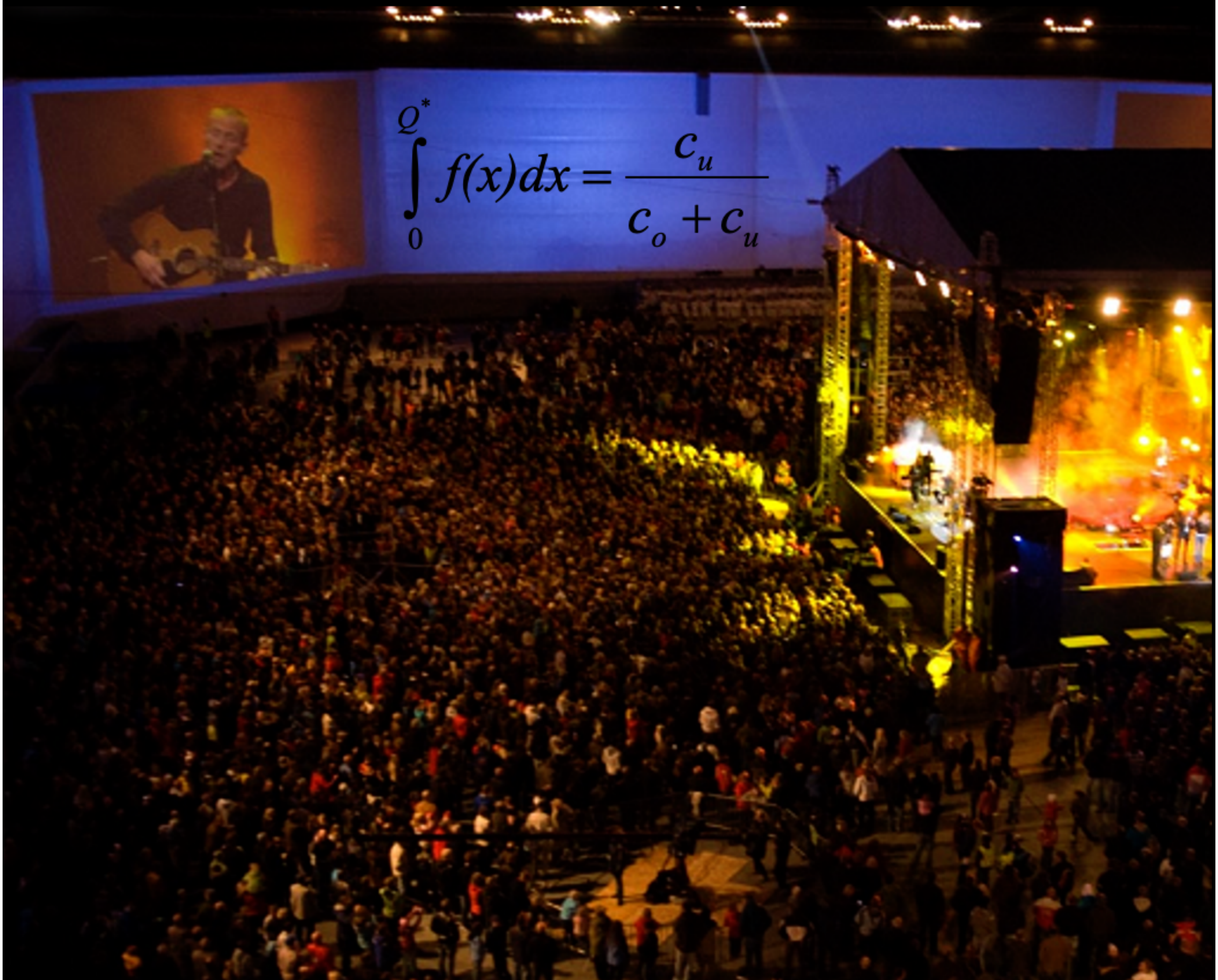
EVENT LOGISTICS

Second Edition



Kjetil K. Haugen

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Preface to the second edition

As mentioned in the original preface, this book was written as teaching material for a course in Event Logistics. It turned out to be used as such over a 5-year period from 2011 to 2015. The course was a part of a master program in Event Management at Molde University College. Unfortunately, this program was stopped in 2015, and commercial demand for the book consequently also stopped. This lead to a transfer of copyright from the original publisher to me personally. As a consequence, I made the book available for free download at various platforms (*Academia* and *Researchgate*). Downloads and reads indicates that the book still is used, maybe even at other institutions as a text book, and it seems reasonable to make a slightly revised version available.

This second edition adds something the original book lacked – exercises. In the 5 year period the course was given, three exams were conducted. These exam exercises with solutions are added in a set of new appendixes. I sincerely feel this version may provide better pedagogical opportunities both for students and teachers in their use of the book.

Kjetil K. Haugen

Molde, Norway
August 2021

Preface

This book is written to be used as teaching material for a course in Event Logistics. The course is planned to be given at Molde University College - Specialized University in Logistics, the first time in fall 2010. This course is a part of the Event Management programme launched in Molde, fall 2010.

To be able to understand this book, a basic knowledge in Logistics is necessary. Some of the material is probably too advanced for readers with only a basic knowledge of Logistics/Operations Management, and several appendixes that signal this type of difficulty are used. So, readers with only a minor level of knowledge in logistics should probably avoid these appendixes.

In order to meet these constraints, the planned course will be accompanied by another (standard) text book in logistics at an intermediate level - for instance "Production and Operations Analysis", by S. Nahmias [21]. The basic idea in teaching the course, is to capture essential Logistics modelling through selected topics in (e.g.) [21] and then continue and finish up with the contents of this book.

The structure of the book is consciously kept at a minimal academic level - in the sense that literature references are kept at a minimum. The reason for such a choice is of course partly laziness, but also the wish to produce something that is more easily accessible than normal research literature.

Kjetil K. Haugen

Molde, Norway - Brno, Czech R. - Vienna, Austria - Budapest, Hungary
June - December 2010, January 2011

Acknowledgements

I wish to thank several of the local (and not so local) planners of the Event Management Programme; Professors Harry A. Solberg (Sør Trøndelage University College), Holger Preuss (Johannes Gutenberg University, Mainz, GER) and Hallgeir Gammelseter as well as Associate Professor Nigel Halpern (both from Molde University College) who made invaluable contributions to the programme.

A group of local Event Arrangers, Head of Molde International Jazz Festival; Jan Ole Otnes, Co-founder of Molde International Jazz Festival; Petter Petterson JR., VP of International sales in Renkus-Heinz Professional Audio Systems; Karl Brunvoll, Producer at the local theatre "Teatret vårt"; Halvard Fiksdal, and local politician; Torgeir Dahl, formed an early planning group which made considerable impact on the final master programme.

Finally, a large group of international professors in sports, tourism and event management have committed themselves to aid the programme through the supervision of masters' theses.

I am very grateful to all of them!

Assoc. Prof. Asmund Olstad has read through the manuscript, thank's a lot Asmund!

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Introduction

1.1 What is Logistics?

1.1.1 Looking for a definition

The term Logistics is old and was originally used in military operations. The massive need for planning related to large transportation of soldiers, supplies and technology in war time situations made military logistics important. Today, this seems obvious from the failure of Napoleon (and Hitler). Still, apart from military operations, logistics as a term is relatively new as a scientific subject. For instance, Molde University College was among the first institutions in Norway - in the mid eighties - to launch academic programmes in logistics.

Logistics as an academic subject may largely be divided into two fairly different sub categories.

- Quantitative Logistics
- Qualitative Logistics

Quantitative Logistics, as the term indicates, focuses on mathematical modelling as the primal toolbox for handling logistics planning problems. Outside of Scandinavia, the term Operations Management may be a fairly good synonym for Quantitative Logistics and many scholars would bring the term even further and define both Operations Management as well as Quantitative Logistics as sub disciplines of Operations Research (OR). Operations Research may be defined as a sub discipline of Mathematical Modelling in general. Operations Research emphasizes discrete optimization, but embraces other mathematical modelling disciplines such as Queuing Theory, Discrete Event Simulation and Forecasting. All techniques are very relevant for logistics planning in general.

The above (perhaps) somewhat blurred discussion, brings us to a possible definition of Quantitative Logistics:

> Quantitative Logistics or Operations Management may be defined as the application of OR techniques limited to the following areas:
>
> - Forecasting
> - Production Planning
> - Inventory Management
> - Transport Planning

The above definition might be viewed as very traditional and conservative by many logistics researchers as of today. Many would claim that the above definition narrows down logistics (as well as Quantitative Logistics) way too much. Some would say that far more of a company's logistics problem is contained in the logistics concept than the above four topics - typical examples may be pricing policies, technology choice, information strategies, human resource management, contractual theory, supply chain management and so on. Still, this text will (mostly) stick to the relatively narrow (but precise) definition outlined above.

The topics listed above; forecasting, production planning, inventory management and transport planning) indicate that logistics and quantitative logistics is related to planning for certain parts of a company's activities. One way of looking at this could be the following:

All companies make decisions affecting their demand. Certain decisions made "early" such as product design choices and technology choices define physical aspects of products[1], while more direct market related decisions such as pricing, marketing decisions as well as decisions related to the company's competitive situation typically are made somewhat later in the life-cycle of a product. Given that all possible decisions in these two groups are made, what remains is to produce (possible store) and transport the given product to the market. This process contains the traditional logistics definition. Consequently, logistics is a lot about streamlining this process of *produce - store - transport*. So, concepts such as "the right amount at the right time to the right place" hence makes sense.

[1]At this point we implicitly assume a focus on manufacturing as opposed to service production. We will return to these important concepts later on.

Given the above definition, many "ordinary people" (whoever they might be) would perhaps argue that the real "sexy" company decisions are not logistics decisions. Defining the physical aspects of the product by creative design and/or marketing strategies and complex pricing strategies are far more challenging than the somewhat boring logistics decisions. To a certain extent, the author may agree and if we take a slight look at the market evaluation, we will probably find support for such a hypothesis - product designers and marketing people normally make more money than those occupied in the storage rooms. Still, a more modern view of logistics may change this traditional thinking.

Before moving into the next subsection, here a few a few words on Qualitative Logistics. Qualitative Logistics approaches logistics problems from a more philosophical perspective. The main difference compared to the quantitative branch is perhaps related to the use of mathematical tools. Qualitative Logistics research uses, as the name indicates, far less formal mathematical tools, and degenerates to a more verbal "social science"-like angle of attack. To some extent a few central topics, which may be found in this category, is discussed in Chapter 8, still with a focus on events and with a quantitative touch.

1.1.2 The importance of logistics, now and in the future

Most people who deal with logistics - either practically or more theoretically - would of course like to be an integral part of "sexy" company decision making. It may be that certain aspects of modern reality may lend a helping hand to frustrated "logisticians". One phenomenon of the world that has been quite obvious in recent years is by many authors termed globalization. (For those seriously interested in the subject, the following literature pointers may be relevant [9], [18], [16], [25].)

Now, many scholars and practitioners argue that in a globalized world (a world with relatively small physical transportation costs and negligible informational transaction costs), competition will increase. This seems like a reasonable hypothesis, increased globalization leads to increased competition in product (and service production) markets. After all, barriers that prevent competition are all sorts of transaction costs. At the same time, certain political processes, for instance, the development of EU has also had, and probably will have, significant impact on reduction of barriers preventing competition. As such, a hypothesis stating increased future competition seems reasonable. Given such an assumption, it likewise seems reasonable to assume less possibilities for maintaining technological and or design advances over significant time periods. A recent example, may be found in the Ipad, which has become an enormous success perhaps due to a combination of design and technology choices.

Still, in a globalized and competitive world, one would expect clones and/or direct copies popping up very fast after such a success. Examples of such has popped up, for instance, the Samsung Galaxy Tab, as one of several responses to the Ipad.

As such, competition makes technological and/or design advantages far more fragile. This argument has lead modern logisticians to argue that in the future, competitive advantages in technology (or markets) will vanish due to increased competition. Then, the only remaining dimension for creating differences between companies is logistics. As such, one could say that in a perfectly globalized and competitive world, the only possible way of creating a difference is by choosing a different logistics system. Hence, it will not be so much about choosing the right product as how to manufacture it.

Moving into events, things change somewhat[2]. A central concept in most events, whether they are from sports or other cultural scenes, is branding. Branding may be defined (simply) as the non (or very hard) copyable part of a product or service[3]. Simply put, it is principally impossible to copy Manchester United FC. One could of course try to copy the player qualities one by one, the organization, manager skills, training skills, even localization, but the final product will still not be MUFC. Copying the music of Beatles or Rolling Stones is actually relatively easy to do, but the market potential of such a strategy is still far from that of the real product.

Hence, we may conclude, and this is to a certain extent more relevant for event production than other types of production, that potentially increased globalization and increased global competitive environments do not necessarily float as freely into event production as into traditional manufacturing or service production[4]. Actually, it seems reasonable to assume that for events, the possibility of maintaining such brand advantages may be possible in spite of a future "perfectly competitive world".

[2]Obviously, the *Event concept* has not been properly discussed or defined at this stage. We will, however, return to a more thorough discussion in the next section, but for the moment it will prove sufficient to think of an event as a gathering of people with a certain objective, which could be entertainment (sports, music, theatre etc.) or knowledge (conferences) and with some sort of organization - the *event producer* - supplying the *event content*.

[3]In terms of economic theory we could perhaps see it as parts of a product which has the potential of a viable monopolistic advantage.

[4]The terms *manufacturing* and *service production* will be discussed in detail in Section 1.2

Even if the above arguments indicate that logistics as such may be viewed as less important in a future competitive setting, it does of course not indicate that logistics problems are irrelevant in event production. On the contrary, organizing big “one-shot” events such as Olympic games possess huge and very challenging logistics problems related to classical logistics topics such as inventory management, production planning, transportation and infrastructural planning. Even relatively small (and size-wise insignificant) events such as a small music festival in a small country like Norway holds numerous logistic challenges.

1.1.3 Logistics theory, practice and research

An alternative view on Logistics

From an academic point of view, logistics theory may seem unclear and hard to define. The fact that most textbooks in the topic presents their own definition of logistics emphasizes such difficulties. However, logistics as a topic is still very much oriented towards how to perform certain parts of company tasks efficiently.

Personally, I prefer to view logistics as an integral and extended part of microeconomic theory. A classic part of microeconomics deals with production theory and the development of supply curves. The simple version of this story typically starts with the concept of a production function; say:

$$f(N) = X \tag{1.1}$$

In equation (1.1), N denotes (a single) input (we can think of it as labour) while X denotes a single output - produced amount of one product. This equation defines what is referred to as production technology and a certain cost of acquiring the input is of course also present. To make it as easy as possible say;

$$C(N) = C_F + w \cdot N \tag{1.2}$$

$C(N)$ is hence the cost of hiring the labour N and it is assumed linear with a fixed part C_F and a proportional part where w is naturally interpreted as the wage. Now, the “microeconomic story” continues, by an assumption of profit-maximising behaviour by the firm and existence of a given market price p, as follows: ($\Pi()$ is company profits)

$$\Pi(X, N) = p \cdot X - (C_F + w \cdot N) \tag{1.3}$$

Then, by applying equation (1.1), (1.3) can be expressed (as a single valued function in N):

$$\Pi(N) = p \cdot f(N) - (C_F + w \cdot N) \tag{1.4}$$

First order conditions for maximization of $\Pi(), \Pi'(N) = 0$ then gives:

$$f'(N) = \frac{w}{p} \tag{1.5}$$

Then, a supply curve can be derived through the following argument: Inverting equation (1.5) (Solving it with respect to N);

$$N = g(\frac{w}{p}) \text{ and utilising equation (1.1) once more } X = h(\frac{w}{p}) \tag{1.6}$$

The point here is of course not the beautiful argument leading to supply curves - a necessary building block in general equilibrium theory - but the basic assumption of equation (1.1) or as shown in figure 1.1

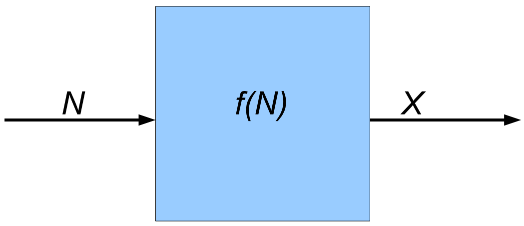

Figure 1.1: The simplified production function of microeconomics

The point here is the extreme simplicity of the mechanism defined through figure 1.1. In a microeconomic context, it is surely easy to extend to both multiple inputs as well as outputs, but the more fine tuned (and in certain instances) important company decisions such as number of set-ups, inventory volumes, safety stock and so on will clearly not fit easily into the above theory. As such, logistics may be viewed as a more fine tuned way of modelling production functions. That is, the simple functional relationship defined by figure 1.1 is simply too simplified to spawn essential decisions for most real-world companies.

Logistics research

The above logistics "defintion" makes understanding (quantitative) research in the field comprehensible. If logistics is viewed as a simple extension of microeconomic production theory with the aim of a more fine-grained modelling of production functions, it should not come as a surprise that optimization is a key research concept. The fact that many obvious logistics problems (and models) naturally contain integer variables (set-up and ordering for instance) and uncertainty related to vital model input, leads to a need for optimization techniques model as well as solution-wise. As modelling typically is not viewed (by most researchers) as very difficult, it is again fairly obvious to expect that Logistics research should emphasize solution techniques for Logistics-oriented optimization problems. Indeed, this seems to be the situation. Many classical Logistics models such as LSP (Lot-Size Problem), CLSP (Capacitated Lot-Size Problem), VRP (Vehicle routing Problem) and many many others, have been extensively studied in research literature. The main focus of these studies have, as indicated above, been on solution techniques. As discrete optimization problems typically need computers to achieve solutions in reasonable time, much of the focus has been on algorithmic techniques.

In this text, such algorithmic techniques will play a minor role. On the contrary, we focus on modelling issues. This seems natural for the intention of the book, but also as Event Logistics raises some different and relevant questions related to how classical Logistics models can and should be "translated" into the Event-setting. This does not indicate that solution related research is less relevant within this topic, more an observed need to look into the basic modelling first. The fact that most students may disagree on the above mentioned easiness of mathematical modelling is of course also a relevant textbook argument.

1.2 Services, Manufacturing and Events

At this point, it seems necessary to investigate the "*Event*"- concept somewhat closer. However, before we address this concept, it may be fruitful to look into more classical logistics, and discuss the concepts of *Manufacturing* and *Services.*

The Business Dictionary [2] defines these two terms as:

Manufacturing:

> *Includes all steps necessary to convert raw materials, components, or parts into finished goods that meet a customer's expectations or specifications. Manufacturing commonly employs a man-machine set-up with division of labour in a large scale production.*

and

Services:

> *Intangible products that are not goods (tangible products), such as accounting, banking, cleaning, consultancy, education, insurance, know how, medical treatment, transportation. Sometimes services are difficult to identify because they are closely associated with a good; such as the combination of a diagnosis with the administration of a medicine. No transfer of possession or ownership takes place when services are sold, and they (1) cannot be stored or transported, (2) are instantly perishable, and (3) come into existence at the time they are bought and consumed.*

The above definitions tell us that most human economic activity that is not defined as *Manufacturing* may be labelled *Services*. Obviously, manufacturing is related to physical goods and the ownership transferability as well as storage possibilities. Typically, most services do not have such properties, but very often parts of services; the report of a lawyer, the prescription or an X-ray photo of the physician or the DVD of a concert are clearly manufactured goods. Still, the main product without this added manufacturing possess the main characteristics of a service.

Our main interest here is of course the "Event" concept. It seems fair to categorize most events within the services category. After all, our common understanding of the concept implies individuals selling certain services to spectators like music, sports or theatre. Still, it cannot be taken that all events naturally fall within the services category. Think, for instance, of a painting sales exhibition. The paintings are sold (hopefully), implying ownership transferability. Furthermore, the paintings are physical objects involving storage possibilities. Still, many painting exhibitions might easily fall into our meaning of events. Consequently, the events concept may perhaps not fall easily into the service category as a sub-group.

The Business Dictionary [2] also defines Events:

Events:

> *Occurrence happening at a determinable time and place, with or without the participation of human agents. It may be a part of a chain of occurrences as an effect of a preceding occurrence and as the cause of a succeeding occurrence.*

This definition, still not very clear, adds an important point; time and place. An event takes place in time and place not necessarily tomorrow or next week, but at a predefined location at a specific point in time (or a set of specific points in time). So, this sheds light on our art sales exhibition. An art dealer shop is (typically) not an event as it is available all the time, while our sales exhibition takes place only a limited time period and may as such be categorized within the event category.

So, what else? Well, we may talk about "one-shot" events or repeated (regular) events. The Molde International Jazz Festival will typically qualify as a repeated event; it takes place more than once, but it is perhaps not an ordinary service, as it is not present all the time. Olympic games or the upcoming[5] cross-country skiing world championship in Oslo are typical "one-shot" events. Not necessarily meaning that they will not take place again. After all, this skiing WC is the third one in Oslo since 1966[6]. The point is simply that the market does not know if and when such an event will return.

This sub-categorization is important from a Logistics planning point of view. It should be relatively obvious that "one-shot" events are significantly more challenging than regular events when it comes to all phases of logistics planning and operation.

Another sub-categorization that might be relevant for Event Logistics is that of entertainment versus professional events. Clearly, when we think about events, our first thought is perhaps related to the entertainment industry. However, many events such as research conferences or seminars have all characteristics of events and may (and should) clearly be defined as such. The main difference between the two is perhaps on the demand side, which may behave significantly different. Still, this difference may not lead to too much differences from an analytic (logistic) point of view.

Let me try to sum things up a bit. Clearly, most events are named events because they are <u>not</u> available all the time. Certain events are predictable in time and place. We know, for instance, that Molde football club will play 15 home matches in the Tippeligaen next season, but definitely not at the

[5] At the time of writing.

[6] Cross country World Championships were arranged in Oslo in 1966, 1982 as well as now in 2010.

location or choice of the market. Others are not very predictable in space; think about the recent WC football at Russia and Qatar. As such, the fact that an event is not necessarily present at any point in time may perhaps be the most striking feature of the concept. The actual content of the event or to what degree it can be placed within the service category is, as I see it, not the main point. Consequently, the time and place dimension will be leading our further analysis of Events and Logistics.

1.3 Event Logistics

Given the previous discussion, it seems straightforward to accept that Event logistics should handle logistics planning and the special challenges that the event-setting brings.

The simple fact that events takes place at (possibly unpredictable) points in space and time obviously imposes special problems in relation to classical logistics modelling.

For instance, the obvious lack of data related to historic demand should force alternative forecasting methods. The fact that most events products are difficult (if not impossibly) hard to store should change the inventory focus on production planning models. The uncertainty related to demand forecasts together with limited event horizons should make significant changes to the focus of inventory management modelling. (The News-boy focus seems to be an interesting candidate.) The fact that in most events, consumers are brought to the product as opposed to the traditional manufacturing situation should indicate different transportation challenges, which also must be reflected in the transportation modelling choices. The fact that many events are effective monopolies must be reflected in a sensible handling of the subject. It opens up some interesting possibilities but at the same time creates some additional problems.

So, this book will discuss, present and in some instances provide solutions to classical logistics problems, tuned to fit the event-setting.

