Redundancy Investments in Manufacturing Systems

The role of redundancies for manufacturing system robustness

by

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Abstract

Today’s manufacturing companies are faced with a large number of fluctuating influence factors, as supply chains in the production environment grow larger with more suppliers and highly sophisticated products. At the same time, throughput times and due date reliability need to stay on a stable level, to fulfill the expectations of short delivery times and high service-levels of increasingly demanding customers. This ability to maintain specific features or a certain performance when subject to fluctuations and disturbances is generally referred to as robustness. As explained above, robustness of performance indicators, such as due date reliability, is a desirable characteristic for producing companies, hence the question arises how it can be achieved or incorporated in a companies manufacturing system. Looking at other scientific disciplines, such as biology or complex network science, robustness of the respective systems is often caused by redundancy, a situation where identical or similar components can replace each other when a component fails. In manufacturing research, redundancy has often been considered as an aspect to be avoided, as it stands in a potential trade-off with cost-efficiency, for example in lean manufacturing where excess inventory is considered as waste. However, as redundancy has been shown to have a strong relation to robustness in other disciplines, the aim of this thesis is to investigate the role that redundancy plays for achieving robustness of manufacturing system performance. In a first step, definitions from literature for both robustness and redundancy are reviewed, with a particular focus on approaches from biology, as the robustness-redundancy relation has attracted a lot of attention in this domain. Definitions for both robustness and redundancy are then derived for a manufacturing context. In addition to these measures based on a manufacturing background, two indicators usually used in a biological context for the analysis of robustness and redundancy, nestedness and elementary flux modes, are considered for measurement of redundancy in manufacturing systems. Using a discrete-event simulation, the relationship between both constructs - robustness and redundancy - is analyzed for a large-scale of different manufacturing system configurations. It is found that both a redundancy indicator derived from a classical manufacturing background, but also elementary flux modes derived from systems biology, are significantly correlated with robustness of performance in manufacturing systems. In a final step, it is presented how the findings of the relationship between robustness and redundancy can be applied to incorporate robustness into the design of manufacturing systems.
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List of Abbreviations

BOM  Bill Of Material

DES  Discrete-Event Simulation

EFM  Elementary Flux Mode

FBA  Flux Balance Analysis

FMS  Flexible Manufacturing System

MS   Manufacturing System

MSD  Manufacturing Systems Design

MSP  Manufacturing System Performance

NTC  Nestedness Temperature Calculator

RMSD Robust Manufacturing Systems Design

T    Nestedness Temperature

WIP  work in process
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1 Introduction

In this chapter, the practical and academic motivation for this thesis are given. This leads to the identification of a research gap, from which the research questions and aims of the thesis are derived. As a final point, the research approach and resulting thesis outline are presented.

1.1 Problem formulation and motivation

Need for robustness to cope with challenges in today’s manufacturing systems

Increasing globalization and thus competition cause today’s manufacturing organizations to be faced with different challenges. Customers demand more sophisticated products and product life-cycles shorten, which leads to an increase of complexity in the environment of and within the manufacturing system (MS) (ELMARAGHY et al. 2012; EFTHYMIOU et al. 2012). On the one hand, structural aspects such as increasing numbers and types of resources, higher connectivity between the resources, or growing product variety add to the structural MS complexity (CALINESCU et al. 1998; KUZGUNKAYA and ELMARAGHY 2006; HU et al. 2008). On the other hand, dynamic aspects, such as customer order changes, machine breakdowns, or fluctuating supply and demand rates influence the dynamic MS complexity (FRIZELLE and WOODCOCK 1995; VRABIČ and BUTALA 2012; PRIMO et al. 2007). It has been shown that the manufacturing system performance (MSP) can be negatively influenced by growing structural or dynamic complexity, such as increased supply disturbances, demand variability, or increased number of products (GUIMARAES et al. 1999; PRIMO et al. 2007; BOZARTH et al. 2009; HEIM et al. 2014). One reason for this is that failures are more likely to propagate through systems and thus negatively influence the performance when systems are more complex. The decrease in performance caused by an increase in complexity is especially relevant for job shop MSs, a type of MS where resources are grouped together according to the manufacturing processes (e.g., milling, drilling) they perform (HAYES and WHEELRIGHT 1979; CHRYSSOLOURIS 2006). They are by definition subject to complex material flows caused by sophisticated product routings between their various types of machines (CIRP 2004; HOPP and SPEARMAN 2008), which become even more sophisticated if product and thus MS complexity rises. Figure 1.1 conceptually depicts this negative influence of increased structural and dynamic complexity with exemplary aspects of structural and dynamic complexity in MSs and exemplary behavior of MSP.

While complexity for manufacturing organizations is increasing, the challenge of increased competition among manufacturers has also lead to a shift from a seller’s to a buyer’s market, which means that customers become more demanding, i.e. their expectations concerning for example product quality, delivery reliability, or delivery times increase (PATIL 2010).
1 Introduction

However, it has been shown that factors such as delivery reliability and delivery times are largely influenced by the performance of the MS of a company (Sarmiento et al. 2007). Delivery dates and thus delivery reliability can for example only be met if the due dates of production orders in the manufacturing process are met. In order to comply with these increased customer expectations, it is crucial for the success of manufacturing organizations to keep their MSP at a steady level, although they might be subject to growing complexity, for example in the form of increased fluctuations. Some companies are even faced with high contractual penalties if they do not deliver their products on time, for example manufacturers acting as suppliers in the automotive industry (Boysen et al. 2015). Moreover, most MSs are part of ever-increasing supply chains in which one tier depends on the preceding tiers. In such networked systems, it is even more crucial that the performance of a MSs stays stable in order for delays not to propagate through the entire supply chain. Incidents where supply chains have been negatively influenced by disruptions have strongly increased in the past, and so has research on disruption propagation in supply chains (Nair and Vidal 2011; Ivanov et al. 2014; Han and Shin 2015).

Thus maintaining an immutable MSP even in the face of internal and external fluctuations and disturbances is a desirable characteristic for MSs (Saad and Gindy 1998). This ability to "maintain specified features when subject to assemblages of perturbations either internal or external" (Jen 2005a) is generally referred to as robustness. The ability of a MS to exhibit an immutable MSP in the face of fluctuations is thus defined as robustness of a MS within this thesis. Robustness in MSs can be measured by analyzing the behavior of a
variety of different MSP measures, such as process and product quality (Mondal et al. 2014), makespan (Leon et al. 1994), or tardiness (Goren and Sabuncuoglu 2008).

Redundancy as a robustness enabler

With robustness in MSs defined, the question arises which factors influence robustness in MSs, i.e. how can it be achieved. Resorting to other scientific disciplines, one of the main causes for system robustness in several engineered or biological systems is redundancy (Stelling et al. 2004; Kitano 2004; Baker et al. 2008), a term that describes that "several identical, or similar, components (or modules) can replace each other when another component fails" (Kitano 2004). In a MS context, different resources or capabilities can be seen as redundancies, for example in job-shop MS machines or raw materials and parts that can fulfill the same function as others (Levitin and Meizin 2001; Emami-Mehrgani et al. 2011).

However, keeping redundant resources and capabilities in a MS partially contradicts the basic idea of lean manufacturing principles, which is eliminating waste (i.e. all aspects of a MS that do not add value to the final product), for example excess inventory or time buffers (Shah and Ward 2003). Since the 1990’s when lean manufacturing principles where introduced to the US-American and European manufacturing domain (Womack et al. 1990), manufacturers have increasingly resorted to them in order to achieve cost reduction (Shah and Ward 2003; Bortolotti et al. 2012; Hofer et al. 2012). Yet it was recently shown that although lean manufacturing principles can lead to cost reduction, they can have a negative influence on MSP (Eroglu and Hofer 2011; Azadegan et al. 2013), which in turn can lead to higher costs, for example as a result of missed due dates. Especially if manufacturing complexity rises and fluctuations increase, this has a negative influence on the MSP of extremely streamlined systems which have eliminated all possible inventories and time buffers (Stecke and Kumar 2009). This has also become evident recently when disruptive events such as natural disasters led to production stops in MSs, and consequently to disruptions of entire supply chains (Marsillac and McNamara 2013). Moreover, high extra production capacity as a form of redundancy was shown to have a positive effect on plant performance, if the factories are subject to frequent disruptions and a high level of complexity (Brandon-Jones et al. 2014).

Designing robust manufacturing systems

The existing body of research on robustness in MSs mainly focuses on incorporating robustness into MS aspects which require short- to medium-term decisions, for example robust production planning and scheduling, robust control, or robust product and process design (Nourelfath 2011; Tolio et al. 2011; Mondal et al. 2014). Robust planning and scheduling approaches try to identify robust production plans or schedules, which they define as robust if a certain performance measure, such as tardiness or flow time, does not change significantly under unforeseen disturbances (Goren and Sabuncuoglu 2010). In robust product and process design, research approaches try to identify and control the variables and noise factors that have an influence on the robustness of a product or manufacturing process, with robustness being achieved if there is minimal variation in end-product quality (Mondal et al. 2014).
MS aspects that require long-term decisions, such as determining the amount of resources necessary for a new MS, are part of manufacturing systems design (MSD) (Chryssolouris 2006). Research approaches that incorporate robustness into MSD can be summarized as robust manufacturing systems design (RMSD) approaches. They define that the design or configuration of a MS is robust if specific performance indicators, such as throughput-times or work in process, do not change significantly when the system is faced with disturbances (Mezgár et al. 1997; Sharda and Banerjee 2013).

**Interdisciplinary methods for robust manufacturing systems design**

Research on the topics of robustness and redundancy exists in many different scientific disciplines. In complex network science, which is the application of graph-theoretical measures to different types of complex natural or man-made networks (Albert and Barabási 2002; Newman 2003; Watts 2004; Boccaletti et al. 2006), one of the network characteristics that researchers have focused on is robustness (Albert et al. 2000; Callaway et al. 2000; Shargel et al. 2003; Bollobás and Riordan 2004; Beygelzimer et al. 2005). Approaches using complex networks measures have been suggested to measure and analyze (Albert et al. 2000; Callaway et al. 2000) or optimize (Shargel et al. 2003; Beygelzimer et al. 2005) the robustness of different complex networks.

Another scientific discipline where robustness has been studied extensively is in biological systems (Roberts and Tregonning 1980; Wagner 2003; Whitacre 2012). Exemplary systems where it has been measured and analyzed are food webs (Dunne et al. 2004), plant-pollination networks (Kaiser-Bunbury et al. 2010), metabolic networks (Edwards and Palsson 2000), or cells in general (Stelling et al. 2004). It has been argued that one of the main causes for robustness in these biological systems is redundancy (Kitano 2004). The application of graph-theoretic measures to analyze robustness in biological systems is common (Jeong et al. 2000), and many of the robustness measures in biological systems are based on structural aspects of the respective systems (Dunne et al. 2004).

The methods developed in complex network research or biology are able to measure and analyze the robustness of challenging large-scale, complex systems that are frequently faced with fluctuations and disturbances. As pointed out in the beginning of this section, these are the same challenges that MSs are faced with today. Due to these striking similarities, an interdisciplinary transfer of methods that have been developed for solving problems in complex or biological systems to MSs seems beneficial for manufacturing research.

**Research Gap**

While numerous approaches in MSD are concerned with incorporating emergent properties, such as flexibility or changeability, into the MS (Tolio 2008; Wiendahl et al. 2007; El-Maraghy 2008), only few approaches are specifically concerned with RMSD. Furthermore, the existing approaches concentrate on creating robust configurations for MSs, but so far no work has focused on identifying factors or conditions that potentially enable or benefit robustness in MSs. Especially the influence of redundancy on robustness in MSs has not been explicitly investigated yet.
Methods developed in complex networks science or biology have been successful in the analysis of robustness in many systems, but their application to MSs is rare. While it has recently been shown that complex network measures can be applied to classical manufacturing problems, such as machine grouping (Vrabič et al. 2012) or anomaly detection (Vrabič et al. 2013), they have not been applied for MSD or RMSD yet. Moreover, approaches from biology, which were developed to cope with system challenges that are similar to those in MSs, have neither been applied to analyze robustness in MSs, nor for RMSD.

1.2 Research questions and scope

Guiding research question and sub-questions

As redundancies play an important role for system robustness in other natural or man-made systems, it is assumed within this thesis that redundancy can also crucially impact the robustness in MSs. Hence the overarching aim of this thesis is to investigate the role of redundancies as a means to achieve robustness of MSP and to conceptually describe how to integrate such findings into RMSD. The guiding research question is formed as follows:

**Guiding research question.** How can redundancies be integrated in manufacturing systems design so that the manufacturing system performance robustness increases?

This question can be split down in several sub-questions. Firstly, it has to be investigated which definitions and measures of robustness exist in general and in the context of MSs.

**Subquestion 1.** How can robustness be defined and measured in manufacturing systems?

As a second question, since the term redundancy is not commonly used in a manufacturing context, it has to be clarified which definitions and measures of redundancy exist in general and how they can be conferred to MSs.

**Subquestion 2.** How can redundancy be defined and measured in manufacturing systems?

After having defined robustness and redundancy in a manufacturing context, it thirdly has to be analyzed whether the relationship between robustness of MSP and redundancy is similar to those in other engineered or natural systems, i.e. whether MSP robustness benefits from increased redundancy.

**Subquestion 3.** How is the relationship between robustness of manufacturing system performance and redundancy characterized?

Lastly it has to be investigated how measures of robustness and redundancy as well as the findings about their relationship can be applied in order to design robust MSs.

**Subquestion 4.** How can redundancy be incorporated in the design and reconfiguration of manufacturing systems in order to increase the robustness of manufacturing system performance?
1 Introduction

Scope

Within this thesis, the developed models and conducted analysis are limited to job shop MSs, which are systems that usually consist of general-purpose machines that accommodate a large variety of part types. Parts move through the job shop according to their pre-defined process plans and route sheets (Chryssolouris 2006), which results in complex routings of the respective products. Hence job shops are a type of MS that is strongly influenced by increasing complexity.

MSP, which can consist of a large amount of different performance indicators depending on the objectives and measurement system of the manufacturing organization (Hon 2005), is narrowed down to a specific MSP indicator within this thesis. The developed models and analysis will focus on lateness of production orders, as this indicator is important to draw conclusions regarding the service-level of a manufacturing organization, as presented in the problem description.

1.3 Research approach and thesis outline

This thesis is divided into seven chapters, which are depicted together with their respective research methods and objectives in figure 1.2. The first chapter serves as an introduction to the problem and motivation of the thesis, as well as for presenting the research questions, scope, methods, and outline. The second chapter sets the theoretical background for the thesis, with an introduction to MSs and to existing definitions and measures of robustness and redundancy. Furthermore, a review of applications of interdisciplinary methods from complex network theory and biology in MSs is given. In the third chapter, measures for robustness and redundancy in MSs are developed. Building up on these measures, a model to analyze the relationship between redundancy and robustness is established. The model is analyzed in a discrete-event simulation study, which is a standard method in MSD and analysis (Negahban and Smith 2014), to investigate whether increased redundancy is beneficial for robustness of MSP. The fourth chapter suggests a modeling approach in which nestedness, which is commonly used as an indicator for robustness in ecologic systems (Bascompte et al. 2003), is analyzed in a manufacturing context. It is further investigated how nestedness is related to robustness of MSP as defined in the third chapter. In the fifth chapter, the concept of elementary flux modes (EFMs), which have been shown to be a suitable measure to analyze redundancy and robustness in metabolic systems (Stelling et al. 2002), is transferred to MSs. Similar to the approach in the fourth chapter, the relation of EFMs to robustness of MSP as defined in the third chapter is analyzed here. The sixth chapter describes how the findings on the relationship between robustness and redundancy and the analyzed robustness and redundancy measures can be applied for designing MSs so that they exhibit a robust system performance. Furthermore, a potential trade-off between robustness, which is induced by redundancy, and cost-efficiency is discussed. In the last chapter, the results are summarized and implications for industry and further research are presented.
### 1.3 Research approach and thesis outline

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<td>give definitions and measures for robustness and redundancy</td>
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| measure robustness and redundancy in manufacturing systems  
analyze relationship between robustness and redundancy |
| measure nestedness in manufacturing systems  
analyze relationship between robustness and nestedness |
| measure elementary flux modes in manufacturing systems  
analyze relationship between robustness and elementary flux modes |
| explain how the analyzed measures can be applied for robust manufacturing system design |
| summarize results, explain contribution to academia & industrial practice, give outlook on further research and application |

Figure 1.2: Thesis outline, research methods, and objectives
2 Related Work

This chapter gives an introduction to aspects and topics that are relevant within the scope of this thesis. In the beginning, the underlying understanding of MSs, their objectives and performance measures, as well as current challenges are introduced. This is followed by an overview on MSD in section 2.1, with a more detailed presentation of specific design methods for job shop MSs, as they are the focus of this thesis. Definitions and measures of robustness and redundancy are reviewed in section 2.2, first in general and then with a specific relation to MSs. Since many of the reviewed definitions of robustness and redundancy are from the context of other scientific areas, the background on the other relevant disciplines, such as complex network science and biology, and the benefits of interdisciplinary transfer between these disciplines are given in section 2.3. As a last step, the research gap is derived from the presented works in section 2.4.

2.1 Introduction to manufacturing systems

2.1.1 Definition and terms of manufacturing systems

In order to answer the guiding research question of this thesis how redundancies can be integrated in MSD to create RMSP, this section first establishes the general definition of a MS. The term production in a general sense refers to "the process of creating goods and/or services" (Bellgran and Säfsten 2009) or "creating something new" (Hitomi 1996), which includes tangible goods such as tools, cars, electronics, or intangible goods such as consulting services, music, or energy production (Hitomi 1996; Bellgran and Säfsten 2009). The term manufacturing is used in a narrower sense, as the 'production of tangible goods' (Hitomi 1996), but also comprises 'the entirety of interrelated economic, technological, and organizational measures directly connected with the process/machining of materials, i.e. all functions and activities directly contributing to the making of goods' (Segreto and Teti 2014). The functions and activities mentioned in the former definition are specified by some authors to be planning, design, procurement, manufacturing production, inventory, marketing, distribution, sales, quality assurance, marketing, and management (CIRP 2004; Hitomi 1996).

A broad range of definitions in standard textbooks, papers, and encyclopedias also exists for the term MS (Black 1991; Wu 1994; Hitomi 1996; Suh et al. 1998; Chryssolouris 2006; DeGarmo et al. 2011; Caggiano 2014). Some authors focus on the tasks and processes of manufacturing (Wu 1994; Hitomi 1996), defining a MS as a system employing 'a series of value-adding manufacturing processes to convert the raw materials into more useful forms and eventually into finished products' (Wu 1994). Others put an emphasis on the most important physical elements (Black 1991; Suh et al. 1998; Chryssolouris...
2.1 Introduction to manufacturing systems

2006; DeGarmo et al. 2011; Caggiano 2014) and define a MS as "a combination of humans, machinery and equipment that are bound by a common material and information flow" (Caggiano 2014). It is important to note here that while some authors see the term production system defined as a subsystem of a MS (Bellgran and Säfsten 2009), within this thesis the two terms are considered to be synonymous as suggested by other authors (Hitomi 1996; Caggiano 2014).

When defining the term MS, several authors stress that these systems can be depicted and perceived according to a systems theoretic approach (Wu 1994; Hitomi 1996; Papadopoulos et al. 2009; Bellgran and Säfsten 2009). Systems theory is a transdisciplinary research field which is based on the idea that different systems from all kinds of scientific fields share common characteristics. A system’s characteristics are, for example, to transform inputs into outputs, to consist of elements which are connected and have interrelations, to exhibit emergent properties, and to have an objective or purpose (Checkland 1999; Bertalanffy 2003; Meadows 2009). Emergent properties are properties that a system exhibits as a whole, but that none of its elements exhibit separately, which is often referred to as the whole is more then its single parts (Skyttner 2005). Such properties are of special interest to many research approaches on MSs, and researchers have focused on incorporating different emergent system properties such as flexibility (Sethi and Sethi 1990; Tolio 2008), agility (Kidd 1994; Yusuf et al. 1999; Sanchez and Nagi 2001), reconfigurability (Koren et al. 1999; Dashchenko 2007; ElMaraghy 2008), changeability (Wiendahl et al. 2007; ElMaraghy 2008) or robustness (Windt 2012; Mondal et al. 2014) into MSs. Within this thesis, a MSs is defined as suggested by DeGarmo et al. (2011), as a 'complex arrangement of physical elements characterized by measurable parameters' (DeGarmo et al. 2011), which stresses the system theoretic aspects of a MS. Figure 2.1 gives an example of a MS with its inputs, outputs, and elements. Possible inputs such as materials, energy, etc, are depicted on the left, possible outputs such as products, information, defectives etc. are shown on the right side. Machines, tooling, or workers are listed as examples for physical elements in the middle.

