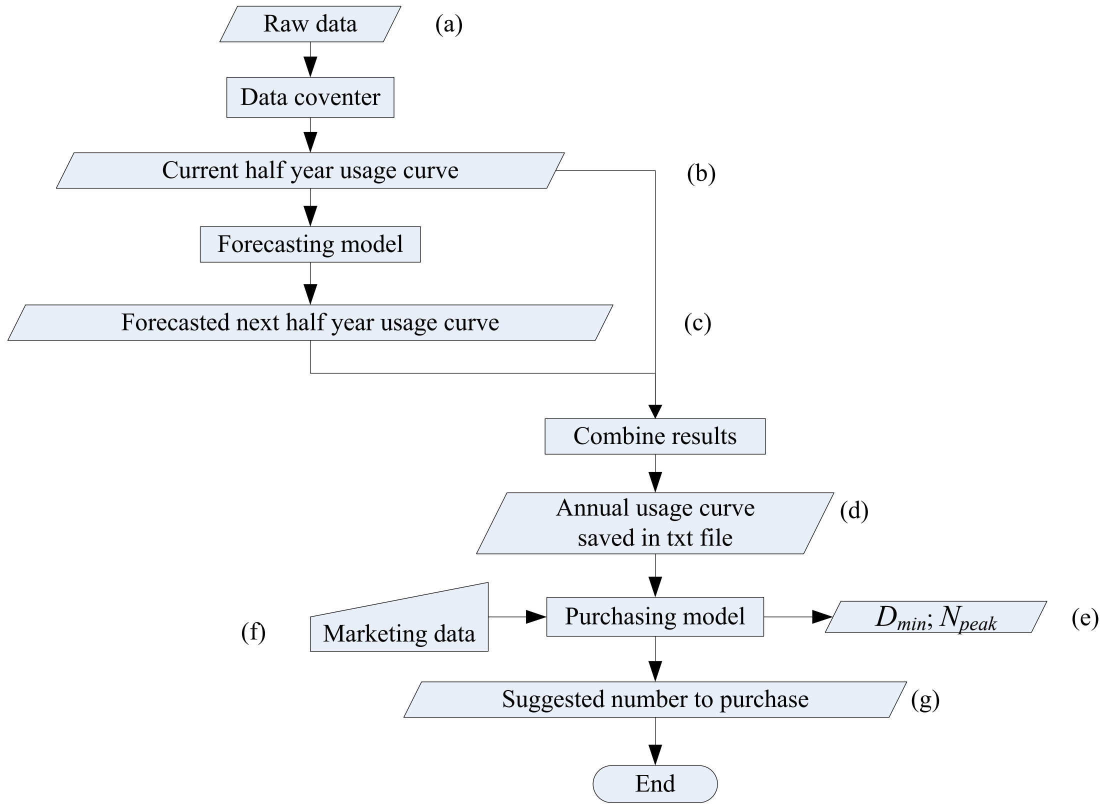


Figure 7.2 Data flow for the purchasing decision support system

The raw data (a) is obtained from the company's current database via a "Stock Usage Utility" program with daily usage for a type of items. Choosing the print from menu, and daily usage, then the extract button, and choose the CSV format, the usage data is extracted into a CSV file. The CSV file needs to be saved as an Excel spreadsheet 97-2003 format. The daily hire and sub-hire number are kept in two columns, so the totals need to be summed up in Excel. This process may not be helpful in general, but helps greatly on the company's perspective.

The data converter reads the raw data from the assigned columns in the Excel spreadsheet, and transforms the raw data into the usage curve format (b). The data usage curves can be saved by right click its name in the workspace.

The forecasting model is designed in MatLab, which loads the usage curves (b) from the workspace. The model calculates the forecasting results for the next half year (c). The current and forecasted half year results are added together as the annual usage (d) for purchasing module.

The annual usage curve is saved in txt file and read into the purchasing model, with marketing data (f) entered by the user. The final output is the suggested number of items to be purchased (g) for the user. The minimum in use days D_{min} and N_{peak} (e) for holding this item are also suggested outputs from the purchasing model.