1.4 Events and Uncertainty

It should not be very hard to realize that the above discussion indicates that uncertainty most certainly will play a significantly more important role in event logistics planning than in traditional logistics planning. Arranging Olympic Games is, as briefly discussed above, probably not carried out at the given spot in the actual country for many years - if ever. As a consequence, the ability to predict both customer demand as well as supply parameters (costs for instance) forms critical and very challenging problems. This lack of certainty both in demand as well as in supply makes the concept of uncertainty far more relevant in events than traditional logistics planning.

The added fact that many of the actual events may take place in a relatively distant future does of course only strengthen the above argument. After all, the football world cup in Qatar in 2022 is defined and placed in 2010, 12 years ahead of the actual event. The simple fact that many of the events that need planning (especially mega-events perhaps) lie in a distant future makes planning not only possible, but also harder. Both future costs as well as workforce availability may be very hard to predict many years in advance

The fact that the above situation defines a long time period between the knowledge of getting the event and the event time also opens up some added possibilities, pre-sales for instance. This is something which is typical for most events, and should in principle make certain parts of logistics planning easier. On the other hand, it opens up for other (and potentially) more complex opportunities; dynamic pricing for instance. The ability to pre-sell tickets to an event surely also opens up the possibility of changing the price virtually very close to the event. (This is often referred to as *Dynamic Pricing*, *Demand Based Management* or *Revenue Management*. A topic which will be closely examined in Chapter 7.)

Chapter 2

Event Forecasting

2.1 Introduction

All logistics planning needs demand forecast data. Even the most extreme JIT-production environment, with a maximal flexible production system and virtually no set-up times or costs, must at some level predict future demand. This is kind of obvious for events, as most resources needed to produce the event normally is proportional to the size of the audience. Typical examples are food, drinks, housing, seating, transportation and so on.

2.2 The fallacy of traditional time-series-based forecasting

Most logistics textbooks (see e.g. Nahmias [21]) recommend time-series based forecasting methods. The reason for such a recommendation is quite obvious. In a modern manufacturing setting, a huge number of products leads to demand for fast, efficient and reasonably good forecasts. The huge product count as well as the need for fast and efficient forecast updates makes (simple) time-series methods appropriate. Even if such methods (perhaps) does not produce forecasts with the highest accuracy nor provide any explanatory power, the simplicity and speed of production makes these methods natural candidates for modern corporate logistics modelling. The fact that historic demand data are readily available (at almost zero cost) is surely also a good argument for this choice.

However, moving into the event-situation, obvious differences exist. Firstly, the number of products is limited. Additionally, the need for speedy forecast updates is obviously not there, at least not to the extent of a running business selling products in their market continuously. (There is normally some real time between events even in the regular or repeated case.) The fact (discussed above) that events takes place relatively seldom should also indicate a certain lack of sufficient demand data. A typical yearly festival (existing for 20 years) will at best have 20 observations of total demand, which from a time-series modelling point of view might be sparse.

But maybe more important, time-series modelling does not (at all) account for a lot of information we normally have related to events. If we plan an event say (some kind of music festival), we would at certain points in time have registered pre-sales (normally a very good indicator for total sales), in addition, we have means of affecting demand through advertising as well as pricing, which definitely should be taken into account when demand forecasting is aimed at.

Such arguments should then lead to different model choices in events as opposed to traditional logistics forecasting for manufacturing situations. Causal (regression) type models seems very much more appropriate as they open up for explanatory information.

2.2.1 A simple example

Let us look at a simple example.

Table 2.1 holds total (yearly) audience for the local theatre -“Teatret Vårt” [5] in the time period 2000 – 2009.

YEAR	AUDIENCE	YEAR	AUDIENCE
2000	28897	2005	31436
2001	38092	2006	37923
2002	39306	2007	39451
2003	34184	2008	31861
2004	50951	2009	29398

Table 2.1: Yearly ticket sales at Teatret Vårt - Molde; 2000 – 2009

In figure 2.1, the data in table 2.1 is plotted. Examining the figure, we observe some (expected) variations between years, but a peculiar bump in 2004. Actually, the number of sold tickets in 2004 was close to 30% larger than the second largest year (2007), and more than 40% larger than the period average.

Examining figure 2.1 further, it is fairly obvious that any seasonal variations are hard to justify. After all, why should some kind of cyclical pattern

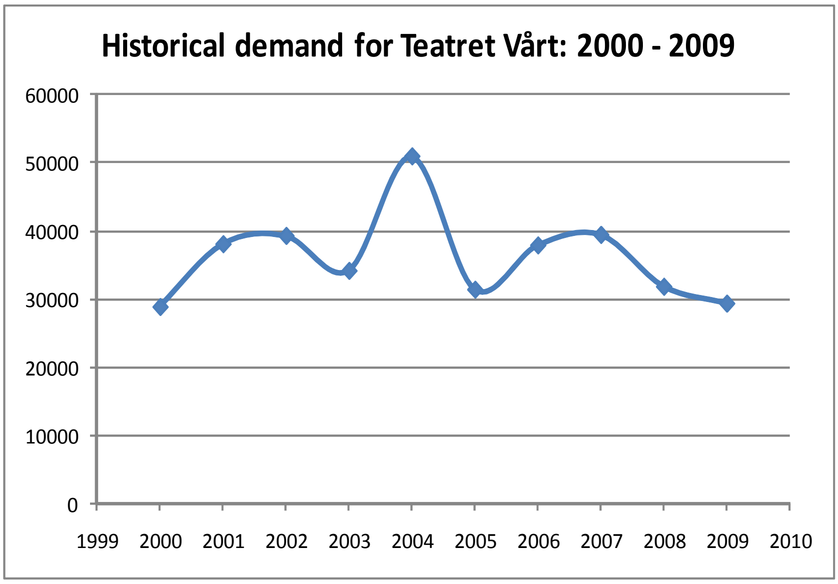

Figure 2.1: Plot of yearly ticket sales at Teatret Vårt - Molde; 2000 – 2009

be available over years[7].

The point here is simple. If no trend or seasonality is present when time-series models are applied, unforeseen bumps are hard to account for. To visualize this, some simple *moving average* forecasting models are incorporated and shown in figure 2.2[8].

As can be seen from figure 2.2, the bump in 2004 is missed by all moving average models, and the effect is being recreated in subsequent years, leading to a very bad forecast fit. This is of course not very surprising knowing the mechanism behind such simple time-series models, still, it points out the typical problems involved in applying time-series modelling in event demand forecasting.

[7]Some kind of cyclical patterns over years may of course be present, for instance, related to leadership changes. Changing top management will in this business very often be triggered by low demand rates and top management changes may be observed as relatively long term cycles. However, predicting such management changes in the future (and the effect of them) may be more or less impossible.

[8]Refer to Appendix A for the actual moving average calculations

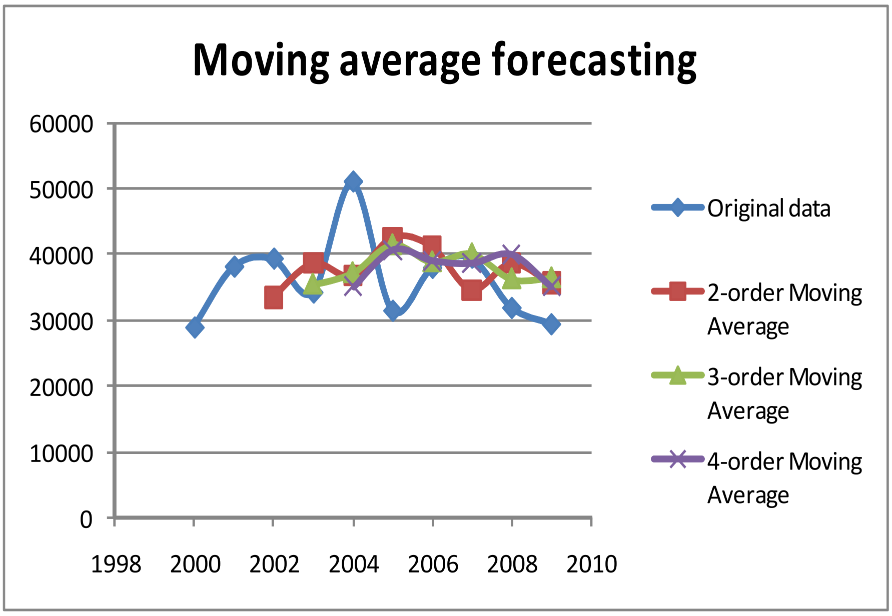

Figure 2.2: Moving average (orders 2, 3 and 4) forecasting on the Teatret Vårt data.

2.2.2 Utilizing explanatory information - the reason behind the 2004 bump

As indicated above, in certain event situations, the explanatory simplicity is so obvious (perhaps typically as opposed to traditional manufacturing situations) that such information both could and should be incorporated in the forecast modelling. Applying some local knowledge [9], it turns out that a very special event took place in Molde in 2004. Then, a special play was staged - "90-metersbakken" written by the local (and later very famous author, musician and former MFK player) Jo Nesbø[10], and even if one did not manage to predict the success upfront, at least such information can and should be applied in retrospect.

The point is of course that this type of play still have and did have a very special (and positive) demand effect. But, and this is the point here, unless the theatre plans to do something similar in the future, such an event

[9] The brother of local Associate Professor Oskar Solenes is an actor, and did perform in a certain play at Teatret Vårt in Molde in 2004 - thanks to Oskar for this great piece of information.

[10] He is actually visible on the front page of this book in the top left corner with a guitar.

should, from a predictive point of view, perhaps be considered an outlier and in some sense removed from the data.

A very simplistic strategy could be to remove the demand in 2004 and replace it by the average demand (in red)[11] as indicated by table 2.2. Now, we apply additional information of explanatory character, which of course is a sensible thing to do if the aim is to build a forecast model that should provide forecasts with reasonable quality

YEAR	AUDIENCE	YEAR	AUDIENCE
2000	28897	2005	31436
2001	38092	2006	37923
2002	39306	2007	39451
2003	34184	2008	31861
2004	34505	2009	29398

Table 2.2: Yearly ticket sales at Teatret Vårt - Molde; 2000 – 2009

As can be observed from figure 2.3, things look a little bit better in the sense that the simple time-series based forecasts hit better. However, this approach to event forecasting is still not good. The main reason is obvious. We do have much and very relevant information, which we, in many instances, control ourselves, that are not (and should be) included in the analysis. In this case, we choose which actors to employ, which plays to stage, which days to play, how many shows, the prices and marketing and so on. All this information is simply not used at all by using a time series approach. And, as this type of information is typically available (more or less) at different time-spots before the actual event takes place, the possibility of using it (efficiently) is interesting.

The answer to this demand would be avoiding time-series based models and instead focus more on causal models (regression models). Such an approach seems far more appropriate for event forecasting. In order to demonstrate this approach, a case from the local football club - MFK will be presented in the next section.

[11]This number is calculated as $\frac{28897+38092+39306+34184+31436+37923+39451+31861+29398}{9} = 34505.333 \approx 34505$

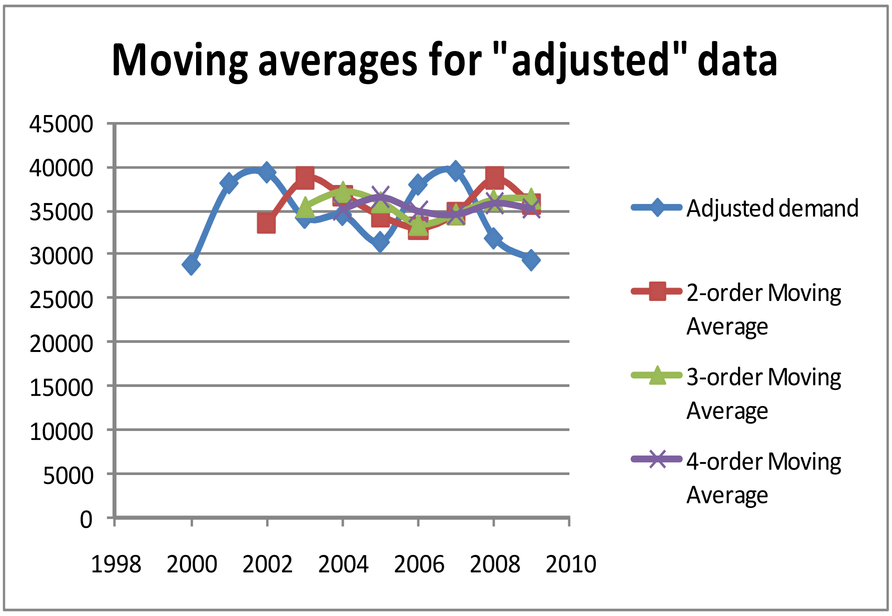

Figure 2.3: Moving average (orders 2, 3 and 4) forecasting on the adjusted Teatret Vårt data.

2.3 The case of football demand forecasting

2.3.1 An old MFK case

Background

The local football team, Molde fotball klubb (MFK), has a glorious history in Norwegian football. The team from the tiny city Molde (around 25000 inhabitants), holds the sixth place on the Norwegian marathon table (All time premier division table) [7] only beaten by large city teams such as VIF (Oslo) , RBK (Trondheim), Brann (Bergen) Viking (Stavanger) and Lillestrøm (Oslo area).

MFK played in the Champions League (CL) in the 1999 season, meeting Olympiakos (Greece), Porto (Portugal) and Real Madrid (Spain). The point score for MFK returned only 3 points, (a home win against Olympiakos), but it is still the only Norwegian team besides Rosenborg BK who has ever participated in this tournament.

As such, this club is interesting to investigate by itself, in many ways being a paradox through it's continuous success over many years while located in a very small city. It is probably safe to say that MFK comes from the smallest city ever to host a football team in CL.

Here, however, we will examine a case of demand forecasting through formal regression modelling to demonstrate how it can be done. The case is not recent, but stems from a presentation that the author gave at a football seminar in Norway (NFF's toppfotballseminar - Gardermoen) back in 2002.

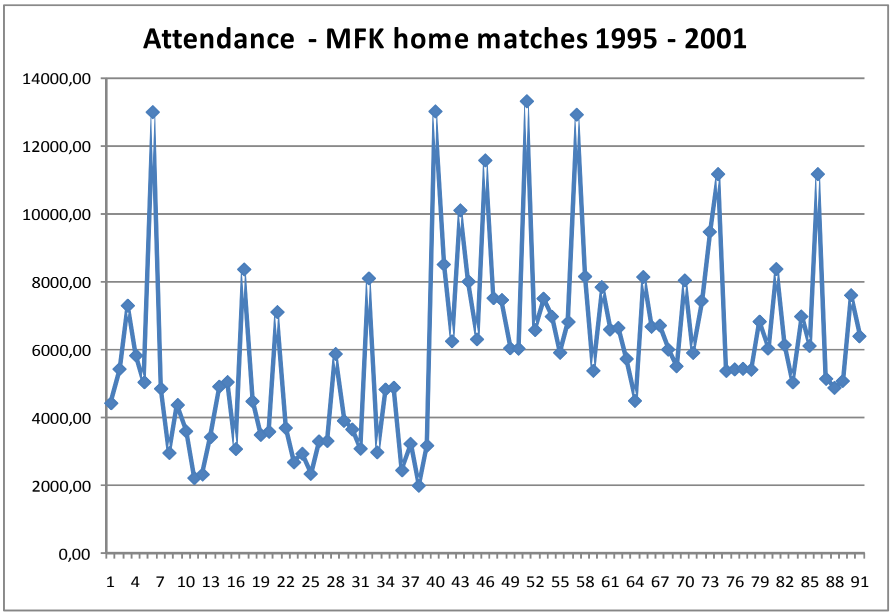

Figure 2.4: MFK - Home match attendance, 1995 – 2001

Figure 2.4 holds home match attendance for MFK during the period between 1995 and 2001. As can be readily observed from the figure, apart from the relatively large variation between matches, something seemed to happen around observation 40 (39 to be exact). This final observation is perhaps easier to observe if average attendance before and after this time is calculated and plotted alongside the original observations. This is done in figure 2.5.

As figure 2.5 indicates, something must have happened around observation 39 or April 1998, which is the corresponding date. Actually, the exact difference in the two averages amounts to $7274 - 4397 = 2877$ or a percentual (average) increase of around 65%. Obviously, something did happen. The happening was a new stadium - today named “Aker Stadion”, nominated for FIABCIs Prix d’Excellence in 1999 and winner of the Norwegian City prize the same year.

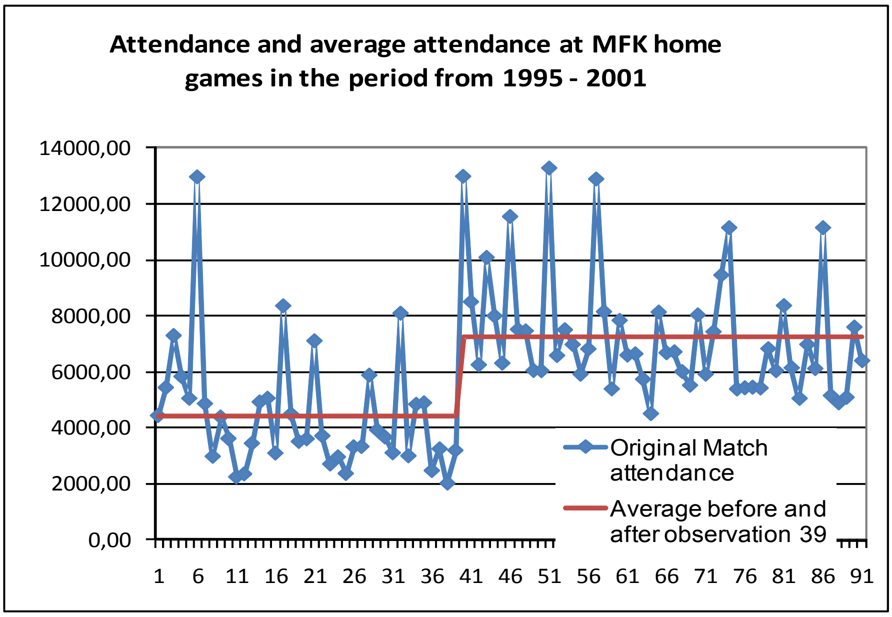

Figure 2.5: MFK - Home match attendance, 1995 – 2001 with average values before and after observation 39

A regression model

A linear multiple regression model postulates a causal type of relationship between an output variable (Y_i) and a set of N input variables $X_{i1} \ldots, X_{iN}$. On mathematical form: (it may prove handy also to define the number of observations say M, hence $i \in 1, \ldots, M$)

$$Y_i = \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} + \epsilon_i \tag{2.1}$$

The point here is not to dig deep into regression theory, but to look at it as a case. As such, additional information related the theory may be found in most logistics type of books (in a simple form) [21] or more advanced specialized texts like e.g. [15].

Roughly, the application of regression modelling in forecasting can be described through a 3 step process:

1) Establish your model (define Y and $X_1, \ldots, X_N$).

2) Estimate regression parameters $\beta_0, \ldots, \beta_N$.

3) Use the finished model (after completing stages 1) and 2)) to find forecasts for a suitable future time period.

Perhaps the most challenging stage is the first one. Ideally, one would like (from a scientific point of view) to have some underlying theory defining the Y and the X's. A classical example from physics may be helpful. Applying Newton's second law of mechanics, the following equation can be used to find the distance s needed in vacuum for some object falling s length units:

$$s = \frac{1}{2}gt^2 \tag{2.2}$$

Now, an experiment can be staged, where various values of s can be defined, 1 m, 2 m and so on. And the time spent in falls t_1, t_2 etc. can be measured. Consequently, a set of s's and t's are the outcome of the experiment. All the t's can be squared and we can define $Y_i = s_i$ and $X_i = t_i^2$. Then, the following version of (2.1) can be formulated:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \tag{2.3}$$

possibly with the added constraint $\beta_0 = 0$. Then, after staging the regression process, the interesting unknown g (standard gravity) can be calculated by the estimated regression parameter $\hat{\beta}_1$ through $\hat{g} = 2 \cdot \hat{\beta}_1$.

This way of doing regression analysis is per se "theoretically correct". However, most practical situations involves neither the ability to control the output variable (e.g. MFK cannot (or will not) define the attendance at a match) nor do we have a unified theory defining what variables (and what relationships between them) explaining MFK attendance demand. Still, various theories may provide sensible variables to be included in a model. As such, most regression cases within economic or logistics theory may prove fairly inadequate from a stringent theoretical point of view.

A regression model for MFK attendance

For the case at hand, it seems fair to divide the possible factors influencing MFK attendance demand into (at least) three different groups:

1) Sports factors

2) Economical factors

3) External factors

The *sports factors* are related to the quality of the team and it's opponents. The basic hypothesis is related to two different mechanisms, absolute and relative quality. We would expect that the better the team is (absolutely) the more people would like to watch it, but in addition, some kind of sports oriented mechanism related to what is commonly defined as "uncertainty of outcome" should perhaps also play some part. That is, if the team is relatively too good compared to a given opponent one would expect that public interest for the match might decrease.

The *economic factors* should largely be related to price and income. Higher product prices ought to bring demand down while increased public income should have an opposite effect. All kinds of marketing and sponsoring choices by the club might of course also have effects.

Surely, there is a "field" of club decisions in between these two groups such as coaching and player choices (made by the club) that in many cases also may influence spectator interest[12].

The final category contains all other possible factors not naturally belonging to the two other groups such as weather, TV-match or not, match day, a new stadium and so on. Back in 2002, I proposed the following list:

- Changed infrastructure (a new stadium for instance)
- Calendar effects (16th of May for instance)
- Derby effects (matches against special teams RBK for instance)
- Home and away teams form (performance in relatively recent matches)
- Home and away teams status (performance in previous seasons)
- Quality relative to each other (table position)
- Week-day and match-time (Sunday vs. Saturday for instance)
- Weather
- TV-match
- Importance of the given match (possibly late seasonal importance) for good or bad tabular position

[12]The recent coach change for Ole G. S. seems for instance to have had a significant positive effect on demand in MFK at least.

The first thing to observe from the list above is the absolute absence of economic variables. No prices, seasonal tickets, marketing, and so on. The reason is simple: lack of this information or, perhaps more correct, a high acquiring cost. Finding historic ticket prices turned out to be a difficult task for the given period. At the same time, MFK has not had a very "active" price policy in the years we discuss here, so it was expected that these information bits should play a minor part in explaining attendance demand anyway.

Furthermore, the list contains blue and red elements. The blue elements were included while the red ones were not. The main reason for not including the red elements was more out of convenience, I had relatively short time to prepare the analysis and chose to do things relatively simple.

The actual model in mathematical form looks as:

$$\begin{aligned} att_i \quad = \quad & \beta_0 + \beta_1 \cdot mfk\_pos_i + \beta_2 \cdot mot\_pos_i + \beta_3 \cdot mot\_3si_i + \\ & \beta_4 \cdot mfk\_form_i + \beta_5 \cdot mot\_form_i + \beta_6 \cdot rbk_i + \\ & \beta_7 \cdot mai\_16_i + \beta_8 \cdot stadion_i + \beta_9 \cdot brann_i + \beta_{10} \cdot jazz_i + \epsilon_i \end{aligned} \tag{2.4}$$

and with the explanation of the actual variables in (2.5) shown in table 2.3. The first part of the table contains continuous variables, while the final part contains binary variables (e.g. variables only taking values of 1 or 0).