![Diagram of manufacturing system](image)

Figure 2.1: Definition of a manufacturing system with its inputs and outputs, modified from (DeGarmo et al. 2011)

Some of the inputs and outputs in MSs are physical, such as machines, manual workstations, material handling or tooling equipment, human workforce, raw material, purchased parts,
manufactured products, or defectives (Hitomi 1996; Chryssolouris 2006; Caggiano 2014). In addition to these physically tangible aspects, there is a large amount of different informational inputs and outputs that are needed to operate the MS. The quantities and types of raw materials, sub-assemblies, or purchased parts that are needed to manufacture a product are listed in the bill of material (BOM) of a product (DeGarmo et al. 2011). A BOM can have different formats, for example just a simple list or a product-structure graph. The sequence of different manufacturing processes that are necessary to transform the materials into the final product are denoted in the process plan of a product (Scallan 2003). The operations, which are the activities in which the materials are changed (Heragu 2006), are a more detailed version of the manufacturing processes denoted in the process plan. If drilling is the general manufacturing process a part has to undergo, the operation specifies the necessary parameters to carry out this process, such as required resources (machines, tools), or processing times. The operations sheet or route sheet of a product then lists the operations necessary to manufacture the entire product in the correct sequence, including information such as resources, processing times on the resources, or set-up times on the resources (Heragu 2006; DeGarmo et al. 2011). This specifies a product’s route, which is defined as “the set of work centers or machines through which a product is processed” (Das and Nagendra 1997). If different resources are able to fulfill the same manufacturing process and thus operation, products can take different, alternative routes through the MS. A production order is what triggers the production of a product in the production department and contains information on the product quantity to manufacture, due dates, the necessary operations, material components and production resources (CIRP 2004). The term job can refer to a series of processing steps necessary to create a product (similar to the production order) (Curry and Feldman 2010), but more commonly, it refers to the working duties and physical materials to be performed on one particular work station (similar to the operation). In the latter case, the relation between jobs and orders is not one-to-one, but an order for a product consists of several jobs (Hopp and Spearman 2008; DeGarmo et al. 2011).

As stated in the introductory chapter, the focus of this thesis is on job shop MSs, and in particular on the design of such systems, as they are by definition subject to complexity (e.g., complex routings (CIRP 2004)) and thus are prone to a negative influence by increasing complexity (e.g. increased fluctuations). In order to be able to properly distinguish approaches for MSD of job shop MSs from design approaches for other MSs, an overview on the different types of MSs is given in the following. Depending on the product types and volumes that are to be manufactured, five general types of MSs can be distinguished: the project shop, the job shop, the cellular shop, the flow shop, and continuous systems (Hayes and Wheelwright 1979; Wu 1994; Suh et al. 1998; Chryssolouris 2006; Heragu 2006; DeGarmo et al. 2011; Caggiano 2014). Figure 2.2 gives a conceptual depiction of four of these five different types. In a project shop or fixed-site production, the product has a fixed position and the resources such as materials and machines are brought to the product as needed (see figure 2.2a). This is usually because of the size and/ or weight of the products, which typically are aircrafts, ships, or large structures such as bridges (Chryssolouris 2006). In job shops, resources are grouped together according to the manufacturing processes (e.g., milling, drilling) they perform (see figure 2.2b). The products move through these machines according to the processes that are denoted in their process plans, so that complex material flows can arise (CIRP 2004). In cellular shops or group production systems, machines are not grouped according to similar manufacturing processes, but according to product families that require similar manufacturing processes (see figure 2.2c).
Thus the material flow induced by a certain product concentrates on the resource center that is responsible for this product (Chryssoulouris 2006). In flow shops, which are also referred to as flow lines, resources are ordered in lines in the specific process sequence of a product, where each product has its own line of resources (see figure 2.2d). A special type of flow shops are transfer lines, also known as paced lines, which are flow lines with a synchronous movement of material flow between the different resources. They are typically found in automotive production (Papadopoulos et al. 2009). The fifth type of MS is the continuous system (not depicted in the figure). Contrary to the previously introduced MSs which all produce discrete parts, a continuous system treats liquid materials, such as fluids, gases, or powder and is thus arranged in a special type of flow line (Papadopoulos et al. 2009).

MSs implemented in the real world usually are a combination of these standard archetypes of MSs, or exhibit slight alterations to these standards. An example for such a hybrid type of MS is the flexible manufacturing system (FMS), which is a combination of a job shop and a cellular shop (Chryssoulouris 2006). The choice of a type of MS strongly depends on the characteristics of the product to be manufactured, such as variety, lot sizes, or volumes (Papadopoulos et al. 2009). In figure 2.3, the five types of MSs are positioned according to the product variety and volumes for which they are mostly used.

2.1.2 Objectives, trade-offs, and performance in manufacturing systems

As this thesis strives to answer the question of how RMSP can be achieved by integrating redundancy, the general objectives and trade-offs in MSs, as well as a definition of performance and important performance indicators in MSs have to presented. In general, the objectives of a MS depend on the product types and volumes to be produced in the MS. Although the fundamental objective of a manufacturing organization in general usually is to make profit and to ensure the existence of the organization (Hitomi 1996; Hopp and Spearman 2008), such strategic objectives like profit or customer-orientation are not suitable for operational decisions within the MS. Therefore the strategic objectives of a company need to be broken down to a more operational level, which allows assessing the performance of sub-systems such as the MS. To achieve this, Hopp and Spearman (2008)
suggest a hierarchical structure for different objectives within a manufacturing organization (see Figure 2.4), which breaks down strategic targets such as high profit to more operational targets such as high throughput or high utilization.

Exhibiting a robust MSP can also be seen as an objective for MS, yet as such it is still an objective on a very strategic level. In order to operationally manage and make decisions according to the objectives that were set for a MS, the objectives need to be made measurable by creating suitable performance measures (SKINNER 1978; KAPLAN and NORTON 1993; MELNYK et al. 2004; DRUCKER 2011). A MSP measure is "a variable whose value quantifies an aspect of the performance of a manufacturing system" (CHRYSSOLOURIS 2006). While some companies still use traditional management cost systems and performance measures, a broad range of frameworks and performance measurement systems that suggest different performance measure categories as well as tangible performance measures for MSs have been developed (BITITCI 1995; GHALAYINI et al. 1997; GOMES et al. 2004; HON 2005; CHEN and HUANG 2006; GOMES et al. 2006). Some of the most frequently mentioned categories are cost, quality and time performance measures. Examples for cost measures are training costs, tooling costs, overhead costs, or work in process (WIP) costs (HON 2005; CHRYSSOLOURIS 2006; HOPP and SPEARMAN 2008). Typical quality measures are defect or rework rates (HON 2005; CHRYSSOLOURIS 2006). The most common time performance measures in MSs include cycle time, throughput time, or lateness (HOPP and SPEARMAN 2008; NYHUIS and WIENDAHL 2009; CURRY and FELDMAN 2010).

As stated in the introduction chapter, the models and analysis within this thesis focus on time performance measures, as these are considered most crucial for customer satisfaction in today’s buyer markets (e.g. high due date reliability). The most common time performance measures in MSs include cycle time, throughput time, or lateness (HOPP and SPEARMAN 2008; NYHUIS and WIENDAHL 2009; CURRY and FELDMAN 2010). The cycle time is defined as "the time that a job spends within a system" (CURRY and FELDMAN 2010). This is similar to the throughput or lead time, which is defined as "the period between the earliest start and the latest finish" (CIRP 2004), either for an order or an operation. Further time-related performance measures are concerned with due dates of jobs or orders. Lateness of a job or an order can be defined as the difference between actual

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Figure 2.3: Suitability of manufacturing system type depending on product variety and volume, modified from (PAPADOPOULOS et al. 2009)
2.1 Introduction to manufacturing systems

![Diagram of hierarchical objectives in manufacturing systems]

Figure 2.4: Hierarchical objectives in a manufacturing organization, modified from (Hopp and Spearman 2008)

completion time and planned completion time (due date) (Nyhuis and Wiendahl 2009; Pinedo 2012; Framinan et al. 2014). A measure similar to lateness is tardiness of a job, which is defined as the lateness of the job in case it is negative and zero for all jobs with positive lateness (Hopp and Spearman 2008; Pinedo 2012; Framinan et al. 2014). In the same manner, earliness of a job is defined as the lateness of the job in case it is positive and zero for all jobs with negative lateness. The percentage of tardy or early jobs is often used to assess schedule reliability of a production schedule (Pinedo 2012; Framinan et al. 2014) or to measure the due date performance towards the customer (Hopp and Spearman 2008).

In the hierarchical structure of objectives as shown in Figure 2.4, some of the objectives, such as high utilization which is shown as a sub-objective of low unit costs, are the opposite of other objectives, such as low utilization which is shown as a sub-objective of fast response. Such trade-offs between different objectives in MS are common and in order to resolve them, the manufacturing organization has to choose a position, since not all objectives can be reached at the same time (Skinner 1969; Hayes and Wheelwright 1984; Mapes et al. 1997; Da Silveira and Slack 2001; Da Silveira 2005). A depiction of objectives for MSs that focuses on these trade-offs is the manufacturing tetrahedron suggested by (Chryssolouris 2006). The authors claim that every decision in a MS should be taken considering the objectives time, quality, costs, and flexibility. The representation in a tetrahedral form (see Figure 2.5) emphasizes the trade-off, i.e. that not all four objectives can be optimized simultaneously. A further definition of MS objectives and their trade-offs is given in the manufacturing planning dilemma (Gutenberg 1983; Wiendahl 2014). It describes the two benefit objectives high due date reliability and short throughput-times on the one hand, and the two cost objectives high utilization and low inventory on the
2 Related Work

other hand (see Figure 2.6). These objectives stand in a trade-off relationship: customers would like to receive their goods at the promised time (high due date reliability) and as soon as possible after they ordered them (short throughput time), companies however would like to keep their utilized machine capacity at a steady level to avoid idle time costs (high utilization) and their spare parts and finished goods inventory low in order to save inventory carrying costs (low inventory). The performance and cost objectives are therefore also referred to as the *customer view* and the *company view* (WIEDAHL 2014).

Such trade-offs could potentially also exist between robust MSP and other objectives in MSs. If robustness of MSP was for example achieved by increasing inventory or excess resources, this would stand in a trade-off to the objective of low inventory costs or low investment costs, which can be summarized as cost-efficiency. A trade-off between robustness and efficiency is for example also described for supply chains by SHUKLA et al. (2011). When it is the objective to design a MS in a way that its performance stays robust in the face of fluctuations and disturbances, the trade-off between robust MSP and cost-efficiency has to be taken into account.
2.1 Introduction to manufacturing systems

2.1.3 Manufacturing systems design

Different sub-tasks of manufacturing systems design

Since the guiding research question of this thesis focuses on how robustness can be achieved by integrating redundancy in MSD, an introduction to the different sub-tasks in MSD is given here. Moreover, existing methods and approaches for the design of job shop MSs are reviewed in the next section. Once the objectives and performance requirements of a manufacturing organization have been set (i.e. which products to produce, at which customer service level), a suitable MS to fulfill these requirements has to be designed (Suh et al. 1998; Chryssolouris 2006). As presented in section 2.1.1, MSs consist of a large amount of different elements (e.g., machines, tooling) and the relations between them (e.g., control procedures for the interaction of elements). Decisions concerning the elements and the relations between them, such as the material processing structure (e.g., the type of manufacturing processes and structure needed to produce the desired products), the resource quantities (e.g., amount of machines, workforce), or the resource layout, are taken in MSD phase (Chryssolouris 2006; Heragu 2006; Schenk et al. 2009). These design decisions usually have a long-term effect (years) on the MS, as the amount of machines and also the general layout are not frequently changed. This is also sometimes referred to as steady state design, whereas decisions such as sizing of buffer inventories, setting of stock order policies, or workforce capacity adjustment are termed dynamic design (Parnaby 1979). Figure 2.7 compares the long-term decisions taken in MSD to mid-term and short-term decisions. Tasks such as production planning, master scheduling, material requirements planning, or capacity planning are considered to involve decisions on a medium-term time horizon (weeks to months), while tasks such as scheduling, dispatching, or shop floor control implicate short-term decisions (hours to days) (Bahl and Ritzman 1987; Altiok 1997; Hopp and Spearman 2008; Pinedo 2012). While some authors also consider medium-term and short-term decisions on the planning and control of MSs to be part of MSD (Davis et al. 1986; Papadopoulos et al. 1993; Cochrane et al. 2001), only the setting of long-term, structural aspects of the MS is considered as MSD within this thesis. MSD often is a complex task and is thus usually decomposed into sub-problems, which are treated hierarchically and sometimes in several iterative loops (Chryssolouris 2006; Heragu 2006; Timm and Blecken 2011).

Figure 2.7: Decision horizons in manufacturing systems, modified from (Papadopoulos et al. 1993; Hopp and Spearman 2008; Pinedo 2012)
MSD starts after the product structure has been established. As depicted in figure 2.8, the product design determines which manufacturing processes - and consequently which types of resources - are necessary to produce the final products, which is done in the phase of process planning (Scallan 2003). This also influences how the BOMs and route sheets of products will look like. Depending on the estimated volumes and different manufacturing processes required to manufacture the desired products (derived from the process plans of the products (Scallan 2003)), the necessary quantities of the manufacturing resources (e.g., machines, tools, workforce) can then be calculated.

Figure 2.8: Relation between product design and resource design

The phase termed resource design in figure 2.8 is also referred to as the resource requirements problem (Chryssolouris 2006), dimensioning (Schenk et al. 2009), or sizing (Roze and Kasilingam 1996; Masmoudi 2006) of MSs. Sub-problems within the resource requirements problem are concerned with determining machine requirements (Miller and Davis 1977; Hayes et al. 1981; Jain et al. 1991) or production equipment requirements (Kusiak 1987; Bard and Feo 1991). After the resource requirements have been determined, a further part of MSD is resource layout design, which describes the problem of optimizing the physical arrangement of the resources within the constrained available space of the manufacturing facility (Rosenblatt 1979; Kusiak and Heragu 1987; Benjaafar et al. 2002; Singh and Sharma 2006).

Most approaches for MSD are tailored to the characteristics and requirements of one of the different types of MSs introduced in section 2.1.1 and are thus not interchangeably applicable. An example for this are approaches for the design of cellular shops, in which it is often first determined which resources should be grouped together in cells and then which dimension (i.e. number of resources) the cells should have (Opitz and Wiendahl 1971; Rajagopalan and Batra 1975; Askin 2013). Another example are design approaches that are specifically tailored for production lines, which for example do not exhibit alternative routes like job shops, as the manufacturing processes are ordered sequentially (Nahas et al. 2009). In addition to that, approaches to determine the resource requirements and resource layout of MSs in the design phase have to be clearly distinguished from approaches for capacity planning, capacity management, or capacity expansion in MSs. The term capacity in a manufacturing context refers to the general ability of a MS to produce a certain output per time period or to perform its expected function (CIRP 2004; Crowson 2005), the more specific machine capacity for example refers to the capability of
2.1 Introduction to manufacturing systems

a single machine to produce output per time period (Crowson 2005). While decisions on resource requirements and resource layout during MSD are taken to create the entire MS, capacity management or expansion decisions are taken on a tactical to operational decision horizon to decide whether capacity investments are necessary in order to meet the upcoming demand of a specified time horizon (Matta et al. 2005; Chryssolouris 2006; Ceryan and Koren 2009). Although some authors consider capacity planning to be the determination of the long-range production capacity in the facility (Askin and Mitwasi 1992), the term resource requirements is used within this thesis.

Determining resource requirements in job shop manufacturing systems

As mentioned in the previous section, approaches for MSD are usually tailored to one of the introduced types of MSs. Since this thesis focuses on job shop MSs, this section presents different modeling approaches that can be applied to job shop MSs. The focus here lies on the presentation of modeling approaches to determine the resource requirements in job shop MS, which was introduced as one of the sub-tasks in MSD in the previous section (see 2.1.3). Modeling approaches to determine resource requirements in other MS types, such as cellular systems or transfer lines, are not covered here, for they substantially differ from approaches for MSD of job shop MS. In cellular shops for example, the grouping and layout of resources needs to be solved simultaneously to the problem of resource dimensioning, which requires different input and output parameters than the design of job shop MSs.

The parameters that need to be determined when the resource requirements of a job shop have to be set are the different types and amounts of necessary resources, such as machines, tools, handling, or transport equipment. The resource requirements depend on a large amount of different influencing factors, for example the products to be manufactured, the demand and its potential fluctuations, or the technological abilities of the resources. An early review paper by Miller and Davis (1977) gives a detailed overview on existing simple analytical models to solve the machine requirements problem in job shop MS, of which an excerpt is shown in table 2.1. The first model in the table is the most general one and determines the amount of resources necessary for a single period and a single machine case, and thus has a very limited system scope. The influencing variables considered by this model are operation times, number of products required, machine capacity, and efficiency. The second model in table 2.1 does take into account multiple machines, but still does not determine the amounts of machines necessary for multiple periods. A more sophisticated model is the third model presented in table 2.1, which recognizes the stochastic nature of the variables under study (such as the production demand) by including distributions for them.

Miller and Davis (1977) conclude that the simple models so far did not take into account factors that have a significant influence on the number of machines necessary, such as cost restrictions or fluctuations in input variables like the demand. Therefore they suggest a linear programming and a mixed integer programming model to find the optimal number of machines under cost constraints and varying demands in a serial, multistage MS (Davis and Miller 1978; Miller and Davis 1978). These early mathematical optimization models have gradually been enhanced, for example by Hayes et al. (1981), who suggest a dynamic programming model for finding the cost-minimal solution to the machine
Formula Variables

\[ x = \left( \frac{t}{60} \right) \left( \frac{p}{hu} \right) \]

\[ x = \text{required number of machines} \]
\[ t = \text{standard time for operation in minutes} \]
\[ p = \text{total number of production units required per day} \]
\[ h = \text{standard number of hours available per day per machine} \]
\[ u = \text{efficiency of the machine (as a percentage)} \]

\[ x_j = \sum_{i=1}^{n} \frac{p_{ij} t_{ij} h_{ij}}{h_{ij}} \]

\[ x_j = \text{required number of machines of type } j \]
\[ p_{ij} = \text{desired production rate for product } i \text{ on machine } j \]
\[ t_{ij} = \text{standard production time for product } i \text{ on machine } j \]
\[ h_{ij} = \text{number of hours available for product } i \text{ on machine } j \]
\[ j = \text{machine type} \]
\[ i = \text{product type} \]

\[ x = \sum_{i} \sum_{j} \frac{t_{ij} p_{i}}{h} \]

\[ x = \text{required number of machines} \]
\[ t_{ij} = \text{performance time for operation } j \text{ on product } i \]
\[ p_{i} = \text{production demand per period for product } i \]
\[ h = \text{standard hours available per period} \]
\[ u = \text{effectiveness factor} \]
\[ j = \text{operation} \]
\[ i = \text{product} \]
\[ h_{1}(t_{ij}) = \text{distribution of the performance time} \]
\[ h_{2}(p_{i}) = \text{distribution of the production demand} \]
\[ h_{3}(u) = \text{distribution of the effectiveness factor} \]
\[ g(.) = \text{joint probability function} \]

<table>
<thead>
<tr>
<th>Formula</th>
<th>Variables</th>
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<td>[ x = \left( \frac{t}{60} \right) \left( \frac{p}{hu} \right) ]</td>
<td>[ x = \text{required number of machines} ]</td>
</tr>
<tr>
<td>[ x = \sum_{i} \sum_{j} \frac{t_{ij} p_{i}}{h} ]</td>
<td>[ x = \text{required number of machines} ]</td>
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Table 2.1: Calculation approaches to solve the machine requirements problem, modified from MILLER and DAVIS (1977)

requirements problem. A further model introduces two simplified linear programming models to determine the cost-minimal amount of machines and handling equipment, arguing that the existing models are too specific in their data requirements to be suitable for application in industrial practice (KUSIKA 1987). The linear programming model of BARD and FEO (1991) offers an even more generalized mathematical formulation of the machine requirements problem, yet it is the first one to account for process flexibility, thus making it more suitable for job shop MSs. Further authors then proposed different formulations to address the machine requirements problem in integer programming models that consider process flexibility (ROZE and KASILINGAM 1996; KASILINGAM and ROZE 1996). MAK and WONG (1999) also developed a mathematical model of the machine requirements planning problem and develop a solution technique based on a genetic algorithm.

The general inputs to the mathematical optimization models are similar among the different models. Apart from cost data on operational and fixed costs of the resources, mathematical programming approaches need as inputs for their models information on the types of products to be manufactured and their demands, the manufacturing processes required to create the products, a list of available machine types, and the operation times or efficiencies for the processes on the different machines (MILLER and DAVIS 1978; BARD and FEO 1991; ROZE and KASILINGAM 1996). An example for model input data for a problem with 4 products, 6 processes, and 5 machines which was presented by BARD and FEO (1991) is shown in table 2.2. Table 2.2a shows which different manufacturing processes a product needs and the time it needs for the respective process. It furthermore gives the demand for the products in a certain time-period. Table 2.2b shows the manufacturing processes, on
which machines they can be carried out and the efficiencies of the different machines for the respective process. It also depicts the discounted costs per machine.

