DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

RISK MANAGEMENT IN PRODUCTION PLANNING

by
Elif SEDEF

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İZMİR

RISK MANAGEMENT IN PRODUCTION PLANNING

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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"RISK MANAGEMENT IN PRODUCTION PLANNING"** completed by **ELİF SEDEF** under supervision of **PROF.DR. BİLGE BİLGEN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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RISK MANAGEMENT IN PRODUCTION PLANNING

ABSTRACT

In this thesis, a problem of production planning and scheduling in the electronics industry is addressed with independent sequence and eligibility constraints. The planning processes of the company which produces LCD TVs and digital consumer products in the electronics industry are studied. A mixed integer linear programming (MILP) model is developed for the independent production planning. The proposed model aims to minimize penalty costs which arise from earliness and tardiness of the orders with eligibility constraints. A real case study is conducted to illustrate the applicability of the proposed model and solution methodology.

Product variety is extending with ever-changing competition environment. High product variety, decreasing prices and short product lifecycles are the key parameters that define the characteristics of the consumer electronics industry. It has short product life cycles owing to developing technology. Therefore, the financial and demand-related risks are critical issues that should be considered to reserve the market share. The proposed MILP model addresses the production planning problem in the electronics industry by considering various uncertainties.

Primarily, risk factors faced in the electronics industry are described. Consequently, two different risk management models are utilized on the MILP in order to conduct a risk management study. For this purpose, the mathematical model is reformulated and scenario trees are created. In the model, Conditional Value at Risk (CVaR) and Upper Partial Mean (UPM) models are applied for examining output of the risk scenarios. The possibilities of each scenario tree according to the determined risk factors are calculated and analyzed.

Keywords: CVaR, UPM, electronics industry, production scheduling, risk management models

ÜRETİM PLANLAMADA RİSK YÖNETİMİ

ÖZ

Bu tezde, elektronik endüstrisinde sıra bağımsız ve uygunluk kısıtlarına sahip üretim planlama ve çizelgeleme problemi ele alınmıştır. LCD TV'ler ve dijital tüketici ürünlerini üreten firmanın bir üretim planlama süreçleri incelenmiştir. Sıra bağımsız üretim planlama problemi için karışık tamsayı doğrusal programlama(MILP) modeli geliştirilmiştir. Önerilen model müşteri siparişlerinin uygunluk kısıtlarıyla beraber termin tarihinden erken veya geç üretilmesinden kaynaklanan maliyetleri minimize etmeyi amaçlamaktadır. Önerilen modelin uygulanabilirliğini ve çözüm metodolojisini göstermek için gerçek bir vaka çalışması yapılmıştır.

Ürün çeşitliliği sürekli değişen rekabet ortamıyla birlikte genişlemektedir. Fazla ürün çeşitliliği, azalan fiyatlar ve kısa ürün ömrü tüketici elektroniğinin özelliklerini tanımlayan önemli parametrelerdir. Tüketici elektroniği endüstrisinde, gelişen teknoloji ile birlikte ürünler kısa yaşam döngüsüne sahiptir. Bu nedenle, finansal ve talebe bağlı riskler, pazar payı için önemli konulardır. Önerilen MILP modeli, elektronik endüstrisindeki üretim planlama sorununu çeşitli belirsizlikleri göz önüne alarak ele almaktadır.

Öncelikle, elektronik endüstrisinde karşılaşılan risk faktörleri bu tez kapsamında açıklanmıştır. Sonuç olarak, bir risk yönetimi çalışması yapmak için MILP üzerinde iki farklı risk yönetim modeli kullanılmıştır. Bu amaçla matematiksel model yeniden düzenlenmiş ve senaryo ağaçları oluşturulmuştur. Model üzerinde, Koşullu Riske Maruz Değer (CVaR) ve Üst Kısmi Ortalama (UPM) modelleri risk senaryolarının çıktılarını değerlendirmek için uygulanmıştır. Belirlenen risk faktörlerine göre her bir senaryo ağacının olasılıkları hesaplanmış ve analiz edilmiştir.

Anahtar Kelimeler: CVaR, UPM, elektronik endüstrisi, üretim çizelgeleme, risk yönetim modelleri

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CHAPTER ONE
INTRODUCTION

1.1 Objective and Motivations

Rapid changes in the environmental conditions cause frequent changes in the plan and target of companies. In an increasingly competitive environment, companies must be proactive and active in order to continue their processes, which require fast action and planning under uncertainty.

Production planning and scheduling is crucial to meet demands of customers at the right time of production and under the right conditions in the electronics industry. Production planning is one of the managerial decisions, which is mostly affected by dynamic and uncertain conditions of the company. Taking into account of the uncertainties that may arise in terms of economic, social, political and environmental factors in the process of planning, provide competitive advantage.

In real applications, production data cannot often be measured accurately or assumptions may not reflect reality. It is necessary to be prepared for any probable uncertain situations. That is why companies should update their long-term proactive plans continuously.

Risk management models contain uncertain mathematical modeling which enable companies to obtain reasonable, more sensitive results in a variety of different conditions that they may encounter during the planning period. Therefore, research on the risk management models have increased rapidly in recent years. Due to the advantages of risk management models in real life applications, they are increasingly preferred on real life applications in recent years.

In this thesis, we consider a production planning problem of an electronic company that is one of the largest OEMs (original equipment manufacturer) and ODMs (original design manufacturer) in the world. The company produces LCD TVs and digital consumer products. This study is based on a real-world production planning and scheduling problem with independent sequence and eligibility constraints in the electronics industry. During the year the company faces with several risks. Three risk measures, e.g. “demand at risk”, “arrival date of panels at risk” and “efficiency of production line at risk” are addressed in thesis.

As a solution approach, a mixed integer linear programming (MILP) model for the production planning problem under uncertainty in the electronics industry is developed. The aim of the model is to minimize penalty costs which ensued by earliness and tardiness of the orders. In addition, we consider variable customer demand throughout different periods, the productivity of production lines and the panel deliveries depending on the ship arrivals in the MILP model. Mostly, it is assumed that production lines are always available in the literature. However, production lines may differ from each other in terms of their characteristics. Therefore, eligibility constraints are added to the MILP model. In addition, uncertain parameters in production planning process in electronics industry are taken into consideration and we study risk management models to overcome the negative impact of uncertainty.

The contributions of this thesis are threefold. First, a mathematical model is developed with independent sequence and eligibility constraints. Second, we set scenario trees for uncertain parameters. Third, we apply two different risk management models to compare the outputs of the scenario trees.

1.2 Outline of the Thesis

This thesis consists of six chapters. In the next chapter, a brief survey of relevant literature on production planning and scheduling problems in consumer electronics industry is given. The third chapter includes an overview of the production system of the company. Additionally, this chapter also describes problem and presents the MILP formulation of the problem. In Chapter four, proposed solution methodology is presented. Chapter five presents computational experiments. Finally, in Chapter six, conclusions and future research directions are drawn.

CHAPTER TWO
ELECTRONICS INDUSTRY AND LITERATURE REVIEW

In this chapter, we introduce electronics industry and review the most relevant and recent literature on production planning problems for the electronics industry and risk management models for these types of problems. These studies are presented in different sections depending on the problem structure and solution approaches.

2.1 Electronics Industry

In this thesis, we focus on the production and scheduling problem in the electronics industry. So that dynamics of the electronics industry is significant to review for our problem.

In today's world, the electronics industry is not a single branch of industry but it also makes contributions to the development of other industries. Due to the increasing competition in the electronics industry, R&D (Research and Development) has become a significant field. Therefore, the electronics industry has been growing in parallel with the technology. The electronics industry has a wide product range. Some of which are listed in below (Tanyılmaz, 2002).

- Components: Circuit elements, picture tubes, coils and transformers, acoustic elements,
- Telecommunication: Devices for connecting telephone and telegraph lines (automatic telephone exchange etc.), end devices (telephone, telefax, etc.), transmission devices (analogue digital multiplex devices, TV transmitters), wireless-telephony / Satellite, etc.,
- Other Professional and Industrial Devices: audio and video systems, industrial electronic devices (static converters, automation devices, signaling and alarm devices, induction cookers), medical electronics, test and measurement instruments, automotive electronics,

- Military Electronic Devices: Communication based on electronic technology,
- Computers: Data processing machines, accessories, software services,
- Consumer Electronics: Electronic scale and devices, audio video tapes, audio devices, TVs, video players and TV.

The electronics industry is mainly controlled by American, European and Japanese international companies. Sub-industries within the electronics industry are dependent on each other both economically and technologically. Today, the most basic characteristics of the electronics industry include;

- An infrastructure required by the main companies and many supplier companies,
- Capital and technology intensive,
- The availability of a wide range of products,
- Having a worldwide scale in production and marketing,
- Having a rapidly changing and spreading technology.

The consumer electronics goods industry contains characteristics such as high product variety, decreasing prices and short product lifecycles (Fisher, 1997). The consumer electronics refer to any device containing electronic circuit boards that are intended towards individuals' everyday use. The consumer goods industry manufactures and distributes several types of goods such as TVs, videos, audio equipment to satellites, receivers, cash registers and electronic calculators. With a high exportation volume of 1 trillion Euro in 2018, consumer electronics good industry is an important part of the world electronics industry (Kick & Gerhardt, 2019).

The consumer electronics field is the leader of the electronics industry. After 1990, the industry shows a rapid development. It has been shown as a candidate for the television base of Europe with the high technology by producing electronics audio and video devices with the most advanced technology (Fındık, 2017).

58 major cities, most of them capital city, and also many technology center can be easily accessible from Turkey with four hours or less fly and that emphasizes the importance of location of Turkey. These cities are easily accessible. The consumer electronics has been experiencing rapid growth in Turkey. In Turkey consumer electronics industry, which is dominated by a TV product group, completed fiscal year with the single-digit growth with positive impact created by the European Championship in June at the second of quarter 2019. Sales in the consumer electronics increased by 7.5 percent in Quarter 1(Q1) 2019, compared to Q1 2018 in Turkey. The industry recorded a turnover of 1.7 billion TL (Sakar, 2019).

Today, the Consumer electronics industry is one of the most dynamic fields and customer demands are increasing gradually for superior quality and low cost. The consumer electronics industry with expanding technology brings uncertainty with many risks. The goal is to achieve high quality with low cost, at the right time of production and on the right conditions.

Several potential risks occur in the electronics industry. Companies face both internal and external risks. Some of external risks include technological developments, increasing costs, changing customer expectations, uncertain demands, natural disasters, economic uncertainties and supplier risks. Supplier risks arise from relationships with suppliers, financial problems, supplier collaboration or mergers. Natural or geopolitical disasters and criminal or terrorist threats are also can be defined as external risks for the supply chain. Some of internal risks include labor risks, process risks and financial risks. Cost risks can be considered as both internal and external risks. There are many different costs like variable costs, fixed cost of production, raw material cost and labor cost. Companies should invest in R&D to reduce costs and to create new products. If a company is unable to fund ongoing development and improvement of products, competitive characteristics will be lost. Large companies allocate more cash for research and development in comparison with small companies as an alternative. Cash reserves often deliver a strong competitive advantage.

External and internal material costs may be extremely variable. The variability affecting production costs increases risks of electronic companies. They protect themselves by identifying alternative suppliers and materials. They also produce for their suppliers' sustainability.

The more companies enter the market; the stronger competition becomes. With the entrance of many Far Eastern companies, the competition has increased in the market. Market competition forces prices to be lower and many companies slash profit margins to maintain competitive pricing. Nowadays, management of risks is becoming more important for reserving the market share. Today, to achieve a sustainable competitive advantage, companies should evaluate the possible risks, analyze these risks and make preventative action scenarios and prepare plans for them. As a result, competitive power and efficiency of companies increase in compare with the other companies in the market.

After evaluating the dynamics in the electronics industry, production efficiency, supplier risk and demand risk are significant factors for our problem.

2.2 Literature Review

In this section we continue with literature review. Section 2.2.1 presents the studies concerning eligibility constraints, earliness and tardiness of the orders in the literature. Production planning and scheduling problems in the electronics industry are examined with two sub-sections in section 2.2.2. These are production planning and scheduling problems without uncertainty and those under uncertainty in the electronics industry. In section 2.2.3, risk and risk management models are studied. In section 2.2.4, production planning and scheduling studies which take into account the risk management models are examined. These studies focus on risk management models and investigate planning problems in different industries.

2.2.1 Literature Review Concerning Eligibility Constraints, Earliness and Tardiness of the Orders

Objectives of the company are satisfying the due dates of the orders and not waiting for the products to be delivered after production. Therefore, we focus on the problem with the aim of minimum earliness and tardiness. On the other hand, all equipment, lines and machines may not be capable of all production items. Handling the process with eligibility constraints makes the problem more realistic. For this reason, we review the studies with eligibility constraints. In this section, we present studies considering earliness, tardiness and eligibility constraints. The summary of the literature review is presented in Table 2.1 at the end of this section.