7.1.2 Evaluation of integration process

There are a number of data formats in use in the full system. Table 7.1 lists the data type, data source, and data format.

Data Type	Data source	Data format
Raw data	Entered by user	HireTrack system data
Stock usage	Generated by HireTrack	csv
Converted data for forecasting	Data converter	MatLab data
Forecasting result	Forecasting model	txt
Final purchasing result	Purchasing model	System output

Table 7.1 Data type list

From Table 7.1, it can be seen that there are 5 different types of data in the full decision making process. Data formats are transferred four times for the decision process. After the full integration of the system, the data flow between every two models has been tested on 20 transactions. All the results showed no error, compared with manually calculation results. Therefore, the integrated system is accurate and effective for the research work.

The full system can be improved and further integrated into one format for commercial system. It can be faster than the current system. The system optimisation is out of this thesis's scope.

7.2 Review of data collection and conversion process

A new data collection method has been introduced to recover the data in the period when the information system was applied on job information and logbook was abandoned. The method collects all jobs' start and end dates and the number of items (laptop) used for each job, and then calculates the daily item usage for the period. There were seven months data recovered by this method. It ensured the missing usage data could be recovered in the most accurate way. Compared with other data recovery methods, e.g. (Miles, 2001), this method takes more time on the data processing. However, the recovered data quality is higher than summing up data in different periods.

Having limited data can be an obstacle for the research result. This recovery method introduced a way to overcome this problem. By producing the unknown data from the existing types of data, plenty of research data can be obtained in this way. The accuracy of the produced data is highly dependent on the existing data, and the method of the recovery. For a larger set of data, the processing time could take longer.

This research introduced a new data transformation method for the usage / demand data forecasting. As the data were available in a daily usage format, a data converter was developed to transform the daily usage into the period (annual or half annual) usage. The data converter calculates the number of days whose daily usage equals or exceeds each level of usage, and gives a usage curve for the forecasting model.

From the view of the application on forecasting and purchasing models, this method allows the forecasting to be extended for a long term period from short term data. For the purchasing decision, this method gives a chance to predict the annual or half annual usage from the collected daily data. This method can be extended to broader application areas, such as business growth forecasting based on collected daily or weekly business related data.

7.3 Evaluation on forecasting case studies and results

In chapter 5, there are short discussions on forecasting results. Based on the works and findings in chapter 5, this section gives an in depth discussion on empirical and theoretical review of the forecasting models, and the influence on the purchasing decisions.

7.3.1 Forecasting method competition results

The input data for the forecasting models simulation in chapter 5 were obtained from the data converter. A number of forecasting methods have been used on the observed data, combination data, and revenue data which are generated from past periods' revenue data. The error results are plotted and compared in Figure 7.3.