Variable	**Explanation**
att_i	Attendance in match i (i runs from the first match 1995 up to last in 2001)
mfk_pos_i	MFK's position on the league table before match i
mot_pos_i	Opponents' position on the league table before match i
mot_3si	Opponent i's average table position the three last years
mfk_form	MFK's average points scored in the last 3 matches
mot_form	The opponent's average points scored in the last 3 matches
rbk	A binary variable; 1 if RBK is the opponent, 0 otherwise
mai_16	A binary variable; 1 if the match is played on May 16th., 0 otherwise
$stadion$	A binary variable 0 up until data point 39, 1 otherwise
$brann$	A binary variable; 1 if BRANN is the opponent, 0 elsewhere
$jazz$	A binary variable; 1 if match is played during the jazz festival, 0 elsewhere

Table 2.3: Explaining the variables of equation (2.5)

To give the reader a more direct feeling for the model and its data, the first 20 data points are shown in Appendix B. Now, the normal procedure is to apply some kind of statistical tool (Excel or as in this case SPSS are typical candidates) to estimate (find values for) the unknown regression parameters $\hat{\beta}_0, \ldots \hat{\beta}_{10}$[13].

The results (parts of the output from SPSS[14]) are shown in figure 2.6:

SPSS: Linear Regression

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	4107,276	955,029		4,301	,000
	MFK_POS	-46,677	72,333	-,045	-,645	,521
	MOT_POS	-67,416	53,200	-,114	-1,267	,209
	MOT_3SI	-20,251	45,626	-,035	-,444	,658
	MFK_FORM	408,916	209,162	,137	1,955	,054
	MOT_FORM	-99,246	214,428	-,037	-,463	,645
	RBK	4718,759	697,742	,493	6,763	,000
	MAI_16	2036,426	632,063	,198	3,222	,002
	STADION	2800,343	315,814	,543	8,867	,000
	BRANN	607,613	607,339	,063	1,000	,320
	JAZZ	1309,096	584,917	,137	2,238	,028

a Dependent Variable: ATT, R^2=0.720

Figure 2.6: SPSS output from the model

We shall limit our interest in figure 2.6 to the third column: **Unstandardized Coefficients** and the last one named **Sig**. The third one contains the values of the parameters $\hat{\beta}_0, \ldots \hat{\beta}_{10}$ while the last column contains significance probabilities. These significance probabilities tells us (popularly described) whether it is probable that the actual estimates really are different from zero. So a very small value indicates that the parameter itself with relatively large probability may in fact be zero. As a consequence, those parameter estimates with (say values larger than 0.1 (90% significance level)) should be removed from the model. In figure 2.6, all these are marked in grey.

The typical next step would then be to take out the insignificant variables and rerun the regression model; now as:

[13] The use of the notation $\hat{\beta}_j$ is due to the fact that the numerical (estimated) values principally are different from the model values in equation (2.5)

[14] All necessary data for this analysis have been found on the RSSSF-website [7]

$$\begin{aligned} att_i &= \beta_4 \cdot mfk\_form_i + \beta_6 \cdot rbk_i + \\ &\quad \beta_7 \cdot mai\_16_i + \beta_8 \cdot stadion_i + \beta_{10} \cdot jazz_i + \epsilon_i \end{aligned}$$

The results of this operation are shown in figure 2.7.

SPSS: Linear Regression

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
1	(Constant)	2978,880	378,094		7,879	,000
	MFK_FORM	476,102	183,154	,160	2,599	,011
	RBK	5156,216	579,584	,539	8,896	,000
	MAI_16	1860,794	623,045	,181	2,987	,004
	STADION	2815,065	309,117	,546	9,107	,000
	JAZZ	1265,718	572,701	,132	2,210	,030

a Dependent Variable: ATT, R^2=0.700

Figure 2.7: SPSS output from the reduced model

Let us take a slight look at the information on the bottom of figures 2.6 and 2.7. The R^2 is an interesting statistic to judge. Roughly, it tells us how much of the variation is explained through our model. Comparison of the two figures, shows a very minor decrease in R^2 indicating that the model (2.5) is a better choice than the big original model. The fact that R^2 is more or less unchanged after the removal of a set of insignificant variables is normally taken as a "proof" of reasonable modelling. The final model's R^2 of 0.7 means that 70% of the total variation is explained by the model. Comparing such a figure to most real world regression models indicates a surprisingly good fit, especially as many obvious relevant variables are excluded initially.

If we sum up the results so far, it seems as if MFK audience only cares about the home team's form, the opponent's form is irrelevant. The same holds for the status of the opponent (mot_3si), which also is insignificant apart from the very significant opponent RBK. So, the only "sporting" or event oriented variable that is included is the home team's form. So, one could say that MFK audience care more about special events (16th of may and the jazz festival) and less about the game itself. The fact that table position before the match both for MFK and the opponent plays no significant role is perhaps somewhat surprising, but does to some sense confirm the fact that MFK audience is less interested in football than showing up at the "right" matches.

The basic results of the model could perhaps be summed up as follows:

> *If MFK want to maximise its attendance, they should play all matches at home on the 16th of May, the jazz festival should be relocated from July to the May-week including the 16th of May, MFK must have won the 3 previous games, and all games should be played against RBK.*

Forecasting the model

Now, let us move to the main point: applying the model to produce forecasts. Let us assume that we do not know the attendance values beginning with the first MFK home game in 2002[15]. Then, the question to study in this paragraph is that of finding forecasts for "future" home matches in 2002. The typical problem with applying regression models in forecasting is that they normally lead to a situation where certain (or in fact all) of the explanatory variables also need to be forecasted. Then, if many explanatory variables are in the model, and many of them must be forecasted (to produce the sought forecast), the aggregated uncertainty of forecasting several variables (as opposed to one) might simply lead to bad forecasts. This is the classical argument for using time-series models, where the need for forecasting explanatory variables is simply not present. Still, previous arguments related to the "nature of events" indicates that time-series approaches might be unsatisfactory, and causal methods might simply be the only relevant alternative.

Moving into the case at hand, we observe immediately that the explanatory variables must be forecasted, but luckily, most of them are relatively easy to predict with almost 100% precision. Table 2.4 below sums up the situation.

The first variable, mfk_form is (given knowledge of the upcoming seasons match schedule) hardest to predict. Surely, this forecast depends heavily on what team we look at, and MFK might be one of the harder teams to forecast

[15] Obviously we do know these values of today, but this thought experiment should still be relevant.

Variable	Forecast accuracy
mfk_form	Poor forecast accuracy
rbk	100% prediction accuracy (when the match schedule is given)
mai_16	100% prediction accuracy (when the match schedule is given)
$stadion$	100% prediction accuracy (without new stadium plans)
$jazz$	100% prediction accuracy (when the match schedule is given)

Table 2.4: Forecast accuracy of explanatory variables

this variable for in Norway. Note also, that the difficulty of using these types of models for forecasting purposes depends a great deal on what variables we turn up including in the model. Roughly in this case, only one variable seems hard to predict. But remember that the original formulation also includes other teams form-variables – a much harder forecasting problem.

Anyway, let us return to the present case. The table below (2.5) sums up MFK's form for the "observed" seasons:

Season (t)	**95**	**96**	**97**	**98**	**99**	**00**	**01**
N_t	26	26	26	26	26	26	26
P_t	47	33	45	54	50	40	44
$\frac{P_t}{N_t}$	1.8	1.3	1.7	2.1	1.9	1.5	1.7

Table 2.5: MFK (point) performance

The first row in table 2.5 contains the observed seasons. The second row contains number of matches (N_t) in each of the observed seasons. The third row contains number of points (P_t) obtained in each season, while the final row contains computed average point score per season ($\frac{P_t}{N_t}$). Now, our task is to find an estimate (in principle dynamic) on the 3 last games average for the next (upcoming) season. It seems very difficult (though perhaps not impossible knowing the schedule) to produce individual match forecasts. So, top make things simple we settle for a static (constant) value for our proposed forecast for mfk_form. Various options exists ranging from a total period average up to using only the previous season. In this case, either of these estimates turns out to be the same as can be seen from the simple average calculation below:

$$\frac{1}{7}\sum_{t=1995}^{2001}\frac{P_t}{N_t} = \frac{1.8+1.3+1.7+2.1+1.9+1.5+1.7}{7} \approx 1.7 \tag{2.5}$$

Now, we can build our forecasts for the upcoming season. We assume that we need to forecast all home matches and that next seasons match schedule is available. This schedule is normally available well ahead of beginning of the season, typically before Christmas. Table 2.6 shows this information (the sequence of home matches for MFK) for the 2002 season:

	Match Schedule	**Variables**
1.	BRANN	-
2.	VIKING	-
3.	LSK	-
4.	MOSS	$mai\_16 = 1$
5.	VIF	-
6.	STABÆK	-
7.	ODD	$jazz = 1$
8.	LYN	-
9.	RBK	$rbk = 1$
10.	BRYNE	-
11.	START	-
12.	B/G	-
13.	SOGNDAL	-

Table 2.6: Home match schedule - 2002 season

Now, the necessary information to build the forecast for all home games in the upcoming season is available. Moving back to figure 2.7 we observe that the constant has a value of 2978.85. This means that no matter what (model-wise), at least this number will show up. The same holds for the *stadium* variable which adds 2815.065 to the attendance forecast. Consequently, under a reasonable assumption of no significant changes in the stadium infrastructure, $2978.85 + 2815.06 = 5793.91$ will show up independently of any other variables. Now, the effect of the performance quality of MFK can be added if we accept the argument above on an average point score forecast of 1.7. We get:

$$BaseForecast = 5793.91 + 1.7 \cdot 476.102 = 6601.5834 \approx \underline{6602} \tag{2.6}$$

Now, apart from the match against RBK (adding 6156.218) to the value of equation 2.6, the match at the 16th of May (adding 1860.794) and the match under the jazz festival (adding 1265.718) the value from 2.6 defines our forecast. Summing up, our forecast for the upcoming season is shown in table 2.7 alongside the observed attendance figures.

	Match Schedule	Forecast	Attendance
1.	BRANN	6602	6204
2.	VIKING	6602	5236
3.	LSK	6602	5055
4.	MOSS	8462	4817
5.	VIF	6602	6868
6.	STABÆK	6602	7810
7.	ODD	7868	8137
8.	LYN	6602	4902
9.	RBK	11758	11167
10.	BRYNE	6602	4303
11.	START	6602	5057
12.	B/G	6602	6105
13.	SOGNDAL	6602	4850

Table 2.7: Forecasted and observed attendance - 2002 seasons

It is perhaps easier to analyse the quality of our forecast model by plotting the forecasts and the observed attendances in the same figure, as shown in figure 2.8:

Examining figure 2.8, we observe reasonably good fit apart from a singular observation, the home match at the 16th. of May. This match (against MOSS FK) produced a surprisingly low attendance. This could of course be due to weather or maybe even an unattractive opponent, but still, apart from this point, the model performs surprisingly well as I see it. Remember that all information used to construct these forecasts are historic info and a relatively naive (simple) way of forecasting the $mfkform$ variable.

Short term forecasting

In this section (to demonstrate the technique), we will investigate short-term forecasting on these type of models. In previous paragraphs, we constructed forecasts for the whole upcoming season made at a single point in time. An alternative forecasting technique (here named short term forecasting) could be constructed by computing forecasts from match to match. Normally, such an approach opens up for producing better forecasts, but we are of course not guaranteed such an outcome in a given case. Still, the technique itself is relevant and will be demonstrated shortly.

First, however, a few words on applicability of these two different approaches. A short term forecast is interesting to apply if the planning or

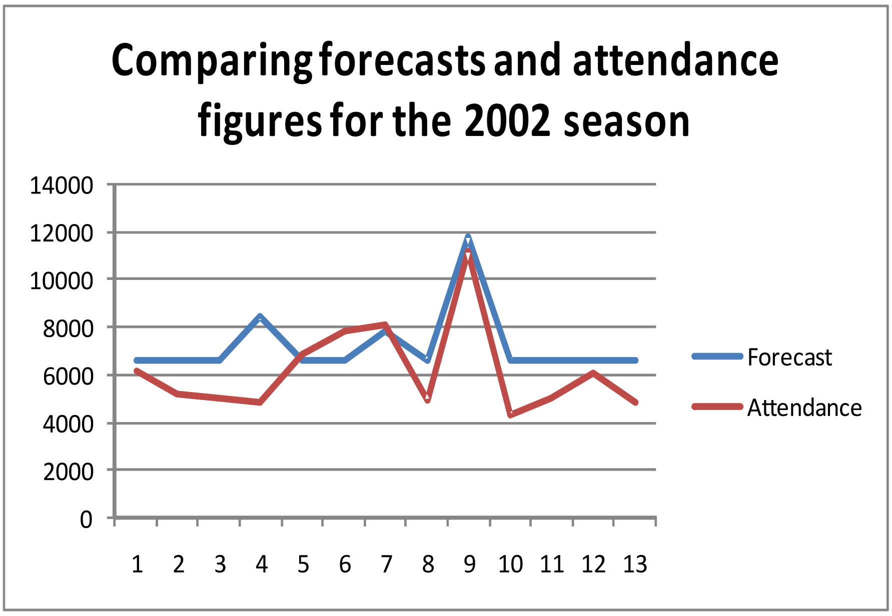

Figure 2.8: Forecasts vs. observed attendance for the 2002 season

decision we need the forecast for, can be executed before the next home game. In a logistics setting, such decisions will typically relate to lead times. Suppose we need to order soda for the next home match, and this soda can be ordered now and be delivered within a time period sufficiently short (the lead time) to reach the next home match. Obviously, we will not need forecasts for the rest of the upcoming home matches for the decision. However, other decisions, stadium capacity, for instance, or other decisions of more long term character (TV rights, sponsor money etc.) might need forecasts for longer periods of time.

In this case, the only difference in the methods relates to the values used for the mfk_form variable. Given a situation, where we produce forecasts from match to match, the forecast for the next match then leads to a different information availability compared to the situation above. (Recall that we used a very simple average over seasons for our value of 1.7 for this variable.)

Now, standing immediately before a match, we know the point score obtained by the home team in the 3 previous matches. Consequently, we can use this information and avoid using the forecasted constant 1.7-value, and can instead compute "correct" values for this variable. Surely, we need more information, but this is readily available at [7]. Table 2.8 holds the necessary information. (In addition, we need the three last home matches of the previous season, which turn out to produce $mfk\_form = 1.33$[16].)

Match	H/A	P	mfk_form	Match	H/A	P	mfk_form
1	H	3	1.33	14	A	0	-
2	A	1	-	15	H	1	1.00
3	H	3	1.67	16	A	1	-
4	A	0	-	17	H	3	0.67
5	H	1	1.33	18	A	3	-
6	A	0	-	19	H	0	2.33
7	A	3	-	20	H	3	2.00
8	H	3	1.33	21	A	3	-
9	A	3	-	22	H	3	2.00
10	H	3	3.00	23	A	3	-
11	A	3	-	24	H	3	3.00
12	H	3	3.00	25	A	0	-
13	A	0	-	26	H	1	2.00

Table 2.8: MFK - complete performance statistics for the 2002 season

As can be observed from table 2.8, MFK had a very decent season in 2002, gaining a total of 50 points ending up being second. What is interesting from our point of view, is the ability to produce dynamical forecasts for the mfk_form-variable. The calculations are straightforward. Recall the definition - the average points scored in the 3 previous games. As a consequence, the first home game (match 1 in the table) is calculated on previous season data (see above.) The second home match (match 3 in the table), is then computed by the two first games of the 2002 season (1+3=4 points) and adding the draw (1 point) from the previous season, giving the value of $\frac{1+3+1}{3} \approx 1.67$. The rest of the numbers are calculated similarly.

Now, the short term forecasts (STF_t) can easily be computed by the following formula: (t runs over all home matches in table 2.8.)

$$\mathrm{STF}_t = \begin{cases} 5793.91 + 476.102 \cdot mfk\_form_t & \forall t \backslash \{8, 15, 19\} \\ 5793.91 + 476.102 \cdot mfk\_form_t + 1860.794 & t \in \{8\} \\ 5793.91 + 476.102 \cdot mfk\_form_t + 1265,718 & t \in \{15\} \\ 5793.91 + 476.102 \cdot mfk\_form_t + 5156.216 & t \in \{19\} \end{cases} \tag{2.7}$$

[16]MFK gathered 4 points in matches 24 (3), 25 (0) and 26 (1) in the 2001 season. As a consequence, the mfk_form variable is computed as $\frac{4}{3} \approx 1.33$

Applying equation (2.7) with the data from table 2.8, results are obtained as shown in table 2.9:

	Match Schedule	***STF***	**Attendance**
1.	BRANN	6427	6204
2.	VIKING	6589	5236
3.	LSK	6427	5055
4.	MOSS	8288	4817
5.	VIF	7222	6868
6.	STABÆK	7222	7810
7.	ODD	7536	8137
8.	LYN	6113	4902
9.	RBK	12059	11167
10.	BRYNE	6746	4303
11.	START	6746	5057
12.	B/G	7222	6105
13.	SOGNDAL	6746	4850

Table 2.9: Short term forecasts and observed attendance - 2002 seasons

Comparing these short term forecasts with the original ones as well as the historical attendance data is easily done through a figure, as in figure 2.9.

It is easily observed from figure 2.9 that the short term forecasts are initially better. The green curve is closer to the red curve (though not very much). In the mid parts we observe some variations, but from around home match 5 up to 7, the new short term forecasts perform better. However, by the end of the season, we see the opposite situation, where the original forecasts perform better than the short term ones. So, it is not obvious which of these two forecast methods that will turn out to be the best one. In order to compare with more exactness, some kind of error measures needs to be calculated. In logistics, MAD[17] (Mean Absolute deviation) is normally used, and in order to shed some more light on this comparison, MAD for the two models are computed in table 2.10.

As table 2.10 indicates, both methods perform relatively equally, but the short term (presumably best) forecasts perform worst. So our initial hypothesis of utilizing more and better data leading to general forecast improvement in the one-step (short term) final method did not work out. In fact this is a good example, because it shows that there are no guarantees when fore-

[17] $MAD = \frac{1}{N}\sum_{t=1}^{N}|F_t - D_t|$ with D_t being actual demand, N number of observations and F_t forecasted demand.

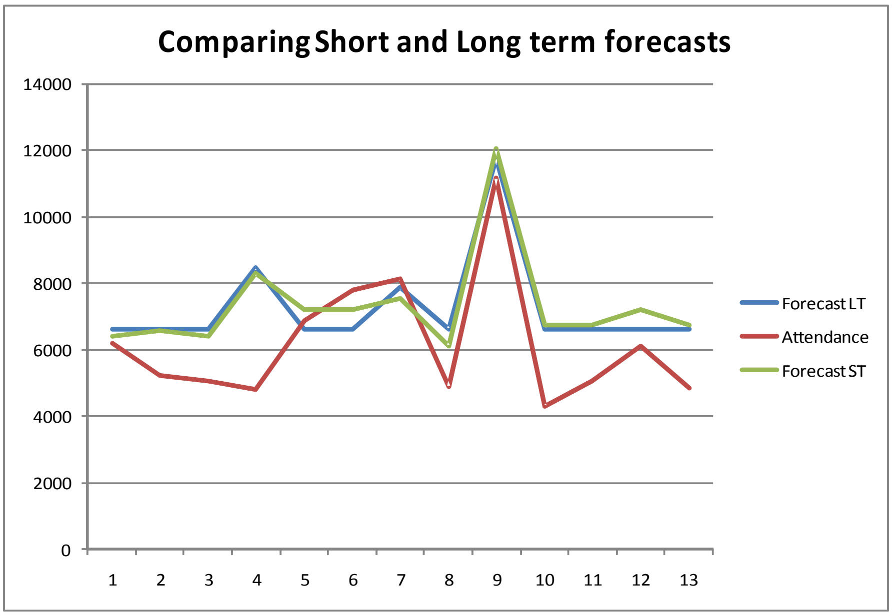

Figure 2.9: Short and long term forecasts compared to actual attendance - 2002

	Match Schedule	MAD *LTF*	MAD *STF*
1.	BRANN	398	233
2.	VIKING	1366	1353
3.	LSK	1547	1372
4.	MOSS	3645	3471
5.	VIF	266	354
6.	STABÆK	1208	588
7.	ODD	269	601
8.	LYN	1700	1211
9.	RBK	591	892
10.	BRYNE	2299	2443
11.	START	1545	1689
12.	B/G	497	1117
13.	SOGNDAL	1752	1896
	MAD	**1314**	**1324**

Table 2.10: Short term forecasts and observed attendance - 2002 seasons

casting is the business. However, the reason for these somewhat unexpected results is actually very easy to find (in retrospect). This season, the 2002 season was a season where the big favourite (RBK) started out very poorly and the dark horse LYN lead the league most of the season. MFK, however, started out reasonably and stayed second most of the season. It might be that this season, turned on fans expectations for a league win (the first one ever), and the form variable turns out to improve the forecasts in the early parts of the season. However, during the season, LYN deteriorated (slowly), while the big favourite RBK started to improve. It might well be that the MFK audience lost their hopes (especially I believe) after the home loss against RBK in home match 9. As such, one might have expected an overestimation of attendance figures by the end of the season - especially by the short term model. The facts are that MFK actually played very well by the end of the season. But it might very well be that the audience had kind of lost hope for the first ever victory. This can kind of be observed from table 2.9 for matches, 10, 11, 12 and 13 where the short term forecasts systematically overestimates attendance compared to the long term forecasts.

This (retrospective) hypothesis can of course be relatively easily tested by restricting the MAD calculations up to and including home match 9, the match against RBK. Doing so, we find a MAD of 1221 in the long term case, and 1118 in the short term case, a MAD (significant) decrease around 10%, which of course corresponds better with our initial hypothesis.

2.3.2 The effect of Pre-sales

Pre-ordering or pre-sales may be defined as deciding to buy or buy a product before it is available for sale. As events tend to take place at discrete time spaces with “some air in between”, pre-sales is possible and interesting for event producers. Actually, this is more of a norm than an exception in this area. In traditional manufacturing, this is perhaps more of an exception, but we observe certain products utilizing these mechanism nowadays. Typically, it may be hyped products such as announced computer games, or certain new technology like IPADs or hyped cell phones. But, we also see this occurring in more traditional markets; cars, for instance, may be pre-ordered these days. From a logistic and forecast point of view, this is obviously a benefit. If you pre sell seats for a concert, then you know (with certainty) that at least this number will turn up or at least you know with certainty that the given ticket money will be certain. This is a typical situation in football matches where seasonal tickets guarantee the income, but may not guarantee that persons show up.

Pre-sales products may take different forms. They may be restricted to a single event or more than one event. Seasonal tickets pre-sells a whole home season of matches, and certain special combined tickets (day-passes) are sold in festivals covering up more than one event. This latter products are often referred to as bundles (bundling) in economic theory.

Some (relatively limited) research has been done mainly on time-series modelling - see for instance [10] and [17]. We will not pursue this models further, but limit our discussion to causal (regression-type) models. We choose to do this, not only due to the complexity of the time-series cases, but also due to the "event-arguments" presented previously.

Obviously, we see different types of pre-sale situations, not only various bundling options as discussed above, but also different choices when it comes to numbers and time periods. Certain event-producers may choose to limit the possible number of pre-sold tickets to less than ticket capacity others may not. Certain event producers may choose to define a pre-sales period ending in reasonable time before the normal sales takes place. A football club such as MFK is a good example of both of these types of situations.

MFK's home ground - Aker Stadion - has a capacity of 11167[1] today. Still, the stadium record is 13308[18] from a game against RBK (who else) back in 1998 [1].