Li & Cheng (1994) address the parallel machine earliness and tardiness scheduling problem without setups and common due dates. They solve the problem with a heuristic, then Cheng et al. (1995) apply the genetic algorithm (GA) to solve the problem. Their model minimizes the maximum weighted absolute lateness. Wang (1995) presents a multi-product multi-process earliness and tardiness from an aggregate planning with capacity limitations. Balakrishnan et al. (1999) & Zhu & Heady (2000) present the problem into one with non-identical parallel machines, sequence dependent setups, and distinct due dates. They address MIP (Mix Integer Programming) to solve earliness-tardiness problems. Chen & Lee (2002) use a branch-and-bound method by using column generation. They solve problems with a maximum number of 40 jobs.

Ma, Chan & Chung (2013) address the problem of integrated production scheduling with shipping information. Their model aims to minimize penalty costs which arise due to earliness and tardiness of the orders. To analyze the optimization reliability, these costs are compared with GA. The results indicate that the total cost is the highest for the case without the shipping information. When they assume the shipping lead time as a constant, they observe that the total cost increases. Therefore, the shipping information is considerable for production scheduling. They propose a two-level GA for their model. As a result, the proposed model has a lower total cost.

Mensendiek et al. (2015) consider to minimize total tardiness. They schedule jobs on identical parallel machines. They propose two approaches to solve the problem. The problem is NP-hard. These are optimal and heuristic solutions. It provides information on how to solve production and distribution timing problems effectively for scheduling and assignment decisions.

Azadian et al. (2015) study a coordination problem of production and transportation operations of a make-to-order contract manufacturer which considers multiple transportation modes. Their objective is minimizing total cost of tardiness penalties, manufacture and deliver multiple customer orders. They address MIP model to solve the problem. They present an exact dynamic programming model. They propose a heuristics approach for solving the sub-problems. Their study is the first to take into consideration production scheduling in detail.

Hung et al. (2017) address the scheduling problem of jobs on unrelated parallel machines with sequence-dependent setup times. They present three methods based on MIP. There are MIP and heuristic methods. According to these methods, heuristic is the most effective for their problem.

Villamizar et al. (2019) study the scheduling problem of independent jobs. They consider earliness/tardiness costs and variable setup times. They propose a MILP scheme. In this study, decision makers have the option to select the suitable solution for planning.

From now on, studies considering eligibility constraints are illustrated. In most of the literature, it is assumed that production lines are available all the time. However, this assumption may not be always true. Production lines characteristics may differ from each other. These characteristics include eligibility, productivity and availability of production lines. The characteristics of production lines generally help to determine for planning. In the related field, many authors study production planning and relevant issues. Sheen et al. (2008) state that eligibility constraints should be considered.

Liao & Sheen (2008) indicate that the parallel machine scheduling problem with the machine availability and eligibility constraints for minimizing the maximum lateness. Their research is the first study that considers the machine availability and the eligibility constraints simultaneously for machine scheduling. They develop branch and bound algorithm.

Gokhale & Mathirajan (2012) consider an unrelated parallel machine scheduling with considering eligibility constraints. Their goal is to minimize the total weighted flow time. Their problem is derived to be NP-hard. They propose a few heuristic algorithms. Hatami et al. (2015) also study distributed unrelated parallel machine scheduling problem with eligibility constraints. Their aim is to minimize the makespan. They propose a mathematical model and two constructive heuristics.

Afzalirad & Rezaeian (2015) propose metaheuristics for various parallel-machine scheduling problem. They consider sequence-dependent setup times, different release dates, machine eligibility and precedence constraints. They develop a hybrid ant colony optimization algorithm and hybrid GA. Su et al. (2017) also state a two-phase heuristic for parallel machine scheduling problem, which is basically a generalization of the Apparent Tardiness Cost rule. The aim is to minimize the total weighted tardiness when there are machine eligibility constraints. For this problem, they create a new composite dispatching rule, namely apparent tardiness cost with flexibility considerations.

Mateo et al. (2018) address a bi-objective parallel machine scheduling problem in order to minimize the final completion date and the total penalty generated by job levels. They propose heuristics algorithm. They develop an improvement algorithm.

Afzalirad & Shafipour (2018) study an unrelated parallel machine scheduling problem with machine eligibility and resource constraints. They propose two different approaches. The first approach is an integer programming model and the second approach is a GA.

After reviewing all these studies, our problem resembles the study of Ma, Chan & Chung (2013) among these studies owing to implementing the penalty cost for earliness and tardiness. Therefore, this study is used for setting our problem. Sheen et al. (2008) & Hatami et al. (2015)'s studies are taken into consideration in terms of eligibility constraint. These studies are related to production planning and scheduling problem. We observe that there is no study in the literature that considers both eligibility constraints, earliness and tardiness of the orders in the electronics industry. In our study, we address the problem of production planning and scheduling by taking these constraints into account in the electronics industry.

Table 2.1 Literature summary of modelling and solution approaches for earliness, tardiness and eligibility constraints

Reviewed literature	**Constraints**			**Modelling approaches**						**Solution approaches**
	earliness/tardiness	availability	eligibility	SM	MP	MIP	MILP	HE	GE	
Li and Cheng (1994)	✓								✓	Genetic algorithm
Cheng et al. (1995)	✓								✓	Genetic algorithm
Wang (1995)	✓							✓		Branch and bound algorithm, heuristic algorithm
Balakrishnan et al. (1999)	✓					✓				MIP formulation
Zhu and Heady (2000)	✓					✓				MIP formulation
Chen and Lee (2002)	✓						✓			Branch and bound algorithm, Column generation approach
Liao and Sheen (2008)		✓	✓	✓						Branch and bound algorithm
Sheen et al. (2008)	✓	✓	✓	✓						Mathematical model and two constructive heuristics
Gokhale and Mathirajan (2012)			✓					✓		Heuristic algorithm
Ma, Chan, and Chung (2013)	✓								✓	Two-level generic algorithm
Hatami et al. (2015)			✓				✓			Branch and bound algorithm
Mensendieka et al. (2015)	✓				✓			✓	✓	Branch and bound algorithm, heuristic algorithm based on tabu list, hybrid genetic algorithm
Azadian et al. (2015)	✓						✓			Successive subproblem solving, Variable target value method with backtracking
Afzalirad and Rezaeian (2015)			✓			✓			✓	MIP formulatıon and Genetic algorithm
Hung et al. (2017)	✓		✓			✓		✓		MIP formulation and Heuristic algorithm
Su et al. (2017)	✓		✓					✓		Heuristic algorithm
Mateo et al. (2018)			✓					✓		Heuristic algorithm
Afzalirad and Shafipour (2018)			✓		✓					Genetic algorithm
Villamizar et al. (2019)	✓	✓					✓			MILP formulation
This research	✓		✓				✓			Mathematical model and Conditional Value at Risk (CVaR) model

✓ defined otherwise undefined, MP - Mathematical Programming MILP - Mixed-Integer Linear Programming, MIP - Mixed-Integer Programming, SM - Simulation, GE - Genetic algorithm, HE - Heuristic algorithm

2.2.2 Production Planning and Scheduling Problems in the Electronics Industry

Now, we illustrate production and scheduling problem without uncertainty and those under uncertainty in electronics industry, subsequently.

2.2.2.1 Production Planning and Scheduling Problems Considering without Uncertainty

In this section, we investigate the studies for production planning in the electronics industry without uncertain parameters.

Park et al. (2008) state that a TFT-LCD (thin-film transistor liquid crystal display) module. It is the key component of LCD products. Many products are produced in an LCD factory all the year around. In the manufacturing processes, there are many constraints and re-entrant flows. Park et al. (2008) indicate the efficiency of planning and scheduling parameters under a big challenge. They present simulation-based DPS (daily planning & scheduling) system for the LCD factory. The daily planning and scheduling system is set regarding three components in the LCD module. Proposed model makes it easier to manage schedule changes. Chang et al. (2013) propose multiple linear programming models for production planning for a light-emitting diode (LED) array assembly. Aim of their model is to reduce the inventory stock while also meeting customer demands.

Chen et al. (2013) develop an advanced planning and scheduling system to generate production schedules automatically for a color filter fab with multiple lines. They propose the tabu-search (TS) and simulate annealing (SA) algorithms to optimize scheduling problem. Milne et al. (2015) investigate two levels of the supply chain which are minimum wafer starts and complementary demand in semiconductor planning. They propose methods based on two-stage linear programming (LP).

Cho & Jeong (2017) study the hierarchical decisions on production planning and scheduling for the bi-objective reentrant hybrid flow shop problem. Their study is based on a real world production planning and scheduling problem in TFT-LCD industry. Their objectives are minimization of delayed customer demand and total tardiness. They propose goal programming based on production planning algorithms and Pareto genetic based scheduling algorithms. Kriett et al. (2017) present an LP formulation with uncertain demand and failure-prone machines for production planning.

2.2.2.2 Production Planning and Scheduling Problems Considering under Uncertainty

In this part, we review the studies for production planning and scheduling problem with under uncertainty in the electronics industry. We also illustrate the solution approach. As technology develops in the world, the electronics industry has become even more important. The consumer goods industry with short product life cycles and demands has several uncertainties. Nowadays, control of these risks is becoming more important (Sodhi, 2005).

Sodhi (2005) studies the risk in supply chain planning. He addresses two risk measures which are: “demand at Risk” and “inventory at Risk”. He uses deterministic and stochastic LP models to manage the risk. It proposes ideal statute under demand uncertainty. He shows how stochastic modeling could be beneficial in a tactical supply chain planning for an electronics company.

Wu et al. (2010) address stochastic production and transportation control (PTC) problems in a hybrid TFT-LCD production chain. Although many traditional PTC problems attend to optimize production-transportation networks in push or pull system, they do not explain demand and price uncertainties. Wu et al. (2010) present stochastic optimization model under demand and price uncertainties in a multi-product. They propose robust optimization, which reduces the variance of objective function values and improves the robustness of decisions.

In the globalizing world, it is important to manage risks to ensure an efficient supply chain management. Park & Kim (2016) propose a simulation-based evolutionary algorithm, which is a hybrid methodology of a multiple queen-bee evolutionary algorithm and simulation that involves risks for source, production, distribution and transportation. Many scenarios are generated for analyzing behavior of the real global supply chain with uncertainty and risks. Their aim is to increase profit.

Beraldi et al. (2017) consider procurement plan to cover its energy needs. They propose a proactive strategy. The proactive strategy covers the energy needs with a high reliability level and integrates the Conditional Value at Risk (CVaR). Stawowy & Duda (2017) present an approach on the uncertainty about the real levels of finished products during production planning and scheduling process. They develop an innovative approach to production planning and scheduling in a foundry. They propose interval lot sizing and scheduling model and GA model. Zhang et al. (2018) address long-term electricity procurement and production planning problem under uncertainty demand. They propose MILP model for multistage problem. They highlight the contribution of stochastic solution for multi-stage problem.

We generally handle our subject of risks in electronics industry considering with Sodhi (2005)'s approach in terms of dealing with the demand-at-risk issues in supply chain which is the most relevant study for our risk-based problem solving models.

2.3 Risk and Risk Management Models

In this part, we give more technical details about risk and risk management models with relevant studies since our problem involves risk.

2.3.1 Risk

Risk is the probability of a random event to occur. The accomplishment of all foundations' goals is adversely affected as risk occurs (Vose, 2002). Risk is perception of these three elements which are listed below:

- the probability of occurrence
- scenario
- impact

Diverse types of assumptions consisting of risk definition can be found in literature. According to Campbell (2005), risk is the expected disutility. The risk is defined as the expected loss (Willis, 2007). The risk is equal to the two-dimensional combination of events/consequences and associated uncertainties (As the events occur, what will be the consequences?) (Aven & Renn, 2009).

Characteristics of Risks

- Risk is generally unknown or unpredictable,
- There is uncertainty,
- Risk varies within time,
- Risk has negative effects on the result,
- Risk is a manageable fact.

Each company has different strategies and goals from each other. Risk management start with strategy formulation and goal setting and their classifications are based on the objectives in the strategy and business plan of the company and the possible outcomes of risks (Reding et al., 2009).

Companies face internal and external risks. Internal risks involve many factors, such as:

- Risks in concern with production management,
- Risks related to economic management,
- Risks concern with the marketing management,
- Risks related to the effectiveness of the human resources management.

External risks are:

- Risks arising from economic uncertainties,
- Risks depending on the political instability,
- Risks arising from technological developments,
- Risks changing legal conditions,
- Risks created by the increased competition and competition conditions,
- The risk changing in customer expectations,
- Natural disaster risks,
- The risk of terrorism.

Risk must be well managed to prevent bad things and provide continuity of good things (Reding et al., 2009). Risk is the uncertainty as a result of plans and decisions. It is a function of strategic targets (Burnaby & Hass, 2009).

2.3.2 Risk Management

Risk management is the identification, assessment and prioritization of risks (defined in ISO 31000 as the effect of uncertainty on objectives). This terminology is based on coordinating economical assets to reduce, supervise, and control the impact of inappropriate conditions as the same time to escalate the realization of opportunities.