<table>
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<td>0.0</td>
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<td>0.2</td>
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</tr>
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</table>

| demand  | 0.92| 0.54| 0.76| 0.79|

(a) Product-process data

| cost    | 249.5| 184.7| 138.3| 221.3| 232.8|

(b) Process-machine data

Table 2.2: Input data to determine machine requirements, modified from (BARD and FEo 1991)

Researchers have also resorted to modeling job shop MSs as queues or networks of queues in order to determine the necessary amount of resources required for a job shop MS (BITRAN and DASU 1992; Buzacott and Shanthikumar 1992; PAPADOPOULOS et al. 1993). A queuing process usually consists of customers that arrive at a service facility, where they wait in a line (queue) if all servers are busy, until they receive service from a server, and then depart from the facility. A queuing model is usually constructed to predict the queue lengths and waiting times of customers in a system (GROSS et al. 2008). It can be described by six characteristics, which are the arrival pattern of the customers, the service patterns of the servers, the queue discipline, the system capacity, the number of service channels, and the number of service stages (GROSS et al. 2008). In the case of MSs, the servers correspond to the resources in a MS, while the customers correspond to manufacturing orders or jobs (PAPADOPOULOS et al. 1993; CHRYSSOLOURIS 2006). To model an entire job shop MS with several resources, the resources are regarded as a network of single server queues, for which performance measures are individually recorded and then averaged for the overall MS (BITRAN and TIRUPATI 1989a; BITRAN and MORABITO 1999; GOVIL and FU 1999). As Bitran and Morabito (1999) describe, queuing approaches can be distinguished into those whose objective it is to minimize the investment in the MS subject to MS performance constraints, or those whose objective it is to maximize the MS performance subject to a limited budget for investment in the MS.

Another method used to solve the resource requirements problem is simulation modeling (LAW and MCCOMAS 1998), which was suggested as early as the first mathematical optimization approaches (REASOR et al. 1977). In Reasor et al. (1977), the number of machines is determined under the assumptions that total costs should be minimized and a given target production quantity should be reached. Their model serves as an experimental tool to evaluate different system configurations, as it allows for changing system characteristics such as machine operating rates or the scheduling logic. More recent approaches do not only focus on cost optimization as early approaches of mathematical optimization, but also consider achieving a certain level of MSP with their system designs. Feyzioğlu et al. (2005) use a simulation model combined with a boot strap approach to identify the minimum number of machines necessary to fulfill certain defined manufacturing performance goals. In a similar approach, a simulation model is coupled with an expert system to find the amount of resources where tardiness is minimized as a primary objective while earliness is minimized as a secondary objective (MASMOUDI
2 Related Work

To sum it up, the methods used in approaches for machine requirements design for job shop MSs are traditional (deterministic), mathematical programming, queuing based, or simulation approaches (Chryssolouris 2006; Heragu 2006; Negahban and Smith 2014).

A further aspect in determining the resource requirements of job shop MSs is the analysis of trade-offs between different conflicting targets (see also section 2.1.2). Trade-offs concerning the resource design of job shop MSs have for example been identified and analyzed between the amounts of resources and certain performance measures such as WIP or lead times (Bitran and Tirupati 1989a; Negri da Silva and Morabito 2009). Negri da Silva and Morabito (2009) for example identify a trade-off between resource investment and expected lead time of the system, where lead time increases with decreasing investment in resources. If such trade-offs are identified, they can be depicted in trade-off curves, which allow an easy positioning for decision makers in the design phase (Bitran and Tirupati 1989b; Bitran and Morabito 1999). An example of a trade-off curve is given in figure 2.9, where the trade-off between resource costs and WIP is depicted conceptually. The trade-off has been intensively studied by Bitran and Morabito (1999), who analyzed the relationship between resource cost and WIP using a queuing model. They first calculated different combinations of resource and WIP costs in an initial scenario (figure 2.9a) and then altered different aspects of the model, such as amount of throughput or product mix, which resulted in curves that are shifted from the initial scenario (curve 2 & 3 in figure 2.9b).

![Figure 2.9: Conceptual representations of trade-off curves between resource costs and WIP costs, modified from (Bitran and Morabito 1999)](image)

The first approaches to determine the number of resources required in job shop MSs considered the resource capabilities, i.e. the manufacturing processes a resource can carry out, as given input variables for their models (Miller and Davis 1978; Kusiak 1987). However, resources have become increasingly flexible in the past years, so that they can often carry out several different manufacturing processes, but at varying efficiencies. Thus the selection of manufacturing processes and necessary amounts of resulting resources has been studied in integrated models using different methods, such as queuing theory (Askin and Mitwasi 1992), or integer programming (Chen 1999). This problem of concurrent
selection of manufacturing processes and equipment selection is still a focus of current research (Kulak et al. 2005; Dagdeviren 2008).

A further issue in the design of job shop MSs is the development of decision support systems to aid in the design phase of MSs. Such approaches use mathematical programming or simulation as an underlying method, but focus on designing user-friendly software systems to present the modeling results in order to facilitate design decisions (Gopalakrishnan et al. 2004; Chtourou et al. 2005; Guldogan 2011; Longo et al. 2012). Longo et al. (2012) for example develop a decision support system, which is based on a discrete-event simulation model, to aid deciding on a plant design during the MSD phase. In their model, industrial plant parameters (such as machine capacity, the arrival time and amount of raw material, the number of workers per department, and the product mix) can be varied and their influence on plant production and performance can be analyzed.

2.1.4 Negative influence of complexity and disturbances on manufacturing system performance

The MSP (as introduced in section 2.1.2) can be influenced by a multitude of different factors, and thus does not constantly stay the same in real life MSs. Even if a job shop MS was designed by considering a certain amount of fluctuations in the input parameters (see section 2.1.3), MS are still prone to uncertainty and unforeseen events. A perturbation, which in a general meaning is "a deviation of a system, moving object, or process from its regular or normal state or path" (Stevenson 2010), is in the manufacturing context referred to as a disturbance or disruption, which is an unplanned or unpredictable event in the state or function of the MS (Kuivanen 1996; Saad and Gindy 1998; Frizelle et al. 1998; Ingemansson and Bolmsjö 2004). In recent years, manufacturing organizations have been increasingly faced with disturbances. A survey among 151 large U.S. companies showed that 73% of the organizations had experienced disturbances (Accenture 2008), and several recent studies point out that disturbances are expected to occur even more frequently in the future (Cook 2008; Bhatia et al. 2013; Deloitte 2015).

Different reviews and classification schemes of disturbances exist in MS research (Farhoodi 1990; Frizelle et al. 1998; Saad and Gindy 1998). Farhoodi (1990) classify disturbances in MSs according to the source of origin of the disturbance, e.g. order related disturbances such as early or late orders, and resource related disturbances such as machine or transport breakdowns. In Frizelle et al. (1998), a classification of disturbances according to when they occur with regard to the manufacturing process is offered. They distinguish between upstream, internal, or downstream disturbances and give examples for all three categories, such as supply delays or incorrect deliveries as upstream disturbances, machine breakdowns or material stock control problems as internal disturbances, and demand variations or changes in orders as downstream disturbances. Saad and Gindy (1998) offer a classification that can be seen as a combination of the two previous ones, as they firstly distinguish between internal and external disturbances, and then between the source of origin of the disturbance. Their classification and exemplary disturbances for each category are depicted in figure 2.10.

If disturbances occur, they are highly likely to negatively effect the MSP, which has been shown for several MSP measures, different types of disturbances, and for a large
2 Related Work

Figure 2.10: Classification of disturbances in MSs, modified from (Saad and Gindy 1998)

In addition to the increase in disturbances, manufacturing organizations are also faced with increasing complexity. Complexity is a term for which no overarching definition that is applicable to all scientific domains exists. Instead, it is rather defined on a systemic level, i.e. systems can be classified as complex systems if they exhibit certain properties (Mitchell 2009). Complex systems are frequently described to consist of large networks of individual components with no central control and simple rules of operation, which enables complex collective behavior (Bar-Yam 1997; Boccaletti et al. 2006; Mitchell 2009). In a manufacturing context, a variety of different definitions and measures of manufacturing complexity exist. Most of them have in common that the authors distinguish between structural complexity, which refers to production structures, such as numbers and types of resources, or connectivity between the resources, and dynamic complexity, which refers to the dynamic behavior of the production procedures over time, such as supply and demand rates, or processing times (Wiendahl and Scholtissek 1994; Frizelle and Woodcock 1995; Calinescu et al. 1998; Deshmukh et al. 1998; Kuzgunkaya and ElMaraghy 2006; Papakostas et al. 2009). Several authors have shown that high structural or dynamic complexity can negatively influence various aspects of MSP (Guimaraes et al. 1999; Vachon and Klassen 2002; Primo et al. 2007; Bozarth et al. 2009; Heim et al. 2014). In a recent global study by KPMG (2011), which surveyed 1.400 senior executives from 22 countries, 70% of the participants claimed that...
increasing complexity is one of the biggest challenges for their company, and a majority of participants also expects complexity to rise even further in the coming years.

Both aspects presented in this section, disturbances and complexity in MSs, are intertwined: complex MSs have manifold interconnections between their large number of individual components, which in turn leads to a higher probability that disturbances will propagate and have an even higher negative influence on MSP than they would in smaller, less complex systems. Therefore the trend towards increasing disruptions and complexity goes along with an increased risk of deteriorating MSP, which in turn necessitates increased robustness in MSs.

2.2 Robustness definitions, measures, and disambiguation in manufacturing systems

2.2.1 Robustness as a general system characteristic

In the Oxford Dictionary of English the term robust in the context of systems or organizations is defined as "able to withstand or overcome adverse conditions" (Stevenson 2010). Since there are a variety of research fields that explore or seek robustness for their respective systems, be it natural or engineered systems, a vast amount of robustness definitions and measures exists in literature. For many of these research fields, robustness can be generally defined as "the ability of a system to maintain specified features when subject to assemblages of perturbations either internal or external" (Jen 2005a). A further definition that assesses robustness as a system characteristic is the one of Kitano (2004), who sees robustness as a "property that allows a system to maintain its functions despite external and internal perturbations" (Kitano 2004). He further considers robustness to be an emergent system property or systems-level phenomenon from a systems-theoretic viewpoint, similar to other system characteristics such as flexibility or adaptability (Kitano 2004). This systems theoretic view is also stressed by Zakarian et al. (2007) who consider a system to be robust "when its functional performance is insensitive to selected design parameters and environmental changes, while satisfying design and customer requirements" (Zakarian et al. 2007). Alderson and Doyle (2010) give a further general, system theoretic definition, which is the most specific of all presented definitions: "A [property] of a [system] is robust if it is [invariant] with respect to a [set of perturbations]" (Alderson and Doyle 2010). It is the most detailed of all presented definitions as it requires to set specifications for the property, the system, the set of perturbations, and the invariance measure under study.

A system characteristic that is similar but not the same as robustness is system stability (Jen 2005b). The general meaning of the word is "not likely to change or fail" (Stevenson 2010), however diverse definitions exist in different scientific disciplines, such as stability theory (Leipholz 2013) or ecological stability (Connel and Sousa 1983). Jen (2005b) define a system as stable if "small perturbations to the solution result in a new solution that stays 'close' to the original solution for all time" (Jen 2005b) and argue that in comparison to stability, robustness is the broader concept as it addresses behavior in a more varied class of systems and perturbations applied to the system. Another term that is related to the concept of robustness is reliability, which the Oxford Dictionary defines as the 'ability
to be relied on with confidence’ (Stevenson 2010). In comparison to the definition of robustness, this definition is bound to a certain confidence value. Again, the definition of this concept is subject to the specific scientific discipline it is used in, which range from statistics (Dovich 1990), to reliability engineering of systems, structures, or products (Zio 2009). A further system characteristic similar to robustness is resilience, for which also a large amount of definitions exist in different scientific disciplines (Jackson 2009; Bhamra et al. 2011). On a general level, resilience can be defined as "the capability and ability of an element to return to a stable state after disruption" (Bhamra et al. 2011), which is in comparison to robustness focused on the recovery or the time to recovery after a perturbation, and not on the performance of the system.

Research on robustness exists in a large amount of different man-made systems, such as supply chains (Kleindorfer and Saad 2005; Meepetchdee and Shah 2007; Nair and Vidal 2011; Han and Shin 2015), infrastructural networks (Solé et al. 2008), economic (Henriet et al. 2012), or engineered systems (Taguchi et al. 2000; Zang et al. 2005). Interest in research in robustness is also particularly high in complex natural systems, such as different types of biological networks, which is why these approaches are also reviewed in more detail at a later stage in this thesis (section 2.3.3).

2.2.2 Robustness definitions and measures in manufacturing systems

In MSs, the concept of robustness has been the subject of interest in many different strands of MSs research, so that no general definition or measure of robustness in MSs exists. Similar to the general definition of robustness in the previous section (see section 2.2.1), most robustness definitions in a MSs context describe a performance measure that should be robust, and an invariance measure to assess the behavior of the performance measure. This section presents different definitions and measures of robustness in MSs research, ordered by their area of application. The areas are chosen according to the tasks in the different decision-horizons in MSs (see section 2.1.3: production control, production planning and scheduling, and MSD). As the focal point of this thesis is RMSD, the respective approaches are presented in a separate section (2.2.3).

Robust (shop-floor) control methods can be summarized as control methods that organize the production order release and production order routing in a way that fluctuations and disturbances do not negatively influence the performance of the MS. In Philipoom and Fry (1990), the robustness of nine different dispatching rules under varying capacity scenarios and job routings is analyzed using a simulation study. The performance measures used are average flow time and tardiness, robustness of the rules is measured by comparing a scenario with capacity and routing changes to an initial base scenario. Kleijnen and Gaury (2003) define robustness as the capability of the MS control system "to maintain short-term service while minimizing long-term work-in-process, under a variety of scenarios" (Kleijnen and Gaury 2003). They analyze the behavior of the performance measure average WIP in scenarios with different probabilities that a disturbance occurs by using a simulation study. Average WIP is then used as a measure to assess the robustness of different production planning and control policies. Telmoudi et al. (2008) define robustness of a MS as "its aptitude to preserve its specified properties against foreseen or unforeseen disturbances" (Telmoudi et al. 2008) and a robust control system as a system that "allows the conservation of the system aptitudes in the presence of disturbances" (Telmoudi et al.
2.2 Robustness definitions, measures, and disambiguation in manufacturing systems

2008). Approaches for autonomous control, which shift control tasks from a centralized control entity to decentralized objects in the shop floor (ARMBRUSTER et al. 2006; JEKEN et al. 2011), also claim to enable RMSP, as in case of a disturbance (e.g. a machine breakdown), parts can for example autonomously choose to be switched to a different machine, which is supposed to render the MSP robust to disturbances. In SCHOLZ-REITER et al. (2005), the robustness of an autonomous control method for a job shop in the face of machine failures is tested using a simulation study. The performance measure analyzed is throughput time, while robustness is measured by comparing throughput time under breakdown and in a base scenario without breakdowns. The authors find that their autonomous control method yields shorter throughput times than a conventional planning method in the face of machine failures (SCHOLZ-REITER et al. 2005).

Robust planning and scheduling methods provide production plans and production schedules that anticipate potential fluctuations and disturbances, and thus result in a better performance under uncertainty. While planning decides on which capacities and operations are necessary to fulfill the demand, scheduling guarantees the execution of the production plans (TOLIO et al. 2011). KAZEMI ZANJANI et al. (2010) suggest an approach to create production plans that exhibit a robust service-level under disruptions, where the performance measure with which service-level robustness is measured is the backorder size. To generate robust plans, they use a robust optimization approach. Robust optimization is a field of mathematical optimization that searches "for designs and solutions that are immune with respect to production tolerances, parameter drifts during operation time, model sensitivities and others" (BEYER and SENDHOFF 2007). Usually, a mathematical optimization model minimizes or maximizes a specific target function with respect to some constraints, given a definite set of input data. MULVEY et al. (1995) define that a solution to a robust optimization model is "solution robust if it remains close to optimal for all scenarios of the input data, and model robust if it remains 'almost' feasible for all data scenarios" (MULVEY et al. 1995). Robust optimization models are applicable to problems from a wide range of fields, e.g., finance, computer science, and most prominently engineering, but are also applied in the context of MSs research, as presented here for example in planning and scheduling. Another example for a robust optimization approach in production planning is presented by NOURELFATH (2011), who also seeks production plans that offer a robust service-level. In his approach, robustness is measured as the fraction of demand satisfied on time. This measure is again integrated into a robust optimization model to generate robust plans. TOLIO et al. (2011) define robust planning as the process to "make production plans insensitive - at least to some degree - to disruptions" (TOLIO et al. 2011). Contrary to many other approaches which use the average of a performance value as an invariance measure, they suggest to measure robustness of production plans using the worst case value of the MSP measure tardiness.

A robust production schedule is defined as robust if "the performance of the schedule remains high in the presence of disruptions" (LEON et al. 1994). LEON et al. (1994) measure the robustness of a schedule as a linear combination of two performance measures, namely expected makespan and expected delay, under machine breakdowns. In KOUVELIS et al. (2000), the authors define the task of robust scheduling as "determining a schedule whose performance (compared to the associated optimal schedule) is relatively insensitive to the potential realizations of job processing times" (KOUVELIS et al. 2000) and they develop an optimization approach to produce schedules that are robust against uncertainty of processing times. Within this approach, they measure robustness as the exposure
Related Work

to the risk of poor system performance (which is measured as makespan). Goren and Sabuncuoglu (2008) define a robust schedule as 'a schedule whose performance does not significantly degrade in the face of disruption' (Goren and Sabuncuoglu 2008) and use the performance measures makespan, total flowtime, and total tardiness to measure the robustness of schedules. However, robust plans and schedules are always based on existing resources of a MS. In the following section, definitions and measures as well as models on how to design a robust MS (i.e. dimension the resources in a robust manner) are reviewed.

### 2.2.3 Robust manufacturing system design

Within this section, it is distinguished between works that suggest robustness definitions and measures in order to be able to incorporate robustness as a characteristic into the design of a MS, and approaches that suggest models that allow for the entire design (calculation of necessary resources etc.) of a robust MS. Several research approaches exist that suggest measures to only assess the robustness of a MS (Rossi 2010; Meyer et al. 2013; Becker et al. 2013; Putnik et al. 2015), but do not present models to create a robust MS. Rossi (2010) suggests to assess the robustness of a configuration of machines in a MS. He defines robustness of a machine configuration as 'its ability to maintain deadline satisfaction despite the disturbances that may affect the forecast demand' (Rossi 2010) and measures it as the minimum magnitude of disturbances that may lead to breaking the deadline (the higher the magnitude, the higher the robustness of the configuration). In Meyer et al. (2013), robustness is measured as the change of four MSP measures (utilization, throughput time, due date reliability, lateness) under machine disruptions, which is analyzed in different capacity configurations in a simulation study. The robustness measure is calculated as a ratio of the performance in a perturbed scenario compared to an unperturbed scenario. A similar definition is also used by Putnik et al. (2015), who analyze the influence of system size and network structure on the robustness against changing demand in production networks with a simulation study. They measure the robustness as the ratio of the performance measure production rate in a simulation scenario with perturbations in comparison to the performance measure production rate in a scenario without perturbations. A further definition by Becker et al. (2013) sees MS robustness as the ratio of operations feasible under disruptions of a specific machine to total operations feasible without disruptions.

Approaches to determine the long-term adequate amount of resources or the configuration in a MS in a way that the system is robust against disturbances and fluctuations can be summarized as robust dimensioning, robust capacity allocation, or robust configuration of MSs. In Scholz-Reiter et al. (2011), a queuing network which is approximated by a fluid model is used to measure robustness of capacity allocations, using the stability radius. The stability radius is a measure commonly used in fluid networks and describes the smallest change of parameter that destabilizes a system. It is incorporated into a mathematical optimization approach that minimizes the required capacity for a desired stability radius. Liu et al. (2011) suggest to measure the robustness of a MS by using the clustering coefficient and the average shortest path of a graph-theoretical depiction of the MS. They implement these robustness measures as objectives into a nonlinear optimization approach to find a cost-optimal resource allocation. In their robust manufacturing system design approach, Sharda and Banerjee (2013) suggest a mathematical optimization
model to design a robust MS. They define robustness of a MS as better behaviour of "performance measures such as throughput and WIP under different manufacturing system uncertainties" (SHARDA and BANERJEE 2013). The performance variables considered for minimization in their optimization model are makespan, mean WIP, and number of machines, while the uncertainties considered are processing times, equipment failure and repairs, and product demand.