MFK chose (before this season) to limit the number of seasonal tickets to less than the capacity. Surely, this is a kind of luxury problem (e.g. having the option of selling out capacity on pre-sales), but certain football clubs have this option (typically the biggest and most popular, like MUFC and Barcelona. But due to some special circumstances this season, (hiring a new coach named Ole G. Solskjær) this option seemed to pop up for MFK. Anyway, they chose to limit the number of pre-sold tickets. Such a strategy, given that demand is bigger than supply, will of course also lead to the second type of situation; that is, pre-sales ends before regular sales starts.

So, as of today, (December 2010), MFK has sold out their defined available seasonal tickets and as a consequence, they know (with certainty) that the total demand for all next year's matches will be larger than or equal to this number. What they do not know with certainty is how many of these seasonal ticket customers will show up on the stadium in each of the matches. From a logistical point of view, these numbers are perhaps just as interesting as the financial consequences of having certain income. After all, most logistics problems is about handling actual demand at the event when it takes place. However, to keep complexity at a reasonable level, we assume that all seasonal ticket customers show up at the stadium in our simplified treatment

[18] The reason for this difference is due to varying FIFA/UEFA regulations on the number of seats.

of the situation.

Let us investigate the situation from a mathematical point of view. Using the notation from above, total demand for a certain match t, att_t, can be expressed as:

$$att_t = att_t^{ST} + att_t^{NT} \tag{2.8}$$

where att_t^{ST} and stt_t^{NT} hold customers buying seasonal and normal tickets respectively. Alternatively and slightly more complex, a new decomposition could be added;

$$att_t^{ST} = att_t^{ST_{su}} + att_t^{ST_{nsu}} \tag{2.9}$$

where $att_t^{ST_{su}}$ holds seasonal ticket customers showing up at match t, while $att_t^{ST_{nsu}}$ are not showing up. Now, suppose MFK (or any general event producer) are able to perform the decomposition (2.8) on historical data. The meaning of this statement is simply that they have registered not only the total demand, but one of the other components of equation (2.8) as well - typically this would be att_t^{ST}. Then, the following strategy for adjusting a regression model to adopt pre-sales situations is feasible:

1) Compute att_t^{NT} by 2.8

2) Establish a regression model with att_t^{NT} as the dependent (Y_i) variable

3) Predict att_t^{NT} by the model from 2) and add the known (or forecasted) att_t^{ST} to produce a final forecast for att_t.

A similar procedure can of course be defined if information of the decomposition (2.9) is available.

There are, however, certain methodological problems related to the above outlined procedure. Firstly, information may be lacking and there may be certain differences between various situations. For instance, seasonal tickets may show very different price profiles over time. MFK is a very good example on this. As such, the informational content about the share of seasonal tickets between seasons may be highly questionable. Secondly, and probably more important, there is an obvious possibility of dependence (correlation) between seasonal and non-seasonal tickets. Suppose MFK have chosen a relatively low price strategy for seasonal tickets in a given season. Then (clearly) one would expect less non-seasonal tickets sold in most matches as opposed to the opposite situation. Such logic will typically produce methodological problems in applying simple regression analysis. Without going into details, the answer is then to do things differently, and model a system of equations instead of a single equation. Such an approach is (surely) feasible, but far ahead into relatively advanced econometric theory, clearly outside the scope of this text.

Consequently, a different approach may be more suitable. Suppose (just as an example) that MFK this season has sold 7000 seasonal tickets. Also suppose that a regression model has produced the forecasts of table 2.7. Even though the numbers of table 2.7 are invalid for the upcoming season, they prove a relevant point.

Given the initial assumption of 7000 sold seasonal tickets, a forecast of 6602 is of course silly. If we know that at least 7000 tickets are sold for all matches, surely we should adjust our forecast to take this information into consideration. A very naive way of adopting this might be simply to adjust all forecasts below 7000 up to 7000, but this is neither correct nor sensible. Remember the basic point in regression, minimizing the squared errors. A strategy of simply adjusting some forecasts will most probably not correspond with a model that minimizes the sum of the squared errors.

Hence, we need to adopt a strategy which is bit more logical and slightly more complex. The general multiple linear regression model is defined in equation (2.1). Solving with respect to the error terms ϵ_i yields:

$$\epsilon_i = Y_i - \left\{ \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \right\} \tag{2.10}$$

Squaring the error terms yields:

$$\epsilon_i^2 = \left[Y_i - \left\{ \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \right\} \right]^2 \tag{2.11}$$

and defining;

$$S^2(\beta_0, \ldots, \beta_N) = \sum_{i=1}^{M} \epsilon_i^2 \tag{2.12}$$

The classical regression problem can then be formulated as

$$\min_{\beta_0 \ldots, \beta_N} S^2(\beta_0, \ldots, \beta_N) \tag{2.13}$$

The meaning of equation (2.13) is straightforward. We want to find values for unknowns $\beta_0, \ldots, \beta_N$ which provide the minimal value for the function $S^2()$.

The situation we have formulated above is, however, somewhat different. We know that the forecasted value of our model should at least be larger than a certain value (7000 in the example). Hence, this information should be added to equation (2.13) as a constraint. In general terms, say that the amount of seasonal cards already sold is named $\underline{\mathrm{Y}}$. Then, the minimization problem of equation (2.13) can be reformulated to:[19]

$$\begin{array}{rl} & \min_{\beta_0 \ldots, \beta_N} S^2(\beta_0, \ldots, \beta_N) \\ s.t & \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \geq \underline{\mathrm{Y}} \end{array} \tag{2.14}$$

The seemingly slight difference between equations (2.13) and (2.14) has significant consequences for solution strategies. The optimization problem of equation (2.13) is unconstrained on a "well behaved" function with a well known analytical solution. However, the problem of equation (2.14) is constrained (a quadratic objective with a linear constraint) and is hence normally classified as a **quadratic programming problem** (**QP**). A **QP** is in general relatively easy to solve (normally marginally harder than an **LP**). However, neat analytical solutions do in general not exist, and in most cases we need to apply specialized software, for instance, LINGO, CPLEX or the Excel solver.

Let me try to sum up a little bit. The fact that events in most situations (naturally) open up the option of pre-sales, should and will in most cases lead to better (more accurate) forecasts. However, to achieve these improved forecasts, the methodology may change and may lead to increased methodological complexity.

2.3.3 Capacity constraints

Capacity constraints on product demand is another concept typical for events. As briefly discussed above, (see Subsection 2.3.2), most events will have certain constraints on maximal attendance. This may be due to physical constraints, size of the concert hall or stadium or related to various security means. Even though most manufacturing markets will have upper bounds on some kind of maximal demand (it may, for instance, be very unlikely to sell an Ipad to each world citizen), in practice such upper bounds for manufacturers are almost never relevant, interesting or binding as we say in OR terms[20]. As a consequence, this is a typical topic for events. Obviously, it is

[19] Recall from regression analysis that the error terms are assumed $No(0, \sigma_\epsilon^2)$; hence when predicting through a regression equation, the expected value of the error terms are always zero.

[20] Actual competitive markets will almost always disqualify a given producer from capturing the whole market

a "luxury problem". If an event producer is in a market situation where customers routinely buy the whole capacity, he should be very happy. Still, in a forecasting perspective, this information must be considered if high quality forecasts are to be produced.

As with the lower bound in the previous section, an upper bound must be added to the basic forecasting model. This will work almost exactly like the pre-sales case in the previous subsection - the only difference is the choice of inequality sign in the constraint. Now, our forecast should be forced to be under the capacity limit. Hence, in the MFK case, a upper bound of 11167 must be added to the simple regression model.

It may be interesting to look back on our previous unconstrained forecasting examples. If we examine tables 2.7 and 2.9, we observe two forecasts actually violating the capacity constraint. Our model produced a long term forecast of 11758 for the RBK-match in the 2002 season. Clearly, the capacity constraint of 11167 is violated. The same is observed in the case of the short term forecast (table 2.9 where the forecast for the same match was calculated to 12059 - an even greater violation. As this upper limit of 11167 was defined before the 2000 season, surely this information was available and should be incorporated in the forecasting model.

Again, it may be tempting just to scale down these two forecasts to the capacity upper bound, but the argument on minimizing sum of squares still should hold. Hence, an adjusted regression version would look like ($\bar{\mathrm{Y}}$ is the upper capacity limit)

$$\begin{array}{rl} & \min_{\beta_0 \ldots, \beta_N} S^2(\beta_0, \ldots, \beta_N) \\ s.t & \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \leq \bar{\mathrm{Y}} \end{array} \tag{2.15}$$

Surely, in most situations, both pre-sales and capacity constraints may be present, and a constrained regression model such as

$$\begin{array}{rl} & \min_{\beta_0 \ldots, \beta_N} S^2(\beta_0, \ldots, \beta_N) \\ s.t & \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \leq \bar{\mathrm{Y}} \\ & \beta_0 + \sum_{j=1}^{N} \beta_j X_{ij} \geq \underline{\mathrm{Y}} \end{array} \tag{2.16}$$

should be used. Both models (2.15) and (2.16) are **QP**'s (like the model of equation (2.14)) and must be solved by mathematical programming software as opposed to standard regression analysis tools like SPSS, which was applied to produce the forecasts in tables 2.7 and 2.9.

2.4 Aggregated versus disaggregated forecasts

The title *aggregated* versus *disaggregated* forecasts relates to different levels of forecasts. In events (as argued previously), the normal situation is a one-time situation or a situation with a lot of time in between events. As a consequence, the main problem for a given event demand forecast is perhaps more the ability to break down an aggregated forecast into a set of disaggregated forecasts. Think about Olympic Games. Surely, it is hard enough to forecast total demand (number of visitors coming to see the games), but it is perhaps even harder and also more relevant from a logistics point of view, to be able to break down the total demand into single event demands. Given a reasonable forecast for total demand, say F_{TOT}, how does this decompose into various events as indicated by equation 2.17?

$$F_{TOT} = F_{\text{100 meters running}} + F_{\text{Handball}} + \cdots + F_{\text{50 M back swimming}} \tag{2.17}$$

In equation (2.17) an underlying assumption of parallel events is (of course) inherent.

In general, it is harder to forecast at an disaggregated level than an aggregate level. Think about a car producer. It may be fairly easy to get a reasonable forecast on the total number of cars sold next year. However, the various brands, engine sizes, extra equipped and coloured cars may be much harder to guess. The same applies in disaggregated event forecasting. Even if you are able to foresee the total number of tickets sold at the Molde International Jazz Festival, the disaggregated level, that is, who will attend the Charlie Parker, Dizzie Gillespie, Dexter Gordon[21] etc. concerts might be way tougher.

In a logistics setting, it is these disaggregated forecasts which are the most relevant. The reason should be obvious. Resource consumption by event audiences are of course mostly related to singular events; proportional to audience numbers, and hence in a logistics setting, we are normally more interested in disaggregated than aggregated forecasts.

A typical (practical) approach could be to use some kind of formal method to arrive at a forecast for total demand $\hat{F}_{TOT}$ and then either formal or less formal try to decompose the total demand into singular event forecasts. Producing some shares, say α_i, as the share of total demand for singular event i could be a reasonable approach. Then, given the existence of a forecast-

[21] RIP.

share $\hat{\alpha}_i$, one could produce the wanted disaggregated forecast for singular event i by:

$$\hat{F}_i = \hat{\alpha}_i \cdot \hat{F}_{TOT} \tag{2.18}$$

There is, however, some obvious practical problems involved in arriving at reasonable $\hat{\alpha}_i$'s. At least, we can differentiate between two types of events. 1) Certain events will have the same content in each event from one arrangement to another. Sports events will typically be like this. The 100 meters run is (more or less) the same from one Olympics to another. 2) Other events, like musical festivals will, however, have different artists on the opening and final days from one year to another. As a consequence, one must be careful by copying consumer preferences in between events.

Another problem, typically arriving in sports mega events, is related to difference in location. Almost always, sports mega events, (Olympic games, football World Championships etc.) are relocated form one instance to the other. And very often very far. For football WC's for instance, it is Europe one year, Latin America 4 years later, and then perhaps Africa or Asia after 4 new years. Consequently, possible $\hat{\alpha}_i$'s fitting good one year might fit very bad 4 years after, as the average spectator may change substantially moving from one continent to another. In such a situation, a combination of information related to the actual mega-sports event but paired with attendance (spectator) behaviour related to localization should perhaps be a guidance for establishing "good" $\hat{\alpha}_i$'s.

In addition to the above mentioned problems, time keeps moving fast. Typically, at least a year (musical festivals) and up to 2 or 4 years (sports mega events) passes between events, and consumer behaviour observed in one event might change simply due to time.

As a consequence, arriving at good forecasts for arrangements within events may be hard. Still, the need is obvious to be able to perform logistics planning.

Chapter 3

Events and Inventory Management

3.1 Inventory Management - Introduction

3.1.1 The EOQ model

Inventory management deals, in its simplest form, with balancing the trade off between inventory and order costs. The basic modelling hence assumes two cost elements; a binary order cost occurring when each order is placed, and an inventory cost, proportional to inventory levels, (actual or average).

The basic classic model, found by minimizing total (average) inventory and order costs, often referred to as Wilson's formula, the square root formula or the EOQ formula, then states that the optimal order quantity Q^*(using the notation of Nahmias [21]) can be found by:

$$Q^* = \sqrt{\frac{2K\lambda}{h}} \tag{3.1}$$

where K is the cost placing an order, h is the cost per unit stored (on average) and λ is demand for the actual planning time period.

The modelling leading to the EOQ formula (3.1) makes some serious assumptions. Among these, the two most relevant are:

1) Constant demand over time

2) Deterministic (perfectly predictable) demand

Both these assumptions are of course highly unrealistic in most practical situations. Typically, we will not know demand with certainty, and the time profile of the demand forecasts will not be constant. Our example from Chapter 2 shows this very clear. Our forecasts did not hit perfectly, and demand throughout the 2002 season did not turn out to be constant.

Still, the simple EOQ formula has proven itself to be practically valuable due to its simplicity and as a tool for finding approximate solutions.

3.1.2 Applying the EOQ approximately

Let us return to our long term forecast from table 2.7, as shown in table 3.1

Home game	1	2	3	4	5	6	7
Forecast	6602	6602	6602	8462	6602	6602	7865
Home game	8	9	10	11	12	13	-
Forecast	6602	11758	66022	6602	6602	6602	-

Table 3.1: Forecasted attendance demand for MFK home games - 2002 season

Let us further assume that MFK's experience is that (on average) 1% of their spectators buys a bottle of coke during a match, and MFK needs to determine how much coke to buy and when. The assumption of 1% coke buyers leads to a simple calculation of future coke demand based on attendance demand by simply dividing all forecasts in table 3.1 by 100 leading to (rounding the numbers) the coke demand forecasts as shown in table 3.2

Home game	1	2	3	4	5	6	7
Forecast	66	66	66	85	66	66	79
Home game	8	9	10	11	12	13	-
Forecast	66	118	66	66	66	66	-

Table 3.2: Forecasted coke demand for MFK home games - 2002 season

By further assuming that the inventory costs (h) between home games are \$0.2 and order costs (K) each time coke is ordered, amounts to \$100, the EOQ formula can be applied as an approximate solver for finding the optimal purchase strategy.

In the formula, the only missing information is λ, average periodic demand, which is easily found by adding all numbers in table 3.2 and dividing by 13 to obtain the average. We find:

$$\frac{10 \cdot 66 + 85 + 79 + 118}{13} \approx 72.5 \tag{3.2}$$

And the EOQ formula (3.1) then becomes:

$$Q^* = \sqrt{\frac{2 \cdot 100 \cdot 72.5}{0.2}} \approx \underline{269} \tag{3.3}$$

As a consequence, each time we order, we should order 269 bottles of coke. In practice, when approximating through the use of this formula, we need to make some adjustments if actual forecasts are not constant. Table 3.3 below illustrates this here.

Home game	1	2	3	4	5	6	7
Forecast	66	66	66	85	66	66	79
Ordered	269	-	-	269	-	-	-
Inventory	203	137	71	255	189	123	46
Home game	8	9	10	11	12	13	-
Forecast	66	118	66	66	66	66	-
Ordered	269	-	-	269	-	-	-
Inventory	247	129	63	266	200	184	-

Table 3.3: Purchase plan for coca cola; MFK home games - 2002 season

Note that we have chosen to buy 269 also before home game 11. As our planning horizon, stops at home game 13, we will end up with "too much" inventory in the final period. Obviously, we could have adjusted to end up with a smaller amount of rest inventory after the last home game, but as this is coke, we might perhaps just as well keep some for the next season.

The total costs of this purchase plan are easy to calculate. We simply add all inventory numbers together, multiply by the inventory cost of 0.2 and add 4 times the order cost of 100. This gives a total cost for the approximate plan of $2113 \cdot 0.1 + 4 \cdot 100 = \underline{611.3}$

3.1.3 The Lot-sizing approach

Classical Lot-sizing relates to production planning, not Inventory Management. Let us, however, examine the classical production lot-size model in a Mathematical Programming setting. As discussed in the course previously, a mixed integer linear programming formulation of the simple lot-size problem is shown below in equations (3.4) – (3.8).

$$\text{Min } Z = \sum_{t=1}^{T} K_t \delta_t + h_t I_t + c_t x_t \tag{3.4}$$

s.t.

$$x_t + I_{t-1} - I_t = d_t \quad \forall t \tag{3.5}$$
$$0 \leq x_t \leq M_t \delta_t \quad \forall t \tag{3.6}$$
$$I_t \geq 0, \quad \forall t \tag{3.7}$$
$$\delta_t \in \{0, 1\} \quad \forall t \tag{3.8}$$

In the production planning setting, x_t is produced amount, I_t is stored amount, δ_t is a binary variable defining if production takes place in time period t. These variables define the decision variables in the optimization model. The parameters K_t, h_t, c_t, T and M_t holds per period Set-up costs, inventory costs, production costs, number of time periods and "Big M's" respectively.

The simple point is that the inventory management or purchasing situation exactly resembles the situation described by the above model with some simple reinterpretation of variables and parameters. If set-up costs K_t are substituted with ordering costs, we achieve the required purchasing logic. That is, if an order is placed, (and only then) a order cost of K_t occurs. Furthermore, if production amounts are substituted by ordered amounts and production costs c_t are interpreted as purchase costs, the model above works perfectly in the inventory management setting.

In order to derive an exact solution, the problem with $h_t = 0.2 \forall t$, $K_t = 100 \forall t$, $c_t = 0 \forall t$, $T = 13$ and d_t picked from table 3.2 must be fed into some kind of solver software. Here, LINGO is used, and the actual LINGO-formulation as well as the solution file is presented in appendices C and D.

As can be observed (Appendix D), the optimal solution costs 607. A relatively modest change from the EOQ-approximate solution of 611.3 (see above). The major structural change between the two solutions is that the optimal solution involves three purchase points (before home matches 1,5 and 9) as opposed to the 4 of the approximation (before home matches 1, 4, 8 and 11). Still, the EOQ approximation turned out quite nice here, as the objective improvement was only around 7%.

Also note that by utilizing a similar reinterpretation as above, an additional intermediate approximative solution could be obtained by the Silver-Meal heuristic - see Nahmias [21].

3.2 Event Inventory Management - "News-boy" setting

3.2.1 "News-boy" basics

The above examples, will not be very representative for what we previously have labelled "one-shot"-events. Both model types above assume the possibility of storing the actual resource in between events. This assumption might work good for running event producers such as a football team or a jazz-club, but not in the case of festivals. Most festivals happen once a year, and the possibility of storing resources between events may be unavailable, either due to durability issues or simply due to festival uniqueness. A typical example on the latter type could be some kind of gadget sold as a proof of entering the given event. The Molde International Jazz Festival (MIJF) sells, for instance, t-shirts.

Another argument (also discussed previously) against the above modelling types, is uncertainty. When the focus is on festivals or mega-sport events with long time periods between event arranging, one should expect forecasting to become significantly harder. Then, it might seem far more sensible to try to take such uncertainty into account - model-wise.

The "News-boy" model seems to be a very adequate candidate for covering such types of situations. In a classical "News-boy" model, a certain demand (assumed, uncertain and described by a probabilistic mechanism) for some product is present. The product is bought at a certain price, and then sold typically at a higher price in the normal demand period. Furthermore, after the normal (in-event) demand period, the product can still be sold, but for a less favourable price (typically assumed smaller than the buying price). Hence, this situation resembles our inherent "one-shot" event definition. During the event, a certain monopolistic situation occurs, creating an in-event demand. This demand changes after the event, typically in a negative direction. The decision to make in the model is the ordering quantity (Q^*). That is, how much to buy of a given resource before the event. Even though we have used the gadget as a symbol of this type of demand, it should be fairly easy to see that this situation actually fits most resource purchases for an event, at least those resources which maybe sold in an in-event market. Food and drinks will of course also have similar characteristics. The beer is typically more expensive within premises of the event than outside. As a consequence, this modelling concept ought to be very interesting for event inventory planning. To some extent, the term inventory management may be somewhat misleading here - as the model is a single period model, but the purchasing dimension is present. Hence, even if normal inventory decisions (how much to store between each model period) is not within the basic "News-boy" modelling concept, this family of models still tend to be placed within the inventory management category (see e.g. Nahmias [21]).

Let us examine the results of the basic "News-boy" model. (We skip the mathematical derivation, and simply refer to Nahmias [21] or Ravindran et. al. [24] for complete background information.)

Input for the model is given by: (Parameters α and β are given lower and upper bounds for demand outcome respectively.)

$$\begin{aligned} f(Q) &: \text{ Probability density for demand } Q \in [\alpha, \beta] \\ c_o &: \textit{ overage cost}\text{, cost per unit of positive remaining inventory} \\ c_u &: \textit{ underage cost}\text{, cost per unit of unsatisfied demand} \end{aligned}$$

The optimal order quantity Q^* is then (in the continuous case) found by solving;

$$F(Q^*) = \frac{c_u}{c_u + c_o} \tag{3.9}$$

where $F(Q^*) = \int_a^{Q^*} f(Q)dQ$. If we choose a discrete probabilistic formulation (e.g. change from the continuous $f(Q)$ to a discrete $P_x(Q) = P(x \leq Q)$), the solution changes slightly to:

$$P_x(Q^*) \geq \frac{c_u}{c_u + c_o} \tag{3.10}$$

3.2.2 A simple T-shirt example

Now, let us illustrate an application of the "News-boy" model from Subsection 3.2.1 through a simple event-oriented example. MIJF sells t-shirts, one or several special made for each festival.

One key question for the festival (apart from the pricing policies for the t-shirts, briefly discussed in Section 3.3) is the amount to order or buy. If MIJF orders too few, they lose potential sales profits, but if they order too many, they will have to sell the remaining t-shirts at a lower price. Let us first assume that the sales of these t-shirts are proportional to attendance numbers. That is, the more tickets to concerts sold, the more t-shirts are sold. This seems to be a reasonable assumption, but it may well be that it is too simplified. Furthermore, let us assume the sales of a single t-shirt to simplify even more. Let us continue by examining some available statistics. Table 3.4 contains total ticket sales from 2005 up to 2009 [26].

Year	2005	2006	2007	2008	2009
#Tickets	28074	27081	29889	30173	34704
#T-shirts	9358	9027	9963	10058	11568

Table 3.4: Tickets (and t-shirts) sold at MIJF: 2005 – 2009

Now, in this example, we are not interested in the number of tickets sold, but the number of t-shirts sold. And our simplifying assumption of a proportionality between tickets and t-shirts comes handy to construct t-shirt demand (the final row in table 3.4). Obviously, to arrive at this row, we must specify this proportionality, and based on some loose information from the MIJF management, we choose the following: for each third ticket sold, one t-shirt is sold. As a consequence, the final row is found simply by dividing the second row by 3.