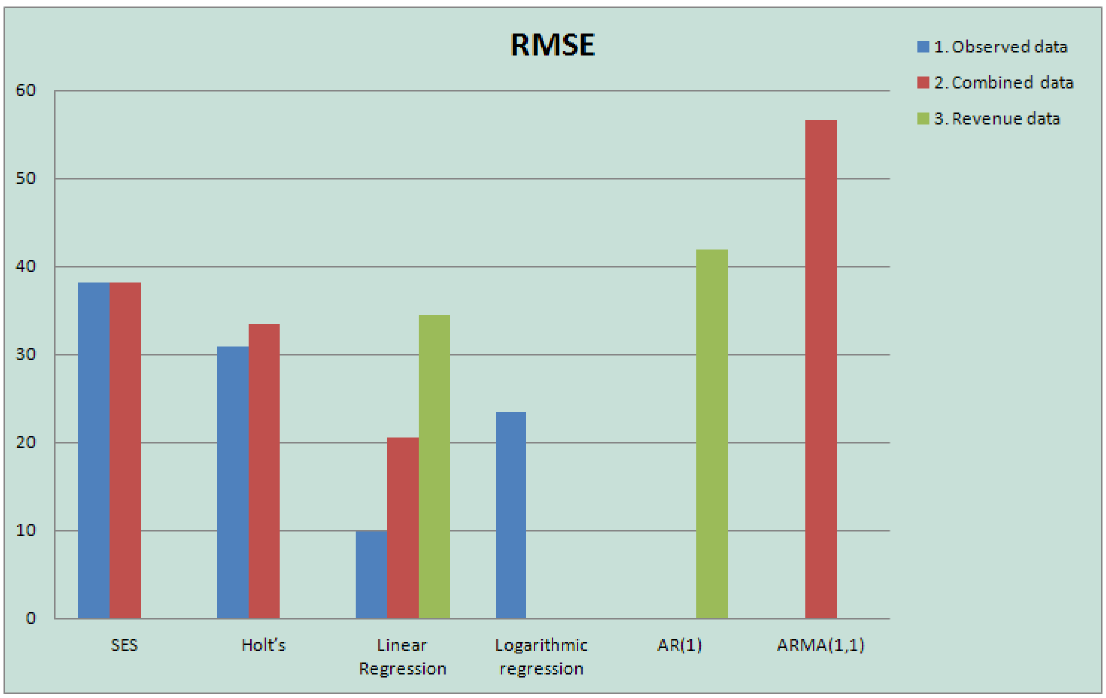


Figure 7.3 Forecasting error competition on observed and combined data

From the combined data, ARMA produces the highest error. A main reason for this could be the high volume of training data required for the ARMA method. The observed data were not applied on this method which is also for this reason. As described in Chapter 4, data collection and converter, the half annual data were set based on the balance on peaks and valleys seasons to decompose the seasonal factors. Therefore, the Holt–Winter's methods were not applied for the half-annual data series forecasting.

Empirical results shown the regression method gives the smallest error among all methods for the combined data and revenue data. For the observed data, the linear regression produced the smallest RMSE, which reduced the SES RMSE by 73.98%, the Holt's RMSE by 67.84% and the Logarithmic regression RMSE by 57.63%.

From the theoretical view on the forecasting methods, the Holt's method performs better than the SES due to the growth trend in the data set. For the regression group, the Logarithmic regression does not give a better result than the linear regression. In general view, the exponential smoothing methods are under performance than the regression method. A main reason for this is the characteristics of these two groups of forecasting methods. The exponential smoothing methods are more dependant on the past period's series, therefore are more suitable to the repeat demand pattern. Although the Holt's method adjusts the trend of the series, it is slower than regression methods. On the contrary, linear regression has a very good characteristic to follow the fast change of trend. Due to the nature of the rental company, it has a fast development trend in the recent years. Therefore, the linear regression is more suitable for this thesis's demand pattern and forecasting problem and is selected as the forecasting method.

7.3.2 Generated past period data V.S. observed data V.S. revenue data

In section 5.5.3, a model was designed to generate another 4 half annual series from the revenue data for the forecasting model training. This aims to bring more available series for the model simulation and decision. The generated 4 period series are then combined with the observed data as the combined data for the forecasting models. In section 5.5.4, another model was designed to forecast the next period's revenue first, and plot the next period's usage by the forecasted revenue data, which is a reverse process of section 5.5.3.

From the first 3 columns in Figure7.3, it can be seen that the errors from the observed data are smaller than the combined data by using same forecasting methods. The RMSE on the combined data is increased by 1.4% on SES, 7.7% on Holt's, and 51.7% by Liner regression. The RMSE on the revenue data is 3.46 times more than the observed data.

From the theoretical view, this is due to the data series characteristics related to the business growth. Because of the fast business growth in the researched company, the trend of the data is significant. The most recent data are more essential to generate an accurate forecast. Adding more previous period data can reduce the accuracy. Since the error difference between the combined and observed series are not apparent due to the characteristics of exponential smoothing methods. Although generating past period data does not fit for this problem, it is still a good practice that can be applied for other forecasting scenarios, e.g. data with repeat periods characteristics.

7.3.3 Hybrid approach

A hybrid approach for the forecasting model was proposed to improve the forecasting accuracy. Simulations were carried out to identify the relationship between company's revenue for a forecasting period and the forecasting error in the same period. Based on the findings of the result, the revenue was added as a new parameter into the forecasting model.