A special role in robust design of MSs can be attributed to robust parameter design, which is also often referred to as robust design. Robust parameter design is "an efficient and systematic methodology that applies statistical experimental design for improving product and manufacturing process design" (TSUI 1999) and was developed and popularized by Genichi Taguchi in the 1980s (TAGUCHI 1986; TAGUCHI and CLAUSING 1990; TAGUCHI et al. 2000). Robustness in the context of robust design is defined as 'the state where the technology, product, or process performance is minimally sensitive to factors causing variability (either in the manufacturing or user’s environment) and aging at the lowest unit manufacturing cost' (TAGUCHI et al. 2000). Robust design approaches have since their introduction quickly gained immense popularity in engineering (a first review paper already appeared in 1992 (TSUI 1992)), and MONDAL et al. (2014) presents a recent review on robustness of manufacturing processes, where robustness is described as a "concept used in quality engineering for the improvement of quality in a manufacturing process" (MONDAL et al. 2014) and a robust process is declared to be "a process which is insensitive to noise variations" (MONDAL et al. 2014).

The general idea in robust parameter design is to analyze how a quality indicator, such as product defects, also called a response variable, is affected by factors that are controlled by the designers, such as the material of the product, called control factors or design parameters, and by factors that are too expensive or impossible to control, such as the temperature, called noise factors (TSUI 1992; MONDAL et al. 2014). In the general robust design approach, the response, control, and noise factors are determined in a first step. Experiments are then run to study the relationships between the response, the control, and the noise factors, for example to find out how the type of material (control factor) and temperature (noise factor) affect the number of defective products (response). The results of these experiments are then analyzed using different statistical methods (TSUI 1992) and a variety of different robustness measures (see MONDAL et al. (2014) for an extensive review). The optimal control factor settings revealed from the analysis are then chosen to be implemented as the system design.

Enhancing Taguchi’s initially proposed method, CHEN et al. (1996) introduce two different types of robustness in robust design that are associated with minimizing performance variations and at the same time bringing the mean performance on target, which they name Type I and Type II robustness. In Type I robustness, control factors $x$ are adjusted to dampen variations in performance $y$ caused by variations in the noise factor $z$ (see figure 2.11a). If the objective is to achieve a performance close to the target $M$, then both control factors $x = a$ and $x = b$ are equally suitable, because their mean value is equally close to $M$. Yet with solution $x = b$, the performance varies much less than with $x = a$, which is seen as the more robust solution in this case (CHEN et al. 1996). In Type II robustness, the performance $y$ is a function of a design variable $x$, and it is the objective to minimize the variation of the performance instead of seeking the optimum (in this case minimum) value (figure 2.11b). Choosing $\mu_{opt}$ as a design, the performance $y$ is at an
optimal value, yet its deviation around the target $M$ caused by the variations of $\mu_{opt}$ is much higher than the deviation of performance $y$ caused by the variations of ($\mu_{robust}$), hence the differentiation into optimal and robust solution (CHEN et al. 1996).

Figure 2.11: Type I and II robustness in robust design, modified from (CHEN et al. 1996)

Many approaches have enhanced what was initially suggested by Taguchi with Response Surface Modelling or mathematical programming approaches (CHEN et al. 1996; DELLINO et al. 2010). Such approaches however can rather be counted in the domain of robust mathematical optimization than in the area of robust parameter design. Although some approaches using Taguchi methods use the expression robust design optimization to describe their work (e.g. (SUNDARESAN et al. 1992)), such approaches should not be confused with robust mathematical optimization, as many of them do not technically make use of mathematical optimization, but of experimental design procedures (SANDGREN and CAMERON 2002). However, in robust parameter design, robustness refers solely to the performance measures product and process quality (MONDAL et al. 2014). It has so far not been used to determine robust system configurations, i.e. numbers of resources that are necessary to render MSP robust against disruptions.

2.2.4 Concepts similar to robustness in manufacturing systems research

As for the general definition of robustness presented in section 2.2.1, robustness in MSs is also related and similar to other terms and concepts existing in MSs research. A term that is frequently used in scheduling and is similar to schedule robustness is schedule stability, which in a manufacturing context has been used to describe the performance of a production schedule. A stable production schedule is a schedule "whose realized events do not deviate from the original schedule in the face of disruption" (GOREN and SABUNCUGLO 2008). The difference between stability and robustness in the definition of GOREN and SABUNCUGLO (2008) lies in the performance aspect: robustness is concerned with the influence of disruptions on MSP, whereas stability is concerned with the influence of disruptions on whether the schedule is executed as planned or not. The term reliability in a manufacturing context mainly refers to resources of the MS, describing "the probability that a device will function without failure over a specified time period or amount of usage" (CIRP 2004). Again, there is no direct link to the MSP in this concept of reliability in the manufacturing context. Definitions and modeling approaches for resilience as a characteristic of MSs have
2.2 Robustness definitions, measures, and disambiguation in manufacturing systems

recently been presented, for example by Hu et al. (2008) or Zhang and Luttervelt (2011), who define resilience of a MS as the ability "to survive a disruptive event" (Hu et al. 2008) or as the "capability to recover their functions after partial damage" (Zhang and Luttervelt 2011).

2.2.5 Redundancy as a general system characteristic

As the guiding research question in this thesis assumes a relationship between the previously introduced robustness in MS and redundancy, this section gives a first introduction to the term redundancy. As the term redundancy has been coined by the domain of safety and reliability engineering, the specific definitions from this field of research are also introduced. Lastly, definitions of redundancy in the context of MSs research are reviewed. The word redundant, which in a general context has the meaning of being "superfluous" or "not or no longer needed" (Stevenson 2010), has a specific meaning in the context of engineering and other scientific disciplines. In the field of reliability or safety engineering, the reliability of systems is increased by introducing reserve capacities or redundancies, which has been intensively studied since the 1950's (Gordon 1957). In this context, redundancy describes "a technique whereby one or more of the components of a system are replicated in order to improve the reliability of the system" (Tillman et al. 1980). A similar definition of redundancy in a general systems context is given by Kitano (2004), who states that "redundancy generally refers to a situation in which several identical, or similar, components (or modules) can replace each other when another component fails" (Kitano 2004), which is also named a fail-safe mechanism. As a large amount of research on redundancy originates from engineering and biological backgrounds, these two domains and their different concepts of redundancy are reviewed here. In addition, the existing definitions and concepts of redundancy in a manufacturing context are presented.

2.2.6 Redundancy in safety and reliability engineering

In general, safety and reliability engineering is concerned with the optimization of system reliability. This can be achieved by several methods, but the larger part of the existing literature on systems reliability optimization is concerned with optimization techniques that resort to redundancy. Redundancy in this context describes "a technique whereby one or more of the components of a system are replicated in order to improve the reliability of the system" (Tillman et al. 1980). Two different types of redundancy, active and passive, are distinguished. While active redundancies (also called hot redundancies) are in an operational state from the time they are inserted in the system, passive redundancies (also called cold redundancies) are only partially or not at all operable when being inserted in the system, and only become active if the original components fail (Blischke and Murthy 2011). The problem of distributing redundant system elements with certain reliability indices under cost constraints in a way that the total reliability of the system is maximized has been addressed as the redundancy allocation problem, which is still subject to recent research approaches (Liang and Chen 2007). It has been studied for different system configurations, e.g. series, parallel, series-parallel, and in combination with different optimization techniques, e.g. integer programming, dynamic programming, linear programming, or heuristic approaches.
2.2.7 Redundancy definitions and measures in manufacturing systems

The term redundancy is not commonly used to describe redundant capacity or fail-safe mechanisms in MSs. In an approach that transfers the concepts from safety and reliability engineering to MSs, redundancy is added to a MS by adding redundant resources (e.g., machines) (Sun et al. 2008). Emami-Mehrgani et al. (2011) proposed a model that integrates passive redundancy into MSs as a cold-stand by system in order to demonstrate that passive redundancy optimizes production and maintenance cost. In their manufacturing context definition, a two machines cold-stand by system is composed of a primary machine and a backup machine, where the backup machine is only called upon when the primary machine fails (Emami-Mehrgani et al. 2011).

In their network model of a manufacturing enterprise, Hu et al. (2008) proposed the terms operational redundancy, which refers to the customer demand being satisfied after a loss of capacity due to additional capacity being available, and inventory redundancy, which refers to the customer demand being satisfied after a loss of capacity because sufficient inventory being available downstream of the capacity loss. In Zhang and Luttervelt (2011), three types of redundancy in MSs are proposed. The first type of redundancy they define are duplicate physical components, of which only one is in operation and the others only become functional in case of a dysfunction of the others, which corresponds to the definition of passive redundancy from safety and reliability engineering. The second type of redundancy they suggest it that two redundant resources are both in operation the whole time, which corresponds to active redundancy from safety and reliability engineering. Their third type of redundancy describes the situation where a particular resource can be used for more than one raw material or processing step (Zhang and Luttervelt 2011).

To assess the structural complexity of a MS layout, ElMaraghy et al. (2014) suggest several indices based on a graph theoretical representation of the MS, of which one is named redundancy distribution index. It measures the amount of redundancy of information flow within the MS layout (ElMaraghy et al. 2014). In their modeling approach for facility layout decisions, Zhao and Wallace (2016) define redundancy as having duplicate machines in the MS system and show that introducing machine redundancy into facility layout designs can reduce material handling costs.

2.3 Complex networks and bio-inspired approaches in manufacturing systems research

2.3.1 Motivation for interdisciplinary research in manufacturing systems research

This sections presents the similarities between complex networks and MSs, and between biological systems and MSs. It further depicts how MSs research can benefit from the transfer of methods from other domains. It thus serves as a motivation for interdisciplinary research, which is the interactions between two or more different science disciplines (Thompson Klein 1990; Moran 2010). Although it is commonly accepted that interdisciplinary research can carry risks, the general notion among researchers is that it is essential and
2.3 Complex networks and bio-inspired approaches in manufacturing systems research

beneficial (Rhoten and Parker 2004). The necessity for an increased use of interdisciplinary methods in operations management, production, and manufacturing research has recently been stated by various authors (MacCarthy et al. 2013; Chiang et al. 2014).

Complex network science describes the study of complex systems, which are systems with a large number of highly interconnected individual components that are not subject to a central controlling entity (see also section 2.1.4). After two pioneering works on insights about characteristics of real world complex networks by Watts and Strogatz (1998) and Barabási and Albert (1999) were published at end of the 1990s, a considerable number of real world systems, such as social, infrastructural, or biological systems, were analyzed and found to display different characteristics of complex systems (Albert et al. 1999; Jeong et al. 2000; Albert et al. 2004; Braha 2007). The analyzed systems can all be depicted as mathematical graphs or networks, which makes it possible to apply the same graph theoretical or statistical mechanics measures to them. The application of such complex network measures has become increasingly popular in recent years (Strogatz 2001; Watts 2004; Cohen and Havlin 2010; Barabási 2012), as they are relatively simple to apply and yield striking insights into the complex system behavior in many natural or man made systems. The probably most commonly known example is the small-world experiment by Travers and Milgram (1969), which originated from the analysis of social networks and attempted at empirically finding the average path length in a network where nodes represent people and links their acquaintance. Travers and Milgram (1969) were able to show that any two randomly chosen U.S. citizens can be connected by on average only six people, which is also referred to as the six-degrees-of-separation theory (Barabási and Frangos 2014). Another prominent example is the analysis of the World Wide Web, where it has been found that any two randomly chosen sites (HTML documents) in the web are on average only 19 clicks apart from each other (measured as the average network diameter), which is surprisingly low concerning the overall number of sites in the World Wide Web (Albert et al. 1999). Complex network measures have also been successfully used to analyze and understand complex supply chains (Kim et al. 2011; Bellamy and Basole 2013; Hearnshaw and Wilson 2013; Kito and Ueda 2014; Kito et al. 2015; Han and Shin 2015; Brintrup et al. 2015), systems that are similar to MSs as they are economically oriented as opposed to naturally evolved systems. As presented in section 2.1.4, MSs can also exhibit all typical properties of complex networks, especially if production control is not done using a central schedule but rather relies on dispatching or similar distributed control rules, as this allows for an emergent dynamic behavior. Moreover, they can also be depicted as mathematical graphs, which was for example shown by Becker and Meyer (2014). Therefore, a transfer of methods and measures from complex network research to manufacturing research seems promising.

Interdisciplinary research between biology and other science disciplines is manifold. If a scientific discipline uses methods derived from biological systems, the approaches are usually referred to as bio-inspired, for example bio-inspired design of materials and surfaces (Munch et al. 2008; Shu et al. 2011), bio-inspired design of transport (Bebber et al. 2007; Tero et al. 2010) or logistics (Helbing et al. 2009) systems. Biological systems generally exhibit properties, such as the ability to self-organize processes without the need of a central controlling entity (Bonabeau et al. 1999) or extraordinary robustness to disruptions (Kitano 2004), which are considered beneficial characteristics for MSs. First works suggest a bionical or bionic manufacturing system (Okino 1989; Okino 1993) and describe the idea that a MS should exhibit properties of biological systems, such as intelligence, self-organization,
or autonomous function and offer modeling approaches. Bionic factories operating with
distributed components (e.g. machines, transport equipment) which can take their own
decisions and communicate with each other in a quasi-life scenario were also described on
a conceptual level (Okino 1993). Other early works use the term biological manufacturing
systems, which defines MSs that exhibit biological functions such as self-formation, self-
recovery, or adaptation (Ueda 1993; Ueda and Ohkura 1996; Ueda et al. 1997). In their
works, Fulkerson and Parunak (1995) review applications of biological phenomena,
such as distributed control by autonomous agents, in a manufacturing context, which
they subsume under the term living factory. In addition to suggesting which properties
of biological systems are beneficial for MSs, several works also draw analogies between
manufacturing and biological systems, to emphasize their similarities and to enable a
transfer of methods from one system to the other (Ueda 1993; Ueda and Ohkura 1996;
Demeester et al. 2004; ElMaraghy et al. 2008). Ueda (1993) and Ueda and Ohkura
(1996) for example consider the material in a MS as a living and developing organism that
carries DNA-type information which codes its manufacturing processing. They create a
model in which material with its included DNA-type information autonomously searches
for a machine (or ribosome) to be treated on, and with this model they show that the
system exhibits adaptive behavior to its environment. However, biological systems do
not only exhibit characteristics that are desirable for MSs, they also share some common
characteristics. Both biological and MSs can be described to be complex systems, and
both exist or operate in changing and fluctuating environments that they have to cope
with (Mill and Sherlock 2000).

However, the similarities of the analyzed systems in both complex network science and biology and MSs as well as the potential creation of beneficial characteristics by method
transfer are not the only reasons why this thesis centers on interdisciplinary research
between the domains. Moreover, the study of robustness is a prominent topic in both
complex network science and biological system (Callaway et al. 2000; Kitano 2004;
Vodák et al. 2015). In the following sections, an introduction to both interdisciplinary
fields is given, and existing approaches that constitute interdisciplinary research between
MSs and a) complex network science and b) biological systems are presented. Additionally,
robustness definitions and measures from both domains are reviewed.

2.3.2 Complex network science and manufacturing systems

Introduction to complex network science and measures

This subsection gives an introduction to the most prominent measures used within complex
network science, as many of the later reviewed approaches on robustness in complex
networks and biology make use of these measures and methods to understand system
robustness. In complex network science, complex natural or man-made systems are analyzed
based on their topology, i.e. a graph theoretical representation of the systems (Watts and
Strogatz 1998; Barabási and Albert 1999; Strogatz 2001; Albert and Barabási
2002; Watts 2004; Cohen and Havlin 2010; Barabási 2012). A graph \( G \) consists of a
set \( V \) of elements called vertices (also often referred to as nodes) and a set \( E \) of elements
called edges (also often referred to as links). An edge connects two vertices and is usually
written as \( i,j \), where \( i \) and \( j \) are the numbers of the vertices which the edge connects. A
2.3 Complex networks and bio-inspired approaches in manufacturing systems research

A graph can be represented as a diagram in the plain (see figure 2.12a). It is called directed if the edges have a direction associated to them, while the edges of an undirected graph have no direction associated to them (BOLLOBAS 1998; DIESTEL 2012; GROSS et al. 2013). Figure 2.12a depicts an undirected graph with the vertex set $V = \{1, \ldots, 8\}$ and an edge set $E = \{\{1, 2\}, \{1, 5\}, \{2, 4\}, \{3, 4\}, \{4, 5\}, \{4, 6\}, \{4, 7\}, \{4, 8\}, \{5, 6\}, \{6, 7\}, \{7, 8\}\}$. Figure 2.12c depicts the graph from figure 2.12a as a directed graph. A graph is frequently represented by an adjacency matrix $A_{ij}$, in which every row and column represent one of the vertices of the graph. An entry in $A_{ij}$ is 1 if a link exists between the $i$th and $j$th vertices. If no edge exists, the entry in the matrix is 0. In a directed graph, this matrix will usually be asymmetrical (COHEN and HAVLIN 2010). Figure 2.12b and 2.12d depict the adjacency matrices for the exemplary graphs from figure 2.12a and 2.12c.

As opposed to this unipartite depiction of nodes, where $G = (V, E)$, a bipartite graph is a graph whose vertices can be divided into two disjoint sets $U$ and $V$, so that $G = (U, V, E)$. The vertices from one set are connected to the vertices of the other set by edges. An exemplary bipartite graph and its adjacency matrix are given in 2.13, with vertice set $U = \{1, 2, 3\}$ and vertice set $V = \{4, 5, 6, 7\}$. As opposed to the unipartite depiction in figure 2.12, the adjacency matrix of a bipartite graph does not have to be square, as the two vertice sets can have a different amount of vertices (see exemplary adjacency matrix in figure 2.13b).

A typical characteristic or graph theoretical measure in complex networks is the degree of a node, which is the number of links connected to it. In a directed graph, it is the sum of all incoming and outgoing links of a node. The in-degree denotes the number of incoming
2 Related Work

![Exemplary bipartite graph](image1)

(a) an exemplary bipartite graph

(b) adjacency matrix of 2.13a

Figure 2.13: Exemplary bipartite graph and adjacency matrix

links of a node, while the *out-degree* denotes the number of outgoing links. In figure 2.14a, the node degree of each node from the exemplary graph from figure 2.12a is depicted in the nodes, while in figure 2.14b, the in- and out-degree of each node from the exemplary graph from figure 2.12c is depicted in the nodes.

![Node degrees](image2)

(a) node degrees for 2.12a

(b) in- and out-degrees for 2.12c

Figure 2.14: Node degrees of exemplary graphs

The *average node degree* of a graph is the average over all node degrees within the graph. The *node degree distribution* describes the probability that a node in the system has a certain degree (Bollobas 1998; Diestel 2012; Gross et al. 2013). Different node degree distributions are characteristic for different types of networks. *Random graphs* are a type of network that is, among other features, characterized by a Poissonian node degree distribution (Bollobás 2001). Random graphs have long been the dominant subject of study in complex network science (Cohen and Havlin 2010), however analysis of the node degree distribution in networks such as the World Wide Web (Barabási and Albert 1999) or metabolic networks (Jeong et al. 2000; Barabási and Oltvai 2004) has shown that the distribution of nodes in many artificial and real life networks does not follow a Poisson, but a power-law distribution. Networks that exhibit this property are called *scale-free* networks, and exhibit an extremely high amount of nodes with a very low node degree, while a very small amount of nodes exists that has an extremely high node degree (Cohen and Havlin 2010).

In addition to the node degree, it is often of interest to know how far the nodes in a network are apart from each other, i.e. how long a *path* from one node to another is, and
in particular how long the *shortest path* between two nodes is (COHEN and HAVLIN 2010). While the maximum of all shortest paths between all node pairs is called the *diameter* of a network, the average of all shortest paths between all node pairs in a network is called the *average path length* or the *average diameter* (COHEN and HAVLIN 2010). Many real life networks exhibit a small network diameter, and networks that exhibit this characteristic were termed *small-world* networks (WATTS and STROGATZ 1998). An example of a shortest path between two nodes and the calculation of the average network diameter of the exemplary graph from figure 2.12a are given in figure 2.15.

![Diagram](image.png)

(a) shortest path lengths \( p \) for node pairs \( n(1,8) \) and \( n(1,2) \)  
(b) shortest path lengths matrix for 2.15a  
(c) average shortest path length \( \bar{p} \) for 2.15a

Figure 2.15: Shortest paths and average network diameter

A further graph theoretic measure often referred to in the analysis of complex networks is the *centrality* of a node, which measures how central, and thus important, a node in the graph is. Different measures of centrality, for example the *betweenness centrality*, have been suggested and analyzed in different systems (BARthéLEMY 2004), such as the internet, biological networks, or social networks (JEONG et al. 2001; ESTRADA and RODRÍGUEZ-VelÁZQUEZ 2005; BRAHA and BAR-YAM 2006). The betweenness centrality \( bc \) of a node \( n \) (\( bc(n) \)) can for example be calculated as suggested by FREEMAN (1977) as the sum of all shortest paths between all node pairs \( j \) and \( k \) of which the particular node \( n \) is part of (\( \sigma(j, i, k) \)), divided by the total sum of shortest paths between all node pairs in the graph (\( \sigma(j, k) \)).

\[
bc(n) = \sum_{jk} \frac{\sigma(j, k, n)}{\sigma(j, k)} \tag{2.1}
\]

This means that nodes with high values of betweenness centrality participate in a large number of shortest paths. An exemplary calculation of the betweenness centrality is given in figure 2.16.