Looking at table 3.4, we observe a positive trend, but not a clear pattern. Hence, some uncertainty regarding the possible ticket sales for the upcoming 2010 festival[22] seems reasonable.

In order to complete the example, finding the number of t-shirts (Q^*) that MIJF should order before the (no gone) 50 years anniversary 2010 festival, we need two bits of additional information:

1) $f(Q)$

2) c_u and c_o

The only available information for addressing the content of the probability density function $f(Q)$ is the content of table 3.4. How to do this is clearly not obvious. Nahmias [21] provides an example where a histogram is constructed and then a discrete probability density. This might be acceptable in a situation where you have a reasonable amount of observations. Unfortunately, our data sources for the ticket sales (and hence also the t-shirt demand) is far from adequate. We are stuck with only 5 observations, far to restricted for such an approach. So, what could we do? One approach could simply be to try to use some continuous density functions roughly spanning the observed area. Figure 3.1 indicates a possible approach.

If we take a closer look at figure 3.1, we observe that two different densities have been suggested. To the left, a somewhat pessimistic approach - a uniform distribution meaning that anything in between 9000 and 1300 t-shirts could be sold with equal probability. To the right, a far more optimistic

[22]At the time of writing, the 2010 festival is long gone, and it is possible to obtain the ticket sales for this year. However, we assume lack of knowledge of this number here.

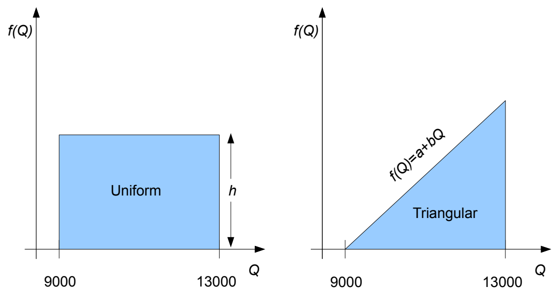

Figure 3.1: An optimistic and a pessimistic density for t-shirt demand.

(triangular) version is suggested where more probability mass is located to the right (more sales). In retrospect, perhaps the left uniform alternative would have been the best, recalling the extremely bad weather during the first part of the festival. However, thinking as if we are standing before the festival, a more optimistic approach may have seen to be better - after all, a 50 years anniversary should indicate some special event with really great artists and much audience.

The numbers 9000 and 13000 are of course important. They are chosen on the basis of the minimal and maximal historic observations from table 3.4 roughly by simply rounding down 9358 to 9000 and rounding up 11568 to 13000. The reason for rounding up more on the positive (right) side is again due to the previous argument on a big anniversary festival. Recall, that the approach of defining $f(Q)$ on a closed interval $[\alpha, \beta]$ effectively means that the probability of selling t-shirt amounts below α and above β is zero.

Now, to be able to apply equation (3.9), the distribution functions $F_U(Q)$ and $F_T(Q)$[23] must be found. The first step in a two stage procedure involves finding mathematical expressions for the densities - $f_U(Q)$ and $f_T(Q)$. The structure of the two density functions may be outlined directly as:

$$f_U(Q) = \begin{cases} h & \text{if } Q \in [9000, 13000] \\ 0 & \text{elsewhere} \end{cases} \tag{3.11}$$

$$f_T(Q) = \begin{cases} a + b \cdot Q & \text{if } Q \in [9000, 13000] \\ 0 & \text{elsewhere} \end{cases} \tag{3.12}$$

[23]The subscripts $_U$ and $_T$ refers to the Uniform and Triangular alternatives respectively.

Then, our task is to identify the three unknown constants h, a and b in equations (3.11) and (3.12).

h is easy to find, as total probability mass (the area of the rectangle of to the left in figure 3.1) must equal 1. We find:

$$h(13000 - 9000) = 1 \Rightarrow \underline{h = 0.00025} \tag{3.13}$$

To establish a and b, we must utilize the same (argument as above), as well as the fact that $f_T(Q = 9000) = 0$. We get:

$$\begin{aligned} \frac{(13000 - 9000) \cdot (a + b \cdot 13000)}{2} &= 1 \\ a + b \cdot 9000 &= 0 \end{aligned}$$

or slightly rewritten as

$$a + b \cdot 13000 = 0.0005 \tag{3.14}$$
$$a + b \cdot 9000 = 0 \tag{3.15}$$

The above linear system of equations with two unknowns are easily solved by subtracting 3.15 from 3.14 giving:

$$(13000 - 9000) \cdot b = 0.0005 \Rightarrow b = \frac{0.0005}{4000} \Rightarrow \underline{b = 0.000000125} \tag{3.16}$$

and

$$a + 0.000000125 \cdot 9000 = 0 \Rightarrow \underline{a = -0.001125} \tag{3.17}$$

The second step would then involve transforming the density functions $f_U(Q), f_T(Q)$ into distribution functions $F_U(Q), F_T(Q)$ by: (it is easier done by keeping the original letters (h, a, b) than substituting in numbers)

$$F_U(Q) = \int_\alpha^Q h dQ \tag{3.18}$$

and

$$F_T(Q) = \int_\alpha^Q (a + b \cdot Q) dQ \tag{3.19}$$

giving;

$$F_U(Q) = \int_\alpha^Q h dQ = [hQ]_\alpha^Q = h(Q - \alpha) \tag{3.20}$$

and

$$F_T(Q) = \int_\alpha^Q (a+b \cdot Q) dQ = \left[aQ + \frac{b}{2}Q^2\right]_\alpha^Q = a(Q-\alpha) + \frac{b}{2}\left(Q^2 - \alpha^2\right) \tag{3.21}$$

Now, the left part of equation (3.9) is taken care of through the two alternative expressions for $F(Q)$ in equations (3.20) and (3.21). The remaining necessary information is then related to obtaining values for c_u and c_o. Luckily[24], this information (at least partially) is available. It turns out that the t-shirt's ordinary (in festival) price last year (2010) WAS 180 NOK, while the post festival price is 30 NOK (see [4]). Unfortunately, we also need information on the buying price (or production cost) for the t-shirts. This information is typically harder to obtain. After all, if the festival buys cheap t-shirts from China and sell them expensively, market knowledge about it may affect demand negatively. Hence, most event producers in this situation will be reluctant in providing this information publicly. As a consequence, we are left by guessing, and a reasonable guess could be 50 NOK as the total buying/producing costs for each shirt. Now, c_u and c_o can be easily calculated. c_u is calculated as the profit loss of ordering under the actual demand. If too little is available, a potential profit of $180 - 50$ is lost; hence, $c_u = 130$. c_o is the profit loss occurring if one orders too much. In that case the t-shirts are bought at 50 and sold at 30 leading to a$c_o = 50 - 30 = 20$. Now, the often referred to *critical ratio* (right hand side of equation (3.9)) can be computed as:

$$\textit{critical ratio} = \frac{c_u}{c_u + c_o} = \frac{130}{130 + 20} \approx \underline{0.867} \tag{3.22}$$

Hence, our two different proposed models for demand uncertainty lead to the following equations to be solved for Q_U^* and Q_T^*:

$$h\left(Q_U^* - \alpha\right) = 0.867 \tag{3.23}$$

and

$$a\left(Q_T^* - \alpha\right) + \frac{b}{2}\left(Q_T^{*2} - \alpha^2\right) = 0.867 \tag{3.24}$$

[24] Thanks to Assistant Professor Olav Hauge for this information

Equation (3.23) is easy to solve. We find:

$$Q_U^* = \frac{0.867}{h} + \alpha = 3466.67 + 9000 \approx \underline{12467} \tag{3.25}$$

Equation (3.24) is quadratic in the variable and will hence involve slightly more complex algebraic manipulation. The solution is left for the reader as an exercise.

The main point to observe her is how "close" the solution (12467) is to the upper demand limit of 13000. The reason is obvious, as we loose a lot (130) on under-ordering, but very little on the opposite (20), it is a good strategy to order many. Actually, the managing director of the jazz festival (Jan Ole Otnes) stated in various TV interviews before the festival that they would order 10000 t-shirts and expecting to get rid of all. Our analysis indicates a slightly different strategy, but again, we lack a lot of information here as opposed to being insiders.

3.3 Extensions of the "News-boy" concept

In previous sections, a simple "News-boy" type event-oriented example was presented. Even though some readers might find this presentation complex enough, it is important to stress that our modelling in most instances are ridiculously simplified. Think about the t-shirt example. We assume only one t-shirt for sale. Reality is different, at the 2010 festival, 2 different t-shirts (different motives, but the same basic shirt) was sold. This seemingly simple change may actually have major consequences for our model concept. It seems fairly obvious, in such a situation, to assume that one t-shirt might be more popular than the other, and a certain demand correlation mechanism must be added to the model - not a straightforward model change to implement.

Furthermore, choice of production process (buying finished shorts or splitting the production process in parts to utilize *postponement*) is something to consider and which surely makes the analysis even far more involved. By preprocessing t-shirts and trying to postpone finalizing them, one can utilize the possibility of observing demand during the festival and hence try to increase finalizing the popular t-shirts as opposed to the less (observed) popular.

The two simple extensions above introduce both multi-period as well as multi-product "News-boy" problems. Luckily, researchers have spent much time and effort on introducing different extensions to this problem, so from an operative point of view, it may be a lot of help to get from research literature. A nice survey by Khouja [19] distinguishes 11 different extension categories, involving both multi- period and product situations, as well as many other.

In addition to the above mentioned possible extensions, another brand of modern research literature is interesting to consider. Recall from our example, that the parameters c_u and c_o were assumed parameters, that is, given exogenous to the model. In reality, certain parts of these parameters are under control of the decision maker. For instance, the two prices 180 (in-event selling price) and 30 (after-event selling price) can and must be determined by MIJF. Choosing different values for these will surely change the problem. Presumably, by increasing 130, less t-shirts at higher prices are sold during the festival while doing the opposite, more t-shirts are sold at lower prices. Obviously, the pricing policy must affect total expected profits. However, to analyse these types of problems within the framework of “News-boy” models, some demand relations (of stochastic nature) must be added to the model. Simply spoken. We need to know how (uncertain) demand changes when prices are changed. This adds even more complexity to the problem, but has gained some research interest the latter years. The excellent review by Petruzzi and Dada [23] sums up most existing research in this area up to date.

3.4 Final comments

The special nature of events indicates that a single period stochastic inventory management model concept (“News-Boy” or Newsvendor) seems as a good starting point. Still, reality demands (perhaps) far more advanced approaches than the simple original “News-Boy” model. Doing this is surely challenging. However, this topic is very much at the research frontier, and one should expect further enhancements and improvements possibly fitting events and service production even better. As such, for those interested in doing research in the field, this “niche” might be an interesting option.

Inventory management in the traditional sense focus a lot on inventory decision in a periodic setting. This problem area is perhaps less relevant for events, still, purchasing in general is very relevant for most event producers, so using the term purchase management is perhaps better from a scientific point of view. In this text, we have still chosen to use the vocabulary of traditional logistics.

Chapter 4

Event Production

4.1 Introduction

Classical production planning of the lot-sizing type is not very relevant in event logistics. The reason ought to be obvious. Deciding how much to produce of each product, and when to change from one product to another, is surely not the most relevant event logistics decisions. Artist booking or artist sequencing may certainly be relevant, but we will treat this subject separately in Chapter 10.

Aggregate planning or workforce planning modelling may, however, be relevant in the event situation as well. The ability to plan correct usage of either an existing workforce, using hired labour or volunteers, may definitely be a problem that most event producers are facing. Especially, the choice of volunteers is very relevant for small and medium sized event producers.

Let us start by reinvestigating the classical aggregate production planning model as outlined by Nahmias [21]:

4.2 The classical aggregate production planning model

$$\text{Min } Z = \sum_{t=1}^{T} [c_H H_t + c_F F_t + c_I I_t + c_R P_t + c_O O_t + c_U U_t + c_S S_t] \tag{4.1}$$

s.t.

$$W_t = W_{t-1} + H_t - F_t \quad \forall t \tag{4.2}$$
$$P_t = Kn_tW_t + O_t - U_t \quad \forall t \tag{4.3}$$
$$I_t = I_{t-1} + P_t + S_t - d_t \quad \forall t \tag{4.4}$$
$$H_t, F_t, I_t, O_t, U_t, S_t, W_t, P_t \geq 0 \quad \forall t \tag{4.5}$$

The variables and parameters of the model can be described as follows:
Variables:

Z = Objective function value - total cost
W_t = Number of employees (workforce) in time period t
P_t = Amount produced (units) in time period t
O_t = Number of units produced through the use of overtime in time period t
U_t = Number of units produced through the use of undertime in time period t
I_t = Amount in inventory by the end of time period t
H_t = Number of people hired in time period t
F_t = Number of people fired in time period t
S_t = Number of units subcontracted in time period t

Parameters:

d_t = Demand forecast for time period t
c_H = Cost related to hiring a worker
c_F = Cost related to firing a worker
c_I = Inventory cost per unit per time period of storage
c_R = Production cost per unit within regular time
c_O = Extra cost per unit related to the usage of overtime
c_U = Per unit undertime cost
c_S = Per unit subcontracting cost
n_t = Number of production days in time period t
K = Number of units produced by a single worker in one day (workforce productivity)
I_0 = Initial inventory volume
W_0 = Initial workforce volume - number of employees before the planning horizon
T = Planning horizon

4.3 Developing an event model alternative

The above model is meant for a traditional manufacturing situation where manufacturing takes place all the time. In an event setting, surely our planning horizon is limited, but it surely also spans some time. For the MIJF (and similar events mega-sports events may last from 5 days up to 3 weeks) the obvious planning horizon is 6 days. But even for one-day events, we can organize our work-force planning in several time periods, for instance, by splitting a day in to several time periods of one or several hours.

Now, this model's[25] basic trade-off is between using inventory to keep a stable work force (if hiring and firing costs are high compared to inventory costs) or hiring and firing very dynamically in the opposite (cost) situation. It ought to be fairly obvious that inventory has no place in the event setting. Remember that this is finished goods inventory, and we cannot choose to produce today and sell tomorrow (at least unless we open up for TV and taping). In any case, the basic event situation must be consumed at the production time, so we need to remodel the inventory parts. This is in fact very simple, as we simply can remove it. However, doing this means (principally) to introduce infinite inventory costs in the model above. If we do so, the solution to that model is obvious. In that case, we will hire and fire dynamically to meet demand as we move along. As a consequence, keeping the above model concept unchanged and simply removing inventory variables makes sense, but produce an obvious model solution.

So, we need to make some relevant changes to the above model to make it suit the event situation better. We have already discussed that in events, different groups of workers contribute to a single final product. The interesting practical situation emerges as the cost structures of these groups vary a lot. Typically, we have professionals (earning a salary) and we have various groups of volunteers with low salaries - some even costless. In addition (to make things reasonable), it seems sensible to assume that hiring and firing costs as well as productivity also may differ between different types of workers. For instance, I would believe that hiring volunteers might be a much tougher job (at least for a new event) than hiring through payment and the labour market. The practical meaning of this statement is of course that hiring costs for volunteers might be higher than for professionals. Another feature may be on the firing side. If one recruits a set of volunteers (say for MIJF), then it might be infeasible (high costs) to fire them before the end of the planning horizon.

In addition to the above arguments, there are issues related to facts such

[25] Equations (4.1) – (4.5)

as this; all worker groups can not perform all tasks involved in the production process. Such issues may be taken care of model-wise, but will introduce a kind of multi-product setting as we have to define different tasks within a single or multi-product setting. So for the time being, we try to keep things simple and overlook such complicating matters.

Following up the above arguments, we define groups of workers. Let us use the subscript j for groups, $j \in \{1, \ldots, J\}$. Given this assumption, we need to redefine some cost elements. Suppose we make the following transition:

New Parameters:

$$\begin{aligned}
c_R &\rightarrow c_j^R : \text{Production cost (salary) per unit in workgroup } j \\
c_H &\rightarrow c_j^H : \text{Hiring cost per worker in workgroup } j \\
c_F &\rightarrow c_j^F : \text{Firing cost per worker in workgroup } j \\
K &\rightarrow K_j : \text{Productivity of worker in workgroup j}
\end{aligned}$$

Furthermore, we have to redefine some of the variables and get rid of some of the others. It seems reasonable to take out I_T, O_t, U_t as well as S_t. The use of over/undertime could be kept, but only for certain professional groups. However, to keep things simple, we take out the above mentioned variables. The new set of variables then becomes:

New Variables:

$$\begin{aligned}
H_t &\rightarrow H_{jt} : \text{Number of people hired in workgroup } j \text{ and time period } t \\
F_t &\rightarrow F_{jt} : \text{Number of people fired in workgroup } j \text{ and time period } t \\
W_t &\rightarrow W_{jt} : \text{Number of employees (workforce) in time period } t \text{ in workgroup } j \\
P_t &\rightarrow P_{jT} : \text{Amount produced in time period } t \text{ by worker from workgroup } j
\end{aligned}$$

Given the above redefinitions, the revised model is easily set up as:

$$\text{Min } Z = \sum_{j=1}^{J} \sum_{t=1}^{T} \left[c_J^H H_{jt} + c_j^F F_{jt} + c_j^R P_{jt} \right] \tag{4.6}$$

s.t.

$$W_{jt} = W_{j,t-1} + H_{jt} - F_{jt} \quad \forall jt \tag{4.7}$$

$$P_{jt} = K_j n_t W_{jt} \quad \forall jt \tag{4.8}$$

$$\sum_{j=1}^{J} P_{jt} = d_t \quad \forall t \tag{4.9}$$

$$H_{jt}, F_{jt}, W_{jt}, P_{jt} \geq 0 \quad \forall jt \tag{4.10}$$

The model above (equations (4.6) – (4.10)) is easily explained. The objective (4.6) adds up all costs through workgroups j and time periods t. Each work group j in time period t contains workers based on the number of workers in the previous period, $W_{j,t-1}$, plus the hired amount minus the fired amount - equation (4.7). The production amount generated by workgroup j is computed by multiplying the productivity (K_j) for the group by possible working days (or hours or whatever might be suitable) and by the number of workers in the group - equation (4.8). Finally in equation (4.9), the common produced amount (for the single product) is computed by adding up all production contribution over all groups to meet demand.

4.4 A simple example

In order to investigate the model a little bit further, we define a very simple example. Let us assume two workgroups, a professional (expensive) group named P and a cheap (volunteer) group named V. Table 4.1 defines various parameters

	C_j^R	C_j^H	C_j^F	K
P	10	100	50	2
V	1	500	300	1

Table 4.1: Data for the event aggregated production planning example

We observe from the example of table 4.1 that the P group costs more salary-wise $C_P^R = 10$ as opposed to $C_V^R = 1$. On the other hand, both hiring and firing is significantly more expensive for the V-group. The P-group is also assumed twice as productive as the V-group.

Furthermore, to keep things simple, we look at a 2-period model where we assume (perhaps reasonably) that demand increases from the first to the second period. (Most events tends to put the most significant artists at the end.) We use $d_1 = 20$ and $d_2 = 50$ to simulate this. Finally, we assume the organization has 5 professional employees before the event, and zero volunteers, that is, $W_{P0} = 5, W_{V0} = 0$. The linear programming model is implemented in LINGO, and model formulation and solution is presented in Appendix E.

Looking at the solution in Appendix E, we observe that in spite of the cheapness of the volunteers, the optimal solution involves only the usage of professionals. To test whether the model seems reasonable, we could try to increase the cost of professionals to see if we get a change in workforce assignment. We change C_P^R from 10 to 1000 to be on the safe side. This change produces the following solution;

Variable	Value	Reduced Cost
HP1	0.000000	101.0000
HP2	0.000000	150.0000
FP1	5.000000	0.000000
FP2	0.000000	0.000000
PP1	0.000000	0.000000
PP2	0.000000	0.000000
HV1	20.00000	0.000000
HV2	30.00000	0.000000
FV1	0.000000	300.0000
FV2	0.000000	1300.000
PV1	20.00000	0.000000
PV2	50.00000	0.000000
WP1	0.000000	2047.000
WP2	0.000000	948.0000
WV1	20.00000	0.000000
WV2	50.00000	0.000000

where we observe that the early (now very expensive) professionals are fired in the first period and the now (relatively) very cheap volunteers are hired up at the necessary level in both periods 1 and 2. As a consequence, the basic logic of our model seems to work.

An interesting question to raise is whether this model only produces either or solutions related to usage of different workforce groups. A proof is left for the reader as an exercise.

4.5 Final comments

The very simplified model presented in previous sections must be judged as a starting point for this type of analysis. It seems obvious that more complex product formulations should be introduced to make such models closer to realism. The reason why certain event producers mix different work groups is of course also related to the fact that there are certain competence demands on certain operations. Sound engineers can and should not be picked at random for instance. As such, our one task type of model is highly unrealistic.

Chapter 5

Event Supply Chains

Lately, Supply Chain Management has grown to be a "hot topic" in traditional logistics. Wikipedia [6] quotes Harlan [11] and defines the term as:

> *Supply chain management (SCM) is the management of a network of interconnected businesses involved in the ultimate provision of product and service packages required by end customers. Supply chain management spans all movement and storage of raw materials, work-in-process inventory, and finished goods from point of origin to point of consumption.*

As globalization and increased global competition has evolved, specialized agents had emerged on the scene, forcing a producer to relate to a vast number of agents on the supply side. The growth of suppliers and the competition between them is good for production efficiency, but creates some "new problems" on the logistics side. The choice of suppliers and the management of supply chains are suddenly important company logistics decisions. As a consequence, the need for supply chain management has emerged.

In events, similar structures have evolved. Think about a modern international football team. In the old days, players, managers and club staff were recruited among locals. Today, the picture has changed dramatically, and even small Norwegian football clubs have their own scouts travelling around the world looking for international players. A modern football club's ability to handle it's contact net of scouts, agents and clubs far away, might very well be the factor that defines success or failure.

The same pattern is evident in other events. A modern international music festival will have to use international performers. These performers are travelling the world all the time, set out by their managers and booking agencies. The ability to recruit such artists for a given event producer leads to a necessity for having vast and efficient information and networking structures available.

Within this framework, competition and cooperation becomes relevant subjects to handle. If the MIJF wants artist A, who is also wanted by a competing festival in Norway (for instance the Kongsberg International Jazz Festival), the ability to handle such competitive/cooperative situations becomes evident. As a consequence, more elaborate tools than ordinary optimization, is needed. Game theory is such a tool that deals with strategic interaction between agents.

Applying game theory as a tool for better understanding and handling the challenges related to competition and collaboration seems to be growing in modern supply chain management analysis. Certain relevant textbooks are arriving like, for instance [8], as well as relevant research material. Some relatively new (personal) research, illustrating how simple game theory may be applied in a kind of event supply chain management setting might even be relevant to investigate - [27], [14].

We will not pursue these topics in more detail here as the lack of relevant event oriented research material is so obvious. Still, it seems fairly easy to predict that future will hold a lot of interesting research material covering event supply management.