Originally, the concept of risk management emerges in the insurance business. In 1967, Edward Lloyd opens a coffee shop where exchanging of information in seamanship developed eventually in London. Thus, it becomes the center of marine insurance in Lloyd, by expanding the capacity of risks' contents that are allocated into the risk pools as the result of this success; risk management concept has been using for a very long time synonymous with the insurance sector. In the 1970s, America begins to implement risk management in the business world. Politics follow in the first half of the 1980s since risks of this segment are the most crucial than others. In the 1990s, all types of risks are recognized to manage and take under control. After this period, the importance given to risk management in organizations increase so it is focused on the risks that may cause the collapse of the institutions (Kızılboğa, 2012).

2.3.3 Risk Management Models

In risk management models, the objective function is evaluated by risk measures. The aim of these models is to minimize the risk. As a result, they are given the right decision for any decision makers. There are many different risk management models in literature as illustrated below.

2.3.3.1 Robust Optimization

Mulvey et al. (1995) propose robust optimization which is a worst-case-oriented approach to evaluate uncertainties using a collection of scenarios.

Robust optimization presents the solution which would have an acceptable performance under the most realizations of uncertain inputs. An optimal solution is robust if it minimizes the maximum relative regret. Robust optimization minimizes the variance of the total cost with the expected cost. The optimal solution can be executed as the lower cost, on the other hand, it has a wide variance. Therefore, risk will be higher than expected risk value. It is important to decide on the variance for the optimal solution. The formulation of the robust optimization is shown as follows (Mulvey et al., 1995).

R^s: optimal objective function under scenario s
w_s : probability of scenario s
Ω : a set of all possible scenarios

$$\min E[R^s] = \sum_{s \epsilon \Omega}^{I} w_s \, . \, R^s \tag{2.1}$$

$$w_s > 0 \tag{2.2}$$

$$\sum_{s\epsilon\Omega}^{I} w_s = 1 \qquad (2.3)$$

2.3.3.2 Managing the Variability Index

In robust optimization it is difficult to solve the problem where the objective function has a wide range of variance.

Ahmed & Sahinidis (1998) define the variability index as a non-negative continuous variable (Δ_s). In the literature, it is also named as Upper Partial Mean (UPM). If the scenario cost is lower than the expected cost, the variability index is 0; if the scenario cost $(Cost1 + Cost2_s)$ is greater than the expected cost $(\sum_{s\epsilon S}^{S}(\rho_s . Cost2_s)$, the variability index is equal to the positive difference between these two values.

The objective function of the variability index management model aims to minimize the weighted sum between total expected variability index and expected cost.

The formulation of the variability index is shown as follows (Ahmed & Sahinidis, 1998):

$$min\ E[cost] + \sum_{s}^{S} \rho_s . \Delta_s \qquad (2.4)$$

$$\Delta_s \geq Cost2_s - \sum_{s\epsilon S}^{S}(\rho_s . Cost2_s) \qquad s\epsilon S \qquad (2.5)$$

$$\Delta_s \geq 0 \qquad s\epsilon S \qquad (2.6)$$

2.3.3.3 Managing the Probabilistic Financial Risk

In some cases, decision makers are concerned with extremes of the cost spread. A lower probability of excessive cost or a higher probability of low cost is desired by decision makers. In such a case, decision makers can use probabilistic financial risk. It is defined as the probability that the actual cost is higher than a target Ω. By reducing the probabilistic financial risk for target Ω, the risk of having excessive costs can be reduced. Using the target Ω, it is defined as the probability of the cost being greater than Ω. Z_s is defined as a binary variable. Z_s equals to 1 if Ω $\geq cost_s(cost\ of\ senario\ s)$, otherwise equal to 0. M is added which is a large number. Barbaro & Bagajewicz (2014) proposed the following Big-M constraints. p_s is probability of scenario s.

The general formulation of the probabilistic financial risk model under the scenario s is shown as follows (Barbaro & Bagajewicz, 2014):

$$\min \mathrm{E[cost]} \tag{2.7}$$

$$\min \mathrm{risk}(x, \Omega) = \sum_{s \epsilon S}^{S} \rho_s Z_s \tag{2.8}$$

$$Cost_s \leq \Omega + \mathrm{M}Z_s \quad s \epsilon S \tag{2.9}$$

$$Cost_s \leq \Omega - \mathrm{M}(1 - Z_s) \quad s \epsilon S \tag{2.10}$$

The model has two objective functions. These are; reducing expected cost value and minimizing the probabilistic financial risk.

2.3.3.4 Managing Downside Risk

A binary variable in probability financial risk increases the size of the model for each scenario. To avoid the integer variable, decision makers use downside risk. In downside risk management model, a positive deviation variable Ψ is defined for each scenario between the target total cost (Ω) and the scenario cost ($\mathrm{cost_s}$). If the scenario $\mathrm{cost_s}$ is higher than the Ω, Ψ equals to 1, otherwise is equals to their difference.

The downside management model is then follows (You et al., 2009);

$$\min \mathrm{DRisk}(x, \Omega) = \sum_{s \epsilon S}^{S} \rho_s \Psi_s \tag{2.11}$$

$$\min E[cost]=cost1+\sum_{s\epsilon S}^{S}\rho_s cost2_s \quad (2.12)$$

$$\Psi_s \geq cost_s - \Omega \quad (2.13)$$

$$\Psi_s \geq 0 \quad (2.14)$$

This model has two objective functions: to minimize the downside risk and the expected total cost.

2.3.3.4.1 Value-at-Risk (VaR). In finance industry VaR is a popular risk measure (Artzner et al., 1999). VaR which depends on standard deviation of normal distribution is defined as a maximum loss in a specified period with some confidence level. VaR involves all outcomes below a specific level. χ is a random variable that indicates the loss from outcome. η that is a decision variable represents the optimal value for VaR.

$$VaR_\alpha[\chi]= \min \{\eta:\Pr(\chi \geq \eta) \leq 1-\alpha) \quad (2.15)$$

2.3.3.4.2 Conditional Value-at-Risk. CVaR is popularized by Rockafellar & Uryasev (see Rockafellar & Uryasev, 2000). Other names known in the literature include average value-at-risk, expected shortfall, tail value-at-risk, and mean excess loss. VaR is difficult to optimize for scenario-based approach. However, CVaR is considered to be a more coherent measure of risk than VaR. CVaR simply calculates the conditional mean of the 100(1−α) percent of worst-case values of a continuous random variableχ. CVaR at the confidence level α ($CVaR_\alpha$) is defined as follows (Amorim et al., 2013):

$$CVaR\ (cost) = \min \{\eta+\frac{1}{1-\alpha}.E\ [\eta\text{-}cost]\} \quad (2.16)$$

Rockafellar & Uryasev (2000) define CVaR. Amorim et al. (2013) use CVaR model for perishable production planning. In thesis, the formulation developed by Amorim et al. (2013) is used.

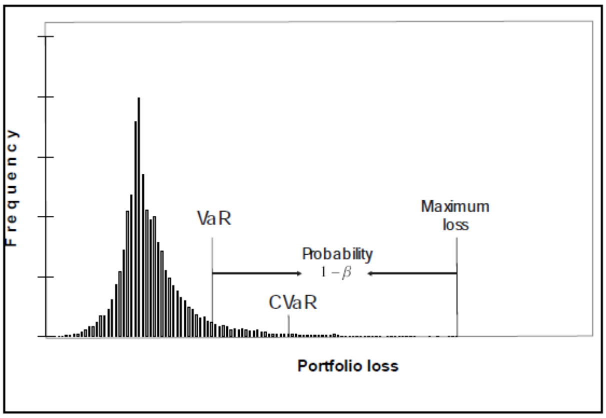


Figure 2.1 Portfolio loss, VaR, CVaR

CVaR deals with situations that exceed the risk level in VaR. It is always higher than VaR. VaR refers to the threshold value for losses, but would not indicate any result and/or what happens when this threshold is exceeded (see Figure 2.1).

Our problem is defined in terms of production planning problem under uncertainty in the electronics industry, so we introduce risk management models. We use two risk management models which are related in our problem. We mention these risk management models in more detail in the fourth chapter.

2.4 Risk Management Models in Different Industries to Develop a Novel Planning and Scheduling Problem in Electronics Industry

Until now we introduced dynamics in the electronics industry. Production planning and scheduling problem in the electronics industry are presented. After that, we mention risk and risk management models. Now, we illustrate the studies including all these concepts. The summary of the literature review is presented in Table 2.2 at the end of the section.

Ziegenbein (2007) states that companies must respond to customer demands at the right time and on the right conditions and at right quantities to be successful in industry. In order to response, companies generally have proper production systems which are organized with activities in many stages. Every stage is integrated with each other. On the other hand, product variety and flexibility are increasing with the globalized world in the manufacturing industry. Globalization escalates competition within the consumer electronics industry. Since purchasing strategies of customers vary; companies must adapt themselves to a high competitive level. Elmaraghy et al. (2013) state that production planning is a decision-making approach that plays a key role in the production. A competition that is developing with the technology among companies creates needs to ensure variety and flexibility in product range. Product variety and flexibility are increasing with the globalized world in the manufacturing industry. To indicate the importance of production variety and flexibility; many authors study in manufacturing systems. Many authors aim at minimizing the total cost of supply chain. One of the main objectives of production planning is to gratify customer requirements in the most effective form (Silver et al., 1998).

Kazaz & Webster (2011) study the impact of yield-dependent trading costs on pricing and production planning under the supply uncertainty. They develop two-stage model for obtaining the optimal production and pricing decisions for agricultural products with the dependent cost without measuring risks.

Alem & Morabito (2012) present two-stage stochastic models for the furniture production plan under stochastic demands and setup time with the uncertainty. Their aim is to reduce the risk by using the risk averse strategy. They propose four different models. The worst-case scenario is evaluated in the first model without the possibility of scenarios. The second model is based on CVaR model by a worst case scenario with a low probability. The third model uses the UPM model which is a mean risk model. The effects of risk preferences on direct constraints are examined in the last model. The CVaR is a suitable model to minimize cost standard deviation and losses of the worst case scenario.

Gebreslassie et al. (2012) present a decision-support tool for designing and planning of a hydrocarbon biorefinery supply chain with supply and demand uncertainty. They offer CVaR model with stochastic programming MILP model. They mention effectiveness of strategy for optimal design of hydrocarbon biorefinery supply chain in the presence of uncertainties.

Amorim et al. (2013) aim to reveal and handle this trade-off by developing risk averse production planning in perishable foods models. Model are included financial risk measures. They evaluate uncertainty in the demand level, decay rates. They propose deterministic and stochastic mathematical models. They mention lot sizing and scheduling decision. They offer two tractable risk approaches and use CVaR and UPM. They compare the different risk measures and see that the one implemented with CVaR is more suitable for measuring to incorporate in production planning.

Eskandarzadeh et al. (2014) consider production planning problem with the price-dependent demand and stochastic yield of production. Price dependent demands and short life cycle for products bring uncertainty with many risks. They use CVaR to show the distribution of profit function according to preferences of decision maker. The impact of risk parameter on the optimal decisions is examined.

Ait-Alla et al. (2014) investigate a risk-constrained profit expected maximization model. They propose mathematical model for a textile industry scenario. They use CVaR model for production planning. Results state that CVaR model provides flexibility to analyze and decide between different scenarios. Murata & Chen (2017) present a risk management model which can optimize the production in Chlor-Alkali products market. They propose CVaR model to take the uncertain factors into consideration such as order delivery, product price. Khalili et al. (2017) develop two-stage scenario-based mixed stochastic-possibilistic programming model. They analyze the ripple effect in the supply chain production and distribution planning problem under risk. For the robustness, they use CVaR model which is one of the risk management models.

Rahimi & Ghezavati (2018) study design and planning a sustainable reverse logistics network design for recycling construction and demolition wastes. They propose a risk averse two-stage stochastic model. They apply risk management model that is CVaR model. Felfel et al. (2018) present a multi-stage stochastic programming model under customer demand uncertainty in textile industry. Their study includes production amount, the inventory and back order levels. Their goal is to maximize the expected profit as well as the worst case profit.

We have eligibility, earliness and tardiness constraints in our problem. Therefore, we examine different studies including these constraints. On the other hand, electronics industry is faced many risk and uncertainty with developing technology. To overcome with the negative impact of risk and uncertainty, we also review the studies related to risk management models and uncertainty (parameters/environment) in the electronics industry and also different industries. Thus, in this thesis, the issue of risk and uncertainty is studied in the context of production planning and scheduling.

We generally handle our subject considering with Amorim et al. (2013)'s approach in terms of studying with the CVaR and UPM models in supply chain, which is the most relevant study for our risk-based problem solving models. The contribution of our study is taking risk management models into consideration for production planning and scheduling in the electronics industry.

Table 2.2 Many different risk management models and uncertainty studies in literature

Reviewed literature	**Risk measures**	**Risk Management Models**		**Modelling approaches**		**INDUSTRIES**	
		CVaR	***UPM***	**SP**	**MILP**	**Consumer electronics**	**Other industries**
Kazaz and Webster (2011)	✓			✓			✓
Alem and Morabito (2012)	✓	✓	✓	✓			✓
Gebreslassie et al. (2012)	✓	✓			✓		✓
Amorim et al. (2013)	✓	✓	✓	✓			✓
Eskandarzadeh et al. (2014)	✓	✓		✓			✓
Ait-Alla et al. (2014)	✓	✓		✓			✓
Murata and Chen (2017)	✓	✓		✓			✓
Khalili et al.(2017)	✓	✓			✓		✓
Rahimi and Ghezavati(2018)	✓	✓		✓			✓
Felfel et al.(2018)				✓			✓
This research	✓	✓	✓		✓	✓	

✓ defined otherwise undefined, MILP – Mixed-Integer Linear Programming, SP– Stochastic Programming.