As betweenness centrality scales with network size (BARthéLEMY 2004), it is usually normalized to get a number in the interval \([0, 1]\) to make networks of different size comparable. The normalized betweenness centrality \( bcn \) of a node \( n \) (\( bcn(n) \)) in a directed graph is calculated as

\[
bcn(n) = \frac{1}{(N - 1)(N - 2)} \sum_{jk} \frac{\sigma(j, k, n)}{\sigma(j, k)} \tag{2.2}
\]

where \( N \) is the total number of nodes in the network. The *average betweenness centrality* of an entire graph or network (\( bc_{avg} \)) or *average normalized betweenness centrality* of an entire graph (\( bcn_{avg} \)) can then be calculated as the average of all (normalized) node betweenness centralities in the graph.
Interdisciplinary approaches between complex network and manufacturing systems research

Modeling MSs as mathematical graphs is not a new approach in MSs research. Early works that depict MSs as a graph are for example concerned with solving the facility layout problem of manufacturing plants (Seppanen and Moore 1970; Foulds and Robinson 1978; Carrie et al. 1978; Hassan and Hogg 1987). Seppanen and Moore (1970) suggest to model the block layout of different departments within a plant as a graph, with nodes being corner points of the block layout where departments meet, and links representing walls between the departments in order to solve the problem of where to allocate departments within a given facility space. A further early use of graph theory in MSs research is the application of graph theory for the grouping of machines in the design of cellular manufacturing systems (Rajagopalan and Batra 1975; King and Nakornchai 1982). In Rajagopalan and Batra (1975), a graph-model is proposed where the nodes represent the machines of the MS, and links are added between such nodes that exhibit a high similarity coefficient. From the resulting graph, machine groups are then derived by identifying cliques. A similar approach is presented by King and Nakornchai (1982), where the MS is modeled as a bipartite graph in which the nodes represent machines and products while the links represent visits of products to machines. This model is taken up in many subsequent works on the cell formation problem, and different methods such as clustering algorithms are applied to find an optimal grouping (Vannelli and Kumar 1986; Chandrasekharan and Rajagopalan 1986; Kumar et al. 1986).

In a more recent approach, Singh and Agrawal (2008) suggest to model MSs using a graph-based model in which the nodes represent different subsystems of the MS, such as support subsystems or manufacturing process subsystems, and the links between the nodes signify a connection or interaction between the subsystems. They suggest to use this model as an approach for restructuring a MS at a conceptual stage (Singh and Singru 2013). Another approach depicts a continuous manufacturing system as a graph, with nodes representing components of the MS, such as pumps or controllers, and links representing interactions between the nodes, such as energy or information flow (Jiang et al. 2009). This graph-theoretic model is used to first analyze the degree distribution of the network, and second to analyze the failure propagation process in the MS. Jenab and Liu (2010)
present a graph based model to measure the complexity of products in a job shop MS. They suggest a directed graph in which nodes represent products and the weight of the links between the nodes denotes which of the two linked products is more complex.

More recently however, researchers have started to analyze complex network measures in MSs, where most of them model the resources of the MS as nodes and the material flows between them as links of a graph (Vrabič et al. 2012; Vrabič et al. 2013; Becker et al. 2014; ElMaraghy et al. 2014). In Vrabič et al. (2012), the authors use a clique percolation on the machine-material flow graph to identify autonomous work systems within the MSs. Analyzing the changes in the machine-material flow graph on the network level (e.g. amount of nodes), on the node neighborhood level (e.g. critical paths), and on the node level (e.g. centrality of a node) was suggested for the detection of anomalies in the MS (Vrabič et al. 2013). Becker et al. (2014) suggest several measures from complex network science, such as nodedegree or betweenness centrality, and analyze their correlation to different MSP indicators to evaluate whether the measures are suitable for assessing designs of MSs during the design phase. In ElMaraghy et al. (2014), six indices that are based on the graph-theoretical representation of the machine-material flow network are calculated and used to evaluate the structural complexity of a MS.

Robustness definitions and measures in complex networks research

As mentioned in section 2.3.1, one of the many characteristics of interest in the context of complex network research is robustness of the analyzed networks. The research on robustness of complex networks can be distinguished in approaches on static robustness and dynamic robustness. In approaches to analyze static robustness, nodes of the network are deleted without consideration of potential loads or capacities that might need to be redistributed, while dynamic robustness refers to approaches that delete nodes and then redistribute the flows in the remaining network (Boccaletti et al. 2006). As a result, static robustness is analyzed using numerical simulation or analytical approaches. Robustness of scale-free networks, namely the Internet and the World Wide Web, was analyzed in a static approach by Albert et al. (2000), who showed that the networks displayed an unexpectedly high degree of robustness against random errors (random removal of nodes), while they were vulnerable in the face of targeted attacks (removal of most connected nodes). They measured robustness of the networks as the change in network diameter, defined as the average minimal path length between any two nodes, under removal of network nodes (Albert et al. 2000). Another approach that analyzes static robustness is presented by Callaway et al. (2000), who apply percolation theory in order to study the effect of random failures on the network. They calculate the size of the giant component in the network to investigate the effect of the percolation and thus network robustness (Callaway et al. 2000). An approach that compares static and dynamic robustness behavior of a network is presented by Albert et al. (2004), who analyze the robustness of the North American power grid under node removal using static random and degree-based node removal as well as dynamic load-based and cascading node removal. In the cascading node removal, nodes with the highest load are removed and the load is re-distributed to the remaining nodes. As the nodes have a limited capacity, they collapse if their capacity is exceeded, which leads to further redistribution and cascading of node removal. They use the connectivity loss caused by a node removal as a measure for network robustness (Albert et al. 2004). Dou et al. (2010) study the relationship between cost...
and robustness in scale-free, random, internet, and power-grid networks in a simulation to analyze cascading failures in networks. Robustness is measured as the ratio of the size of the largest connected component in the network before and after cascading failures occur (DOU et al. 2010).

The robustness of more economically oriented networks, such as worldwide supply chains, has also been analyzed using complex network measures. MEEPETCHDEE and SHAH (2007) measure supply chain robustness as the extent to which the supply chain is still able to fulfill demand despite a damage (removal of nodes) done to the logistical network. They find that in supply chains, a trade-off between robustness and both complexity and efficiency exists (MEEPETCHDEE and SHAH 2007). The vulnerability of supply chains is further analyzed by WAGNER and NESHAT (2010), who model vulnerability drivers as nodes and interdependencies between them as links and calculate a vulnerability index based on this model. A further suggested robustness measure for supply chains based on measures from complex network theory is the behavior of the average node degree of the network under node deletion (XUAN et al. 2011).

2.3.3 Biological systems and manufacturing systems

Introduction to ecological and metabolic systems

Within this thesis, the scope concerning interdisciplinary research on biological systems is further narrowed down to two types of biological systems, namely ecologic and metabolic systems. Ecology is defined as "the study of organisms in relation to the surroundings in which they live" (CHAPMAN and REISS 1999), hence an ecosystem consists of "the biological community and the physical, non-living, or abiotic environment" (COTGREAVE and FORSETH 2002). Ecosystems can also be depicted in a graph-theoretical representation, and are then referred to as ecological networks (MONTOYA et al. 2006). Specific types of ecologic systems are for example food webs, which depict predator-prey relationships among species (DUNNE et al. 2002a). They can be modeled with species as nodes and links as the trophic relations (i.e. who eats who) between them. Another type of ecologic system are mutualistic systems, which are systems of mutually beneficial "interactions between plants and their animal pollinators or seed dispersers" (BASCOMPT and JORDANO 2013). They can also be modeled as graphs or networks, however they are usually bipartite, with for example nodes representing plants and pollinators, and links representing interactions between them (JORDANO 1987; MEMMOTT 1999; JORDANO et al. 2003; BASCOMPT et al. 2003). A long-standing area of interest within research in such ecosystems has been the survival of species within the systems. This question of biological conservation, i.e. how and when do species go extinct, goes together with the search for the reasons for the inherent robustness against extinction in ecosystems (DUNNE et al. 2002b; MONTOYA et al. 2006; STANICZENKO et al. 2010). Numerous robustness measures and analysis approaches have been developed in ecosystem’s research, which have contributed largely to the understanding of robustness mechanisms and the link between structure and function (JORDÁN et al. 2008) in these systems.

Both ecosystems and MSs exhibit a lot of common system characteristics. Ecosystems are complex systems that are faced with similar external challenges as MSs, such as fluctuating
inputs and dynamic system behavior (Solé and Montoya 2001). Battini et al. (2007) describe in detail three striking similarities between industrial systems, such as MSs, and ecosystems, which they cluster into similarities in network structure, in flows, and in their nodes. They argue that ecological networks are collections of plants and animal species that are organized in a web-like structure and that transform energy and matter. Likewise, supply chains or MSs also consist of single entities that in turn transform energy and matter (Battini et al. 2007).

The second type of biological system considered in this thesis are metabolic systems. The word metabolism describes the chemical transformations within the cells of living organisms with which cells acquire energy to survive and reproduce (Alberts et al. 2008), which is a key role in sustaining the functionality or viability of a cell. The complete set of these chemical reactions within the cell constitutes the metabolic system of the cell (Palsson 2015). The chemical reactions of the metabolic system contain the substrates and their concentrations, usually given as stoichiometric coefficients. The reactions that transform the substrates, which can be compounds such as metabolites or co-factors, are catalyzed by enzymes (Palsson 2015). Metabolic systems can be depicted in various forms of a graph-theoretical representation, for example as a bipartite network where nodes represent enzymes or metabolites, while links represent chemical interactions between them. They are then referred to as metabolic networks. The metabolic network thus also indicates the chemical reactions taking place in the metabolic system. It is also possible to transform the bipartite depiction of a metabolic network into a unipartite enzyme-centric or metabolite-centric view, which is shown in figure 2.17 (Tretter et al. 2010; Becker et al. 2011; Palsson 2015).

![Figure 2.17: Three different ways to model metabolic networks, modified from (Tretter et al. 2010)](image)

A focal point of interest in research on metabolic systems is to understand the system structure and function in general (Jeong et al. 2001), but in particular the reasons for

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1Within this thesis, in the context of metabolic network modeling the term metabolites is used synonymously for metabolites, co-factors, and other proteins. These are referred to as compounds by other authors (see for example (Palsson 2015)).
the robustness of metabolic systems. An example for the outstanding robustness of cell metabolism is its ability to carry out its normal function under mutation or deletion of enzymes (Edwards and Palsson 2000; Stelling et al. 2002; Wilhelm et al. 2004; Smart et al. 2008) or under fluctuating metabolite concentrations (Fischer and Sauer 2003).

Several authors have described striking similarities between metabolic systems and MSs. One of the first papers to suggest similarities between manufacturing units (e.g. machining centers) and biological cells is presented by Tharumarajah et al. (1998). They draw the analogy that cells in biology have a chemical flow that is regulated by enzymes and hormones, which in manufacturing cells can be regarded as a material and information flow that is regulated by coordinators and policies. Demeester et al. (2004) give a detailed description of the similarities they see in cell metabolism and MSs: both systems operate a production process in which inputs are transformed into outputs, exhibit complex production flows, and need to be fast and responsive to environmental changes. They further draw the analogies that enzymes in metabolic systems can be seen as the MSs machines, and metabolites as material. They argue that solutions developed by metabolism, since it has been subject to evolution to its current state over a tremendous amount of time, should offer beneficial insights for MSs. Finally, they argue that MSs should be organized as organic production systems by using the same production principles as biological cells, which they derive as customized local production, universal components, just-in-time tools, and local recycling loops (Demeester et al. 2004). Armbruster et al. (2005) also point out similarities between biomolecular machines and industrial production, mentioning the existence of self-organization or the stochasticity present in both systems. Within this thesis, we consider three substantial similarities between cell metabolism and MSs, which are summarized in figure 2.18. The system function of both systems is the transformation of either nutrients into biomass or raw materials into products. Furthermore, they both operate in environments that are subject to fluctuations and unforeseen events, such as disturbances in nutrient or material supply. Lastly, both systems have to cope with internal disturbances, such as enzyme failure or resource breakdowns.

Figure 2.18: Similarities between manufacturing and metabolic systems

In summary, both systems need to show high performance under typical environmental conditions and, at the same time, maintain certain functions under a broad range of perturbations and varying conditions. Since this robustness with respect to large environmental
changes is already inherent in metabolic networks, it makes them a very interesting role model for MSs.

**Interdisciplinary approaches between biological systems and manufacturing systems research**

In this section, existing research on the transfer of research on ecological and metabolic systems to MSs is presented. The *self-organization* of ecological systems (Bonabeau et al. 1999), also referred to as *swarm intelligence*, can be defined as "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies" (Bonabeau et al. 1999). From the way how insects such as ants or bees search for food, several mathematical optimization models and algorithms have been derived, for example the *ant system* (Dorigo et al. 1996), the *ant-colony optimization algorithm* (Dorigo and Gambardella 1997), the *bee system* (Sato and Hagiwara 1997), or the *bees algorithm* (Pham and Castellani 2009). These optimization models and algorithms have been applied in a manufacturing context to traditional *scheduling problems* (Bonabeau et al. 1999; Chong et al. 2006; Pham et al. 2007), to tackle different types of *facility layout problems* (Solimanpur et al. 2004; Hani et al. 2007), or to achieve *autonomous control* within the MS (Armbruster et al. 2006; Scholz-Reiter et al. 2008). A thorough review of further manufacturing problems solved by approaches derived from the phenomenon of swarm intelligence is also given by Leitão et al. (2012).

A further strand of research is analyzing the biological mechanism of *evolution* and *classification* in MSs (ElMaraghy et al. 2008; Tolio et al. 2010; AlGeddawy and ElMaraghy 2010). ElMaraghy et al. (2008) apply *cladistics*, a classification technique used in biological systematics, to parts of a product in MSs in order to identify new design possibilities and alternatives for future products. It was further proposed that products and their underlying MSs are subject to *co-evolution*, which is a phenomenon occurring in interdependent and symbiotic biological species (Tolio et al. 2010; AlGeddawy and ElMaraghy 2010). AlGeddawy and ElMaraghy (2010) suggest a model for the co-evolution of product design and manufacturing capabilities, which is based on the previously introduced cladistics. In a similar approach, Baldwin et al. (2012) apply cladistics for the classification of different types of MSs, which allows them to depict their evolutionary history.

Of equal importance for this thesis are approaches that build on the analogy between *metabolic systems* and MSs. In Becker et al. (2011), a unifying modeling approach to compare traffic, manufacturing, and metabolic systems is developed in order to show that optimization strategies from one domain can be successfully applied to the other domain. The network topology, network elements, flow organization, and system dynamics of the three systems are first compared and then analogies are drawn. All systems are finally analyzed using the same model, a flow control procedure derived from traffic light control (Becker et al. 2011). Building up upon their analogies between cell metabolism and MSs, Becker et al. (2012) analyze several metabolic and manufacturing networks using complex networks measures, such as degree distribution or betweenness centrality, and compare the structures of both networks.
Robustness definitions and measures in biological systems

A large amount of different biological systems are generally characterized as being robust (Whitacre 2012), however, as stated in section 2.3.3, the focus of this thesis concerning biological systems is on ecological and metabolic systems. This section presents robustness definitions and measures from these two sub-fields of biology. As environmental changes or disruptions can negatively influence an ecosystem and in the worst case lead to extinction of species, a large body of research in ecology is concerned with biological conservation, i.e., how and when do species go extinct and what are the reasons for the inherent robustness against extinction in some ecosystems (Chapman and Reiss 1999; Levin 2009; Pocock et al. 2012). A type of ecologic system where biological conservation is extensively studied are food webs (Pimm 2002). As mentioned in section 2.3.3, they can be depicted as a graph or network. One of the first network studies on food webs by Williams et al. (2002) analyzes seven empirical networks and finds that the different species are on average only two links apart, thus they characterize the networks as potential small world networks (despite their low clustering). These findings are coherent with Montoya and Sol (2002), who investigate data sets of three food webs and find the networks to exhibit high clustering and short path lengths, both characteristics of small world networks. Dunne et al. (2002b) analyzed the robustness of food webs by investigating how the random removal of species influences the food web. They used data from 16 different ecosystems and measured robustness as the fraction of species that has to be removed from the networks to result in a loss of more than 50% of the species. They found that the investigated food webs exhibit a strong robustness against random removal of nodes, similar to the findings on many other real-life, scale-free networks (Albert et al. 2000), and that the robustness against species removal increases with connectance (Dunne et al. 2002b). Using the same robustness measure as in their previous studies (Dunne et al. 2002b), Dunne et al. (2004) analyzed three data sets of marine food webs and found that they display an even higher robustness to removal of species as other food webs. Staniczenko et al. (2010) enhance the existing approaches on food webs by not only calculating the secondary extinctions after the removal of a species, but by rewiring nodes after the removal of a species. This procedure mimics the forming of new trophic interactions among the remaining species after a species loss. 12 different food webs were analyzed by Staniczenko et al. (2010), using secondary extinction after species removal as a robustness indicator (as suggest by all previous studies). They find that certain types of species can react as overlap species in the case of species removal, which significantly promotes robustness of the networks. To assess the importance of a species for the overall robustness of a food web, Jordán et al. (2007) apply 13 different centrality measures to the trophic flows of nine different food webs. In a further study, they compare their static centrality measures with traditional simulations of the behavior of trophic flows in food webs, and find that some of the static measures show the same behavior as the traditional, dynamic measures (Jordán et al. 2008).

Another example for the interest in biological conservation and robustness in ecologic systems are mutualistic systems, which as introduced in section 2.3.3 can also be depicted as graphs or networks. Similar to food webs, the structure of mutualistic networks has thus been analyzed using measures from complex networks science. Jordano et al. (2003) analyzed 53 plant-pollinator and plant-seed disperser networks, which mostly showed a broad-scale degree distribution, indicating a high robustness against removal of highly connected nodes (targeted attacks). In their study on 37 mutualistic networks, Olesen
et al. (2006) first transform the bipartite mutualistic networks into unipartite networks and then analyze their shortest path length and clustering. They found that the characteristics of the bipartite and unipartite networks correlate strongly and that both shortest path length and clustering are very low for all pollinator networks, indicating that they exhibit very strong small-world properties (Olesen et al. 2006). A further approach by Memmott et al. (2004) analyzes the robustness of mutualistic networks to species extinction according to the method Dunne et al. (2002b) used for food webs. In two mutualistic networks, they removed pollinators at random, from most linked to least linked, and from least to most linked, and found that the mutualistic networks are strikingly more robust to removal of species than food webs (Memmott et al. 2004). This robustness of mutualistic networks is generally attributed to the strongly nested structure of mutualistic networks (Memmott et al. 2004; Burgos et al. 2007). In contrast to measures originating from physics or complex networks science, such as degree distributions or node centrality, nestedness is a concept that originated from the study of island habitats (Patterson and Atmar 1986; Atmar and Patterson 1993). It was originally described as the situation in which pollinators that interact with only a small amount of plants (specialists) are proper subsets of pollinators that interact with a large amount of plants (generalists) (Atmar and Patterson 1993). It was then shown, for example in a large-scale investigation of 52 mutualistic networks by Bascompte et al. (2003), that most real world mutualistic networks are significantly nested.

Further biological systems where it is of interest to researchers how changes in the environment or disruptions within the system affect the performance of the system are metabolic systems. An example for changes within the environment of a metabolic system could be a change in nutrient concentration, while an example for a disruption within the metabolic system could be a gene mutation or a gene deletion. As explained in section 2.3.3, metabolic systems can be modeled in a graph or network representation. The robustness of biomass production of metabolic systems under perturbations can be studied using flux balance analysis (FBA), which is a mathematical programming method that allows to analyze the flow of metabolites through a metabolic network using reconstructed in silico metabolic systems (Orth et al. 2010). FBA was used to analyze the robustness of cellular growth in different metabolic networks under varying environmental conditions (Edwards and Palsson 2000; Segrè et al. 2002), and it was shown that the in silico predictions of the mathematical models of metabolism were consistent with experimental data on the same systems (Edwards et al. 2001; Segrè et al. 2002). Popular topological measures from the analysis of complex networks were also applied to analyze robustness to disruptions (e.g. lethal mutations of genes) in metabolic networks (Jeong et al. 2000). Jeong et al. (2000) study the metabolic networks of 43 organisms and observe that they are scale-free networks, which means they display an insensitivity to the removal of random links. They also calculated the network diameter, which is the same for all 43 networks, and via a simulation study found that the diameter increases rapidly upon removal of the most connected nodes (Jeong et al. 2000). Barabási and Oltvai (2004) give a summary of further complex network measures used in metabolic systems to understand the functional organization of the cell. A particularly interesting topological measure that has shown to be more successful in predicting the effects of gene deletions and thus the robustness of a metabolic network compared to the measures from complex network science is the number of EFM s (Stelling et al. 2002; Wilhelm et al. 2004; Behre et al. 2008). EFM s are non-decomposable chemical reaction paths in the metabolic network that allow for autonomous function of the underlying organism (Schuster and Hilgetag 1994).
many of the presented approaches on biological robustness, *redundancy* is named as one of the main causes of system robustness (Stelling et al. 2002; Memmott et al. 2004). A more detailed analysis of redundancy definitions and redundancy as an enabler for system robustness in biological systems is given in the following paragraph.