Empirical results shows the hybrid approach reduces the RMSE by 85.3% than using the single forecasting method, or Liner regression. This is a significant improvement on the forecasting accuracy.

The identification on the hybrid approach was not a simply testing process that combined two different forecasting methods in different ways.

As described in chapter 5, a single forecasting method, linear regression, was proved to be the best performance, according to the lowest error performance. Based on the selected forecasting method, the error pattern was modelled with the revenue data to develop the hybrid forecasting approach.

Revenue data in use for the error adjustment are also forecasted result from the previous series. Apparently, the current period's revenue data will not be available until the end of the period. Theoretically, using the forecasted revenue data to predict the usage data may bring more uncertainty. However, the simulation result shows that overall forecasting error has been significantly reduced (85.3% in RMSE).

To further test the hybrid approach, which method was also applied on external data, which is cash machine transaction data over two year period. The forecasting errors for cash machine data could not be modelled in normal distribution. Due to the lack of supporting data for the error adjustment, the cash machine error in this research was not modelled. However, results show that the error adjustment approach still works for the cash machine data. Therefore, this new approach could then be extended to similar usage demand forecasting.

Viewing the linear regression forecasting results plotted in Figure 5.17, the largest gap occurs in the middle part. Considering the experimental results on purchasing decisions, the middle part is more important for the final decision making. Therefore, the hybrid approach does not only improve the forecasting result, but also a greater improvement on the result of purchasing decision.

7.4 Full system strength and weakness evaluation

The strength of the proposed system is using half annual usage as the output of forecasting model. The forecasted second half annual usage together with the observed first half annual usage generate a whole year's usage, which is used as input data for the purchasing model. By using this technique, the input of purchasing model has more factors on recent data. This further reduces the uncertainty by using a year's forecasted data. This also reduces the intervals of the forecasting series, and hereby avoids the long waiting time for data.

The benefit of purchasing model will reduce the company's stock holding cost. As a result shown in Chapter 6, there were six laptops which should not be purchased for year 2007, which was 24% of the laptop stock. With an average price of £1350 for a single laptop, this cost the company £8100 on a single equipment category, laptop. Considering 8000 equipment items, the cost reduced by the purchasing model will be a huge difference than “Doing nothing”. This has been passed back to the company as one of the main contribution for the research project.

The main limitation of this proposed system is lack of training data. This is caused by the lack of company previous data. Two of the data generation methods have been used to overcome this problem as described in 5.5.3 and 5.5.4. However, more forecasting methods could be tested if more data series were available.

From the view of the overall purchasing decision support system, there would be a number of forecasting models available. The user can then select from the various methods in different cases. This was not designed in this system, which is a weakness point. However, after consulting with the staff from the company, feedback shows their understanding on forecasting models and techniques are limited. Therefore, they would like a system with all the tested forecasting approach in this thesis. Further details will be discussed in chapter 8.

7.5 Summary

The integration of the three models has been introduced at section 7.1. It details the process that integrates the forecasting model into the purchasing decision making. At the end of the section, the evaluation of the integration process has been discussed. Section 7.2 reviews the data collection and conversion described in chapter 4. It further evaluates how the converter works on the forecasting and purchasing models.

Deeper analysis and evaluation on the forecasting case studies and results has been carried out in section 7.3, with the application efficiency on purchasing decision model. The full system evaluation is discussed in section 7.4, which including a strength and weakness of the purchasing model.

8. Conclusions and future works

This chapter concludes the research in this thesis. Section 8.1 summarises the experience and observations in this research project. The contributions of this research are discussed in section 8.2. The further research directions are suggested in section 8.3.

8.1 Summary and observations

8.1.1 Research experience

The research idea was proposed based on a real world problem from a rental company. Initially, a number of research directions were brought and discussed. The purchasing decision support system was decided to fit both the company's requirements and the academic research needs.

In-depth literature review was carried out to find out a framework of the purchasing DSS. Then forecasting methods have been reviewed to give an idea on the forecasting simulations. The data collection process was a challenge that consists of three methods due to the storage of the company data. All the data were in daily usage format. However the purchasing decision requires annual data as the input. Therefore, a data converter was designed to resolve this problem.