CHAPTER THREE
THE INDUSTRIAL APPLICATION

This chapter initially gives detailed information about the company and its production system. On this bases, a production and scheduling problem is defined by considering independent sequence of orders and eligibility constraints. A MILP model is formulated in order to solve this problem. In addition, the mathematical model is extended by integrating two alternative risk management models. Details of the models is provided in the following sub-section.

3.1 Information about the Company

The company is among the largest OEMs and ODMs in the world. The company produces LCD TVs which are ranging from 20” to 84” and digital consumer products in the electronics industry. The company's major product is LCD TV. It produces for foreign and domestic markets by following make-to-order strategy. Approximately 15 percent of sales have been made for the domestic market, and the remaining 85 percent have been made for the foreign markets. The company which is the export champion for 18 years in Turkey exports to 152 countries. It has been the first company in the European TV production market. It meets 20% of TV production in Europe. At the company; an average of 8.5 million TVs are produced per year. An average of 130 product groups and 38217 products are managed by the company. There are over 900 different customers on TV. An average of 850 various products are manufactured on production lines each month. The company’s production system is make-to order. The company produces with mass customization for many distinct brands. In mass customization, products are produced for TV customer request. Each passing day with recent technology LCD TVs are introduced in market. Companies face many challenges in the market.

The challenges that companies face in the TV industry can be described as follows;

- Price competition,
- Lack of customer loyalty,

- OEM/ODM business model,
- Change of technology/market focus.

They must respond to customer demands at the right time and on the right conditions and in the right quantities to be in the market.

3.1.1 Overview of the Production System in the Company

The production system of the company is make-to-order. There are 550 components on average in LCD TV. The components of an LCD TV are as follows. These are; panel, chassis & power cards, cables, speakers, back covers, led bars, fronts, plastic cabins, reflector, optical films, middle frame, cartoon boxes and artworks.

The panel is an optic component which provides display. Cabin is an important mechanical part of the TV with numbers of variations. There are many units within it: metal components, cables, speakers. Chassis is the power unit and the second high-priced part of the TV; therefore, most of the cost-down projects are made for this critical high-cost component. Back cover is the other plastic unit with different mold types; led-bar effects product's brightness and color value. The reflector allows the led bar light to be directed towards the panel. Optical films are used to reach the target brightness of the product and to ensure that the light is evenly distributed over the entire surface. The middle frame is used for optic construction and fixing the place of the panel in the product. It is the outer face of the front cosmetic product and the inner face of the panel holding structure. Source Board Cover protects against external impact, loudspeaker group, 220V / rocker positions are plastic part where Wi-Fi / Bluetooth cards are located.

While 90% of the orders are from Europe, 90% of supplied materials are procured from the Far East. The average order fulfilment period is 20 days, and the materials are supplied at an average of about 90 days (The company has a strong capability to cover the orders in 20 days cycle, under the weak lead time as 12 weeks). These time differences require correct plan for demand and supply of materials in the long term.

3.2 Problem Definition

At first we illustrate the components of the production system and then we define our problem.

Firstly, the production capacity is determined by the orders given by the Marketing and Foreign Trade department. The Demand Planning Department determines the due date of customer orders according to the plastic and metal (front, back cover etc.) production capacity of the company and then the production planning and scheduling process are arranged in accordance with this capacity.

The Production Planning Department prepares production schedule according to;

- Due date
- Production line capacity
- Quantity
- Materials from both the internal and external suppliers
- Evaluating feasibility constraints (line product group eligibility)

In this thesis, the production planning and scheduling problem with independent sequence with eligibility constraints and with arrival of critical materials in the electronics industry are examined. This thesis aims at minimizing penalty cost due to earliness and tardiness of the orders.

The main goal of the production scheduling is to prevent an extension of the due date of orders. Delays of the customer orders are derived from many different problems. A Pareto analysis is used to investigate the causes for delays of customer orders in the first three months of 2018. Causes of delays are listed as follows: delay of panels, customer prioritization, delay of cartoon box, delay of external material, delay of production, and technical hold.

When the results of Pareto analysis have been analyzed, three types of causes (delay of panels, customer prioritization, and delay of external material) corresponded to 78% of all causes. And, these mentioned problems are related to the material supply. Besides, delay of panels corresponded to 43%, which is the highest rate.

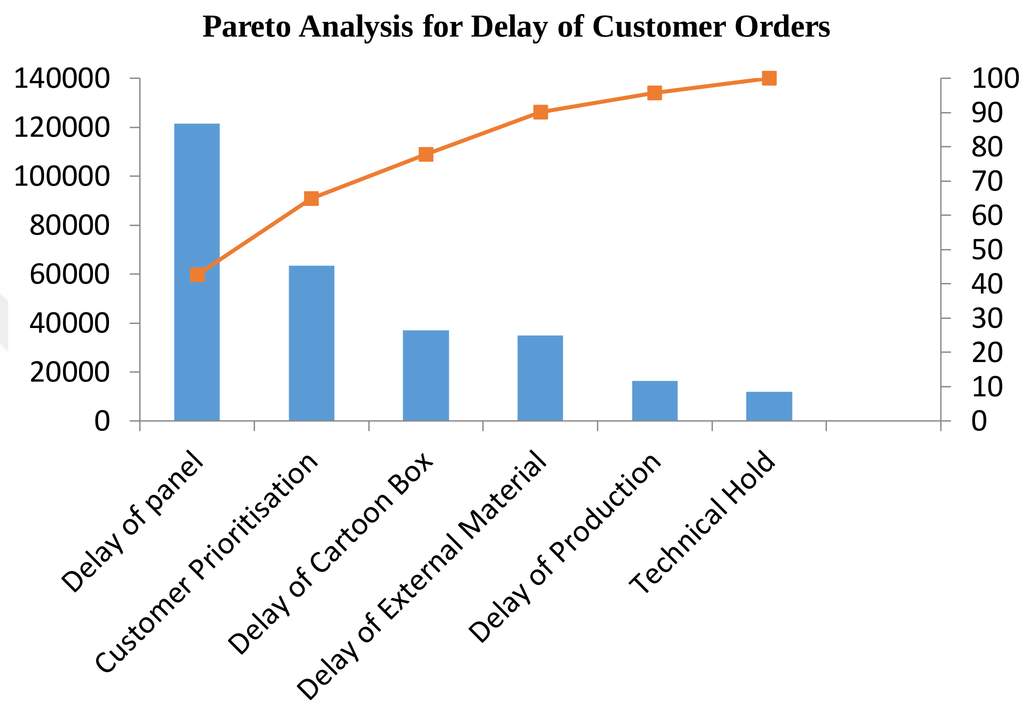
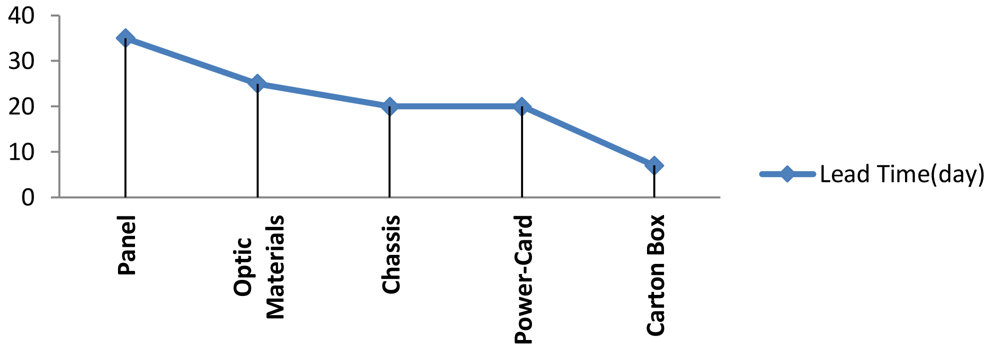


Figure 3.1 Pareto analysis for delay of customer orders

Components are procured from Europe, Turkey and The Far East. The panel, which is an optic component in LCD TV, is the most crucial component. There are 174 different panel codes in the company system. There are also 187 other optic components in LCD TV varying with the panel assigned. Nevertheless, by using different combinations of panel and optic components, technically similar TVs can be produced.

There are no companies with panel production in Turkey. 90% of the panels are supplied from the Far East, and the rest is supplied from Europe. As a result, the average supply time of this component is the longest one when compared to other components (see Table 3.1).

Table 3.1 Lead time of materials



Due to the critical position of the panels in the electronics industry, the company have to consider the supply and strategic decisions for any economic changes in panel suppliers. Price changes of LCD panels, constraints needed for the supply process and strategic reasons affect the panel suppliers. Price of panels is variable depending on economic conditions of the countries. Therefore, panel suppliers are reevaluated and redefined in every month. Each customer's orders are specific in the company. Different panels are used for the same LCD TV according to the specification of customer orders. All these conditions point out that panel has a critical role in the production planning.

On the other hand, 130 product groups on average are managed by the company. 7.4 million TVs are produced in 2018: 900 thousand TVs, between 20”-28” in size, 6.5 million TVs, between 32”- 75” in size. It is principally targeted on 32” product group’s as it is the most ordered TV’s by inch on the market. The production amount for different product sizes in 2018 are illustrated in Figure 3.2. 32” product group has the highest percentage.

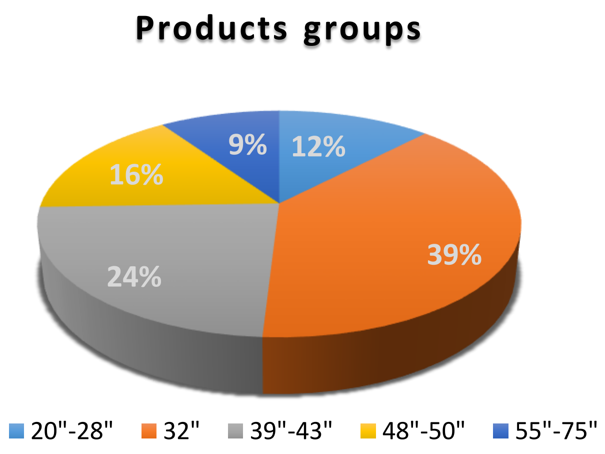


Figure 3.2 Product groups

The company should meet the customers' expectations seasonally. The 32" TV group, which takes an important part within all types of television with different screen sizes, has a critical place in the market.

Our problem is to minimize penalty cost due to earliness and tardiness with eligibility constraints in 32” TV groups, by considering arrival of panels.

There are five production lines designed for 32" TV production. All the customer orders are required to be delivered on the requested due date according to the panel control. The assumptions of the problem considered in the thesis are stated as follows:

The following considerations further define and delimit the problem.

1. The eligibility and productivity of the production lines are different from each other.
2. Other materials for the TV production are controlled and prepared beforehand.
3. The interruptions in production are ignored.
4. A production line manufactures a single order at any time.
5. A customer order can be processed if and only if the previous one is completed.
6. Customers send their daily orders for the next 4 weeks to the demand planning department. The demand planning department assigns the due date of customer orders

according to the plastic and metal (front, back cover etc.) production capacity of the company.

7. Production planning department schedules customer orders whose due date is between 7 days and 15 days ahead.

8. Customer orders cannot be produced in partial quantities.

Under these assumptions a mathematical model minimizes earliness and tardiness by taking into account eligibility constraints. Accordingly, key decision variables of the model are summarized as follows.

i. The starting and finishing time of production of each customer order on each line and sequence.

ii. Number of storage days of each customer order.

iii. Number of tardy days of each customer order.

3.3 Mathematical Model

In this section the proposed MILP model is presented and explained in detail.

Sets

i, j: customer orders $\{i \in I\}$, $\{j \in J\}$

l: production line $\{l \in L\}$

k: sequence of the customer order in the production line $\{k \in K\}$

Deterministic Parameters

c_i^p: penalty cost of tardiness per day for customer order i, in TL/day

c_i^w: storage cost of warehouse per day for customer order i, in TL/day

d_i : due date of customer order i (promised delivery time of customer order i)

p_{il} : processing time of order i on production line l, in day

cap_l : capacity of line l, in unit/day

H_{il} : equals to 1 If the customer order i can be assigned to the production line l, 0 otherwise

e_l : efficiency of production line l

Q_i : demand of customer order i ,in unit

AR_i : arrival date of panels for customer order i, in day

M : extremely big number

Decision variables

s_{ilk}: starting production time of customer order i in the production line l k^{th} sequence, in day

f_{ilk}: finishing time of customer order i in production line l k^{th} sequence, in day

u_i: number of tardy days of customer order i (tardiness)

w_i: number of storage days of customer order i in warehouse (earliness)

Y_{ilk}: equals to 1 if customer order i is assigned to k^{th} sequence at line l, 0 otherwise

X_{ijlk}: equals to 1 if customer order i is finished immediately before customer order j at production line l k^{th} sequence, 0 otherwise

The formulation of the proposed MILP model is introduced as follows.