**Redundancy definitions and measures in biological systems**

The term *redundancy* is commonly used in the context of biological systems, to describe that the same function is performed by identical elements (Tononi et al. 1999; Kitano 2004; Wagner 2005; Albert et al. 2011). An example for this is the existence of redundant, back-up copies of genes in the genome (Wagner 2005). A related concept is *functional redundancy*, which describes a situation where different elements perform the same or similar functions (Walker 1992; Rosenfeld 2002; Vieten et al. 2005). The term is for example used to describe that different species perform similar or the same roles in communities and ecosystems (Walker 1992; Rosenfeld 2002), or that different proteins can perform the same tasks (Vieten et al. 2005). In metabolic systems, the possibility to produce the same biomass products via different chemical pathways is referred to as *pathway redundancy* (Stelling et al. 2002), which can also be seen as a form of functional redundancy. Figure 2.19 conceptually depicts the difference between redundancy and functional redundancy. In figure 2.19a, an element (triangle) can be transformed into a different element (square) by using either of three identical elements (circles). In figure 2.19b, an element can be transformed into a different element by either of three different elements.

![Figure 2.19: Comparison of redundancy and functional redundancy](image)

A concept that is similar to functional redundancy and often synonymously used is *degeneracy*, which is the ability of structurally different elements to perform the same functions (Tononi et al. 1999; Edelman and Gally 2001; Albert et al. 2011). Edelman and Gally (2001) list numerous examples of degeneracy, such as overlapping functions of proteins or metabolic pathways, that are elsewhere referred to as functional redundancies. Some authors suggest that, to make a clear distinction between redundancy that is based on identical replication of elements and substantially different elements that perform the same functions, the term degeneracy should rather be used instead of functional redundancy (Whitacre and Bender 2010; Mason et al. 2015).
2.4 Research Gap

Redundancy is claimed to be the cause of robustness in several biological systems. For mutualistic networks, the robustness of the systems has also been attributed to the functional redundancy of species (Walker 1995), which also manifests itself in the nested structure of the systems (Memmott et al. 2004). Wagner (2005) name gene redundancy as one of the main causes of robustness against mutations. It has further been argued that the robustness of metabolic systems is strongly linked to pathway redundancy (Stelling et al. 2002). Chen (2008) identify redundancy, modularity, and decoupling as factors that cause robustness in metabolic systems.

2.4 Research Gap

2.4.1 Lack of robustness considerations in the design of manufacturing systems

The existing approaches to design job shop MSs are either focused on designing a solution that is cost-optimal, in particular with mathematical optimization approaches to determine resource requirements (see section 2.1.3), or to create a model based on the structural data to analyze which MSP could potentially be reached with the design, which is done using queuing or simulation models (see section 2.1.3). However, streamlined, cost-optimal systems are vulnerable to unforeseen disturbances, and MSP can easily be negatively influenced. The design approaches using queuing models and simulation are used to make assumptions about the MSP, but so far do not consider robustness of MSP when designing a MS and its resource requirements (with the exception of designing a robust product or process quality, see section 2.2.3).

2.4.2 Influence of redundancy on the robustness of manufacturing system performance

In order to design MSs so that they exhibit a robust MSP, the factors that favor or impair robustness in MSs have to be identified. As presented in section 2.2.2, a variety of different MSP measures are used to assess the robustness of MSs, such as flow times, WIP, or makespan, and many models have been suggested that analyze how design, scheduling, or control can positively or negatively influence them. However, the robustness of the MSP measure lateness, which is gaining in significance in today’s customer driven markets (see section 1), has not been as intensively investigated as the robustness of other MSP measures yet. Especially factors that favor or impair the robustness of lateness have not been subject of interest in the manufacturing context so far.

Judging from the presented approaches from complex network science and biology, redundancy is seen as a key enabler of system robustness in these domains (see section 2.3.3). What is regarded as a redundancy in a manufacturing context has not been clearly defined yet (see section 2.2.7), least has the influence of redundancy on robust MSP with regard to lateness been analyzed. In order to subsequently analyze the relationship between redundancy and robustness in MSs, a definition of redundancies in MSs needs to be established and a measure found to analyze the potential influence of redundancy on robust MSP.
2.4.3 Motivation for using interdisciplinary methods for robust manufacturing systems design

The information that is available at the design stage of job shop MSs is limited to information regarding the system structure, such as products, their characteristics, the subsequently necessary manufacturing processes and machines, and the potential material flows (see section 2.1.3). The models created for MSD are a means to predict the potential system behavior. However, the queuing and mathematical optimization approaches used to determine resource requirements in job shop MSs lack applicability to more realistic, large-scale and complex MSs, as they are limited to relatively small sizes of MSs (see section 2.1.3). Likewise, forming a simulation model that adequately depicts a large-scale, complex MS is a time and resource consuming task, and the simulation model might not adequately depict the system. As demonstrated in section 2.3.1, both complex and biological systems share striking similarities with MSs. As metabolic and ecological systems, MSs face fluctuating environmental influences and internal disruptions and thus share the common challenge to maintain a high level of efficiency for a variety of different conditions (see section 2.3.3). Similarly, MSs exhibit the typical properties of complex networks (see section 2.3.2). The methods developed in both domains seem to be able to tackle the previously identified shortcoming of methods traditionally used in manufacturing research for MSD (i.e. queuing and mathematical optimization), as they are made for large-scale, complex systems. Different analogies between ecological, metabolic and MSs have already been described in the past (see section 2.3.3), yet only in few works did these analogies ever evolve past a conceptual state. However, transferring methods used for analyzing ecological or metabolic systems can result in gaining new insights, as was shown for example by Becker et al. (2011). Especially nestedness and EFM analysis presented in section 2.3.3 have been outstandingly successful in their respective disciplines. Both are calculated solely based on topological information about the respective systems, but still show a striking relation to system robustness. They are able to predict the dynamic system behavior based on the structural characteristics of the respective system. Moreover, they implicitly consider different forms of redundancies (functional and pathway redundancy) and thus, due to the assumed positive influence of redundancy on robustness, seem suitable to measure and analyze system robustness based on the structural data in MSs.
3 Analyzing the relationship between robustness and redundancy in manufacturing systems

In the third chapter, the relationship between robustness and redundancy in MSs is analyzed. Therefore, the underlying measures for robustness and redundancy used within this thesis are given in section 3.1 and section 3.2, based on measures that were introduced in section 2.2.1 and section 2.3.3. Robustness is measured as the change of a MSP measure in perturbed and unperturbed situations as suggested by Alderson and Doyle (2010). Redundancy is measured as two different types of machine redundancy, based on the differentiation between duplicate redundancy and functional redundancy in biological systems (Kitano 2004; Walker 1992), which was introduced in section 2.3.3. Subsequently, the potential relationship between robustness and redundancy is described in section 3.3. Considering findings from other real world systems like biological systems where redundancy is supposed to have a positive effect on system robustness (Stelling et al. 2002), it is assumed that the relation between the two concepts is also positive in MSs. Furthermore, it is investigated whether two measures from complex network science - node degree and betweenness centrality - which show a significant relation to robustness in other real world networks (Albert et al. 2000) as described in section 2.3.2, are also related to robustness in MSs. To analyze the relation of robustness with redundancy and complex network measures, simulation modeling is chosen as a research method, as it seems to be the only method fit to cope with the complexity of job shop MSs and the dynamic system behavior necessary to study robustness, which necessitates an analysis of MSs in perturbed and unperturbed conditions. Thus a simulation study is conducted in section 3.4. The section first gives a short introduction to the general procedure of simulation modeling and criteria for valid and realistic simulation models in MSs (3.4.1). To build the simulation model as realistically as possible, a large range of different MS configurations are created with a mathematical optimization approach for cost-optimal resource requirements design in MSs by Bard and Feo (1991) (3.4.2). The created MS configurations display different amounts of machines, redundancy, and network characteristics. Subsequently, the simulation model and the experiments conducted with it are described in detail and robustness (defined as the behavior of the MSP lateness in perturbed and unperturbed scenarios) of each MS configuration is measured (3.4.3). Robustness of each MS configuration is then correlated to the redundancy and complex network characteristics of the respective MS configurations (3.4.4). A significant positive linear and rank correlation between robustness and one of the machine redundancy measures is observed, while no significant linear correlation is found between node-degree or betweenness centrality and robustness in MSs. As a last step of this chapter, the intermediary results are summarized and discussed in section 3.5.
3 Analyzing the relationship between robustness and redundancy in MSs

3.1 Defining and measuring robustness in job shop manufacturing systems

As stated in many of the works cited in section 2.2, robustness is a concept or an abstract that cannot be observed or measured directly (Félix and Wagner 2008; Alderson and Doyle 2010; Mondal et al. 2014). It is rather a characteristic of an object or system and thus is measured indirectly from the performance of the object or system under study. The measure for robustness within this thesis is based on the definition of a robustness measure given by Alderson and Doyle (2010) (see section 2.2.1), who state that to measure robustness, the system under study, the property that should be robust, the set of perturbations against which the system should be robust and an invariance measure need to be defined. Many of the presented measures for robustness in a manufacturing context (section 2.2.2) incorporate the four aspects of a robustness measure set up by Alderson and Doyle (2010), without explicitly referring to them. As an example, in their approach for robust scheduling, Goren and Sabuncuoglu (2008) define the system under study (production schedule), the properties that should be robust (makespan, total flow time, total tardiness of jobs), the invariance measures (expected sum of absolute deviations in job completion times), and the perturbations (random machine breakdowns) against which the property should be robust. Yet none of the approaches that give a thorough definition of robustness in the manufacturing context are concerned with overall MSP as the property under study. On the other hand, some of the existing definitions for robustness in a manufacturing context only measure static network values (e.g., shortest path length (Liu et al. 2011)), which is a shortcoming as networks in a manufacturing context are not static but change over time. When MSs are represented as machine-material flow networks, the links (material flows) between the nodes (machines) can vary drastically depending on the products ordered in the analyzed time-span, as different machines and material flows are active. This has also been shown for example in social communication networks, where the roles of the different nodes in the network change over time (Braha and Bar-Yam 2006). Thus definitions for robustness in a manufacturing context that are only based on average network values from a graph theoretical depiction of the MS do not seem to be sufficient measures. As the significance of certain nodes for the robustness changes dynamically, integrating a time-component into the robustness definition is crucial.

In the following section, the system, performance, perturbations, and invariance measures of the robustness measure suggested within this thesis are explained. The system under study is the MS of a manufacturing organization. The property or function that should be robust in the face of perturbations usually is declared to be a specific manufacturing performance indicator, for which the abbreviation MSP was introduced earlier. The MSP of a MS does usually not stay on an exact same level, but varies over time (t), even if no unplanned perturbations (p) occur, which is conceptually depicted in figure 3.1a). In a realistic manufacturing environment however, unplanned perturbations occur and negatively influence the MSP (MSP'), as shown in figure 3.1b.

As reviewed in section 2.1.2, different performance measures exist to assess MSP (Bititci 1995; Ghalayini et al. 1997; Gomes et al. 2004; Hon 2005; Chen and Huang 2006; Gomes et al. 2006), with different categorizations such as cost, quality, or time performance measures (Hon 2005; Chryssolouris 2006). As stated in the introduction and scope of

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2Parts of this section have been published in similar form in (Meyer et al. 2013).
3.1 Defining and measuring robustness in manufacturing systems

In this thesis (see section 1), the developed models and analysis focus on time performance measures, as these are considered most crucial for customer satisfaction in today’s buyer markets. In particular, the focus will be on lateness, as introduced in section 2.1.2. Lateness \( l \) can be evaluated for every single job, and for every single order. In general, it is measured as the difference between actual end time \( e_a \) and planned end time \( e_p \) of jobs or orders (Nyhuis and Wiendahl 2009; Pinedo 2012; Framinan et al. 2014).

\[
l = e_p - e_a
\]  

(3.1)

In case a job or order is late, the difference is a positive value, in case a job or order is early, the difference is a negative value. Both positive and negative lateness values are regarded as negative for the MS as both can incur additional costs: early jobs or orders cause higher inventory costs as there is more inventory than necessary and late jobs or orders cause a decrease in MSP towards the customer as due dates are missed. In addition to this general definition, several more detailed lateness specifications are depicted in figure 3.2. Input lateness \( l_{in} \) is the deviation of the actual start date of a job or order \( s_{actual} \) from the planned start date of the job or order \( s_{planned} \). Similarly, the output lateness \( l_{out} \) is the deviation of the actual end date of a job or order \( e_{actual} \) from the planned end date of the job or order \( e_{planned} \). Relative lateness \( l_{rel} \) of a job or order is calculated as the difference between the actual start date and the planned end date. In addition to job or order lateness, a depiction of lateness is also possible on a workstation or MS level. Workstation lateness can be calculated as the average lateness of all jobs.
or orders that are treated on a workstation, while MS lateness can be calculated as the average lateness of all jobs or orders within the MS. When an average of the job, order, workstation, or MS lateness is calculated (either on the workstation or MS level), the absolute values can be used to prevent negative and positive lateness values from averaging out, which is called the average absolute lateness.

As also depicted in figure 3.1b, different perturbations can have a different impact on MSP. This impact depends on the type or duration of the perturbation, a machine breakdown could for example lead to a higher and longer decrease of MSP than a shortage of a certain material. As reviewed in section 2.1.4, a multitude of different perturbations exist in a manufacturing context. In this work, the perturbation against which the performance measure should be robust is a machine breakdown.

The invariance measure for robustness in this thesis is the ratio that results from the comparison of the MSP in a scenario without perturbations to the MSP in a scenario with perturbations, where perturbations are machine breakdowns. As the focus of this thesis is on the MSP lateness, robustness will be calculated as the ratio of lateness in an unperturbed (l) and a perturbed (l′) scenario, where perturbations are machine breakdowns.

\[ r = \frac{l}{l'} \]  

A similar invariance measure has previously been suggested in a manufacturing context for example by MEYER et al. (2013), who measure robustness as the ratio of four different MSP measures (utilization, due date reliability, throughput-time, lateness) in scenarios with and without capacity fluctuations. Similarly, PUTNIK et al. (2015) measure robustness in a MS as the ratio between the drop in production rate of the MS under perturbation and the production rate in a stationary state. Another possible invariance measures for robustness in a MS context is to take the standard deviation of a MSP measure, which was proposed for example by LEON et al. (1994) in their collection of robustness measures for robust scheduling. In contrast to invariance measures such as the standard deviation, the ratio-based measure chosen in this thesis makes it possible to compare the robustness values of different MSs, as it is a normalized measure. Although the chosen measure can serve to compare different MS, its shortcomings are that it is only applicable if a model of the MS under study exists, as it is not feasible to declare and observe perturbed and unperturbed scenarios in real MSs or when recorded feedback data is analyzed.

3.2 Defining and measuring redundancy in job shop manufacturing systems

This section gives a definition of what is considered to be a redundancy in the context of job shop MSs. Similar to the definitions from biological contexts, redundancy in MSs is the existence of exact identical copies of an element that fulfill the same function, while functional redundancy in MSs is considered to be the existence of non-identical elements that are able perform the same functions. Elements in this context refer to elements in the MS, for example resources such as machines, equipment, or workforce, which were already introduced in section 2.1.1. The existence of several machines of the same type is very common in job shop MSs, for example when more capacity than one
3.2 Defining and measuring redundancy in job shop manufacturing systems

A machine can offer is needed. Likewise, machines can also fulfill what is seen as a functional redundancy in biology: flexible machining centers in FMS can for example sometimes perform the same processing steps (e.g., milling, drilling), although they are not exact duplicates of each other, and can thus be regarded as a functional redundancy. Further physical elements that can be regarded as redundant elements are the different types of material in MSs. It is common for raw-materials that identical copies are kept in storage, for example a company that uses steel profiles as raw materials will usually have more than one of each type on stock, which can be seen as a redundancy. However, a raw material could also be seen as functionally redundant, if it can be used instead of another type of raw material. In reality, only few examples can be found where this is actually the case. The same holds true for sub-assemblies or semi-finished parts: they can be redundant, if several identical copies of them are kept in stock, or they can be regarded as functionally redundant if they can replace structurally different sub-assemblies or semi-finished parts in a product. Finished products can be seen as redundant as well, if in case of a make-to-stock strategy a company keeps an inventory of finished goods. Transport and handling equipment can also exist as duplicates, or they can be used to process different materials or parts and thus can be seen as functionally redundant. Keeping duplicate raw-materials, sub-assemblies, or products is conceptually similar to safety-stock, which was introduced as a means to counteract the negative impact of disturbances on MSP in MSs in section 2.1.4. The redundancy categorization is summarized in table 3.1.

<table>
<thead>
<tr>
<th>resource</th>
<th>redundancy</th>
<th>functional redundancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>machine</td>
<td>duplicate machines</td>
<td>different machines can fulfill same function</td>
</tr>
<tr>
<td>transport &amp; handling</td>
<td>duplicate transport &amp; handling</td>
<td>different transport &amp; handling equipment can fulfill same function</td>
</tr>
<tr>
<td>workforce</td>
<td>duplicate workers on the same skill level</td>
<td>differently skilled workers can fulfill same function</td>
</tr>
<tr>
<td>raw-materials</td>
<td>duplicate raw materials</td>
<td>different raw materials can fulfill same function</td>
</tr>
<tr>
<td>sub-assemblies</td>
<td>duplicate sub-assemblies</td>
<td>different sub-assemblies can fulfill same function</td>
</tr>
<tr>
<td>final products</td>
<td>duplicate final products</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3.1: Redundancy and functional redundancy in manufacturing systems

Within this thesis and the following analysis, the focus will be on machine redundancy and machine functional redundancy. Therefore the differences and similarities between these identified redundancy types and related other terms in MSs research are discussed in detail in the following, and a measure for each of the concepts is given. Both machine redundancy or machine functional redundancy allow for the existence of alternative routes for a product: if several duplicate machines of one type exist, products can be treated on either of them, and each choice would represent a separate path. Likewise, if two machines are not identical but can perform the same manufacturing process, the product could be treated on either of them and each choice again would represent a unique path. Alternative product routes are conceptually the same as pathway redundancy found in metabolic networks. They are a very distinct characteristic of job shop MSs or FMS, and are not present for example in cellular manufacturing systems, where a set of product families is assigned to a specific cell with a dedicated routing.
The definition of machine redundancy as duplicate machines needs to be related to the aspect of machine capacity (for a definition see section 2.1.1). A machine usually has a defined capacity, measured in shifts, hours, work content etc., and the number of machines (and thus its capacity) in a job shop MS is usually carefully determined according to the capacities needed (see section 2.1.3). In case the demand for products and their related manufacturing processes exceeds the capacity of a machine, another one or several ones of the same type need to be installed. So having several redundant machines in the MS does not necessarily mean that excess capacity is held. We measure machine redundancy ($mr_i$) in a MS as the average amount of machines $m_i$ of type $i$.

$$mr_i = \frac{1}{n} \sum_{i=1}^{n} m_i$$

(3.3)

The prerequisite for machine functional redundancy is that machines are able to process several different manufacturing processes. This ability of a machine "to perform more than one type of processing operation efficiently" (DAS and NAGENDRA 1993) is also referred to as $machine\ flexibility$. In the context of research on flexibility in MSs, machine flexibility is seen as an enabler for $routing\ flexibility$, which is the "ability of the system to manufacture products via a variety of different routes" (DAS and NAGENDRA 1993). This is coherent with the previously given definition that machine functional redundancy acts as an enabler of alternate production routes. A vast amount of different measures have been suggested for machine flexibility and routing flexibility in the past. The number of different manufacturing operations a machine can perform is among the simplest definitions to measure machine flexibility (SETHI and SETHI 1990), and it will be used within this thesis to measure machine functional redundancy ($mfr$). It is measured as the average amount of manufacturing processes $p$ a machine $m$ can fulfill ($m_p$).

$$mfr = \frac{1}{n} \sum_{p=1}^{n} m_p$$

(3.4)

For routing flexibility, the most important definitions include the number of routes per product or average number of available routes for each part type, which are presented together with other measures in an extensive review by YU and GREENE (2009). In addition to the many existing definitions for machine and routing flexibility, the effect of both on different MSP measures has also been extensively studied (DAS and NAGENDRA 1993; CAPRIHAN and WADHWA 1997; CHAN 2001; ALI and WADHWA 2010). In DAS and NAGENDRA (1993), the influence of routing flexibility on flow time and WIP inventory in FMSs is studied using a simulation model. The authors find that increased routing flexibility leads to shorter lead times and decreased WIP inventory. CAPRIHAN and WADHWA (1997) analyze the influence of routing flexibility in FMSs on the MSP measure makespan, using also a simulation study. Their results indicate that routing flexibility is not always beneficial, as they identify an optimal flexibility level above which system performance deteriorates. CHAN (2001) also analyze the effect of routing flexibility on makespan in FMSs using a simulation study, but also incorporate an analysis of robustness against machine failure, using Taguchi methods. They conclude that routing flexibility is especially important for MSs in which many disruptions occur. In ALI and WADHWA (2010) the influence of routing flexibility and other parameters on the performance measure makespan is analyzed in a FMS using a simulation study combined with Taguchi methods. Similarly to CAPRIHAN and WADHWA (1997), the authors find that routing flexibility does not significantly increase performance, and that large flexibility levels even worsen performance.
3.3 Potential relationship between robustness and redundancy

Many of the presented approaches show that routing flexibility, which is only enabled by machine flexibility, increases MSP (Das and Nagendra 1993; Caprihan and Wadhwa 1997; Chan 2001). Yet none of the approaches so far studied the influence of routing flexibility on the robustness of MSP, although many works concerned with flexibility in manufacturing claim that flexibility - and in particular routing flexibility - acts as an enabler of robustness (Swamidass and Newell 1987).