Chapter 6

Event Transportation

Transportation is a classical problem area within manufacturing. If you produce cars in Japan, and want to sell them in Europe, you can not expect your customers to travel down to Japan, and organize transportation of their new vehicle back home. As a consequence, most manufacturers will have to organize their own transportation scheme. Such organizing involves many important decisions, such as choice of volume (how many items and what type of items to transport at each shipment), mode (which type of transportation, car, boat, plane etc.), frequency (how often), use of professional transporters and so on. As a consequence, a lot of effort has been put into formulating and solving various transportation problems such as the classical transportation problem, transshipment problems, vehicle routing problems etc. Many of such problems pose great challenges in solution. Especially, various versions of the vehicle routing (how to find cost efficient routes given a set of customers to visit) problem are hard to solve efficiently. As a consequence, a vast literature in logistics transportation research exists.

In the event setting, things are to some extent turned around. As most event producers are located somewhere, and their product is immaterial, it can not be transported to the customers, at least not in the original form. (Broadcast versions can of course be fed to the customers, but this line of production falls into traditional manufacturing, and will hence not be further discussed here.) As a consequence, most small and middle sized event producers face the opposite situation. Instead of transporting their product to the customers. They face the problem of transporting their customers to the product.

This may of course propose similar challenges as for the manufacturer. However, in most situations, event producers rely on existing public or private transportation means to fulfil such transportation demand. Obviously, certain situations, special locations, or very large (mega) events may lead to transportation problems that need to be solved, still such problems are mostly solved by agents other than the event producer. An example may clarify. Before the 1994 Lillehammer Olympics, analysis of road quality and forecast demand pointed out a need for better quality and capacity of roads between Oslo and Lillehammer. As a consequence, a part of the contract between IOC and the organizers resulted in a major upgrade of this road - finished immediately before the games. But, and this is the point here. This road upgrade was made by those who do it all the time, “Vegevesenet” not a part of the event production team.

The above argument points out that for small and medium sized events, transportation problems - in the normal sense - do perhaps not classify as necessary problems to care about for event producers. Surely, if the event is big, or the location is vast or far away from everything, some resources must normally be spent on attacking transportation needs, but still in most case, more by convincing politicians to make the “right” decisions than actually solving the transportation problem.

Chapter 7

Events and Dynamic Pricing

7.1 Dynamic Pricing - Introduction

In many event markets, black market activity is present. Black market activity can be defined as a situation where a certain good which is sold can be sold again relatively fast to a higher (or lower) price than the buying price. Black market activity is normally regulated by law to be illegal.

The first situation (selling to a higher price) is the most common one in event markets. Most of us have been offered tickets to events (immediately) before the event at prices significantly higher than the price tag on the ticket.

How can this occur? As we have discussed earlier, the option of pre-selling tickets is good for the event producers because it makes certain logistic decisions easier. On the other hand, pre-selling tickets opens up a problem for the event producer, namely that of controlling, understanding and forecasting future demand. If an event producer guesses wrong on the dynamic demand situation after pre-selling a ticket, it may well be that demand increases and opens up for possible profits for a ticket owner. Additionally, certain event producers are not allowed (or choose not) to change the price of tickets over time. If this is the situation and a ticket owner observes increased demand, the option of reselling the ticket may become tempting.

What has this to do with logistics? The question is obviously relevant, as we already have claimed that pricing decisions typically are not defined into the logistics toolbox. So, let us imagine another example. Think about a grocery store, selling food. If we follow the daily demand patters of most grocery stores, we observe that demand has two peaks. One in the morning, and one (typically very big) in the afternoon. So, the customers tend to use our store in a certain predictive but time-varying pattern. Our costs are (surly) dependent on the number of customers we serve. So, if we could choose we would probably prefer a constant daily demand pattern (shifts, and overtime would be minimized then). Now suppose furthermore, that we are monopolists. If that is the case, we can assume the existence of dynamic demand curves defining the relation between the price and the quantity for our customers. Suppose we name such demand curves $f_t(p_t)$. That is, if we choose the price p_t in time t, we receive the sales quantity (demand) $f_t(p_t)$. Normal goods would lead to a situation where a high price will return less sales and vice versa. Then, given these assumptions, it is easy to realize that a constant demand pattern ought to be obtainable for the grocery store by simply increasing prices somewhat in the morning, somewhat more in the evening and perhaps increasing them somewhat in between. The point is simple. If we can control the price (and quantity; as monopolists we can) we can exercise this control to affect our demand. And as demand affect logistics costs, we must coordinate such decisions if, for instance profit maximization is our objective.

Why do we need an assumption of monopoly? Let us again rethink our grocery store example. If we exercise our price changing strategy, prices on our products will be higher in the morning and quite high in the afternoon. If the price on milk is 100 NOK per litre around 4 o'clock in the afternoon, surely our customers will go to the next store if it exists (a non-monopolistic situation). So, the consequence will (in a competitive situation) not be a stable demand pattern after all.

In the event case, monopoly is more of the standard than the exception. As such, these ideas should fit events far better than most manufacturing or service situations. That is of course also the reason why black markets emerge far more often in event settings than in normal manufacturing situations.

So far, we have argued as if all dynamic pricing situations involve an increasing demand as time goes by. This is of course not necessarily the case. Personally, I have experienced (on several occasions) the possibility (and even the reality) of buying tickets for football games, just before the game starts, at lower prices than the official ticket price. Surely, if demand may increase over time, it may also decrease.

Let us try to sum up: given that the event producer has a profit-maximizing objective, and is able to predict demand curves in a set of future periods, and is (at least approximately) a monopolist, and if his future period demand varies, then he should consider dynamic prices on his product. If he chooses not to, black market activity is a certain consequence, and profit that could have entered the pockets of the event producer is instead entering other's (black market seller's) pockets.

Surely, most of these assumptions may not fit reality perfectly. For instance, whether event producers are profit maximizers could be strongly questioned. Would IOC naturally be considered profit maximizers, What about MUFC or MIJF? The ability to forecast future period demand as demand curves may of course be hard in practice, to judge a monopoly assumption the same.

Finally, a few words on dynamic pricing in reality. Right before Christmas, Norwegian retailer Elkjøp got heavy media on their Christmas pricing policy. (See for instance [3].)

The prices (on various electronic equipment) turned out to differ (in one direction) immediately before and after the initiation of Christmas shopping. Normally, it is almost impossible to identify a conscious dynamic pricing policy. However, in this case a secret note revealing the strategy was found.

Most of us know and accept that airline tickets are dynamically priced. This seeming paradox is interesting if one would try a dynamic pricing policy in practice. It seems as if customers accept dynamic pricing in certain markets, not in others. The reason might be habit or the fact that airline tickets are also dynamically low priced. Anyway, modern technology (mainly accessible and cheap Internet) opens up the possibility of using dynamic pricing. If prices are to change rapidly over time, it is of course necessary to be able to communicate such prices to the consumers. (This is not necessarily related to the fact that a conscious underlying dynamic pricing strategy, but that the prices must be communicated to be able to get trade.) Personally, I would not be surprised if more service, manufacturing and especially event producers start applying dynamic pricing in the near future.

7.2 Dynamic Pricing in Manufacturing

Let us start by looking at a classic manufacturing situation and look back on the simple lot-size problem we formulated in Section 3.1.3 in equations (3.4) – (3.8). Now, we adopt the assumptions above, and reformulate the problem to take pricing into account. Recall that demand is no longer given as parameters, but endogenously taken care of in the model through a new set of decision variables - p_t price on the product in time period t. In order to move forward, we must specify the structure of the demand functions. Let us make it as easy as possible and assume linear demand functions. That is;

$$d_t = \alpha_t - \beta_t \cdot p_t \tag{7.1}$$

where d_t is the calculated demand if price p_t is chosen in time period t and α_t and β_t define the time varying linear demand curves.

Now, to make things reasonable, we need to change the objective to include revenue. When we allow ourselves to change prices (include prices as decision variables), it dos not make sense to minimize costs as the original lot-size model did. Hence, we need to move to profit maximization and as profits are calculated by subtracting costs from revenue we need to calculate the per period revenues of this problem. This is straightforward: (quantity times price)

$$R_t = (\alpha_t - \beta_t \cdot p_t)p_t \tag{7.2}$$

Now, the pricing version of the lot-size problem of equations (3.4) – (3.8) can be formulated as:

$$\text{Max } Z = \sum_{t=1}^{T} R_t - K_t\delta_t - h_t I_t - c_t x_t \tag{7.3}$$

s.t.

$$x_t + I_{t-1} - I_t = d_t \quad \forall t \tag{7.4}$$
$$0 \leq x_t \leq M_t\delta_t \quad \forall t \tag{7.5}$$
$$I_t \geq 0, \quad \forall t \tag{7.6}$$
$$\delta_t \in \{0, 1\} \quad \forall t \tag{7.7}$$
$$\frac{\alpha_t}{\beta_t} \geq p_t \geq 0 \quad \forall t \tag{7.8}$$

with d_t and R_t defined in equations (7.1) and (7.2).

The above problem (equations (7.3) – (7.8)) was originally formulated and solved by J. Thomas in 1970 [28]. Thomas proposed a Dynamic Programming-based algorithm (inspired by Wagner and Whitin's famous paper [29]) which solves large problem instances very fast.

If we study this problem closer, we observe that the objective is nonlinear; quadratic to be specific, and it contains binary variables. In general, this means that standard (MI)LP-solvers such as LINGO and CPLEX not necessarily are able to handle it. Later relevant work includes this author among others in multi-product and capacitated extensions [12], [13]. Interestingly enough, such extended problems turn out be easier to solve than their cost minimizing (CLSP) counterparts.

7.3 Dynamic Pricing in services - Revenue Management

In the previous section - Section 7.2 - we discussed briefly how dynamic pricing might be adapted to a manufacturing situation including storage possibility and set-up. If we move our vision to services, which by the way resembles events much more, we observe (naturally) that set-up as well as storage are of less importance. This is of course in accordance with previous discussion on the topic (see Chapter 4). Hence, a strategy in to adopt this situation to services or events for that matter could simply be to remove storage possibilities (take out the I_t variables) as well as set-up (remove the δ_t variables). This is of course possible, and if this is done, we are left with a problem (basically) only containing the objective. This problem is simply a multi-period (decoupled) classical monopoly, and the solution is straightforward: $(MR = MC)$

$$p_t^* = \frac{\alpha_t - c_t}{2\beta_t} \tag{7.9}$$

This is of course a very simple solution, and given that reality fits, it could definitely be applied. However, as usual, reality may not fit. For instance, in both service and event production, certain dependencies may exist. If one applies a dynamic pricing strategy say for pre-sales of tickets to a concert known to the audience, the cheap tickets (if unlimited) will sell fast and hence affect future demand after this point in time. Furthermore, the ability to actually predict independent demand curves over time might be difficult and in some sense fairly infeasible. Given these two arguments, it is perhaps obvious to think about uncertainty of demand and the concept of Revenue Management is focusing on this as well as the above modelling features. The point is basically very simple. If one really wants to apply dynamic pricing in events, reality may be too complex to just use the simple approach of equation (7.9). We will not pursue these topics further here, just point at some survey literature that may be both relevant and helpful in investigating further options in event dynamic pricing and/or revenue management. The paper by McGill and Van Ryzin [20] may be a good starting point

Chapter 8

Events and "hype logistics"

8.1 Introduction

Logistics is a somewhat immature discipline and (perhaps especially) the less quantitative agents on the research and application side tends from time to time to spend a lot of time on buzz-words. Logistics vocabulary is full of such buzz-words, as *JIT* (Just in time), *Modularization* and *Postponement* to name the most important ones. Let me try to be slightly clearer: the intention here is *NOT* to say that these words and their meaning is unimportant, neither for manufacturing, service nor event production agents. Still, one might get the feeling from time to time that these words introduce ground breaking news. The main point of this short chapter is to explain the most relevant concepts and outline their importance for event logistics.

8.2 Just In Time - JIT

Let us start by looking at the model underlying the simple EOQ model and formulate total costs:

$$TC(Q) = K\frac{\lambda}{Q} + h\frac{Q}{2} \tag{8.1}$$

Now let us do exactly the opposite of what we did in Subsection 3.1.3 of Chapter 3, interpreting K as a set-up cost instead of the normal (Inventory management) order cost, and hence $\frac{\lambda}{Q}$ as number of set-up's. In addition, we need to assume that production runs infinitely fast, but these assumptions play little or no role in the argument.

Now, the standard argument goes as follows. We minimize total costs by solving $TC'(Q) = 0$, which produces the EOQ formula (3.1).

Now, this argument is based on several assumptions, one of them (not very often discussed by the way) is that K is given and unchangeable. This K, the set-up cost in our production, is a technology parameter underlying our technology choices, so in principle we can change it. Normally, changing it significantly costs a fair sum of money. But still, the option is there. Let us assume we choose to change it from K to zero. What effect does it have on our argument? In that case, the total cost function simplifies to:

$$TC(Q) = h\frac{Q}{2} \tag{8.2}$$

and we minimize it by minimizing Q. Minimizing Q (it can of course not be zero) means a very small Q and negligible average inventory. This is the basic point in JIT. Keep almost no inventory and produce small series or demand as it emerges, and this is important. Either, you will have to invest large sums of money in both technology and the right manpower to be able to force both set-up costs and times to zero. (Whether this turns out to profitable is of course another story.) Alternatively, you could be lucky, living in a part of the world where labour is cheap and flexible, yielding similar consequences.

Looking at event production, inventory is not a topic for the finished goods. As such, the main point in JIT of minimizing inventory is simply not relevant; however, this is important. The above argument also has consequences related to uncertainty in demand. If demand is highly uncertain, the value of a flexible production system is higher than in the deterministic case. So, by increasing organizational flexibility the producer also manages to handle uncertainty much smoother. The necessity of forecasting is of course (in principle) far less if the producer can meet any kind of demand at any point in time with the given technology and manpower. An event producer will in many cases face considerable demand uncertainty. As such, a JIT-type of production system is good. The reason for choosing volunteers is of course a part of this, as a volunteer plays the role of a cheap and willing worker, able to show up at any point in time and do whatever is needed. Hence, JIT is nothing new in event production, actually it is the oldest concept of all in the event setting.

8.3 Postponement

Postponement means, as the word indicates, to postpone or delay the production process. In a situation with demand uncertainty, it may be a good idea to try to postpone major parts of production as late as possible or at least as late as necessary until uncertainty is revealed. Think about our example of selling t-shirts at MIJF from Chapter 3, Subsection 3.2.2. If MIJF are very much uncertain on t-shirt buyers taste, they could postpone the whole t-shirt colouring and printing process until they observe what the festival customers prefer. Or even better, they could stage a poll before the festival, letting potential t-shirt buyers vote on their preferred t-shirts, letting them buy it before the festival. This would be considered extreme postponement. We see a lot of postponement in modern manufactured products. Modern cell phones have a lot of visual tuning possibilities for backgrounds, menus, transparency, animation and so on. Why? This is again postponement. Instead of guessing how customers would like their cell phones, let them decide themselves.

So, if postponement is "manna from heaven" why not always do it. The reason might be lack of uncertainty or costs. Postponing will typically involve increased costs. T-shirts finished with print will normally be cheaper and perhaps of better quality than those "home-made" at the festival. Finally, postponement may not be possible. Think about postponement in a concert setting. The idea is simple, if you do not know what the audience wants, let them choose. So in a concert setting, if some of the audience wants Frank Zappa and others the Beatles at the same time, it becomes kind of complex to fix. Especially as both Zappa and the Beatles no longer are here. Letting the home audience in a football match decide that now is the time for a home goal is a pleasing idea, but still obviously infeasible.

To sum up, in situations with high demand uncertainty, postponement may be good, but not at all cost. In the event setting, it may be high demand uncertainty, but pre-sales soften the effect.

8.4 Modularization

Modularization means being able to produce a maximal number of finished products with a minimal number of components (modules). Apart from the fact that being able to modularize a production process may be cost efficient (cheaper than the alternative), it is a strategy to achieve postponement. If you are able to produce everything based on a small number of basic components, you can postpone until customer preferences are revealed. The classical example is a car engine, with which minimal tuning can change from 100 HP until 350 HP. The single module engine can hence spawn a lot of different products meeting customer preferences fast.

In events, we actually see modularization resemblance. Again, the local jazz festival is a brilliant example. In latter years, the festival has chosen something referred to as *artist in residence*. This single artist will have several concerts of different types (a multitude of products) from a single module. Presumably, the main point of doing this is cost efficiency rather than postponement, but the postponement strategy is definitely there. A good advice for the festival could be to postpone the programme for the artist in residence shows, letting customer demand decide. So, if Nils P. Molvær stays until Saturday in the jazz week and the audience at that day would prefer country music, let him perform it (given that he is able to).

Again, this kind of strategy is harder to foresee in sports events. But in principle, keeping a minimal number in a football squad with flexible players, that is, having 15 players, who could play well in all pitch positions could be a possible modularization strategy in football.

Chapter 9

Event Facility Location

Facility location in classical logistics is related to the problem of choosing (and designing) locations for production. If we again consider MIJF (or any other festival for that matter), they have the choice of picking among a set of possible predefined production locations. In Molde, these locations may be Teatret Vårt, Alexandria Hotel, Bjørnsonhuset, Idrettens Hus, Molde Cinema, The new "Teater and Jazz" house", Aker Stadium and so on.

So, let us assume the existence of a set of locations $L_i, i \in 1, \ldots, I$. Let us furthermore assume that each of these locations has some set of associated attributes. Such attributes could be costs, capacity, quality, transport distance etc. Suppose in the absolute simplest possible situation, we consider only cost attributes and define C_i as the cost attribute of location i. Suppose furthermore that a given event should be assigned to one (and only one) location at a minimal cost. In a mathematical programming setting, this task can easily be formulated by introducing a set of binary variables: say δ_i defined as:

$$\delta_i = \begin{cases} 1 & \text{if location } i \text{ is picked} \\ 0 & \text{elsewhere} \end{cases} \tag{9.1}$$

and formulating the following MILP (PIP[26])

$$\text{Min } Z = \sum_{i=1}^{I} \delta_i C_i \tag{9.2}$$

s.t.

$$\sum_{i=1}^{I} \delta_i = 1 \tag{9.3}$$

$$\delta_i \in \{0, 1\} \forall i \tag{9.4}$$

The above problem (equations (9.2) – (9.3)) is of course ridiculously simple in a Mathematical Programming context. It merely picks out the smallest of a set of given costs. Hence, it is no point feeding it into LINGO or CPLEX. Still, as a building block for more advanced situations it may be handy.

Now, let us furthermore assume that it is not only costs but also the quality of the location that are interesting to judge. Let us assume that each location has a certain quality attribute, say Q_i, where a high value on Q means better quality and that a given lower bound of quality $\underline{\mathrm{Q}}$ is given (either by law or by our own choice.). The above problem can then easily be extended to handle the new situation simply by adding

$$\sum_{i=1}^{I} \delta_i Q_i \geq \underline{\mathrm{Q}} \tag{9.5}$$

to the problem defined by equations (9.2) – (9.3).

Again, it is easy to derive at a specialized algorithm. Pick the smallest C_i where (9.4) is satisfied.

A far more challenging situation (solution-wise) emerges if we change our focus slightly. Let us now assume that we have booked a set of artists A_i and that a set of possible locations L_i are picked. Obviously, the set of possible locations must be larger than the set of artists if we consider a parallel set of events, which we indeed intend to do. However, to simplify, let us furthermore assume that the number of booked artists equals the number of possible locations I. In order to progress, we also need to make a slight change in the cost structure. It seems reasonable to assume that artist costs may be dependent on location. If a certain artist is booked at a low-quality location, he or she may accept smaller fees. If this is the case, C_{ij} must exist. That is the cost of assigning artist i to location j[27]. In order to formulate

[26] Pure Integer Program

[27] It is perhaps easier to see this structure if we look at revenues instead of costs, but the main logic is unchanged from a model point of view.

a model for this situation, we need a slightly more complex binary variable. We define:

$$\delta_{ij} = \begin{cases} 1 & \text{if artist } i \text{ is located at location } j \\ 0 & \text{elsewhere} \end{cases} \tag{9.6}$$

Then, a minimal total cost artist-location-assignment can be found by solving the following problem:

$$\text{Min } Z = \sum_{i=1}^{I} \sum_{j=1}^{I} \delta_{ij} C_{ij} \tag{9.7}$$

s.t.

$$\sum_{i=1}^{I} \delta_{ij} = 1 \forall j \tag{9.8}$$

$$\sum_{j=1}^{I} \delta_{ij} = 1 \forall i \tag{9.9}$$

$$\delta_{ij} \in \{0, 1\} \forall i, j \tag{9.10}$$

Above, (9.8) picks one (and only one) artist to each location j, while (9.9) secures that each artist i gets a location.

The problem defined by equations 9.7 – 9.10 is commonly referred to as an *Assignment Problem* in logistics or OR research literature. This problem, as most name-tagged mathematical programming problems in logistics, has undergone a vast research effort related to extensions and specialized algorithmic development. Because of space concerns, the chapter concludes here and the interested reader is directed to the excellent review by Pentico [22].

Chapter 10

Event Sequencing

Event Sequencing may be defined as how to sequence (or schedule) sub events within a bigger event optimally.

Sequencing in classical manufacturing logistics is related to relatively short-time or operational decisions and is normally defined in a machine setting. How should jobs be fed into a single or a set of machines (serial, parallel or networking structure) to achieve certain targets. In most cases, such targets are related to efficiency in the form of various measures of speed or capacity utilization. So a classical machine scheduling problem focuses on job sequence decisions (sorting jobs) to achieve certain efficiency goals.

In events, typically neither speed, nor capacity utilization is a big issue. On the other hand, demand is a big issue, and if demand may be affected by certain event sequencing decisions, then event sequencing might be both commercially important and challenging.

Identifying sequence demand links on the event scene is straightforward. Think about a football league, the sequence of games may obviously affect demand both positively and negatively. A simple example may clarify: suppose the local team should meet the main opponent RBK. If this match (say a match in Molde) takes place at a point in time (late in the season) where much of table placement uncertainty is revealed, local attendance demand may be low. On the other hand, if the table placement (and season timing) is such that this given match is very important for final placement, demand might be very high. Strictly speaking, this problem is not solved by the event producer, but by the league owner or the regulator. It is of course still relevant, but perhaps of less importance for most event producers.

The same situation is also present for festivals. Normally, demand (in general) is higher towards the end of the festival[28]. Then the question of how

[28]Most festivals start before a week-end and ends during a week-end. The same type of

to sequence the artists may be relevant. For instance, a certain very high quality artist may draw audience more or less independent of the timing of his performance, while other artists may need some "calendar help".

Another point, is the booking situation. Most artists have schedules already, and the possibility of fitting certain artists into certain specific time-slots may affect not only local demand, but also costs related to hiring the artists.

So, we can conclude that event scheduling is relevant. Various mathematical models can now of course be discussed and adapted to the situations described above. This is an important point, and in order to actually do this, some critical input information is needed, namely the "demand link". In order to have any hope of solving such problems formally, information on how the schedule (or sequence) affects demand must be quantitatively present. Such information is hard to establish and in most cases simply unavailable. Obviously, scheduling decisions must be made, and they are made all the time by all event producers; still a formal analysis of such problems may demand data that is not present, and (perhaps) very costly obtained[29].

Due to the above arguments, we refrain from more formal modelling approaches in this chapter. Still, it seems fairly obvious to this author that most event producers could get far better products if some more systematic approaches are applied in their event scheduling.

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pattern may also be present, even at one-day events, where attendance demand may grow through the event independently of artist scheduling.

[29] If the cost of obtaining necessary input information is very high, the question of performing formal analysis becomes a trade-off, which does not necessarily point at doing the analysis as the optimal solution.