The Proposed Model

$$Min \sum_{i\epsilon I}^{I} c_i{}^p \,.\, u_i + \sum_{i\epsilon I}^{I} c_i{}^w \,.\, w_i \tag{3.1}$$

Objective function aims minimizing the storage cost and warehouse cost.

$$\sum_{l\epsilon L}^{L} \sum_{k\epsilon K}^{K} Y_{ilk} = 1 \qquad \forall i \in I \tag{3.2}$$

Constraint 3.2 guarantees that every customer order must be assigned to only one sequence in only one line.

$$\sum_{i\epsilon I}^{I} \sum_{k\epsilon K}^{K} Y_{ilk} \geq 1 \qquad \forall l \in L \tag{3.3}$$

Constraint 3.3 satisfies that each line must be occupied with at least one customer order.

$$\sum_{i \epsilon I}^{I} Y_{ilk} \leq 1 \qquad \forall l \in L, \forall k \in K \tag{3.4}$$

Constraint 3.4 enforces that each customer order must be assigned to at most one sequence in only one line.

Constraints 3.1, 3.2, 3.3 and 3.4 are key constraints in this study. Constraint 3.1, 3.2, 3.3 and 3.4 are adapted from the literature by Moghaddam et al. (2006).

$$\sum_{k \epsilon K}^{K} Y_{ilk} \leq H_{il} \qquad \forall i \in I, \forall l \in L \tag{3.5}$$

$$\sum_{j \epsilon J}^{I} Y_{jlk+1} - \sum_{i \epsilon I}^{I} Y_{ilk} \leq 0 \qquad \forall l \in L, \forall k \in K \tag{3.6}$$

These equations control whether order i is before order j. Constraints 3.5 and 3.6 guarantee customer orders should be assigned in ascending sequence in the scheduling of each production line.

$$X_{ijlk} + 1 \geq Y_{ilk} + Y_{jlk+1} \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall k \in K \quad (i \neq j) \tag{3.7}$$

$$2. X_{ijlk} \leq Y_{ilk} + Y_{jlk+1} \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall k \in K \quad (i \neq j) \tag{3.8}$$

Constraints 3.7 and 3.8 enforce that when customer orders i and j are placed in sequence k^{th} and $k+1^{th}$ of production line l, respectively X_{ijlk} must be equal to 1.

$$\sum_{i \epsilon I, k \epsilon K}^{I} Y_{ilk} \,.\, Q_i \leq cap_l . e_l \quad \forall l \in L \tag{3.9}$$

Constraint 3.9 limit customer orders assigned to a production line must not exceed production line capacity.

$$S_{ilk} \geq \ AR_i . Y_{ilk} \ \ \forall i \in I, \forall l \in L, \forall k \in K \tag{3.10}$$

Constraint 3.10 satisfies a customer order can be assigned to a production line when panel of this customer order arrives.

$$Y_{ilk} . M \geq S_{ilk} \quad \forall i \in I, \forall l \in L, \forall k \in K \tag{3.11}$$

$$f_{ilk} = s_{ilk} + p_{il} . Y_{ilk} \quad \forall i \in I, \forall l \in L, \forall k \in K \tag{3.12}$$

Constraints 3.11 and 3.12 guarantee that the finishing time of customer order i in the production line l.

$$s_{jlk+1} \geq f_{ilk} - M.\left(1 - X_{jilk}\right) \quad \forall i \in I, \forall j \in J, \forall l \in L, \forall k \in K \ (i \neq j) \tag{3.13}$$

Constraint 3.13 enforces that a customer order cannot be at the same time both the predecessor and the successor of another customer order.

$$u_i = max\{0, (f_{ilk} - d_i)\} \quad \forall i \in I, \forall l \in L, \forall k \in K \tag{3.14}$$

Constraint 3.14 gives the number of tardy days of customer order i.

$$u_i \geq 0 \quad \forall i \in I \tag{3.15}$$

$$u_i \geq f_{ilk} - d_i . Y_{ilk} \quad \forall i \in I, \forall l \in L, \forall k \in K \tag{3.16}$$

$$w_i = max\{0, (d_i - f_{ilk})\} \quad \forall i \in I, \forall l \in L, \forall k \in K \tag{3.17}$$

Constraints 3.15, 3.16 and 3.17 give the number of storage days of customer order i in warehouse

$$w_i \geq 0 \quad \forall i \in I \tag{3.18}$$

The number of tardy days and storage days of customer order i are calculated using tardy days which are adopted from Ma et al. (2013).

CHAPTER FOUR
THE METHODOLOGY FOR PROBLEM SOLVING

Throughout the problem definition part, the scenario tree is used to make the decision-maker ready for any probable situations. These scenario trees include three parameters which include uncertainty conditions: efficiency of production line (e_{lt}), demand of customer order i $(Q_{it})$and arrival date of panels for customer order i (AR_{it}).

To conduct a risk management study on the model, two models, CVaR and UPM, which are risk management models are proposed. Within the scope of these models, the mathematical models are reformulated.

CVaR model provides flexibility to analyze and decide between different scenarios with a confidence level. The CVaR model shows us that at which level we have to avoid the risk. UPM model aims to minimize the sum of total expected variability index and expected cost. Both of these risk management models minimize the risk. MILP is used for these models. In the following sections, we explain the two risk management models used for evaluation of MILP's results.

4.1 CVaR Model

After getting solutions, risk model is applied to evaluate the results under alternative scenarios. To conduct a risk management study on the model, the conditional value at risk model, which is a downside risk model, is used. Within the scope of this model, the mathematical model which designed before, is reformulated. In this thesis, the scenario trees are formed by the combination of three stochastic parameters. These trees include efficiency of production line (e_{lt}), demand of customer order (Q_{it}), arrival date of panels for customer order i (AR_{it}).

CVaR expands from VaR. CVaR describes expected profit of the $(1-\alpha)\times 100\%$ scenarios exhibiting the lowest profit. CVaR accounts for the expected profit below a measure η called VaR at the confidence level α. VaR is the maximum profit such that its probability of being lower than or equal to this value is lower than or equal to (1 −α). CVaR at the confidence level α ($CVaR_{\alpha}$) is defined as follows (Amorim et al., 2013):

$$CVaR\,(cost) = \min\,\{\eta + \frac{1}{1-\alpha}.E\,[\eta\text{-}cost]\} \tag{4.1}$$

The illustration of applying the risk management model is shown above. Some stochastic parameters are added. The relevant notation is given below.

t: scenario $\{t \in T\}$

Objective function is updated as (4.2). Additional constraints (4.3) and (4.4) are added.

Stochastic Parameters

e_{lt}: efficiency of production line l in scenario *t*
Q_{it}: demand of customer order i in scenario *t*
AR_{it}: arrival date of panels for customer order i in scenario *t*
A_t : positive deviation between η and the cost of scenario t
O_t : probability of scenario *t*

$$Min\ \sum_{i \epsilon I}^{I} c_i{}^{p}\,.\,u_{it} + \sum_{i \epsilon I}^{I} c_i{}^{w}\,.\,w_{it} + \frac{1}{1-\alpha}\sum_{t \epsilon T}^{T} O_t\ \ .\,A_t \tag{4.2}$$

$$A_t = cost_r - \eta \qquad \forall t \in T \tag{4.3}$$

$$A_t > 0 \qquad \forall t \in T \tag{4.4}$$

Subject to deterministic constraints (3.2)-(3.8), (3.11)-(3.13)
Stochastic constraints (3.9)-(3.10), (3.14)-(3.18)

In the model, CVaR model will be applied, in order to analyze;

- the differences in quantity of customer orders,
- the dependence of panel deliveries on ship arrivals,
- the differences in the productivity of production lines.

4.2 UPM Model

In this model, the variability index defined by Ahmed & Sahinidis (1998) is used. Variability index (Δ_s) is equal to the positive difference between the scenario cost ($cost_s$) and expected cost($cost_{ec}$). The objective function of the UPM is aimed to minimize the sum between total expected variability index and expected cost.

The formulation of the variability index is shown as follows (Ahmed & Sahinidis, 1998):

$$min\, E[cost_{ec})] + \sum_{s\epsilon S}^{S} \rho_s \,.\, \Delta_s \qquad (4.5)$$

$$\Delta_s \geq Cost_s - \sum_{s\epsilon S}^{S} (\rho_s \,.\, Cost_s) \qquad s\epsilon S \qquad (4.6)$$

$$\Delta_s \geq 0 \qquad s\epsilon S \qquad (4.7)$$

To include the UPM, stochastic parameters are added in the mathematical model.

Stochastic Parameters

e_{lt}: efficiency of production line l in scenario t
Q_{it}: demand of customer order i in scenario t
AR_{it}: arrival date of panels for customer order i in scenario t
S_t : positive deviation between expected cost and the cost of scenario t
O_t : probability of scenario t

Objective function is updated as (4.8). Additional constraints (4.9) and (4.10) are added.

$$Min\ \sum_{i\epsilon I}^{I} c_i{}^{p} . u_{it} + \sum_{i\epsilon I}^{I} c_i{}^{w} . w_{it} + \sum_{t\epsilon T}^{T} O_t\ \ . S_t \qquad (4.8)$$

$$S_t \geq cost_r - \sum_{t\epsilon T}^{T} O_t\ \ . S_t \qquad \forall t\ \epsilon\ T \qquad (4.9)$$

$$S_t \geq 0 \qquad \forall t\ \epsilon\ T \qquad (4.10)$$

Subject to deterministic constraints (3.2)-(3.8), (3.11)-(3.13)

Stochastic constraints (3.9)-(3.10), (3.14)-(3.18)

In the model, UPM will be used, in order to analyze;

- the differences in quantity of customer orders,
- the dependence of panel deliveries on ship arrivals,
- the differences in the productivity of production lines.

CHAPTER FIVE
COMPUTATIONAL EXPERIMENTS

In this chapter, we aim to display the effects of stochastic parameters which are efficiency of production line, demand of customer order and arrival date of panels for production planning of the electronics industry. The impact of these parameters is analyzed. Computational results are evaluated in terms of the total cost incurred by earliness and tardiness of customer orders. This chapter is organized as follows. Section 5.1 addresses the scenario tree structure. Section 5.2 consists of submitted scenario data. Section 5.3 presents illustrative example results.

The mathematical formulation is solved using IBM ILOG CPLEX Optimization Studio 12.6.1on an Intel® Core™ i7-4700-2.40 GHz 8 GB memory.

5.1 Scenario Tree Structure

A scenario tree is a set of nodes and branches used in the models of decision making under uncertainty. Combination of three stochastic parameters are used in the scenario trees. These are demand of customer order(Q_{it}), arrival date of panels for customer order i (AR_{it}) and efficiency of production line (e_{lt}). These parameters are highly uncertain due to the technological developments in the product lines and products, change in the labor force, economic structure of the suppliers and customers, international sport events. Then, risk scenarios are applied, accordingly these parameters to track the changes in them.

Stochastic parameters, which are independent random variables, are used in scenario trees. The total number of scenarios is calculated by multiplication of demand of customer order i (Q_{it})×arrival date of panels for customer order i (AR_{it}) × efficiency of production line (e_{lt}).There are 27(=3x3x3) different scenarios. Demand of customer order i (Q_{it}) is defined by three levels which are high/medium/low level of the demand. Three different conditions are evaluated for the arrival date of panels for each customer order i (AR_{it}) which are coming early, coming on time, coming late compared to lead time of panels. Efficiency of production line (e_{lt}) is categorized as high/medium/low level. The levels of the stochastic parameter values are categorized as low, medium and high. We have composed scenario tree according to different levels of demand, arrival date of panels and efficiency. Figure 5.1 illustrates the scenario tree. We have 27 scenarios in total as shown in Figure 5.1.