3.3 Potential relationship between robustness and redundancy

In many real world systems, for example in metabolic or ecological systems, redundancy in pathways (Stelling et al. 2002) or species (Memmott et al. 2004; Burgos et al. 2007) was found to have a positive influence on robustness. In a manufacturing context, the influence of redundancy on robustness in MSs (as defined in section 3.1) can also be assumed to be positive, which can be illustrated with the following example: when a production order is released to the shop floor and the raw material needed for production is not present due to a delivery delay from the supplier, the planned due dates for the production order usually cannot be met, which results in an increased lateness. In case redundant raw materials had existed, the delays could be shortened or prevented completely. Similarly, if unforeseen machine breakdowns occur and no alternative routes exist, production orders will not be able to meet their originally planned due dates as they pile up in front of the machine under breakdown. If machine or machine functional redundancy had existed, the production order could have used an alternative routing and could have been treated on a different machine. Thus lateness would not be negatively influenced, which can be seen as a high robustness of lateness against machine breakdowns. From a holistic point of view, it is not known how successful redundancy in MSs can buffer against or reduce the negative effects on MSP incurred by disturbances: a disturbance can often affect subsequent activities, i.e. it propagates through the system. In case of a machine breakdown, this means for example that the production order is delayed at a certain machine under breakdown, but carries this delay through the entire MS, as it will also not meet the initially planned due dates on subsequent machines. It is a core assumption of this thesis that redundancy (machine redundancy and machine functional redundancy, as defined in section 3.2) has a positive effect on robustness (robustness of the MSP measure lateness against machine breakdowns, as defined in section 3.1). This relationship is conceptually depicted in figure 3.3, where increased redundancy in a MS results in increased robustness. However, it is not known how exactly the relationship between the two variables behaves, which is why two different potential relationships are shown as examples in the figure. The relationship could for example be depicted by a linear function, where both values increase proportionally, or by an exponential function, where one value increases by a constant factor with each step of the other value. One of the aims of this thesis is to investigate the above described relationship between robustness and redundancy in MSs.

In general, the ways to exploratively analyze a system or its behavior are experiments with the actual system or experiments with a model of the system (Law 2014). In the scientific fields where similar relations are of interest (e.g. metabolic or ecologic networks) such relationships are usually investigated by analyzing a variety of different real world systems. This is possible as in these domains, large, publicly available databases containing data sets of real world systems exist, for example the KEGG database (Kanehisa and
Analyzing the relationship between robustness and redundancy in MSs

Goto 2000). Original data sets are also often published completely, as for example used in Bascompte et al. (2003). Similar to approaches in other real world systems, the relationship between robustness and redundancy should not only be analyzed in one single MS, but in several MSs with different characteristics, to be able to draw generalizable conclusions. However, conducting experiments with real MSs is an unfeasible option, as it would be too time consuming to gather data for a statistically significant amount of real world MSs. Moreover, manufacturing organizations are usually reluctant in providing data concerning their MSs, as they see it as a core competency of their business. Thus it was chosen to use a model of MSs to analyze the relation between robustness and redundancy within this thesis. Different types of models exist to analyze MSs, for example process or mathematical models, of which the latter can be further distinguished into analytical or simulation models (Brandimarte and Villa 1995; Altink and Melamed 2010; Law 2014). Analytical models, such as queuing models (Buzacott and Shanthikumar 1992; Papadopoulos et al. 1993; Gershwin 1994) or mathematical optimization models (also referred to as operations research) (Brandimarte and Villa 1995; Rao et al. 2010), result in exact answers. However, they are usually restricted to small sizes of MSs and not applicable to more complex systems, in which it is "impossible to find an analytical relationship between decision variables and performance measures" (Brandimarte and Villa 1995). So if the MSs to be analyzed are complex, an analytical solution can be unfeasible or result in unreasonably high modeling efforts (Law and McComas 1987; Brandimarte and Villa 1995; Law 2014). As job shop MSs are seen as complex systems with a multitude of different resources and connections between the resources within this thesis (see sections 2.1.1 and 2.1.4), an analytical model seems unfeasible for the modeling task. Therefore a simulation model was chosen to analyze the relationship between robustness and redundancy in MSs. In the following section, the specific simulation method employed and its applicability in a manufacturing context are presented in more detail.

![Figure 3.3: Conceptual depiction of the potential relationship between robustness and redundancy in MSs](image)

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3.4 Simulation analysis of the relation between redundancy and robustness in manufacturing systems

3.4.1 Simulation as a research methodology in manufacturing systems research

As mentioned in the previous section, a simulation model of a MSs serves as a surrogate for conducting actual experiments or analysis in a real MS, as these are often infeasible or not cost-effective (Law and McComas 1987; Law and McComas 1998; Law 2014). Simulation in general is a well-established research method within the domain of MS research, and is used for design and operation of MSs (Iwata and Oba 1984; Law and McComas 1987; Alting et al. 1988; Law and McComas 1998; Miller and Pegden 2000; Smith 2003; Jahangirian et al. 2010; Silva et al. 2014; Negahban and Smith 2014). For the general procedure of conducting a simulation study in a manufacturing context, various approaches have been suggested in literature. Several authors split the general simulation procedure into three steps: a conceptional or design phase, a development or implementation phase, and a deployment or analysis phase (Chance et al. 1996; Fowler 2004; Montevichi et al. 2007). In the design or conceptional phase, the goals of the modeling process, the system under study, as well as the participants involved in the model design are determined. It also includes the construction and validation of a first conceptual model. This is followed by the development or implementation phase, in which based on the conceptual model, a modeling approach is chosen. A computer model is then built, and verified and validated. In the last phase, the deployment or analysis phase, experiments to be executed with the model are designed, the simulation model is executed, and the results are analyzed (Chance et al. 1996; Fowler 2004; Montevichi et al. 2007).

The specific simulation method chosen within this thesis is a discrete-event simulation (DES) model. DES is a simulation method used to model the behavior of a system as a discrete sequence of events, which mark a change of state in the system (Altiok and Melamed 2010; Law 2014). In a manufacturing context, an event could be the arrival of a new job at a machine or the end of processing of a job on a machine. An experiment describes the configuration of the MS or the scenario which is analyzed with the simulation model (Altiok and Melamed 2010). Miller and Pegden (2000) give a summary of the features a DES model of a MS can comprise, which are for example resources, material handling devices, control logic, workstation logic, buffers, as well as order or process plans. Variables or parameters like these can be changed along the different experiments conducted with the simulation model. The simulation clock is a variable which gives the current value of simulated time (Law and McComas 1987; Law 2014). The run time is the total number of time units for which the simulation model is run. If the time units are for example measured in days, the total run time of the model is a specific number of days. The first values of simulated time in a simulation run are often described as the warm-up period of the simulation model (Law and McComas 1987; Chance et al. 1996; Altiok and Melamed 2010; Law 2014). Several authors argue that performance values measured during the warm-up period should be disregarded, as the simulation model needs a certain ramp-up time to get into a state of steady functioning (Law 2014).

DES has been used in a manufacturing context for analyzing the impact of different factors, for example scheduling or dispatching rules, inventory policies, or characteristics such as
An analyzing the relationship between robustness and redundancy in MSs

flexibility and self-organization, on MSP (Schroer and Tseng 1988; Das and Nagendra 1993; Nagarur and Azeem 1999; Holst 2001; Usher 2003; Koh and Saad 2003; Longo et al. 2012; Sharma and Garg 2012). Das and Nagendra (1993) used a simulation study to analyze the influence of routing, machine, and product-mix flexibility on the MSP measures average flow time and WIP inventory. Similarly, Nagarur and Azeem (1999) analyze the influence of machine flexibility and part standardization on the MSP measures makespan, average machine utilization, and factor productivity using a DES. A further study analyzes the impact of alternative plans and thus alternative routes on the MSP measures tardiness, also employing DES as an analysis method (Usher 2003). The existing simulation studies on flexibility however do not focus on analyzing the MSP in unperturbed and perturbed situations (for example under machine breakdowns). They merely depict the behavior of MSs under normal operating conditions, and no conclusions regarding robustness of MSP can be drawn from them. However, DES can easily be used to also analyze the impact of disruptions on the MSP performance. This was for example suggested by Koh and Saad (2003), who analyze the influence of machine breakdowns on late deliveries using DES, or by Padhi et al. (2013), who analyze the impact of production line disturbances on production efficiency under different levels of cycle time, operator efficiency, and automation using a DES model. A recent study by Putnik et al. (2015) uses a DES to analyze the robustness of the production rate with regard to perturbations in customer demand. As the analysis of the relationship between robustness and redundancy is conceptually similar to the previously presented applications of DES for analyzing the influence of different factors on MSP measures, it is seen as a suitable research method for this thesis.

Most simulation approaches in MSs especially stress the importance of model verification and validation. In general, simulation model verification means ensuring that the simulation model produces a correct output given a specific input (Kleijnen 1995; Carson 2002; Sargent 2005; Rabe et al. 2008; Law 2014), which can also be expressed as "ensuring that the computer program of the computerized model and its implementation are correct" (Sargent 2005). Model validation on the other hand serves to determine whether the simulation model is an accurate and realistic representation of system that is being studied (Kleijnen 1995; Carson 2002; Rabe et al. 2008; Sargent 2005; Law 2014). In addition to being verified and valid, a simulation model also needs to be credible, which means that decision makers and experts involved in the design and use of the model accept it as correct (Balci 1989; Law 2009). An overview of validation techniques and credibility criteria for simulation models, for example comparisons to other models that have been validated or expert opinion validation, is given by Balci (1990) or Sargent (2005). In Carson (2002), a review of different modeling errors, for example data or logic modeling errors, that should be avoided in order for simulation models to be valid, are summarized. However, it also has to be stressed that a complete validation of any simulation is never possible (Law 2014).

Several authors summarize criteria for the validity, credibility, and quality of DES models specifically tailored for a manufacturing context (Law and McComas 1987; Chance et al. 1996; Law and McComas 1998; Fowler 2004; Wenzel et al. 2007; Rabe et al. 2008). The importance of considering a warm-up period in MS simulations is stressed and suggestions for the length of warm-up periods (around 10-15% of total run time) are given by several authors (Law and McComas 1987; Chance et al. 1996). It is further stressed in literature that the length of each simulation run and the number of independent simulation
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

runs should be chosen appropriately, with the number of simulation runs ranging between 3 to 10 runs in many approaches in MSs research (Law and McComas 1987; Law and McComas 1998; Chryssoulouris et al. 2013). Fowler (2004) state that incorporation of detail on the MS may increase the credibility of a simulation model, however an excessive level of detail can render a model hard to build, debug, understand, deploy, and maintain. In the following, a DES model is set up to analyze the potential relationship between robustness and redundancy in MSs.

3.4.2 Configuration of realistic exemplary manufacturing systems

The goals for the use of simulation within this thesis have been described in section 3.3. Following the procedure for building simulation models introduced in the previous section, this section starts with the presentation of the MSs to be analyzed. Many approaches in MSs research that investigate general properties of MSs with a simulation model use minimal examples or minimal models of MSs in their analysis (for example Koren et al. (1998), Scholz-Reiter et al. (2005), Chryssoulouris et al. (2013), and Blunck et al. (2014)). In these papers, a minimal model in a MS context means that the studied MSs consist of only a small amount of resources, e.g. three to ten resources. In Koren et al. (1998), the influence of the configuration of a MS (serial line or multiple parallel lines) on different MSP measures is analyzed using a Monte Carlo simulation on six minimal models of MS configurations, each consisting of six machines. Similarly, Scholz-Reiter et al. (2005) study the effects of autonomous control on different MSP measures, using a simulation model of a MS that contains nine machines and three different product types. Another example of the use of a minimal model to analyze the effects on MSP is an approach by Chryssoulouris et al. (2013), in which the trade-off between flexibility and complexity in MSs is analyzed in a MS that consists of ten products and ten resources. Blunck et al. (2014) use minimal models of flow shops consisting of five work stations per operating step, of which there are also five, to test improvement heuristics for manufacturing systems design. Minimal models are for example commonly used in the study of metabolic systems, where minimal metabolic network models are used for computationally simulating and predicting the behavior of the real world metabolic systems (Palsson 2015). Minimal models can be beneficial as they reduce complexity and can thus lead to gaining universal understandings and insights of the functioning of various complex systems (Batterman and Rice 2014). However, as a large amount of published case study data indicates, job or flow shop MSs can easily consist of between 20 to 200 resources and manufacture between 20 to more than 1000 different products (Rovithakis et al. 2001; Molleman et al. 2002; Yang et al. 2004; Meyer et al. 2013; Becker and Meyer 2014). Furthermore, a description of how the capacity or layout of the networks were decided upon is lacking in most minimal model approaches in MS research. In Blunck et al. (2014) for example, capacities of all resources are set to a value of 1 for each resource in general. This was also observed by Alhourani (2016) who criticize minimal models in the MS context for often using unrealistic infinite capacities. Thus it is doubtful whether the results of simulation studies based on minimal models of MSs are valid and credible (as defined in the previous section 3.4.1), as it can be argued that they do not represent realistic MSs.

Within this thesis, the MSs in the simulation study should be representative for a broad range of different job shop MSs and be as realistic as possible, to ensure credibility of the model. Instead of focusing on one specific MS or on MSs with only a small amount of...
resources, the results should be valid for job shop MSs with different amount of resources, different amount of products to be manufactured, and different amounts of redundancy. To create such a broad range of MSs artificially but yet realistically, a MSD approach for job shop MSs from manufacturing research literature is chosen. The amounts and types of resources that are adequate for a certain product demand and available types of resources are determined by a mathematical optimization approach suggested by Bard and Feo (1991) (see also section 2.1.3). Their optimization model was initially suggested to determine the investment cost-optimal machine requirements for job shop MSs in the design phase, when only information about the products and their required manufacturing processes is available. According to the model by Bard and Feo (1991), a MSs configuration is determined based on six input variables, which are the different product types to be produced \((k)\), the demands for the product types \((d_k)\), the amounts of each manufacturing process \(i\) needed to manufacture each product type \(k\) \((b_{ik})\), the efficiencies with which each machine type \(j\) can perform a manufacturing process \(i\) \((a_{ij})\), and the discounted costs of each machine type \(j\) \((c_j)\). Table 3.2 summarizes the variables. An exemplary depiction of values for these input variables was already given in section 2.1.3, Table 2.2.

![Table 3.2: Input data to determine the machine requirements according to Bard and Feo (1991)](image)

In order to create a broad range of different MS configurations with varying characteristics, three of the six input variables, namely the number of manufacturing processes in the MS \((i)\), the number of different products to be manufactured \((k)\), and the number of machine types \((j)\) are varied. In addition to that, another variable that is not explicitly mentioned in the model by Bard and Feo (1991) is introduced, the process flexibility of a machine \((f)\). It is defined as the amount of different processes a machine of type \(j\) can fulfill and is introduced in order to create configurations where machine functional redundancy will exhibit different values. Process flexibility \(f\) is measured by the percentage of overall existing processes a machine can fulfill: if 20 different manufacturing processes exist and a machine can fulfill 10 of these processes, its process flexibility is 0.5. The variables and the values they can take are summarized in Table 3.3. The values have been chosen to represent MSs with low, medium, and high amount of the different variables, and are coherent with data of real MSs found in case studies on number of processes, products, and machine types per MS (see for example Rovithakis et al. (2001), Molleman et al. (2002), Yang et al. (2004), Meyer et al. (2013), and Becker and Meyer (2014)). Since the resource requirements are dimensioned with a mathematical optimization model, too large values for the variables are likely to result in a long run-time of the model, which is why MSs with an extreme product variance (larger than 50) and an extremely diverse amount of different manufacturing processes (larger than 20) have been excluded from the analysis.
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

<table>
<thead>
<tr>
<th>variable</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>processes ($i$)</td>
<td>5 10 20</td>
</tr>
<tr>
<td>products ($k$)</td>
<td>5 25 50</td>
</tr>
<tr>
<td>machine types ($j$)</td>
<td>5 10 20</td>
</tr>
<tr>
<td>process flexibility ($f$)</td>
<td>0.2 0.5 0.8</td>
</tr>
</tbody>
</table>

Table 3.3: Variable input factors in the creation of MS configurations

The variable factors presented in table 3.3 can be combined into 81 unique combinations, meaning that 81 different MS configurations will be analyzed in the following sections of this thesis. Analyzing a larger or smaller amount than 81 MS configurations is of course possible (if the intervals were not chosen as small, medium, and high), however increasing the analyzed values per variables from three to four would already result in an increase to 256 configurations, which in turn would increase the simulation effort while not offering any real merit in statistical significance. The same argumentation and similar instance sizes are also suggested for example by Rardin and Uzsoy (2001) as adequate numbers of experiments in a manufacturing scheduling context. A full list of the 81 configurations and the values of their variables is given in Appendix A. In addition to the four variables which are different in all 81 configurations, the optimization model by Bard and Feo (1991) needs three further input variables, as presented in table 3.2. The remaining variables investment costs ($c_j$) and processing times ($b_{ik}$) follow a random distribution in an interval from 100 to 300 and from 2 to 30 respectively in each of the 81 configurations. The values for the demand per product ($d_k$) were chosen from a random distribution and then normalized, so that they range between 0 and 1 in each of the 81 configurations. This was decided to ensure comparability among the different MS configurations, as each of the created MS is then subject to the same overall demand.

This approach to create realistic MS configurations is similar to the use of test instances in job shop scheduling. A test instance describes the setting of a specific MS, which is characterized for example by a number of machines, a certain range of processing times per operation, or the amount of jobs in the MS, depending on the specific scheduling problem (Taillard 1993). Test instances are usually used in manufacturing research to make scheduling algorithms and results from different scheduling approaches comparable. Examples for test instances for the flexible job shop scheduling problem are given by Brandimarte (1993) and Hurink et al. (1994), of which a small selection is shown in table 3.4.

<table>
<thead>
<tr>
<th>instance</th>
<th>jobs</th>
<th>machines</th>
<th>operations</th>
<th>equal machines</th>
<th>processes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>6</td>
<td>5 – 7</td>
<td>3</td>
<td>1 – 7</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>6</td>
<td>5 – 7</td>
<td>6</td>
<td>1 – 7</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>8</td>
<td>10 – 10</td>
<td>5</td>
<td>1 – 20</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
<td>8</td>
<td>3 – 10</td>
<td>3</td>
<td>1 – 10</td>
</tr>
</tbody>
</table>

Table 3.4: Exemplary test instances used by Brandimarte (1993) for job shop scheduling

The creation of these test instances as described for example by Brandimarte (1993) is similar to the creation of the MS configurations described in the previous paragraph, especially with regard to the random distributions used for the distributions of investment costs and processing times. In section 2.1.3, different approaches for determining the adequate amount of resources for a MS were introduced, such as queuing or mathematical optimization models. To determine the adequate amounts of resources for the 81 MS con-
figurations, a mathematical optimization model and solution algorithm proposed by BARD and FEO (1991) is used. This model determines a cost-optimal solution for the necessary numbers of machines and material flows for the given MS configurations, with an objective function that minimizes investment costs. Compared to other available methods for MSD, this approach is considered to be the one that yields the most accurate results. The model outputs are the time spans for which a machine type \( j \) is configured to do a process \( i \) (\( x_{ij} \)) and the number of machines of each type \( j \) (\( y_j \)) per MS configuration. Table 3.5 summarizes the output variables of the optimization model. Not necessarily all possible machine types \( j \) will be present in the cost-optimal output given by the mathematical optimization model. This is because a manufacturing process can always be carried out by several different machine types, and some of the machine types might simply not be part of the cost-optimal solution. The input and output parameters of each of the 81 configurations are used in this and the subsequent chapters 4 and 5 as input parameters for the different analysis methods.

| \( j \) | \( y_j \) | \( x_{1j} \) | \( x_{2j} \) | \( \ldots \) | \( x_{nj} \) |
|---|---|---|---|---|
| 1 | \( y_1 \) | \( x_{11} \) | \( x_{12} \) | \( \ldots \) | \( x_{1n} \) |
| 2 | \( y_2 \) | \( x_{21} \) | \( x_{22} \) | \( \ldots \) | \( x_{2n} \) |
| \( \vdots \) | \( \vdots \) | \( \vdots \) | \( \vdots \) | \( \vdots \) | \( \vdots \) |
| \( n \) | \( y_n \) | \( x_{n1} \) | \( x_{n2} \) | \( \ldots \) | \( x_{nm} \) |

Table 3.5: Output data giving the machine requirements according to BARD and FEO (1991)

The mathematical optimization model was implemented in the programming language Phyton, using the C-plex solver. It was run with the input variables of the 81 MS configurations given in Appendix A. With this the cost-optimal number of machines and the distribution of material flows on the machines are calculated for each configuration according to the suggestions of BARD and FEO (1991). Figure 3.4 gives an overview on the resulting amount of machines per configuration.