Experiments were carried out on the forecasting models to obtain a best method for the equipment usage problem. The main challenge was to propose a forecasting method that further reduces the errors.

The purchasing model was designed in two stages. In the first stage, it only considers whether a single item should be owned or sub-hired. The final decision should be a total number of items that need to be purchased. This was designed in the second stage by using the forecasted annual usage data.

This research project gives a very good experience on working with industrial partners. This gives a view from the application area apart from the pure research theory. More ideas were created to fit the real world situation rather than research data. For example, most research data for the forecasting models are generated data sets that can be used directly. However, in this research, the data collection process needs to design three methods to be carried out. This is due to the difficulty of data collection and analysis for real-world problems than for academic benchmarks.

8.1.2 Contributions of the Thesis

The main contributions of this research are as follows:

1) Identified gaps between decision support systems research and practical rental industry problems

Limited research activities were carried out rental industry's purchasing decisions, according to the current references. Previous relevant research was only on hotel and flight booking, which was not specific on equipment rental.

2) Proposed a purchasing decision support system to fill this gap

This thesis identified and filled the research gap by proposing a new purchasing decision support system. The system is designed based on a rental company's running data, which gives a solution for any type of rental companies.

3) Developed a data converter to resolve daily usage and required annual usage transform problem

In this research situation, the semi-annual data was required for the purchasing decision. However, the collected data is in daily format. A data converter is developed to resolve this problem, by calculating the accumulative usage data.

4) Tested forecasting methods for the particular research problem

Various forecasting methods have been tested according to the particular research problem. Models were selected based on relevant previous research. The final model selection is based on simulation of the company data.

5) Proposed a new hybrid forecasting approach for the usage demand forecasting.

This thesis proposed a new hybrid forecasting approach for the purchasing decision system. The new method improved RMSE by 85.3% on forecasting accuracy, compared to the lowest RMSE by using a single forecasting model. It also further reduced the purchasing decision error.

8.1.3 Limitations

There are three main limitations in this research.

1) Short of forecasting data

The main limitation for this research is limited training data on the stock usage. As explained in chapter 4, only 2 year's data has been collected from the company. To overcome this problem, company's revenue data has been used to adjust the forecasting errors.

2) Data from one company only

The research data was collected from a single company. As the final system will be used in one company rather than the full industry, this will not be a significant problem for the system performance, and while the results to be generally applicable to problems of this type, there is only one point of evidence to support this.

3) Grouping stock did not considered

The system did not consider the relationship among relevant equipment which can be considered as group kit. In this research, the usage data were from the most popular rental equipment, laptop, which can be seen as an independent kit. For other kit as large projectors, one or more could be hired out together with any of the project all times. Therefore the usage of the lens can be dependent of the projectors. This is also due to the short of data.

8.2 Discussion

By carrying out the research project, the following findings can be concluded as bellow:

- Data collection is a main problem for industrial project especially in SMEs

This is due to the data storage methods in use for most SMEs. To lower the cost, the SMEs normally use paper based system to keep data records on operations. This caused huge difficulty on research data collection.

By introducing a new information system “HireTrack” helps the company to record the exact usage data. However, it has been implemented for only one year, and cannot provide sufficient data. Therefore, other sources of data have to be brought in to recover the missing data. The financial data in jobs and revenue were then used for the data recovery. This ensured the input data to be accurate maximally.

- Data converter is a important model to produce the required data format

Another problem on the industrial research project is the data format. The collected data were in the daily usage format, according to the nature of business. However, the data required for the purchasing and forecasting model should be in annual or at least half annual format. To resolve the problem, a data converter was designed in the research to transform the data format.

- Single exponential smoothing works very effective on short period usage data

From the view of the error comparison, forecasting results, and implementation, the single exponential smoothing (SES) method using daily series is found the “best” method on the collected usage data, compared with other methods in this research. The SES also performances lower forecasting errors than the Holt's method in monthly data forecast. As the data contains zero values, it is also found that the Holt's methods output the negative results.