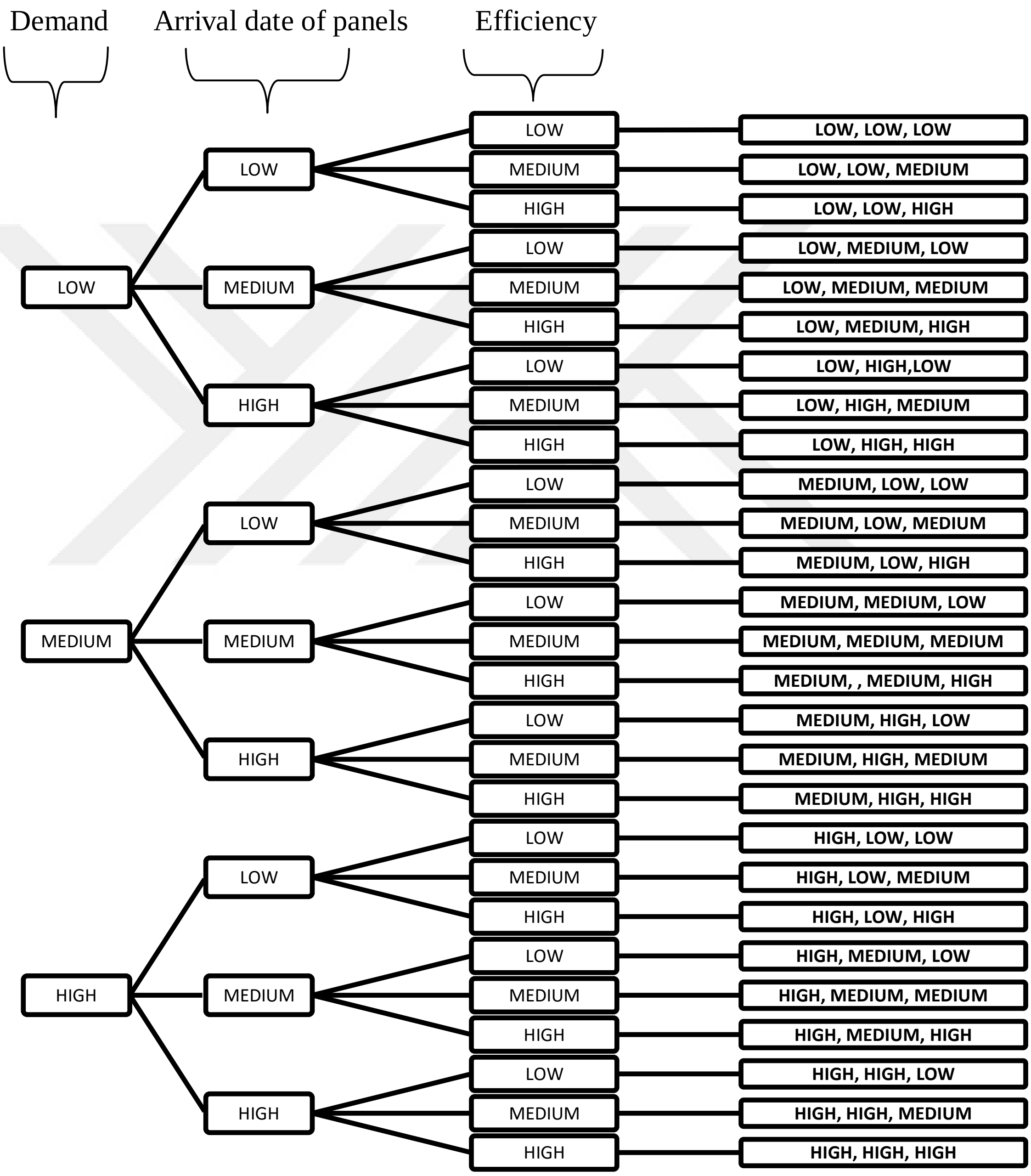


Figure 5.1 Scenario tree categorized with different levels of demand, arrival date of panels and efficiency

5.2 Scenario data

The production planning horizon is 15 days. The production planning is updated each day. In this thesis, we focus on 32" product group's as it is the most ordered TVs by inch on the market. That production group which belongs to 47 customers, is produced in five production lines.

Three parameters in the scenario data, which are Q_{it}, e_{lt} and AR_{it} are uncertain. We use real-data of the LCD TV production planning in this thesis. Demand of the customer has a normal distribution (Q_{it}) with given means and variances. It is uncertain and it follows normal distribution in the scenarios between 19 and 27 as shown in the Figure 5.2.

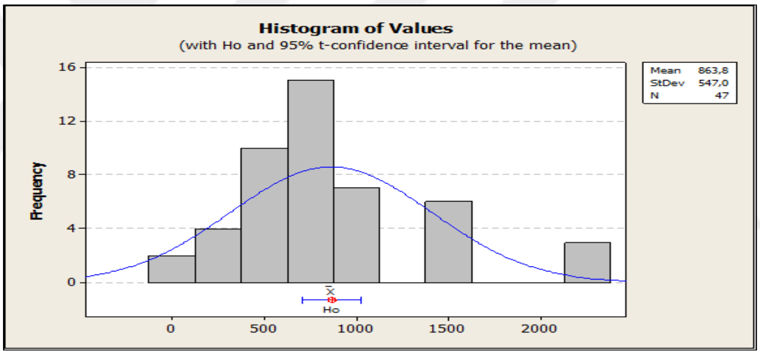


Figure 5.2 Illustrative example of the generation of the customer demand

Arrival date of panels are defined based on the real data in the last six months of 2018. Mean values and standard deviations of arrival date of panels are indicated (AR_{it}). The frequencies of the panels used in the thesis are shown in the Figure 5.4. The time specified by the courier company for the arrival of the panel is 31 days and mean value is 36.23 days. Standard deviation is 5.1 days. Minimum transit time is 31 days. Maximum transit time is 57 days. Due date of customer orders and arrival date of panels are date values. We convert them to discrete numbers beginning from the "1" which is indicated by 01.01.2018 as shown in Figure 5.3.

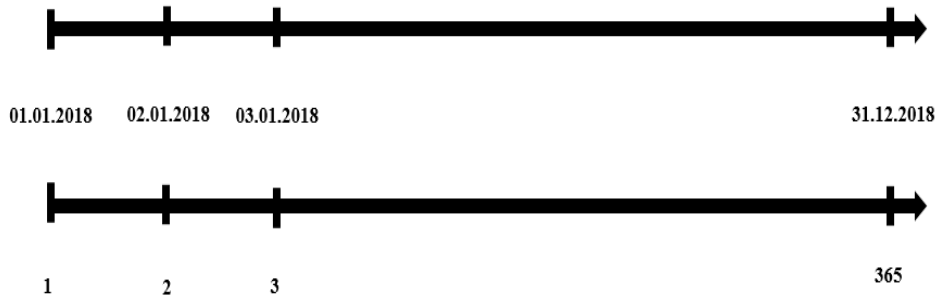


Figure 5.3 Data bar for scenario trees

We use discrete number in scenario trees for due date of the customer orders and the arrival date of panels.

We state that standard deviation for arrival date of panels is approximately 5 days. Therefore, we add five days to state arrival time for late panel arrival and subtract five days to state arrival time for early panel arrival. For instance, if arrival time of a panel is 110th day (corresponds to 20.04.2018), early arrival is defined by 105th day (corresponds to 15.04.2018) and late arrival is defined by 115th day (corresponds to 25.04.2018).

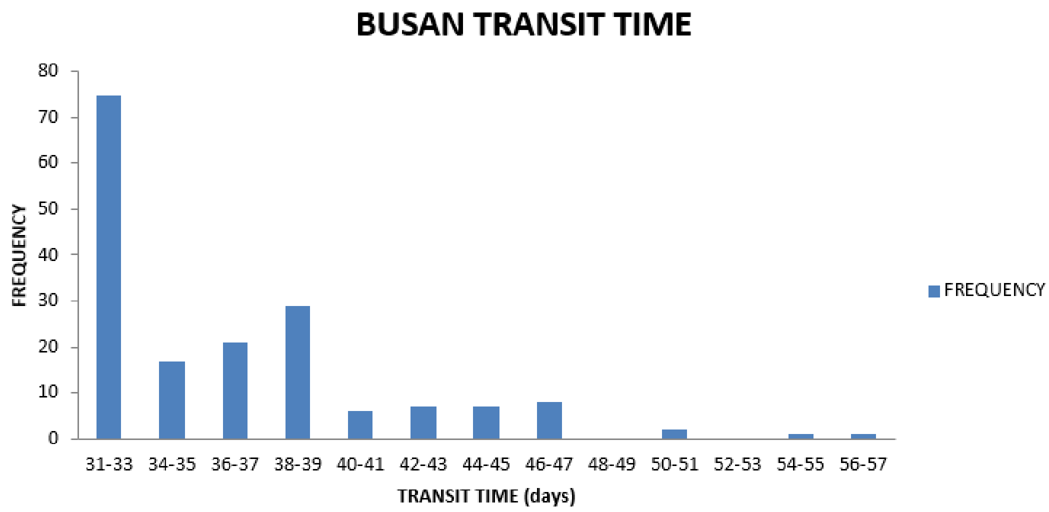


Figure 5.4 Frequencies of the panels in days

Our last parameter is efficiency and it is also based on the actual values for efficiency (e_{lt}). In real life cases, lines do not always work with the 100% efficiency. The company work on lower levels of efficiency of lines due to unexpected problems in production. The efficiency of production line is categorized as high/medium/low level. The efficiency values for production lines used in each scenario tree are shown in Table 5.1.

Table 5.1 Efficiency of production lines (%)

Efficiency	low	medium	high
line 1	0.9	0.95	1
line 2	0.9	0.95	1
line 3	0.95	1	1
line 4	0.95	1	1
line 5	0.8	0.9	1

We use probability for evaluating risk management models. So, we assume that 0.2, 0.3 and 0.5 are low, medium and high levels, respectively, for stochastic parameters. The scenario trees are created according to these levels and probabilities. The probabilities of scenarios are given on Figure 5.5.

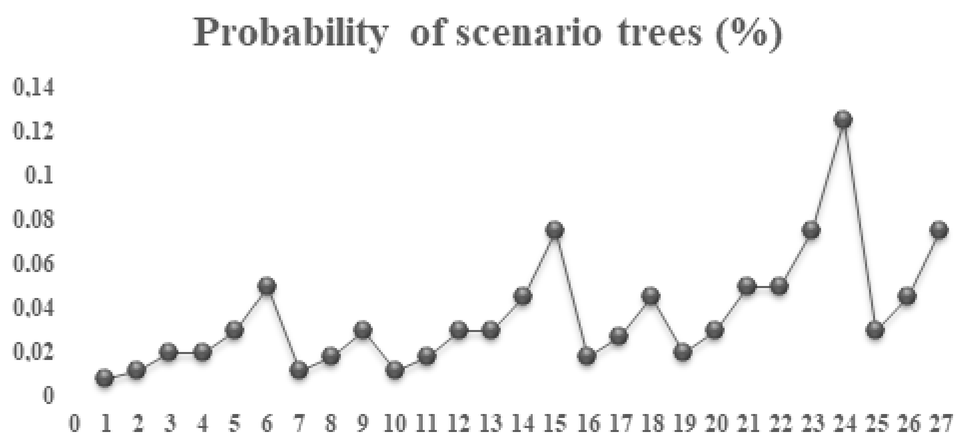


Figure 5.5 Probabilities of scenario trees (%)

5.3 Illustrative Example Results

According to scenario trees, 27 models in total are solved and analyzed. For each scenario tree, the results are evaluated within the data ranging from 21 to 47 customer orders. The customer order, penalty cost, warehouse cost, arrival date of panels, due date, eligibility for each line are shown in the Tables 5.2 and 5.3 below for 1st and 27th scenario trees. 7th and 21st scenario trees are presented in Appendices 1 and 2, respectively.

Table 5.2 1st scenario tree for production planning

Customer order	**Penalty cost (TL/unit)**	**Warehouse cost (TL/unit)**	**Due date (day)**	**Arrival date of panels (day)**	**Quantity (unit)**	**Eligibility**				
i	cp_i	cw_i	d_i	AR_i	Q_{it}	**Line 1**	**Line 2**	**Line 3**	**Line 4**	**Line 5**
1	15203	7602	91	85	1000	1	1	1	1	0
2	16718	8359	91	14	1000	0	0	0	0	1
3	13087	6543	91	76	840	1	1	1	1	0
4	1615	807	91	14	100	1	1	1	1	0
5	12268	6134	92	85	778	1	0	0	0	0
6	22352	11176	92	85	1500	1	0	1	1	0
7	3154	1577	92	85	200	1	1	1	1	0
8	3129	1565	93	88	200	1	1	1	1	0
9	1454	727	93	85	100	1	1	1	1	0
10	12635	6318	93	14	936	1	0	1	1	0
11	11303	5652	93	81	778	1	1	1	1	0
12	13134	6567	94	81	778	1	1	1	1	0
13	9864	4932	94	81	778	1	1	1	1	0
14	11162	5581	95	81	778	1	1	1	1	0
15	11162	5581	95	81	778	1	1	1	1	0
16	11162	5581	95	81	778	1	1	1	1	0
17	11762	5881	95	81	778	1	1	1	1	0
18	11762	5881	96	90	778	1	1	1	1	0
19	11762	5881	96	90	778	1	1	1	1	0
20	11762	5881	96	76	778	1	1	1	1	0