Appendices

Appendix A

Calculations in figures 2.2 and 2.3

The actual moving average calculations underlying figures 2.2 and 2.3 are given in tables A.1 and A.2:

YEAR	**DEMAND**	$\hat{F}_t^2$	$\hat{F}_t^3$	$\hat{F}_t^4$
2000	28897			
2001	38092			
2002	39306	33494,5		
2003	34184	38699	35431,67	
2004	50951	36745	37194	35119,75
2005	31436	42567,5	41480,33	40633,25
2006	37923	41193,5	38857	38969,25
2007	39451	34679,5	40103,33	38623,5
2008	31861	38687	36270	39940,25
2009	29398	35656	36411,67	35167,75

Table A.1: Moving average calculations underlying figure 2.2

In the above tables, the forecasts $\hat{F}_t^j$ are computed by the standard formula:

$$\hat{F}_t^j = \frac{1}{j} \sum_{i=1}^{j} D_{t-i} \tag{A.1}$$

where $\hat{F}_t^j$ denotes forecasted demand for time period t given moving average of order j and D_t is observed historic (actual) demand data.

YEAR	**DEMAND**	$\hat{F}_t^2$	$\hat{F}_t^3$	$\hat{F}_t^4$
2000	28897			
2001	38092			
2002	39306	33494,5		
2003	34184	38699	35431,67	
2004	50951	36745	37194	35119,75
2005	31436	34344,5	35998,33	36521,75
2006	37923	32970,5	33375	34857,75
2007	39451	34679,5	34621,33	34512
2008	31861	38687	36270	35828,75
2009	29398	35656	36411,67	35167,75

Table A.2: Moving average calculations underlying figure 2.3

Appendix B

Data for the case in Subsection 2.3.1

att	mfk_pos	mot_pos	mot_3si	mfk_form	mot_form	rbk	mai_16	stadion	brann	jazz
4430,00	1,00	3,00	5,30	3,00	3,00	0,00	0,00	0,00	0,00	0,00
5434,00	1,00	11,00	15,00	3,00	1,00	0,00	0,00	0,00	0,00	0,00
7300,00	1,00	3,00	15,00	3,00	4,30	0,00	1,00	0,00	0,00	0,00
5830,00	2,00	8,00	13,00	2,30	2,00	0,00	0,00	0,00	0,00	0,00
5046,00	2,00	10,00	9,00	1,30	1,30	0,00	0,00	0,00	0,00	0,00
12990,00	2,00	1,00	1,00	2,00	2,30	1,00	0,00	0,00	0,00	0,00
4857,00	2,00	5,00	5,00	1,30	2,00	0,00	0,00	0,00	0,00	1,00
2966,00	2,00	14,00	15,00	1,30	0,00	0,00	0,00	0,00	0,00	0,00
4379,00	2,00	5,00	5,30	2,00	2,00	0,00	0,00	0,00	0,00	0,00
3606,00	2,00	7,00	7,00	1,30	1,30	0,00	0,00	0,00	0,00	0,00
2228,00	2,00	13,00	7,70	0,70	1,00	0,00	0,00	0,00	0,00	0,00
2335,00	2,00	4,00	3,00	1,30	1,00	0,00	0,00	0,00	0,00	0,00
3435,00	2,00	9,00	6,70	0,30	0,70	0,00	0,00	0,00	1,00	0,00
4918,00	13,00	12,00	15,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
5051,00	9,00	10,00	15,00	1,00	1,00	0,00	0,00	0,00	0,00	0,00
3083,00	7,00	12,00	8,00	1,00	1,30	0,00	0,00	0,00	0,00	0,00
8365,00	4,00	1,00	3,00	3,00	2,00	0,00	1,00	0,00	0,00	0,00
4486,00	4,00	6,00	6,30	2,30	1,30	0,00	0,00	0,00	0,00	0,00
3500,00	3,00	12,00	10,30	1,70	1,30	0,00	0,00	0,00	0,00	0,00
3592,00	5,00	6,00	4,00	1,30	1,00	0,00	0,00	0,00	0,00	0,00

Table B.1: The first twenty data points for the regression analysis

Appendix C

LINGO model in Subsection 3.1.3

The LINGO version of the MIP-problem of equations (3.4) – (3.8) is presented below:

```
Min = 100*d1 + 100*d2 + 100*d3 + 100*d4 + 100*d5 + 100*d6
    + 100*d7 + 100*d8 + 100*d9 +100*d10  + 100*d11 + 100*d12 + 100*d13
    + 0.2*I1 + 0.2*I2 + 0.2*I3 + 0.2*I4 + 0.2*I5 + 0.2*I6 +0.2*I7
    + 0.2*I8 + 0.2*I9 +0.2*I10 +0.2*I11+ 0.2*I12 + 0.2*I13;

X1-I1 = 66;
X2 +I1 - I2 = 66;
X3 +I2 - I3 = 66;
X4 +I3 - I4 = 85;
X5 +I4 - I5 = 66;
X6 +I5 - I6 = 66;
X7 +I6 - I7 = 79;
X8 +I7 - I8 = 66;
X9 +I8 - I9 = 118;
X10 +I9 - I10 = 66;
X11 +I10 - I11 = 66;
X12 +I11 - I12 = 66;
X13 +I12 - I13 = 66;

X1 <= 942*d1;
X2 <= 942*d2;
X3 <= 942*d3;
X4 <= 942*d4;
```

```
X5 <= 942*d5;
X6 <= 942*d6;
X7 <= 942*d7;
X8 <= 942*d8;
X9 <= 942*d9;
X10 <= 942*d10;
X11 <= 942*d11;
X12 <= 942*d12;
X13 <= 942*d13;

@BIN(d1);
@BIN(d2);
@BIN(d3);
@BIN(d4);
@BIN(d5);
@BIN(d6);
@BIN(d7);
@BIN(d8);
@BIN(d9);
@BIN(d10);
@BIN(d11);
@BIN(d12);
@BIN(d13);
```

Appendix D

Case solution in Subsection 3.1.3

The LINGO solution for the MIP problem of equations (3.4) – (3.8) with data for the MFK 2002 season is presented below:

```
Global optimal solution found.
  Objective value:                              607.0000
  Objective bound:                              607.0000
  Infeasibilities:                              0.000000
  Extended solver steps:                              23
  Total solver iterations:                           765

  Model Class:                                      MILP

  Total variables:                   39
  Nonlinear variables:                0
  Integer variables:                 13

  Total constraints:                 27
  Nonlinear constraints:              0

  Total nonzeros:                    90
  Nonlinear nonzeros:                 0

                      Variable           Value        Reduced Cost
                            D1        1.000000            100.0000
                            D2        0.000000           -88.40000
                            D3        0.000000           -276.8000
```

D4	0.000000	-465.2000
D5	1.000000	100.0000
D6	0.000000	-88.40000
D7	0.000000	-276.8000
D8	0.000000	-465.2000
D9	1.000000	100.0000
D10	0.000000	-88.40000
D11	0.000000	-276.8000
D12	0.000000	-465.2000
D13	0.000000	-653.6000
I1	217.0000	0.000000
I2	151.0000	0.000000
I3	85.00000	0.000000
I4	0.000000	0.8000000
I5	211.0000	0.000000
I6	145.0000	0.000000
I7	66.00000	0.000000
I8	0.000000	0.8000000
I9	264.0000	0.000000
I10	198.0000	0.000000
I11	132.0000	0.000000
I12	66.00000	0.000000
I13	0.000000	1.000000
X1	283.0000	0.000000
X2	0.000000	0.000000
X3	0.000000	0.000000
X4	0.000000	0.000000
X5	277.0000	0.000000
X6	0.000000	0.000000
X7	0.000000	0.000000
X8	0.000000	0.000000
X9	382.0000	0.000000
X10	0.000000	0.000000
X11	0.000000	0.000000
X12	0.000000	0.000000
X13	0.000000	0.000000

Appendix E

LINGO - the problem in Section 4.4

Formulation:

```
min = 100*HP1 + 100*HP2 + 1*FP1 + 50*FP2 + 10*PP1 + 10*PP2 +
      500*HV1 + 500*HV2 + 300*FV1 + 300*FV2 + 1*PV1 + 1*PV2;

WP1 = 5   + HP1 - FP1;
WP2 = WP1 + HP2 - FP2;
WV1 = 0   + HV1 - FV2;
Wv2 = WV1 + HV2 - FV2;

PP1 = 2*WP1;
PV1 = 1*WV1;
PP2 = 2*WP2;
PV2 = 1*WV2;

PV1 + PP1 = 20;
PV2 + PP2 = 50;
```

Main parts of solution:

```
Global optimal solution found.
  Objective value:                              2700.000

                      Variable           Value        Reduced Cost
                           HP1        5.000000            0.000000
                           HP2        15.00000            0.000000
                           FP1        0.000000            101.0000
                           FP2        0.000000            150.0000
                           PP1        20.00000            0.000000
                           PP2        50.00000            0.000000
                           HV1        0.000000            0.000000
                           HV2        0.000000            9.000000
                           FV1        0.000000            300.0000
                           FV2        0.000000            1291.000
                           PV1        0.000000            0.000000
                           PV2        0.000000            0.000000
                           WP1        10.00000            0.000000
                           WP2        25.00000            0.000000
                           WV1        0.000000            0.000000
                           WV2        0.000000            432.0000
```

Appendix F

Exam exercises – 2011

MOLDE UNIVERSITY COLLEGE
SPECIALIZED UNIVERSITY IN LOGISTICS
FACULTY OF ECONOMICS, SOCIAL SCIENCE
AND INFORMATICS

Contact during exam:
Name: Kjetil K. Haugen
Phone: (cel.): 99456006
Phone: (office): 71214255

EXAM IN
EVM710 – EVENT LOGISTICS
Monday 23. of May 2011
Tid: kl. 09.00 - 13.00

All written aids + (K)
The exam contains **4** pages including the front page

Exercise 1 (50%) An event producer stages an outdoor event (for instance one of the outdoor concerts at "Romsdalsmuseet" during the jazz-festival).

a) Name a set of (dependent) variables you believe may influence attendance numbers (number of spectators) for this concert.

b) Given your choice of variables in a), make a list of prioritization when it comes to attendance number importance. Discuss and state reasons for your answer(s).

Variable names	*Estimated parameters*	*Variable ranges* (possible values)
Weather	100	$\in \{1, 2 \ldots 5\}$
Ticket price	-2	$\in \{100, 200 \ldots 500\}$
Week day	3	$\in \{1, 2 \ldots 7\}$
Artist quality	500	$\in \{1, 2 \ldots 5\}$

The table above contains results of a (multiple linear) regression model based on historical data done by the event producer for the given concert. The weather variable measures weather quality with value 5 as the best possible weather. The ticket price is limited to choices ranging from 100 up to 500 NOK per ticket. The week day 1 is Monday, while 7 is Sunday. Finally, artist quality is measured like the weather, with the value 5 as the highest possible artist quality.

c) Look at the estimated parameters (in the table on page 1), and examine the signs of the estimates. Do you find them sensible? what about the values? (discuss and state reasons for your answers.)

d) Predict (forecast) attendance for a Rolling Stones concert (artist quality = 5, ticket price = 500) on a Saturday with the worst possible weather conditions.

e) What is the maximal possible attendance given this model? Find also average (or expected) attendance given equally probable weather conditions for the given concert.

f) In the course text-book ("Event Logistics"), the terms *short term* versus *long term* forecasting is defined. Explain the difference between these terms and discuss whether applying short term versus long term forecasting may imply differences when forecasting is performed by the model in the table on page 1.

g) Make necessary assumptions and discuss what artist costs this event producer can handle.

Exercise 2 (20%)

$$Q^* = \sqrt{\frac{2K\lambda}{h}} \tag{F.1}$$

$$\text{Min } Z = \sum_{t=1}^{T} K_t\delta_t + h_t I_t + c_t x_t \tag{F.2}$$

s.t.

$$x_t + I_{t-1} - I_t = d_t \quad \forall t \tag{F.3}$$
$$0 \leq x_t \leq M_t\delta_t \quad \forall t \tag{F.4}$$
$$I_t \geq 0, \quad \forall t \tag{F.5}$$
$$\delta_t \in \{0, 1\} \quad \forall t \tag{F.6}$$

$$F(Q^*) = \frac{c_u}{c_u + c_o} \tag{F.7}$$

The mathematical expressions above express solutions (F.1), (F.7) and a mathematical programming formulation (F.2) – (F.6) for inventory management problems we have discussed in this course.

a) Highlight the main differences in underlying assumptions between these 3 different mathematical models.

b) Give 3 examples of real world event situations that you feel might fit each of these 3 mathematical models.

L_i	1	2	3	4	5	6	7	8
C_i	10	15	14	20	8	9	16	10
Q_i	5	6	5	7	3	5	6	6

Table F.1: Location data

Exercise 3 (30%) Table F.1 contains location data for an event arranger wanting to pick a **single** location for an event. The arranger can pick one of 8 possible locations each with a cost C_i and a quality attribute Q_i (high Q_i's are preferred by the event arranger.).

a) A friend of the event arranger states that the data table is unnecessary complicated, and that location 1 just as well may be removed. What do you feel about this suggestion?

b) Formulate an explicit mathematical programming model (objective function and constraints) in a format that the LINGO-system may take, given a certain law stating that the location quality of the planned event at least must be higher than 6.

c) Suppose now, that the event arranger opens up for more than a single event (and location) (say n events, where n is some given integer), and that the law regulating location quality is changed to average quality standards. Formulate a new mathematical program covering this situation.

d) Suppose $n = 4$ and find one feasible solution for this problem if the average quality at least must be 6. Determine if the feasible solution you have found is the optimal solution.

Appendix G

Exam exercises – 2013

MOLDE UNIVERSITY COLLEGE
SPECIALIZED UNIVERSITY IN LOGISTICS
FACULTY OF ECONOMICS, SOCIAL SCIENCE
AND INFORMATICS

Contact during exam:
Name: Kjetil K. Haugen
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Phone: (office): 71214255

EXAM IN
EVM710 – EVENT LOGISTICS
Tuesday 29. of October 2013
Time: kl. 09.00 - 13.00

All written aids + (K)
The exam contains **3** pages including the front page

$$Q^* = \sqrt{\frac{2K\lambda}{h}} \tag{G.1}$$

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FACULTY OF ECONOMICS, SOCIAL SCIENCE
AND INFORMATICS

Exercise 1 (50%)

a) Equation (G.1) contains the so called EOQ formula. Explain the meaning of K, λ and h in the formula, and show how it can be derived by minimizing total costs.

An event producer hosting a 12-day event plans to sell pancakes to his audience. Forecasts for Pancake-demand is shown in table G.1 for all 12 event days.

Day	1	2	3	4	5	6	7	8	9	10	11	12
Demand forecast	50	50	50	50	60	60	60	60	70	70	70	70

Table G.1: Pancake demand forecasts

b) Assume that $K = 100$ and $h = 0.18$, and establish a (pancake) purchasing plan for the event producer based on the EOQ approximation.

c) Calculate the cost of this plan.

d) Does the EOQ approximation secure an optimal solution? If not – why not?

e) Formulate a model in LINGO that will secure an optimal solution to this problem.

Suppose an alternative set of demand forecasts, as shown in table G.2, had been used:

Day	1	2	3	4	5	6	7	8	9	10	11	12
Demand forecast	59	59	59	59	60	60	60	60	61	61	61	61

Table G.2: Alternative pancake demand forecasts

f) Which of these two demand forecasts would you expect to be the better approximation? (State reasons for your answer.)

g) Would the new demand forecasts in table G.2 affect the solution from b)?

Assume finally that the event producer has experienced a proportionality between order costs and order quantity. That is $K = K(Q) = \alpha \cdot Q$ where $\alpha > 0$.

h) Analyse the purchasing problem under these circumstances.

Exercise 2 (30%)

$$F(Q^*) = \frac{c_u}{c_u + c_o} \tag{G.2}$$

Equation (G.2) contains the solution to a so called Newsboy problem.

a) Why are Newsboy models considered important in Event Logistics?

b) Suppose you consider an event Newsboy situation. How would you apply equation (G.2), and what information is needed?

Suppose now, that you consider a newsboy situation characterized as follows: $c_u = c_o$ and $f(Q)$ is symmetric. Furthermore, the expected demand is given as 50.

c) What is the optimal order quantity given these assumptions?

Suppose alternatively that c_u is very very big compared to c_o ($c_u \to \infty$ while c_o is finite.)

d) What impact would this information have on solving the Newsboy model? (State reasons for your answer.)

e) Find optimal order quantities in any Newsboy model when

1) $c_u \to \infty$ while c_o is finite
2) $c_o \to \infty$ while c_u is finite

Exercise 3 (20%)

a) Explain (shortly) the following concepts:

- *JIT*
- *Postponement*
- *Modularization*

b) Discuss shortly why and how these concepts may be important in practical event planning..

Appendix H

Exam exercises – 2015

MOLDE UNIVERSITY COLLEGE
SPECIALIZED UNIVERSITY IN LOGISTICS
FACULTY OF ECONOMICS, SOCIAL SCIENCE
AND INFORMATICS

Contact during exam:
Name: Kjetil K. Haugen
Phone: (cel.): 99456006
Phone: (office): 71214255

EXAM IN
EVM710 – EVENT LOGISTICS
Tuesday 3. of November 2015
Time: kl. 09.00 - 13.00

No written aids + (KT) + English dictionary
The exam contains **3** pages including the front page

Exercise 1 (55%) In this course, we have discussed various forecasting methods, for instance the *moving average method* and the *linear regression method*. The moving average method is an example of a *time series method*, while linear regression is an example of a *causal method*.

a) Explain (briefly) the main differences between time series and causal methods.

b) If you were to forecast some demand for an event producer, which class of the above mentioned methods would you choose, and why?

t (time periods)	1	2	3	4	5	6	7	8	9
d (observed demand)	0	10	20	10	0	10	20	10	0

Table H.1: Historic demand observations

$$F_t^2 = \frac{d_{t-1} + d_{t-2}}{2} \ , \ F_t^3 = \frac{d_{t-1} + d_{t-2} + d_{t-3}}{3} \tag{H.1}$$

Table H.1 above contains observed demand for some event. Equations (H.1) contain formulas for forecasts (F_t^2, F_t^3) by the moving average method with orders 2 and 3.

c) Find forecasts, using the moving average method, for both orders, (order = 2 and order = 3), for the next upcoming time period ($t = 10$).

d) Which of the two forecasts would you choose if you only were interested in this single forecast for $t = 10$? (State reasons for your answer.)

e) Suppose alternatively that you are interested in choosing more permanently among orders 2 and 3. Make a short discussion on how you would solve this problem?

f) How would a linear regression model with time (t) as the X-variable and demand (d) as the Y-variable perform in this situation? *(Hint*: You are not meant to perform lengthy calculations here.)

g) An external forecasting expert suggests to drop the classical methods in this case, and defines the following forecast model:

$$F_t = \begin{cases} 10 & \text{if } t = \{4, 8, 12 \ldots\} \\ 10(t - C_t) & \text{for all other } t\text{'s} \end{cases} \tag{H.2}$$

and $C_t = 1$ if $t \leq 3$, $C_t = 5$ if $5 \leq t \leq 7$, $C_t = 9$ if $9 \leq t \leq 11$ and so on. How would you judge the expert's suggestion?

h) Could there be reasons why the expert's suggestion is a bad choice of forecast model? (State reasons for your answer.)

i) Could you think of any practical events that could produce such a demand pattern as the one in table H.1? (Use your creativity!)

Exercise 2 (25%)

a) Why is uncertainty considered more important in Event Logistics than in traditional Logistics?

b) The News-Boy model handles uncertainty and the solution involves solving the following equation:

$$F(Q^*) = \frac{c_u}{c_u + c_o}. \tag{H.3}$$

Explain all symbols in the model and give a brief explanation on how it can be used.

c) Suppose $F(Q) = \alpha Q + \beta$, that is a linear function. How much should be ordered optimally? What probability density function would such an assumption imply?

Exercise 3 (20%) Assume you have finished your master in Event Management and face an interview situation where a potential employer asks you on the contents of Event Logistics and why such competence may be valid to his/hers organization. Formulate an answer to this question. (Not longer than 2 pages.)