- Regression methods performs best in observed half annual usage data

The past four periods (two year) data was recovered by using the company revenue data. Plus the four periods observed data, this gives a combine data on 8 periods for simulation. Comparing the combined and observed data, the later one obtained smaller errors. This is due to the fast growth of the business that the long past data have less effects, which means the observed data is less uncertain.

Compared the various forecasting methods in use, the linear regression method performs best on the RMSE, whereas ARMA model obtains highest RMSE. Therefore on the accumulated usage data forecasting simulations, the smallest RMSE is obtained by using Linear Regression method with observed data only.

- A hybrid forecasting model can further reduce error

A hybrid forecasting model was designed in with the adding error adjustment. Simulations on the new approach were carried out to further reduce the errors.

The RMSE by the hybrid forecasting method was given 1.459 from the model. Compared with the lowest RMSE, 9.937, by using a sole forecasting model, the RMSE was significantly reduced by 85.3%. As discussed in chapter 7, the main reason for the improvement is adding more forecasting parameters, which are the company revenue data to adjust the errors.

- Two stages to make final purchasing decision

To obtain the final purchasing decision, two stages are required for the purchasing model. In the first stage, the marking and cost data were required to compare the cost on purchase/own or sub-hire. It gives a measurand on whether a single item should be purchased owned or sub-hired.

The second stage aims to determine the number of total items that should be owned in the company, with the aid of purchasing model uses the data output from the forecasting model. If the number calculated by the model is greater than the current stock level, the system will suggest the number to be purchased. Otherwise, the company may need to consider reducing the stock level to release the cash flow as well as warehouse space.

From the company staff's comments, there were a larger number of expensive equipment that not used for every job. This costs the company's investment as well as warehouse space. There were also situations that the company did not have enough number of certain equipment, and had to hire from the competitors at high prices, which also cost the company unnecessary expenses. With the two-stage system, the above problems can be solved with no further cost. The decision makers of the company have been given the results from the system, and now considering the results when making the purchasing decisions.

8.3 Future works

With the limited time and resource in this MPhil research, there are a number of areas not been covered. The following points suggest the future works can be carried on based on this project.

- Data collection and recovery methods analysis

In chapter 4, a data recovery method was proposed to recovery the missing usage data. The data were recovered by job periods and the number of equipment used on each job from the reference of job handlers. A mini project can be designed to evaluate the data recovery method. The actual usage data can be collected from the "HireTrack" system. Using the recovery method, a set of recovered data can be calculated as well. Comparing the actual data with recovered data, the analysis process can than evaluate how accurate the method is. From the evaluation result, the recovery method can be further developed to solve other business/research problems. An extended study on the issues of capturing data within SMEs can be another research area. This requires case studies in a number of SMEs in different business sectors, and proposes data capture methods for each sector.

- Further test and development of forecasting model

More forecasting methods, such as ARIMA method, can be applied for this research if sufficient data collected after another 2 years running with the "HireTrack" system. Simulations can be carried out on selected forecasting methods to evaluate the results of the methods. The forecasting model can be then further tailored to fit the company's growth.

- Group equipment usage data decision

Due to the shortage of data, this research only considered the equipment usage in a single category. After running the implemented “HireTrack” system for 4-5 years, the equipment usage data can be available on all the categories. Therefore, forecasting model can be applied on other equipments to test the error performance, such as plasma and lens categories. However, only major equipment groups will be considered as small / cheap equipment such as cables can be stored and purchased at a very low cost. The relationship of different equipments can also be considered, to add Group Seasonal Indices (GSI) in to the forecasting model.

- Full system designed for Windows user

The system was designed and tested in both MatLab and C#.Net in this project for research purpose. The full system can be integrated all into C#.Net in Windows application for the final users. The final system will be in MS Windows based with simple and friendly user interface. The HireTrack data can be automatically imported into the system’s database. Purchasing staff can apply the system to suggest the quantities of certain equipment to buy and when to buy, and to avoid business loss. This system will be used for all required major equipments. It is not restricted to one single company, and can be used for all hire companies if the usage data can be imported from HireTrack or a similar system.