Table 5.2 continues

21	14151	7076	96	91	936	0	0	0	0	1

Table 5.3 27th scenario tree for production planning

Customer order	Penalty cost (TL/unit)	Warehouse cost (TL/unit)	Due date (day)	Arrival date of panels (day)	Quantity (unit)	Eligibility				
i	cp_i	cw_i	d_i	AR_i	Q_{it}	Line 1	Line 2	Line 3	Line 4	Line 5
1	15203	7602	91	85	1000	1	1	1	1	0
2	16718	8359	91	14	1000	0	0	0	0	1
3	13087	6543	91	76	840	1	1	1	1	0
4	1615	807	91	14	100	1	1	1	1	0
5	12268	6134	92	85	778	1	0	0	0	0
6	22352	11176	92	85	1500	1	0	1	1	0
7	3154	1577	92	85	200	1	1	1	1	0
8	3129	1565	93	88	200	1	1	1	1	0
9	1454	727	93	85	100	1	1	1	1	0
10	12635	6318	93	14	936	1	0	1	1	0
11	11303	5652	93	81	778	1	1	1	1	0
12	13134	6567	94	81	778	1	1	1	1	0
13	9864	4932	94	81	778	1	1	1	1	0
14	11162	5581	95	81	778	1	1	1	1	0
15	11162	5581	95	81	778	1	1	1	1	0
16	11162	5581	95	81	778	1	1	1	1	0
17	11762	5881	95	81	778	1	1	1	1	0
18	11762	5881	96	90	778	1	1	1	1	0
19	11762	5881	96	90	778	1	1	1	1	0
20	11762	5881	96	76	778	1	1	1	1	0
21	14151	7076	96	91	936	0	0	0	0	1
22	24325	12163	97	85	1600	1	1	1	1	0
23	6100	3050	97	85	376	1	1	1	1	0
24	26065	13033	98	91	1556	1	0	0	0	0
25	10074	5037	98	85	556	0	0	0	0	1
26	7131	3566	98	85	500	1	1	1	1	0
27	7167	3583	98	64	500	1	1	1	1	0
28	34525	17262	99	85	2250	1	0	1	1	0
29	3520	1760	99	14	200	0	0	0	0	1
30	15579	7790	100	85	1000	1	1	1	1	0
31	18119	9059	100	14	1000	1	0	1	1	0

Table 5.3 continues

32	33487	16744	100	93	2334	1	1	1	1	0
33	33487	16744	100	93	2334	1	1	1	1	0
34	5800	2900	101	85	400	1	1	1	1	0
35	12163	6081	101	85	800	1	1	1	1	0
36	8379	4189	101	76	500	0	0	0	0	1
37	7800	3900	101	14	500	1	1	1	1	0
38	5490	2745	102	64	376	1	1	1	1	0
39	3575	1788	102	64	282	1	1	1	1	0
40	6876	3438	102	91	440	1	0	1	1	1
41	11150	5575	102	64	1556	1	1	1	1	0
42	5654	2827	103	85	778	1	1	1	1	0
43	5612	2806	103	96	778	1	1	1	1	0
44	7254	3627	103	85	1000	1	1	1	1	0
45	26065	13033	104	91	1556	1	0	0	0	0
46	6800	3400	105	71	500	1	1	1	1	0
47	23094	11547	105	96	1556	1	1	1	1	0

5.3.1 Results of the MILP Model

We present different levels of uncertain parameters, main inputs and objective function for each scenario tree in Table 5.4. Main inputs are total customer demand, average arrival date of panels for customer orders and average efficiency of production lines. Objective function value is sum of total cost. For instance, total customer demand is 15370 units, average arrival date is on 69th day and average efficiency of production line is 1for the scenario 3.

Table 5.4 Results for 27 scenario trees

Scenario	Demand (Unit)	Arrival date of panels (days)	Efficiency of lines (%)	Total demand of customer orders (units)	Average Arrival date of panels for customer orders (days)	Average efficiency of production lines (%)	Total cost(TL)
1	L	L	L	15370	69	0.9	0
2	L	L	M	15370	69	0.96	0
3	L	L	H	15370	69	1	0
4	L	M	L	15370	74	0.9	0
5	L	M	M	15370	74	0.96	0
6	L	M	H	15370	74	1	0
7	L	H	L	15370	79	0.9	6752
8	L	H	M	15370	79	0.96	6752
9	L	H	H	15370	79	1	6752
10	M	L	L	23908	69	0.9	0
11	M	L	M	23908	69	0.96	0
12	M	L	H	23908	69	1	0
13	M	M	L	23908	74	0.9	0
14	M	M	M	23908	74	0.96	0
15	M	M	H	23908	74	1	0
16	M	H	L	23908	79	0.9	6752
17	M	H	M	23908	79	0.96	6752
18	M	H	H	23908	79	1	6752
19	H	L	L	40598	69	0.9	0
20	H	L	M	40598	69	0.96	0
21	H	L	H	40598	69	1	0
22	H	M	L	40598	74	0.9	0
23	H	M	M	40598	74	0.96	0
24	H	M	H	40598	74	1	0
25	H	H	L	40598	79	0.9	6752
26	H	H	M	40598	79	0.96	6752
27	H	H	H	40598	79	1	6752

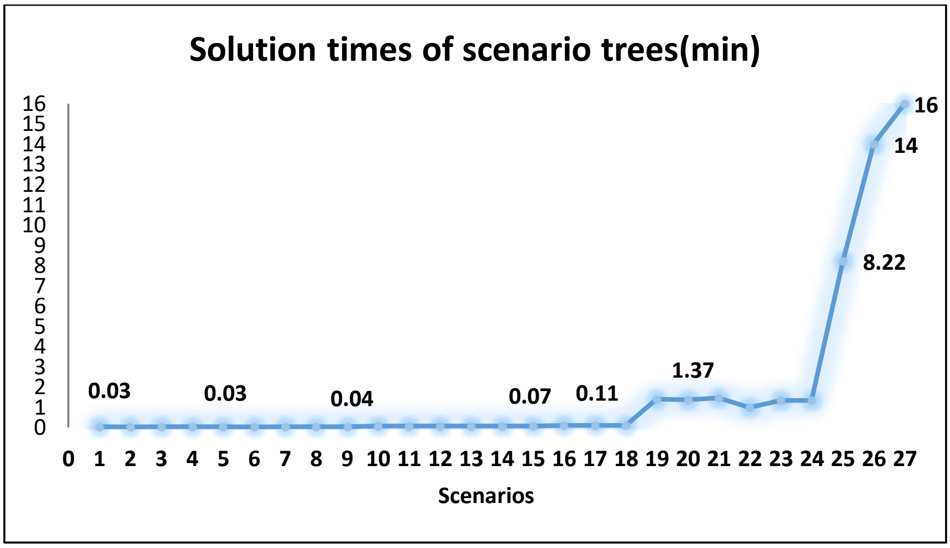


Figure 5.6 Solution times of scenario trees

Solution time (sec) gives the performance of the model. The solution time of scenario trees is indicated by minutes in Figure 5.6. The solutions of 18 scenarios are obtained within one minute. Solution times are between 1.40 -2 minutes. The solution times of the last 3 scenario are between 8.22 -16 minutes.

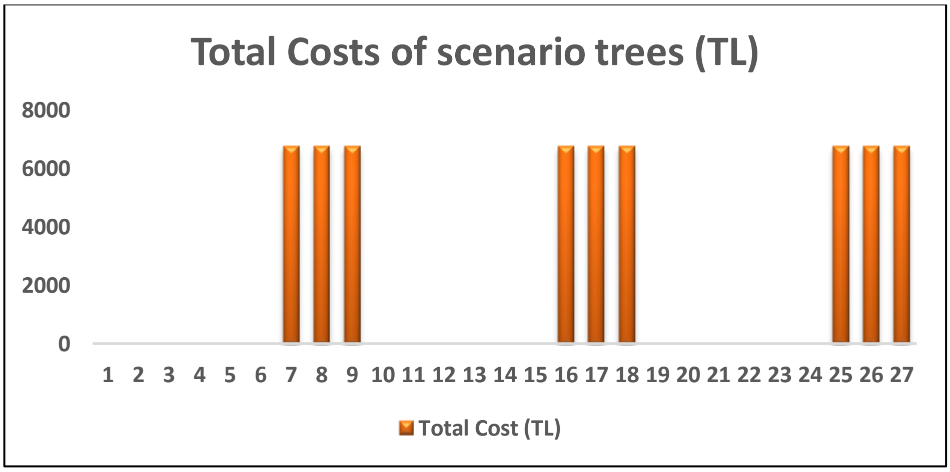


Figure 5.7 Total costs of scenario trees

It is probably stemmed from customer orders and arrival date of panels. Demand of customer orders gradually increase in the scenario trees. Arrival date of panels are late in 7th, 8th, 9th, 16th, 17th, 18th, 25th, 26th and 27th scenario trees. That is why problem gets more complex to be solved. Figure 5.7 indicates the total cost for each scenario tree. For 18 scenarios, there is no cost incurred by earliness and tardiness.

The number of customer orders are 21 in the scenarios between 1 and 9. Due date is 91 for order 1. Due date is 96 for order 21. Medium and high level customer orders are created by adding new customer orders on formerly created 21 low level customer orders. For medium level customer orders, the number of customer orders are 30 in the scenarios between 10 and 18.These scenarios are created by adding 9 customer orders to 21 customer orders. Due date is 97 for order 22. Due date is 100 for order 30. For high level customer orders, the number of customer orders are 47 in the scenarios between 19 and 27.These scenarios are created by adding 17 customer orders to 30 customer orders. Due date is 100 for order 31.Due date is 105 for order 47. Customer orders cannot be produced without panels. Delayed customer orders in scenarios 7-8-9, 16-17-18 and 25-26-27 are the same orders. Delayed orders are customer order 8 and customer order 21. Arrival date of panels are equal to customer orders due date for order 8 and order 21. That is why total cost is 6752 TL for nine scenarios.

Figure 5.8, Figure 5.9 and Figure 5.10 show the starting and finishing times of customer orders assigned to production lines in different scenarios. The number of customer orders in Figure 5.8, Figure 5.9 and Figure 5.10 are 21, 30 and 47, respectively.

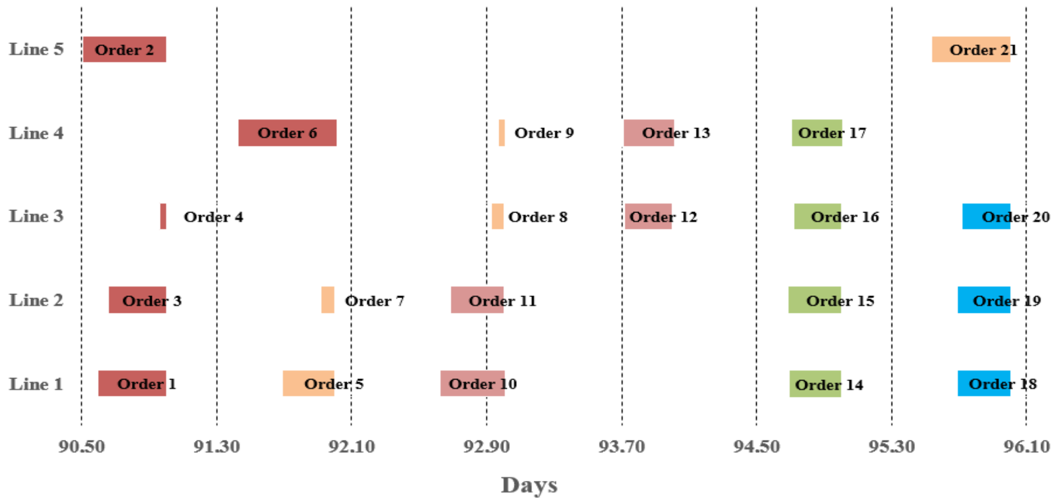


Figure 5.8 Production planning for between 1st -9th scenario trees

Blank areas correspond to idle time between orders. Because we have penalty cost for earliness in the objective function. If there were no penalty cost for earliness, there would be no stopping time between orders. Another reason for stopping time is the obligation of waiting for the arrival date of panels. Before panel arrives, we cannot produce the orders. In Figure 5.8, the stopping time between customer orders is quite high. As the number of customer orders increase, stopping time between customer orders decrease because there are more orders to complete in the same duration.

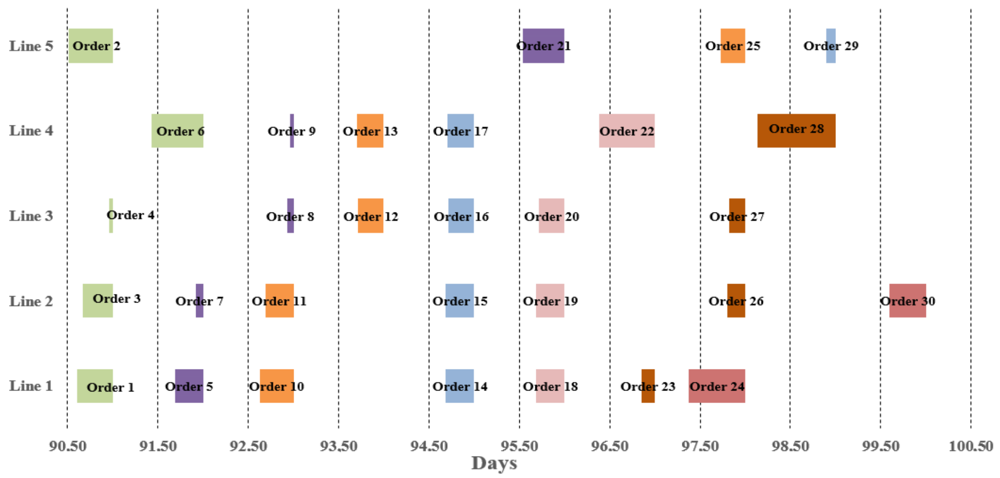


Figure 5.9 Production planning for between 10th-18th scenario trees

On the other hand, the latest time to start for each customer order is defined by the due date of customer order. For instance, panel arrival time is 76th day and due date is 96th day for order 20 in the scenarios between 1 and 9. The earliest time to start is 76th day for order 20, but order is assigned to 95.7th day since there is a penalty cost for earliness. The latest time to start is equal to subtraction of processing time from due date which is equal to 95.7th day.