Appendix I

Solution to exam exercises – 2011

EXERCISE 1

a) One easy starting point is obviously to start by examining the table in sub-question b) which surely contains variables that seems reasonable to use in order to (partially) explain attendance demand. **Weather**, **ticket price**, **week day** as well as **artist quality** should definitely influence the number of spectators on such an outdoor event. The main question to investigate here should hence be related to alternative variables. **Substitution** seems relevant. After all, if other competing events take place at or around the same timing either locally or globally, it may very well lead to decrease/increase in attendance numbers. **Venue quality** (e.g. what investments are made into nice infrastructure) seats, shelter for rain, sound equipment, etc. may also (at least to some extent) influence concert attractiveness. Furthermore, choices related to **marketing** of the event may be important. Surely, the single ticket price is not the only pricing factor affecting attendance. The choice of **pricing mechanism**; pre-sales, price bundling etc. may also be influential.

b) This question does (of course) not have a single correct answer. Here. I am looking for some discussion on the different chosen variables. In my opinion, the choice of artist seems to be the most significant. However, a price too high may still lead to few spectators. Weather and week-day seems less important, given the "right" artist choice, but could play an important role if the artist is less famous. Substitution, venue quality or pricing mechanism seems perhaps even less important than other variables, at least if we fix our case to the Molde festival. Some empirical evidence indicate that the right artist choice may dominate almost all other variables, still, times are changing, and audience preferences may change as well.

c) The Estimated parameters in the table are all positive except the price parameter which is negative. This seems reasonable as an increased price (given all other variable values kept constant) should lead to less audience. (It seems unreasonable to assume ' snob" effects related to this kind of event.) The values of the estimated parameters indicate that artist quality as well as price influence attendance most. A one-step increase in artist quality leads to 500 more spectators. Increasing the price from one level to another leads to a decrease in attendance of 200, while a positive weather change leads to 100 more in the audience. The week day plays a less important role only contributing with 3 extra through a one day change. The fact that Sunday is "better" than both Friday and Saturday could perhaps be commented on. This is clearly not sensible in the case at hand. To conclude, the discussion in sub question b) seems reasonably covered by the given estimated parameter values.

d) Given the textual information in the exercise, this should be straightforward:

$$\text{Attendance } = 100 \cdot 1 - 2 \cdot 500 + 3 \cdot 6 + 500 \cdot 5 = \underline{1618} \tag{I.1}$$

e) Answering the first part should be straightforward. As all variables except price has positive signs we would maximise contribution my maximising variable values (Weather= 5, week day= 7, Artist quality= 5). The price variable however, contributes negatively and should be minimized (Ticket price= 100). Hence, the maximal possible attendance given this model is:

$$\text{Max attendance } = 100 \cdot 5 - 2 \cdot 100 + 3 \cdot 7 + 500 \cdot 5 = \underline{2821} \tag{I.2}$$

The given concert (The Rolling Stones concert) has defined Artist quality, Ticket price as well as Week day. This contribution ,which by the way is:

$$\text{Attendance without weather} = -2 \cdot 500 + 3 \cdot 6 + 500 \cdot 5 = \underline{1518} \tag{I.3}$$

is given. The only uncertain factor is hence weather, and given an equal probability of each weather instance, the expected (or average) weather contribution is:

$$\text{Expected weather att.} \; = \frac{1}{5}\left(100 + 200 + 300 + 400 + 500\right) = \underline{300} \tag{I.4}$$

Consequently, the total expected attendance number given this situation is $1518 + 300 = \underline{1818}$.

f) The concept of long versus short term forecasting is related to a situation where one forecasts series of events. If one must (for practical reasons) forecast the whole event series before all events start, we talk about long term. On the other hand, given a situation where certain decision for instance related purchasing can be done after some of the events has taken place, one could wait and update various information in order to try to improve short term forecasts. In this situation, it is clearly a singular event, and as such, the difference on long vs. short term becomes dubious. And, as the only relevant variable to forecast is weather (all other variables are in fact user decision variables), it would boil down to possible quality differences between long and short term weather forecasts. Personally, I really do not see much quality difference on weather forecasts either long or short, they all seem just as bad. So, for the case at hand, this effect would probably be minor. (Surely, students arguing good for the opposite is very much allowed to do so.)

g) This question is perhaps a little bit trickier (at least that was the intention). Firstly, let us make a starting assumption on the event producer here. Let us assume that he/she is greedy. Without such an assumption, it is hard to make anything out of this exercise. Given greed, the producer would like to maximise profit. In order to find possible profits, revenues must be calculated. So let us start by doing so. Furthermore, we need to look at our model (silly as it is, it is the only description we have) and it seems obvious that this model must govern the solution of the exercise. Again , given greed by the producer, he should obviously choose to stage his event on a Sunday. In practice, this day may simply not be available, but according to the information we have, the producer may choose this variable freely. As Sunday produces more attendance regardless of price, quality choices, it must be economically sensible to choose Sunday. What about weather? This is a variable outside of the producers choice, so to make things easy, let us assume average weather; that is a variable value of 3 and hence an attendance contribution of 300. Given the choice of day and weather, the attendance contribution amounts to $3 \cdot 100 + 3 \cdot 7 = 321$, which i attendance amount the producer will get independent of other decision variable choices. Now, various revenue numbers can (easily) be calculated. Let us look at an example. It seems evident (doesn't it) that when it comes to artist costs we can bear, we must open up for the possibility of artist costs dependent of artist quality. What we however avoid (in order to simplify) is artist costs dependent of our price choice. (In practice this could actually be a case, and would make the following analysis significantly harder.) Anyway, we are free to make the assumptions we like here, and do so. So, back to the example. Suppose the producer choose Artist quality = 1 and Ticket price = 100. Then, our model produces attendance $= -200 + 500 + 321 = 621$. The revenue consequence is of course the price of each ticket multiplied by the number of tickets sold (attendance). Hence, revenue in this situation amounts to $621 \cdot 100 = 62100$. This kind of exercise could (obviously) be performed for all possible combinations of Artist quality and ticket prices producing the table below:

	100	200	300	400	500
1	62100	$\boxed{84200}$	66300	8400	-89500
2	112100	184200	$\boxed{216300}$	208400	160500
3	162100	284200	366300	408400	$\boxed{410500}$
4	212100	384200	516300	608400	$\boxed{660500}$
5	262100	484200	666300	808400	$\boxed{910500}$

The squares in the table denotes the maximal revenue in each line (for each choice of artist quality). Given our assumptions, this kind of analysis provides sensible decision support for the event producer as he for any artist quality choice can see immediately what revenues he has to cover possible artist costs. Simultaneously, optimal pricing is also a consequence.

EXERCISE 2

a) The main difference is related to assumptions on future demand behaviour. The first 2 models, (EOQ and lot-sizing) assume deterministic (perfectly predictable) demand, while the last one (News-boy) assumes uncertain or stochastic demand. Additionally, the first two models open of for multiple periods, EOQ infinitely many future periods and constant demand, lot-sizing a given time horizon but variable demand. The News-boy model assumes a single time period.

b) The key point in finding practical (sensible) examples for the 2 first models is to look for event situations with nearly perfect predictable constant and variable demand. A (close) to constant predictable demand situation could arise through pre-sold tickets, but in practice we would not be able to guarantee people showing up. A better example might be a tournament with a given number of participants (predefined programme) where all participants stay in the tournament. given such a situation, food needs (say breakfasts) would often be predetermined and hence a predictable constant demand is the result. Similarly, a tournament with participants leaving opens up for a predictable but varying demand (typically decreasing in such a situation). The News-boy-situation is perhaps easier to define; a single event with uncertainty in demand would suffice. Surely, a lot of other possible examples exist here - left for student creativity.

EXERCISE 3

a) Table information suggests that the friend has a point. Location 1 costs 10, the same as location 8, but location 8 has better quality ($6 > 5$). Given a reasonable greed-assumption, the friend's advice should be followed.

b) The model which seems natural to pick in this situation is the model in the text-book (9.2) – (9.5), shown below: (I.5) – (I.8).

$$\text{Min } Z = \sum_{i=1}^{I} \delta_i C_i \tag{I.5}$$

s.t.

$$\sum_{i=1}^{I} \delta_i = 1 \tag{I.6}$$

$$\sum_{i=1}^{I} \delta_i Q_i \geq \underline{Q} \tag{I.7}$$

$$\delta_i \in \{0, 1\} \forall i \tag{I.8}$$

It is possible to use LINGO in a modelling language framework, but we have not learned this. So, the type of answer I would expect would be the model written out in full as (applying the advice from question a) and keeping the original i-definition):

$$\text{Min } Z = 15\delta_2 + 14\delta_3 + 20\delta_4 + 8\delta_5 + +9\delta_6 + 16\delta_7 + 10\delta_8 \tag{I.9}$$

s.t.

$$\delta_2 + \delta_3 + \delta_4 + \delta_5 + \delta_6 + \delta_7 + \delta_8 = 1 \tag{I.10}$$

$$6\delta_2 + 5\delta_3 + 7\delta_4 + 3\delta_5 + 5\delta_6 + 6\delta_7 + 6\delta_8 \geq 6 \tag{I.11}$$

$$\delta_i \in \{0, 1\} \forall i \in \{2, \ldots, 8\} \tag{I.12}$$

Obviously, to actually enter the model into LINGO, $15\delta_2$ must for instance be written like `15*d2` etc., and (I.12) like `@BIN(d2);`

c) A model for this situation could be:

$$\text{Min } Z = \sum_{i=1}^{I} \delta_i C_i \tag{I.13}$$

s.t.

$$\sum_{i=1}^{I} \delta_i = n \tag{I.14}$$

$$\sum_{i=1}^{I} \delta_i Q_i \geq n \cdot \underline{Q} \tag{I.15}$$

$$\delta_i \in \{0, 1\} \forall i \tag{I.16}$$

d) When $n = 4$ it means that we should pick 4 locations with an average quality of at least 6. A feasible solution could be picking locations

$2, 4, 6, 8$ with an average quality of $\frac{1}{4}(6+7+5+6) = 6$ satisfying the (average) quality constraint. The question of optimality is easy to handle. It ought to be obvious that location 5 ($Q_5 = 3$) can not yield feasibility. Any combination including a quality of 3 will not reach an average of 6. Then, what remains to check is whether any other 5's or 6's could be interchanged with the existing ones yielding less costs. Looking at the table, we observe that locations 3 and 7 are more expensive than existing counterparts. Hence, the given solution is optimal.

Appendix J

Solution to exam exercises – 2013

EXERCISE 1

a) in equation (J.1), K is the order cost (or alternatively set-up cost given EOQ in production), λ is demand and h is per unit inventory cost.

EOQ is derived by forming the total cost function:

$$TC(Q) = K\frac{\lambda}{Q} + h\frac{Q}{2} \tag{J.1}$$

and minimizing by equating first order derivative to zero:

$$TC'(Q) = -K\frac{\lambda}{Q^2} + \frac{h}{2} = 0 \Rightarrow Q^2 = \frac{2K\lambda}{h} \Rightarrow Q^* = \sqrt{\frac{2K\lambda}{h}} \tag{J.2}$$

b) First, we apply the EOQ-formula. K and h is given, but λ must be established. In such a situation, we approximate by average demand. Based on the information in table 1, the average demand is:

$$\lambda = \frac{4\cdot 50 + 4\cdot 60 + 4\cdot 70}{3\cdot 4} = \frac{200 + 240 + 280}{12} = \frac{720}{12} = \underline{60} \tag{J.3}$$

Then, utilizing equation (J.2) we find:

$$Q^* = \sqrt{\frac{2\cdot 100\cdot 60}{0.18}} = \sqrt{66666\frac{2}{3}} \approx \underline{258} \tag{J.4}$$

Then, we can establish the purchase plan, as shown in table J.1: (an implicit assumption of no ingoing inventory is needed). Additionally, we adjust Q^* to 204 in period 10 to finish up with zero inventory in period 12, hence actually minimizing total costs. The plan is shown in table J.1.

Day	1	2	3	4	5	6	7	8	9	10	11	12
Demand forecast	50	50	50	50	60	60	60	60	70	70	70	70
Q^* (adjusted)	258	-	-	-	258	-	-	-	-	204	-	-
Inventory	208	158	108	58	256	196	136	76	6	140	70	0

Table J.1: Purchase plan for pancakes

c) The cost of the plan is calculated by the cost of 3 purchases (in period 1,5 and 10) and total inventory costs:

$$= 3 \cdot 100 + 0.18(208+158+108+58+256+196+136+76+6+140+70) = \underline{554.16} \tag{J.5}$$

d) As the EOQ-approximation assumes constant demand, and this example contains varying demand (from 50 gradually up to 70), we can not expect the approximation to produce the optimal solution to the cost minimization problem.

e) In order to arrive at a guaranteed optimal solution we have to formulate a mathematical programming model for instance in the spirit of the model in the text-book on pages 57-58. A LINGO version for such a model may for instance look like the LINGO screen-dump in figure J.1

f) As the latter demand forecasts have a much smaller variability $[59, 61]$ compared to the original forecasts $[50, 70]$ we should expect that the EOQ-approximation would work better in the latter case. Here, all demand forecasts are "closer" to being constant than in the first case.

g) That depends on what we mean by the solution in b). The optimal purchase quantity Q^* does not change, as the average demand is unchanged - 60. However, the actual plan will change as demand forecasts are different. However, the changes will not be major. We do not compute these changes here, as it is not asked for it.

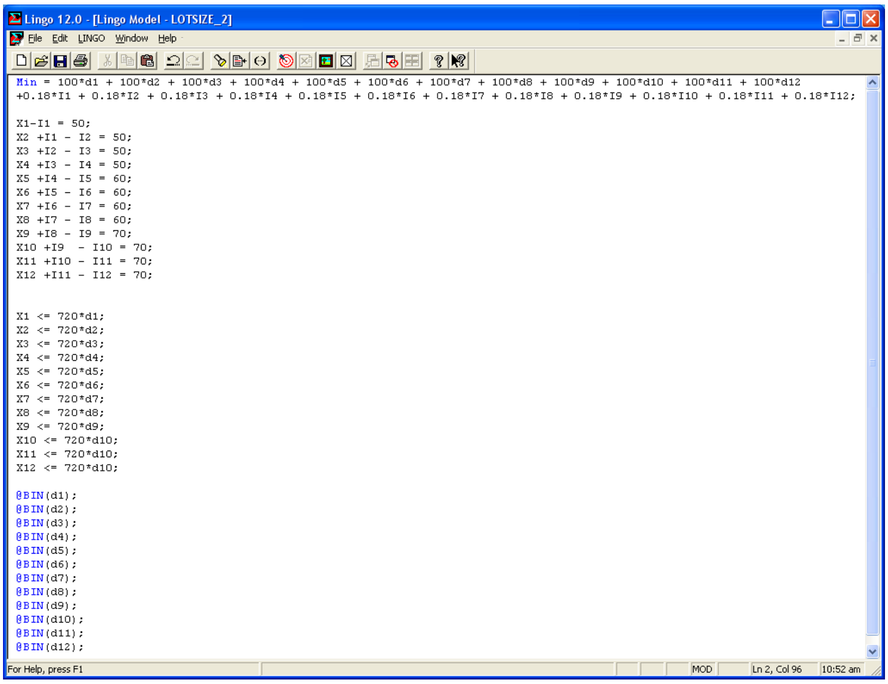

Figure J.1: The LINGO model from Exercise 1 sub-question e)

h) If the order cost is not longer a constant ($K(Q) = \alpha Q$), but depends on the order quantity Q, the total cost function must be redesigned as follows:

$$TC(Q) = K(Q)\frac{\lambda}{Q} + h\frac{Q}{2} = \alpha Q\frac{\lambda}{Q} + h\frac{Q}{2} = \alpha\lambda + h\frac{Q}{2} \tag{J.6}$$

$\alpha\lambda$ is a constant and the optimization problem degenerates to:

$$\min\, TC(Q) = h\frac{Q}{2} \tag{J.7}$$

The optimal solution to this problem is (clearly) $Q^* = 0$ theoretically, but in practice buying as little as possible without building inventory and we end up with the "Just-in-time" solution.

EXERCISE 2

a) Newsboy models are considered important in event Logistics because events are characterized by significant demand uncertainty as well as a limited event period where the need to formally model in-between storage possibilities are less important.

b) The information which we need is an expression for $f(Q)$, or $F(Q)$ given directly. In addition, we need values to compute c_u and c_o. Typically we have information on the buying and selling price of the given resource but we also the need the so-called salvage value or the price after our event. These three pieces of information is used to compute c_u and c_o. Given this information, equation (2) needs to be solved - an integral equation. Given a "distributional" shape with analytic integration possibilities the next step is the to solve an (often non-linear) equation in a single variable Q^*. Distributions lacking analytic solution to the transformation $f(Q) \to F(Q)$ need numerical methods.

c) In a symmetric distribution, the mean equals the median. If, in addition, $c_u = c_o$, the fraction on the right hand side of (2) becomes $\frac{1}{2}$. Then, a Newsboy problem may be solved (simply) by ordering expected demand. That is, in this case: $\underline{Q^* = 50}$.

d) A very high c_u compared to c_o would (in the limit) lead to a right hand side value in (2) of 1. No matter the shape of the distribution, the solution is then evident, as ordering the maximal amount or the upper limit of the distribution.

e) Case 1) is discussed above. Case 2) leads to a right hand side value of 0. Hence:

   1) $Q^* = \beta$
   2) $Q^* = \alpha$

   given $f(Q) \sim [\alpha, \beta]$.

EXERCISE 3 All answers to this exercise are directly available in the text-book.

Appendix K

Solution to exam exercises – 2015

EXERCISE 1

a) In a regression model, the variable of interest (Y) is explained through other variables (X_i). That is $Y^t = f(X_1^t, X_2^t, \ldots)$. In a time series model, the variable of interest (Y_t) is explained through previous instances of itself. That is $Y_t = f(Y_{t-1}, Y_{t-2}, \ldots)$.

b) In general, this question could of course not be answered. However, the text book argues that Logistics of manufacturing often needs **many forecasts** (many products) as well as **speedy forecasts** (short time between forecast periods). In events, the need for many and speed is not so obvious. In addition, as the example on football forecasting in the text-book indicates, the inherent need for forecasting the X_i variables which normally is troublesome related forecast quality, not necessarily is such a big problem in the event setting. In short. events are often planned long time before the event, which opens up for spending a little more time on forecasting. Hence, more complex models like for instance regression models may be more useful in this setting.

Normally, making a plot of the data may be helpful when certain forecast computations are demanded. Hence, we start by making a plot of the given demand data.

As figure K.1 indicates, the given demand data shows a "wonderfully" regular pattern.

c) As both formulas for the needed computations are given, they should be easily computed by:

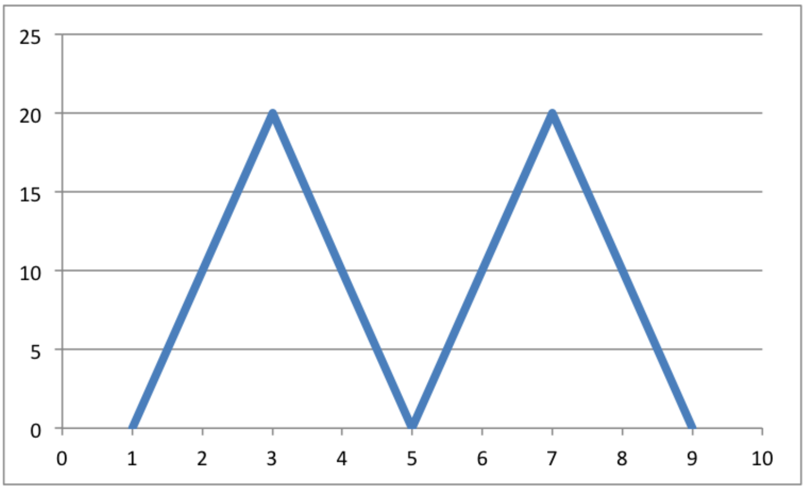

Figure K.1: A plot of the given historic demand data

$$F_{10}^2 = \frac{10+0}{2} = \underline{\underline{5}} \text{ and } F_{10}^3 = \frac{20+10+0}{3} = \underline{\underline{10}} \tag{K.1}$$

d) We have no more information than the historic demand pattern (see figure K.1), which shows remarkably structured behaviour. As a consequence, the moving average of order 3 which produces a forecast of 3 fits perfect to a simple reproduction of historic demand. Hence, $F_{10}^3 = 10$ seems an appropriate choice of forecast.

e) Observe here that actual computations are not demanded. Hence, something like: In order to pick among two forecast models, given (only) historic data, we calculate forecasts which can be compared over all possible historic data points. Then, forecast errors can be calculated and either by MAD or MSE (or both) a final single number (representing total forecast error) could be compared to choose among the two models.

For completeness I have also done the calculations. Figure K.2 sums up:

time	1	2	3	4	5	6	7	8	9			
demand	0	10	20	10	0	10	20	10	0			
MA-order 2				15	15	5	5	15	15			
MA-order 3				10	13,3333333	10	6,66666667	10	13,3333333			
e-2				-5	-15	5	15	-5	-15		MAD-2	10
e-3				0	-13,333333	0	13,3333333	0	-13,333333		MAD-3	6,66666667

Figure K.2: Excel calculations for the two models

As can be observed from figure K.2, the order-3 model fits best historically, with a MAD of ≈ 6.7, while the order 2 model produced a MAD of 10. Still, as figure K.3 indicates, none of the fit very well.

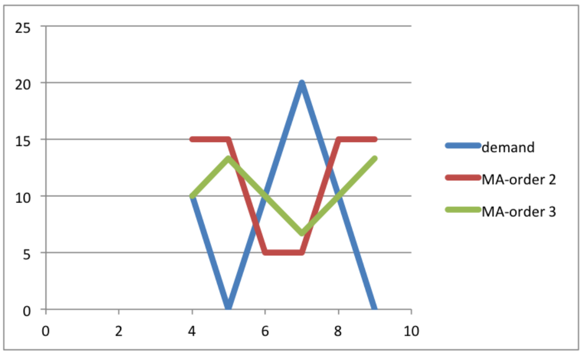

Figure K.3: Plot of forecast errors for the two models.

f) Here, one is explicitly not asked to perform regression calculations. Hence what is asked for is an ability to make an argument on how a regression line would be in this situation. Take a look at figure K.4:

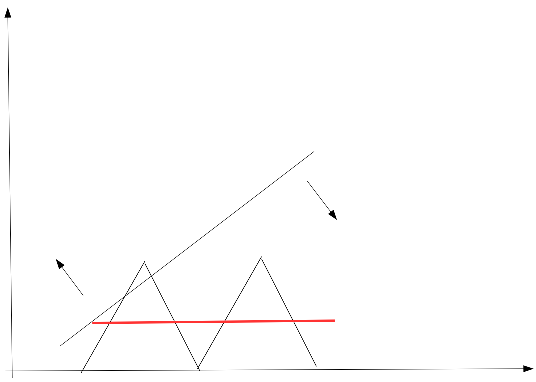

Figure K.4: Location of the regression line.

The black line (with arrows) in figure K.4 is placed randomly together with the demand data graph. It ought to be obvious that a rotation downward reduces errors or “makes a better fit”. A similar argument could be used if the line pointed in other directions. Hence we should end up with a regression horizontal regression line as shown in red in figure K.4.

Of course, this one does not fit very good either. It hits in half of the situations, but misses by 10 in the other half of the situations, which should indicate a MAD around 5, only slightly better than the moving average model of order 3.

g) Here, some mathematical construct is presented and the question then is if the students are able to understand what it means. It should not be that hard. for $t = 4, 8, 12, \ldots$ the value is 10. If we look back on the demand data, this hits perfectly. For all other t's a straight line $10(t - C_i)$ is the answer. Let us look at $t = 1, 2, 3$. $t = 1$ produces $10(1-1) = 0$, $t = 2$ gives $10(2-1) = 10$ and $t = 3$ gives $10(3-1) = 20$. This fits perfectly. The same holds for all other values of t. In addition, the saw-pattern of demand is also replicated into the future. Hence, this model produces a MAD of zero historically, and simply reproduces the same pattern into all future. Given a "pattern-recognition" and future "pattern interpolation" objective this seems like a perfect model.

h) Yes there could. Remember that 'patter recognition" not necessarily is the same as forecasting. If future duplicates the past, this is a good model. However, if future does not duplicate the past (as it normally dos not), it may be a very bad model.

i) The given pattern [0, 10, 20, 10] is of course a very simple example of a seasonal pattern. So, any events, say of winterly character (as we are in Norway) could resemble this type of pattern. a summer season roughly a quarter of the year (0-demand), 2 low seasons early and late winter (10, 10 demand) and a top season (mid winter, demand = 20) could fit nicely. A practical case; Aurora Borealis tourism may for instance seem like a good candidate

EXERCISE 2

b) This question is discussed a lot in the text book. The main points are related to the fact that many events have a long planning horizon often at locations where they have not been arranged before, all making demand more uncertain.

b) Q^* is the optimal ordering quantity in a News-Boy model. $F()$ is the distribution function, and expresses the probability that some event is below or equal to its input. c_u is the cost of under-ordering, while c_o is the cost of over-ordering.

Usage means solving a certain equation with respect to Q^* to find the actual order quantity that minimizes expected costs. For given values of c_u, c_o and a specified $F()$, such a solution can be found; either analytically or numerically.

c) A given liner distribution function means the the optimal order quantity is found by solving the equation:

$$\alpha Q^* + \beta = \frac{c_u}{c_u + c_o} \Rightarrow \alpha Q^* = \frac{c_u}{c_u + c_o} - \beta \Rightarrow Q^* = \frac{1}{\alpha}\left(\frac{c_u}{c_u + c_o} - \beta\right) \tag{K.2}$$

As $f(Q) = F'(Q) = \alpha$, the density function must be a constant or a uniform density.

EXERCISE 3 This is left to student creativity:)

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Index

Events take place at possibly unpredictable points in space and time and therefore impose special problems in relation to classical logistics modelling. Examples include the obvious lack of data related to historic demand, also most event products are difficult to store, there is uncertainty related to demand forecasts as well as limited event horizons, consumers are brought to a product (in most events) as opposed to the traditional manufacturing situation, and many events are effective monopolies.

Event Logistics discusses, presents and provides solutions to logistics problems related to events and includes the following key topics:

- Forecasting
- Inventory Management
- Production
- Supply Chains
- Transportation
- Dynamic Pricing
- "Hype Logistics"
- Facility Location
- Sequencing

This book is designed for students taking courses in Event Logistics and others who need an updated review in this field.

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