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Appendix 1

C #.NET code for purchasing decision model

```
using System;
using System.Collections.Generic;
using System.Text;
using System.ComponentModel;
using System.Data;
using System.IO;
using System.Security;


namespace ConsoleApplication1
{

    class Purchasing
    {
        int i = 0;
        int Npur, Dmin, Npurx, Nown;
        double Ppur, dep, Cm, Ps, DDmin;

        public int minDays()
        {
            Console.WriteLine("Please enter the puschasing price for this item");
            Ppur = Convert.ToDouble(Console.ReadLine());

            Console.WriteLine("Please enter the first year depreciation percentage for this item");
            dep = Convert.ToDouble(Console.ReadLine());

            Console.WriteLine("Please enter the first year maintenance cost for this item");
            Cm = Convert.ToDouble(Console.ReadLine());

            Console.WriteLine("Please enter the one day subhire price for this item");
            Ps = Convert.ToDouble(Console.ReadLine());

            DDmin = (Ppur * dep + Cm) / Ps;

            Dmin = (int)DDmin;

            if ((DDmin - Dmin) != 0)

                Dmin++;

            return Dmin;
        }

        public int NumberRequired(int Dmind)
        {
            Console.WriteLine("Please enter the total number of this type owned by us:");
            Nown = Convert.ToInt32(Console.ReadLine()); // Obtain owned number of this type


            List<int> DaysInUse = new List<int>();
            try
            {

                StreamReader sr = new StreamReader(@"D:\MPhil\Chapter6Purchasing\Models\level_d.txt");
                while (true)
                {

                    //Read the next line
                    string line = sr.ReadLine();
                    if (line == null)
                    {
                        break;
                    }
```

```
                //write the line to console window
                Console.WriteLine("This item added is {0}", Convert.ToInt32(line));
                DaysInUse.Add(Convert.ToInt32(line));
            }
            //close the file
            sr.Close();
          //  Console.ReadLine();
        }
        catch (Exception e)
        {
            Console.WriteLine("Exception: " + e.Message);
        }


        Npur = DaysInUse.Count;

        Console.WriteLine("The peak usage level is {0}", DaysInUse.Count);

        for (i = DaysInUse.Count - 1; i >= 0; i--)
        {
            if (DaysInUse[i] < Dmind)
                Npur--;
            else break;
        }
        Npurx = Npur - Nown;
        return Npurx;

    }

    public static void Main()
    {

        Purchasing pur1 = new Purchasing();

        int Dmin1 = pur1.minDays();
        int purchase = pur1.NumberRequired(Dmin1);

        Console.WriteLine("The minimum number of days on hire is {0}", Dmin1);        //output Dmin1 here

        Console.WriteLine("The suggested number need to be purchased is {0}", purchase); //output Npur
here

        Console.WriteLine("Press any key and enter to return");
        string x = Console.ReadLine();//just a break point for viewing the result, press any key to stop

    }
  }
}
```

Appendix 2

Model test results - The model is tested with laptop usage

INPUT1 Apple powerbook			System output	Manual result
Purchasing Price	2200		Min days	
First year depreciation	0.5	(50:40:10)		
First year maintain cost	10			
SubHire price	135		9	8.22
Hire period 1.1	Days		Number required	
5 on hire	2			
4 on hire	5			
3 on hire	17		3	3
2 on hire	19			
1 on hire	24			
Hire period 1.2	Days		Number required	
5 on hire	2			
4 on hire	3			
3 on hire	4			
2 on hire	6		1	1
1 on hire	11			
INPUT 2 HP 8220 notebook			System output	Manual result
Purchasing Price	1035		Min days	
First year depreciation	0.5	(50:40:10)		
First year maintain cost	0			
SubHire price	65		8	7.96
Hire period 1.1	Days		Number required	
6 on hire	0			
5 on hire	7			
4 on hire	8		4	4
3 on hire	25			
2 on hire	36			
1 on hire	50			
Hire period 1.2	Days		Number required	
6 on hire	8		6	6
5 on hire	9			
4 on hire	11			
3 on hire	25			
2 on hire	36			
1 on hire	50			