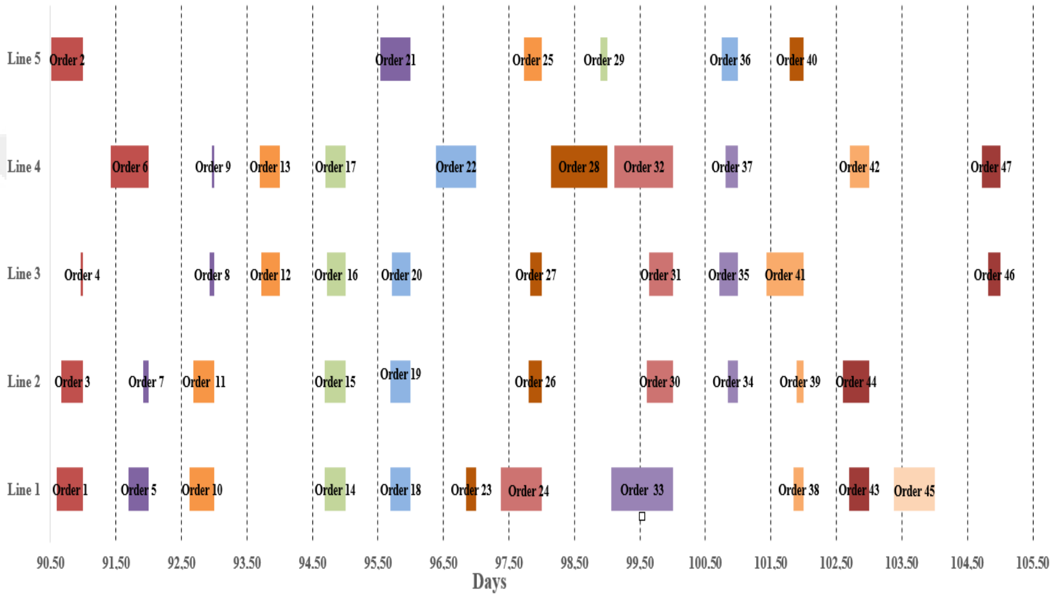


Figure 5.10 Production planning for between 19th-27th scenario trees

The earliest time to start for each customer order is determined by the arrival date of panels. If there were no such restriction, order 8 might not start earlier and might not be late because there is a stoppage between order 4 and order 8 in line 3 as shown in Figure 5.10.

The production lines have different characteristics; thus, the orders are distributed to the production lines according to their characteristics. There are varying numbers of customer orders on each production line because each customer's orders have their own characteristics and cannot be produced on every production line.

Customer orders are not delayed in changes in demand of customer orders and changes in the efficiency of the production line. Solution times increase as the number of customer orders increase. However, delays on the arrival date of the panels induce delay of customer orders. Total cost is 6752 TL for the 9 scenario trees. The reason of this is delay of the arrival of the panel of the order 8 and order 21.What makes difference for the objective function value is that arrival date of panels. Thus, we can state that arrival date of panels are significant when 27 scenarios are evaluated.

5.3.2 Evaluation of the Results with Risk Management Models

Until now, we have introduced the results of the model for each scenario. Then, we have implemented the risk management models in order to evaluate risk factor for the production planning in the electronics industry.

We apply two risk management models to reduce the expected loss in relation with a specific threshold approach for objective function value.

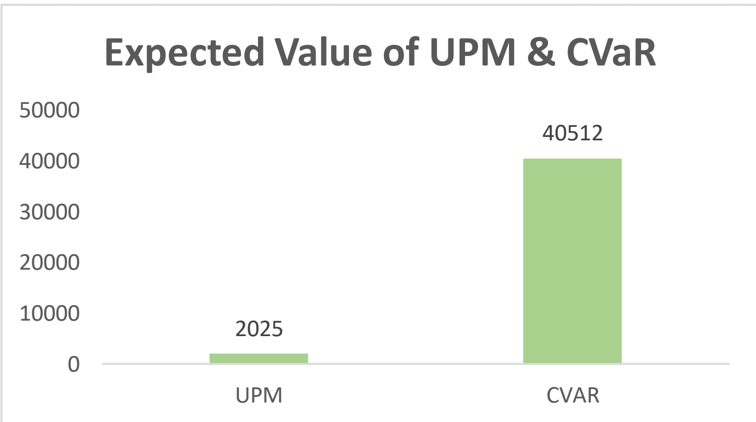


Figure 5.11 Expected value of CVaR & UPM (TL)

The expected values of UPM and CVaR are shown in Figure 5.11. A 95% confidence level is chosen in CVaR model. The CVaR model shows us that at which level we have to avoid risk. CVaR model provides flexibility to analyze and decide between different scenarios. The motivation for using CVaR is to avoid solutions influenced by very pessimistic scenarios since results rely on a 5% percentile of the worst-case realizations of the random variables.

Although the expected value in the CVaR model is initially larger than the UPM model. CVaR model takes into consideration of decision maker's confidence level. That is why, CVaR model is more important in this thesis. In the CVaR model, we evaluate three different confidence levels of the decision-maker. The expected values of three different the confidence level are given in Table 5.5. While confidence level is increasing, expected value of CVaR model is increasing. The corresponding results for the scenario 27 are similar with the results of both models, we observe arrival date of panels are significant to consider.

Table 5.5 The different confidence level and expected value of CVaR (TL)

Confidence Level	**CVaR (TL)**
0.90	20256
0.95	40512
0.99	202560

The CVaR model presents the expected profit of the $(1 - \alpha) \times 100\%$ worst scenarios in our minimization problem. The CVaR model's reaction is quicker than UPM, since the CVaR model improves the least positive profits. When we compare the different risk management models, it seems that the CVaR is the most suitable model to apply in the production planning in the electronics industry. The CVaR model shows us which situations we have to avoid from. Diminishing probable increase of expected costs' and also at least hedging against such a condition can provide a possible support necessary to achieve improvement on production planning in the uncertain electronics industry.

CHAPTER SIX
CONCLUSION & FUTURE RESEARCH DIRECTIONS

In this thesis, we examine the production planning process in a company competing in the electronics industry. There are five production lines working for 32” production group which we focus on. Eligibility constraints are taken into consideration since all products cannot be produced in each production lines. Our objective is to minimize the earliness and tardiness. Then we formulate a MILP model for production scheduling problem. On the other hand, some uncertain parameters, which are customer demands, arrival date of panels and production line efficiencies are considered. Therefore, scenario trees are generated in order to observe each possibility of uncertain parameters. Since each parameter has three different levels, we have 27 scenarios in total. After that, we solve each scenario with our proposed the MILP model.

To compare the outputs of the model, we apply two risk management models. Firstly, we have implemented the UPM model. Secondly, we have used the CVaR model. We observe that the CVaR model is more sensitive to variations in the risk than the UPM model. Besides, CVaR model involves confidence level which is not presented in the UPM model. It shows how the solution changes with the risk factors. In conclusion, the CVaR model is the most suitable one to apply for the production planning in LCD TV production process.

As a result, arrival date of panels for customer orders are more important than other parameters. As we have mentioned before, the panel, which provides display, is the key component in LCD-TV production process; therefore, the results of the models give similar results to predictions and experiences. Eventually, the average supply time of panel is the longest one when compared to other components. We can only procure 90% of the panels shipped from the Far East. There are no alternatives except the panel supplier companies in the Far East. While there are alternatives for other materials, the alternative for the panel remains limited. Therefore, this constraint remains as an external factor.

In this study, our goal is to know the risks regarding the customer demands, production line efficiencies, and arrival date of panels and to create the production plan. In addition, we try to optimize the expected value between outputs. However, the results show that there are still some external factors and different aspects that could be developed of this planning problem. The contribution of this thesis is taking eligibility, earliness and tardiness constraints into consideration with risk management models for production planning and scheduling in the electronics industry in literature. There are several future research directions for this thesis. One research direction would be to extend the model for other production groups in the company. Another research direction could be to add the other stochastic parameters that may affect the model for production planning. The most important research direction could be a decision support system assisted by CVaR. It could be developed for the whole manufacturing system in the company.

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APPENDICES

Table A.1 7th scenario tree for production planning

Customer order	Penalty cost (TL/unit)	Warehouse cost (TL/unit)	Due date (day)	Arrival date of panels (day)	Quantity (unit)	Eligibility				
i	cp_i	cw_i	d_i	AR_i	Q_{it}	Line 1	Line 2	Line 3	Line 4	Line 5
1	15203	7602	91	90	1000	1	1	1	1	0
2	16718	8359	91	19	1000	0	0	0	0	1
3	13087	6543	91	81	840	1	1	1	1	0
4	1615	807	91	19	100	1	1	1	1	0
5	12268	6134	92	90	778	1	0	0	0	0
6	59605	29802	92	90	4000	1	0	1	1	0
7	3154	1577	92	90	200	1	1	1	1	0
8	3129	1565	93	93	200	1	1	1	1	0
9	1454	727	93	90	100	1	1	1	1	0
10	12635	6318	93	19	936	1	0	1	1	0
11	11303	5652	93	86	778	1	1	1	1	0
12	13134	6567	94	86	778	1	1	1	1	0
13	9864	4932	94	86	778	1	1	1	1	0
14	11162	5581	95	86	778	1	1	1	1	0
15	11162	5581	95	86	778	1	1	1	1	0
16	11162	5581	95	86	778	1	1	1	1	0
17	37797	18899	95	86	2500	1	1	1	1	0
18	11762	5881	96	95	778	1	1	1	1	0
19	11762	5881	96	95	778	1	1	1	1	0
20	11762	5881	96	81	778	1	1	1	1	0
21	14151	7076	96	96	936	0	0	0	0	1

Table A.2 21th scenario tree for production planning

Customer order	Penalty cost (TL/unit)	Warehouse cost (TL/unit)	Due date (day)	Arrival date of panels (day)	Quantity (unit)	Eligibility				
i	cp_i	cw_i	d_i	AR_i	Q_{it}	Line 1	Line 2	Line 3	Line 4	Line 5
1	15203	7602	91	80	1000	1	1	1	1	0
2	16718	8359	91	9	1000	0	0	0	0	1
3	13087	6543	91	71	840	1	1	1	1	0
4	1615	807	91	9	100	1	1	1	1	0
5	12268	6134	92	80	778	1	0	0	0	0
6	22352	11176	92	80	1500	1	0	1	1	0
7	3154	1577	92	80	200	1	1	1	1	0
8	3129	1565	93	83	200	1	1	1	1	0
9	1454	727	93	80	100	1	1	1	1	0
10	12635	6318	93	9	936	1	0	1	1	0
11	11303	5652	93	76	778	1	1	1	1	0
12	13134	6567	94	76	778	1	1	1	1	0
13	9864	4932	94	76	778	1	1	1	1	0
14	11162	5581	95	76	778	1	1	1	1	0
15	11162	5581	95	76	778	1	1	1	1	0
16	11162	5581	95	76	778	1	1	1	1	0
17	11762	5881	95	76	778	1	1	1	1	0
18	11762	5881	96	85	778	1	1	1	1	0
19	11762	5881	96	85	778	1	1	1	1	0
20	11762	5881	96	71	778	1	1	1	1	0
21	14151	7076	96	86	936	0	0	0	0	1
22	24325	12163	97	80	1600	1	1	1	1	0
23	6100	3050	97	80	376	1	1	1	1	0
24	26065	13033	98	86	1556	1	0	0	0	0
25	10074	5037	98	80	556	0	0	0	0	1
26	7131	3566	98	80	500	1	1	1	1	0
27	7167	3583	98	59	500	1	1	1	1	0
28	34525	17262	99	80	2250	1	0	1	1	0
29	3520	1760	99	9	200	0	0	0	0	1
30	15579	7790	100	80	1000	1	1	1	1	0
31	18119	9059	100	9	1000	1	0	1	1	0
32	33487	16744	100	88	2334	1	1	1	1	0
33	33487	16744	100	88	2334	1	1	1	1	0
34	5800	2900	101	80	400	1	1	1	1	0
35	12163	6081	101	80	800	1	1	1	1	0
36	8379	4189	101	71	500	0	0	0	0	1
37	7800	3900	101	9	500	1	1	1	1	0
38	5490	2745	102	59	376	1	1	1	1	0
39	3575	1788	102	59	282	1	1	1	1	0

Table A.2 continues

40	6876	3438	102	86	440	1	0	1	1	1
41	11150	5575	102	59	1556	1	1	1	1	0
42	5654	2827	103	80	778	1	1	1	1	0
43	5612	2806	103	91	778	1	1	1	1	0
44	7254	3627	103	80	1000	1	1	1	1	0
45	26065	13033	104	86	1556	1	0	0	0	0
46	6800	3400	105	66	500	1	1	1	1	0
47	23094	11547	105	91	1556	1	1	1	1	0