![Number of machines per MS configuration](image-url)
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

The MS configurations display a broad variety of machine amounts, with the average amount of machines per configuration being 8.27 with a standard deviation of 6.96, which indicates a large variety in machine amounts. Thus as intended, a broad range of differently sized MSs was created with the approach. A complete overview of all 81 MS configurations and their amount of machines is given in Appendix B.

In the following, the 81 generated MS configurations are analyzed with regard to their redundancy and network characteristics. First, machine redundancy \((mr)\) and machine functional redundancy \((mfr)\) are calculated for each MS configuration according to equations 3.3 and 3.4. The MS configurations display different values for machine redundancy \((mr)\) and machine functional redundancy \((mfr)\), which are given in figure 3.5. A complete overview of the \(mr\) and \(mfr\) values per MS configuration is given in Appendix C.

![Graphs of Machine Redundancy and Machine Functional Redundancy](image)

(a) Machine redundancy per MS configuration

(b) Machine functional redundancy per MS configuration

Figure 3.5: Redundancy in the 81 created MS configurations
As intended, the 81 created MS configurations exhibit different redundancy values for both redundancy types, so that the relation of robustness with low and high amounts of redundancy in MSs can be analyzed in the following sections. The average machine redundancy (mr) over all configurations is 1.68, which means that on average two machines of the same type exist in a MS configuration. The maximum number of identical machines in a configuration is 5.8. The relatively high standard deviation of 0.99 is caused as many scenarios with no redundant machines (mr = 1) exist. The average machine functional redundancy (mfr) is 5.89, which indicates that on average a manufacturing process can be carried out by six different machine types per configuration, with a standard deviation of 4.49. The pattern that is visible in figure 3.5b is caused by the variable f (manufacturing process flexibility) which was added to the original variables of the optimization model to make sure that MS configurations with different mfr values are created. As clearly visible from the figure, mfr is directly related to the size of variable f.

The input and output data used by the mathematical optimization model that generates the 81 MS configurations can also be depicted as a machine-material flow graph (as introduced in section 2.3.2). The number of machines of a MS configuration corresponds to the number of nodes in the machine-material flow graph, while a link exists between two machines if one of the machines is a predecessor of the other in the route sheet of any of the products manufactured in the MS configuration (which means that there exists a material flow between them). This graph-theoretical depiction of the MSs allows the calculation of the two measures average node degree (ndavg) and average normalized betweenness centrality (bcnavg) according to the explanations given in section 2.3.2 and equation 2.2. Average node degree and normalized betweenness centrality were introduced as measures for robustness in complex network science in section 2.3.2 and are calculated here to later analyze whether they are also related to robustness in a MS context. The calculation of ndavg and bcnavg was done in Matlab using the MIT Matlab Tools for Network Analysis package. Figure 3.6 shows the average node degree (ndavg) and average normalized node betweenness centrality(bcnavg) per MS configuration. A complete overview of the ndavg and bcnavg values per MS configuration is given in Appendix C.

The mean over all average node degrees per configuration (ndavg) in the 81 MS configurations is 10.09, with a standard deviation of 10.66. These findings are similar to findings from other real world networks in the domain of complex network science, which for example exhibit ndavg values ranging between 1.2 up to 113.43 (Newman 2003). Concerning the betweenness centrality, seven of the 81 MS configurations only consist of two resources, which makes a betweenness centrality calculation for these networks unfeasible (see equation 2.1). These seven configurations are thus excluded from further analysis. In 49 of the 81 configurations, the amount of resources is rather small (two to nine machines) and nodes only exhibit a maximum of one link, rendering the betweenness centrality per node to 0. Therefore the respective networks also exhibit an average normalized betweenness centrality (bcnavg) of 0, which can be seen for several MS configurations in figure 3.6b. Calculating the mean over all average normalized betweenness centralities for all 81 MS configurations results in a mean of 0.01, with a standard deviation of 0.02. Kim et al. (2011), who analyze complex network measures in automotive supply chains, report values for average normalized betweenness centrality between 0.2 and 0.8. Since the betweenness values calculated by Kim et al. (2011) are normalized between 0 and 100, this would correspond to values of 0.002 and 0.008 when applying the normalization used within this thesis. However, the values still range in a similar order of magnitude.
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

For other real world networks such as the Internet or co-authorship networks, $bc(n)$ values per node that range roughly between 1 and 1000 are reported by Goh et al. (2003). However these networks are all significantly larger, which explains the larger $bc(n)$ values. In other real world networks, for example social networks, where $bcn(n)$ was analyzed, values in similar ranges than those in the 81 MS configurations (from $10^0$ to $10^{-4}$) were found (see for example Kitsak et al. (2007)). In the following sections, the dynamics of the simulation model are described and robustness of the MSP measure lateness to machine breakdowns is measured.

3.4.3 Simulation model description and discussion of results

In this section, the dynamics of the DES model that measures robustness of the 81 generated job shop MS configurations are described. In the model, each product $k$ in the MS has a route sheet that determines which processes it has to undergo, how long the respective
processing times are (input variable $b_{ik}$), and on which machines the respective processes can be carried out (input variable $a_{ij}$). When demand for a product $k$ arises (demand frequency is determined by input variable $d_k$), the product is released to the job shop for production. Products are then routed between the machines according to their route sheets. Dispatching of products to machines is organized in the first-in-first out (FIFO) principle, which is the most commonly used dispatching rule in manufacturing practice, as it was found by a number of researchers that this rule performs substantially the same as a random selection with respect to mean throughput-time or mean lateness (Blackstone et al. 1982). It is thus also used in numerous other simulation studies that analyze robustness aspects or behavior under breakdown in job shop MSs (see for example Wild and Pignatiello (1991), Das and Nagendra (1993), Koh and Saad (2003), and Blunck et al. (2014)). Applying FIFO as dispatching rule means that if for a machine type $j$ several machines exist (e.g., five machines of type 'milling'), they are combined into a machine group with one single server queue in which all products queue and from which they are dispatched to the next machine of the same group which becomes available. When a product has finished treatment on a machine, it is routed to the next machine or machine group that it needs treatment on (as noted in the product’s route sheet) and gets into that machine’s or machine group’s queue.

As stated in section 3.1 and equation 3.2, robustness of MSP in this thesis is measured as the ratio of the MSP measure lateness in a scenario with and without disturbances. Thus two different scenarios need to be analyzed with the simulation model: the behavior of the MS in a perturbed and in an unperturbed situation. Similar to the simulation approach proposed by Ingemansson and Bolmsjö (2004), MS disturbances are incorporated in the simulation model as machine breakdowns. A machine breakdown is simulated by removing (also often referred to as knocking out) a machine for a certain time period from a simulation run. For the scenario with machine breakdowns, the total run time for each simulation run is 8,000 time units, with a warm-up period to allow ramp-up within the MS of 1,000 time units. This warm-up period is in accordance with other studies analyzing MSP performance, where the warm-up period is set to be 10-15% of the entire simulation run-time (Law and McComas 1987). As explained in the previous section, MSP values (in case of this simulation study lateness) within the warm-up period are not included in the analysis. The machine breakdowns occur at the same time in each experiment and run, from time units 3,000 to 5,000, which means a machine is down for 28% of the simulation run time. If only one machine of type $j$ exists, the products that need processing on that machine type have to wait in the queue of the respective machine until it is available again (after time unit 5,000), as there are no redundant machines. The queue in front of such machines will thus become extremely long under breakdown and lateness of products that need treatment on the respective machine will deteriorate. For each of the 81 configurations, the number of experiments that are set up depends on the number of machine types $j$ of the MS configuration. For each machine type, a single experiment is made in which a machine of the respective type is knocked-out. This means that $j$ experiments are conducted per MS configuration, each of which is run 10 times. This number of runs per experiment is derived from similar simulation studies found in literature, which suggest using 3-10 runs per experiment (Law and McComas 1998; Chryssoulouris et al. 2013).

To measure robustness of the MSP measure lateness as defined in section 3.1, the variable lateness needs to be recorded in a scenario with and in a scenario without machine breakdowns for each of the 81 MS configurations. However, in order to calculate lateness
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

in the MS configurations, planned due dates need to be attributed to jobs or products, which can then be compared to the actual due dates the jobs or products finally achieve (as introduced in section 3.1 and equation 3.1). How due dates are determined depends on how the scheduling, i.e. the allocation of resources to tasks (CHRYSSOLOURIS 2006), is carried out (VINOD and SRIDHARAN 2011). In static job shop scheduling problems, heuristic algorithms are used to calculate a fixed schedule that determines which job is using which resource at what time (MACCARTHY and LIU 1993), which hence creates due dates for jobs. In dynamic job shop scheduling problems, dispatching rules are used to assign jobs from queues to resources. In these cases, due dates are set by using different estimation techniques (EILON and CHOWDHURY 1976; BLACKSTONE et al. 1982; GORDON et al. 2002).

In the simulation model presented here, a form of such an estimation technique, backwards scheduling, is used on the product level: the due date or planned end date of a product $k$ ($ep_k$) is determined based on the average estimated throughput time of the respective product $k$ ($aett_k$). The average estimated throughput time of a product (and its distribution) signifies the average time a product spends in the job shop MS when being manufactured. It is recorded for each of the 81 configurations in an initial set-up scenario without machine breakdowns. In this initial set-up scenario, one simulation run was conducted per MS configuration with the run time of 80.000 time units, in which the average throughput times and their distributions per product were recorded. The run time for determining these estimated throughput times was chosen to be outstandingly longer then the run time of the simulation experiments for the machine breakdown scenarios, in order to get statistically significant predictions for throughput times per product. Running the simulation model without machine breakdowns, it was also tested whether the capacity in the system is set realistically as a validity cross-check. As the throughput of the system stays constant over a long run time without workload piling up in the system, no bottlenecks exist and the capacity was set realistically. Table 3.6 summarizes the experiment set-ups for the scenarios with machine breakdowns and the initial set-up scenario.

<table>
<thead>
<tr>
<th>scenarios with machine breakdown</th>
<th>initial set-up scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>configurations</td>
<td>81</td>
</tr>
<tr>
<td>experiments per configuration</td>
<td>$j$</td>
</tr>
<tr>
<td>runs per experiment</td>
<td>10</td>
</tr>
<tr>
<td>time units per run</td>
<td>8.000</td>
</tr>
<tr>
<td></td>
<td>80.000</td>
</tr>
</tbody>
</table>

Table 3.6: Experiments conducted with the simulation model

After the above described experiments are carried out, the overall absolute lateness of all products in the MS ($l_{abs}$) can be calculated as the difference between the attributed planned end date or due date of a product $k$ ($ep_k$) and the actual end date when product $k$ is finished ($ea_k$)

$$l_{abs} = \langle|ep_k - ea_k|\rangle_k$$

(3.5)

where the brackets denote the average over all products $k$ that were finished during the run time of the simulation. Note that this does not include products that were still in processing at the end of the simulation run and products that were finished during the warm-up period. Similarly, overall absolute lateness in the MS in scenarios with machine breakdowns ($l'_{abs}$) is calculated as

$$l'_{abs} = \langle|ep_k - ea_k|\rangle_k$$

(3.6)
where the brackets denote the average over all products \( k \) that were finished during the run time of the simulation. Robustness of the MSP measures lateness is then calculated as

\[
r = \frac{l_{abs}}{l'_{abs}}
\]

A full list of all conducted experiments, the recorded performance values (\( l_{abs} \) and \( l'_{abs} \)), and the resulting robustness values (\( r \)) per experiment are given in appendix Appendix C.

The robustness values for each of the 81 configurations were calculated according to equation 3.7. As defined there, robustness of a MS configuration should take a value between 0 and 1, with 0 indicating lowest and 1 indicating highest robustness possible. At a robustness of 1, the MSP measure lateness is not affected at all by a machine breakdown and exhibits the same behavior as in the scenario without knockouts. However, in 13 of the 81 analyzed configurations, the values for \( r \) are larger than 1. This might seem unrealistic, as it means that lateness in these cases is improved after machine breakdown. However, similar paradoxical phenomena are known to appear for example in traffic research, where BRAESS (1968) described that the adding of new roads impedes the traffic flow instead of making it smoother. It was for example shown for several real world transportation networks of major cities that blocking certain streets can partially improve the traffic conditions and travel times (YOUN et al. 2008). Similarly, the removal of a machine, which might have been the preferred machine for a specific routing, leads to a significant change in routing options, which in turn improves overall lateness in some of the MS configurations. The 13 robustness (\( r \)) values larger than 1 and their respective configurations were excluded from the following analysis, so that the subsequent correlation analysis would not be negatively affected. The robustness values for the 68 remaining MS configurations are summarized in figure 3.7.

\[\text{Figure 3.7: Robustness values of the 81 MS configuration}\]

The 68 MS configurations in figure 3.7 exhibit strongly different robustness values, with the average robustness lying at 0.389, with a relatively large standard deviation of 0.321. A complete overview of the \( r \) values per MS configuration is given in Appendix C. Within this analysis, only a single breakdown of one machine at a time is included, meaning that the calculated robustness value \( r \) only indicates how robust the MS is against single-machine breakdowns. One could argue that a more realistic scenario would include multiple
3.4 Simulation analysis of the relation between redundancy and robustness in MSs

Machine breakdowns, however using single break-downs or knock-outs is commonly used and sufficient as a first explorative analysis of the matter. Furthermore, the behavior of MSP values recorded in simulations, such as lateness or throughput times, usually depends strongly on the scheduling or dispatching method employed (see for example VİNOĐ and SRİDHARAN (2011)), meaning that a different dispatching rule in the simulation model could result in different performance and thus different r values. It is for example known that FIFO dispatching produces a lower variance of performance measures than does for example random selection dispatching, however it is still the most commonly used methods due to its benefits (BLACKSTONE et al. 1982), which is why it was chosen for this study. Compared to approaches using simplified, minimal models of MSs and simulation to analyze factors that influence MSP (KÖREN et al. 1998; SCHOLTZ-REITER et al. 2005; CHRYSSOLOURIS et al. 2013), the approach presented in this section uses a larger amount of more realistically set-up MS configurations, making the results more valid for a larger range of MSs. Yet the optimization model chosen to create the MS configurations is focused on creating cost-optimal MS configurations. Using a method that specifically stresses the creation of MS configurations that can handle uncertainty (i.e. robust manufacturing system design method), higher values for mf r, mr, or r could have been achieved. However, no such mathematical optimization methods exists to the knowledge of the author (see also review on mathematical optimization methods in section 2.1.3).

3.4.4 Correlating robustness, redundancy, and complex network measures

After the robustness of each MS configuration has been determined with the simulation model, it can be related to the previously determined redundancy and complex network values of each MS configuration. To relate the measures machine redundancy (mr), machine functional redundancy (mf r), average node degree (ndavg), and average normalized betweenness centrality (bcnavg) to robustness (r), their linear and rank correlation is calculated for each MS configuration. Figure 3.8 shows the relation between r and the redundancy measures mr and mf r.

Although the relation is not necessarily as straightforward as depicted in figure 3.3, the tendency of an increase in robustness with an increase in redundancy is visible. Pearson’s correlation coefficient (c_P) between robustness and each of the two redundancy measures as well as Spearman’s correlation coefficient (c_S) were calculated to quantify the relation between the two measures with a linear and a rank correlation metric. r and mr exhibit a low, negative linear correlation c_P of -0.01, with a p-value of 0.91, indicating no significance. The respective rank correlation exhibits a low, positive c_S of 0.04, with an equally unsignificant p-value of 0.73. Contrary to that, r and mf r display a positive linear correlation c_P of 0.34 and a p-value of 0.005, meaning that the linear correlation is significant at the 0.5% level. Also the rank correlation between robustness and machine functional redundancy shows a positive correlation with c_S being 0.43 and a p-value of 0.0003. While the first redundancy metric mr does not allow conclusions as to a positive or negative correlation with r, the functional redundancy metric mf r is clearly and significantly positively correlated with robustness r, meaning that one value increases when the other increases. Figure 3.9 shows the relation between r and the network characteristics ndavg and bcnavg.

Similar to the previous findings depicted in figure 3.8, the relation between r and the two network characteristics ndavg and bcnavg is not unambiguous. Both linear and rank
3 Analyzing the relationship between robustness and redundancy in MSs

(a) Robustness ($r$) and machine redundancy ($mr$) of the 81 MS configurations

(b) Robustness ($r$) and machine functional redundancy ($mfr$) of the 81 MS configurations

Figure 3.8: Relation of robustness and redundancy

correlation between $r$ and $nd_{avg}$ are positive, with values of 0.14 for $c_P$ and 0.31 for $c_S$. While the linear correlation between $r$ and $nd_{avg}$ exhibits a $p$-value of 0.26 indicating no significance, the rank correlation between the two values shows a high significance, with a $p$-value of 0.01. Both linear and rank correlation between $r$ and $bcn_{avg}$ show low negative correlations of $c_P=-0.18$ and $c_S=-0.19$ and no significance ($p=0.15$ and $p=0.13$ respectively).
In this chapter, a modeling approach for measuring redundancy in MSs was introduced, together with the assumption that an increased redundancy in a MS increases its robustness. Two redundancy measures for MSs that were suggested in the modeling approach were then analyzed in 81 different MS configurations generated from a MSD approach using mathematical optimization, revealing that the generated configurations exhibit a broad range of different redundancy values. Furthermore, two measures from complex network science that are typically used to evaluate the robustness of complex systems, node degree and betweenness centrality, were introduced and analyzed within the 81 MS configurations. Robustness of the MS configurations was then analyzed with a simulation study, by measuring the behavior of the MSP measure lateness under machine breakdowns. The results of the simulation study show that configurations with high and low robustness values exist. Finally, the robustness values of each configuration where correlated to the suggested redundancy and complex network measures, to investigate whether a relationship between redundancy and robustness exists in MSs. The correlation analysis showed that...
the metrics that generally perform well for analyzing robustness in complex networks, node degree and betweenness centrality, show a rather weak correlation to robustness in MSs, and hence are deemed to have a low suitability as predictors for MSP robustness. However, a significant, positive linear and a significant, positive rank correlation were found between robustness and the indicator machine functional redundancy. From all metrics analyzed in this chapter as potential robustness indicators, machine functional redundancy is the only indicator derived from the idea of functional redundancy in biology (see section 2.3.3 and section 3.2). As one of the key assumptions of this thesis is that the transfer of concepts and methods from biological applications to MSs is beneficial and promising, two further metrics that are used to quantify system redundancy in biological contexts are introduced and applied to MSs in the following chapters 4 and 5, and their relation to MSP robustness is analyzed. Moreover, the strong correlation between robustness and machine functional redundancy further supports the initial assumption stated in the problem formulation of this thesis that robustness in MSs is raised with increasing redundancy. Machine functional redundancy can thus serve as an indicator for robustness in MSs for example during the design phase of MSs, which will be further discussed in chapter 6.
4 Analyzing nestedness of the part-resources network in manufacturing systems

In this chapter, the relationship between robustness and nestedness, which was introduced as an indicator for robustness of mutualistic networks in section 2.3.3, is analyzed in MSs. Similar to one of the redundancy metrics used in the previous chapter 3, the concept of nestedness can be seen as a form of a functional redundancy. A mutualistic network exhibits a nested structure when specialist species (show few interactions with others) only interact with proper subsets of those species interacting with generalist species (show a lot of interactions with others) (Bascompte et al. 2003). This is a functional redundancy, as several species perform the same function as other species. Therefore metrics that measure nestedness can equally be regarded as measuring functional redundancy. Nestedness metrics are used as an indicator for system robustness, as they give an insight on how the removal of an element in the mutualistic network affects the overall network behavior with regard to biological conservation (Atmar and Patterson 1993). In case a species disappears, the function of said species is not necessarily lost, as due to the nested structure of the network there is a high probability that another species can still perform the function of the lost species. A large amount of studies on ecologic networks that applied nestedness analysis revealed general insights on robustness of mutualistic networks, showing that it is caused by the inherent redundancy of the networks (Memmott et al. 2004; Burgos et al. 2007; Bascompte and Jordano 2007). As it was pointed out in section 2.3.3, MSs share many characteristics with ecologic networks, for example a large network structure that favors the application of structural indicators or the existence of external, fluctuating influencing factors. Therefore an application of nestedness analysis, which helped to discover striking insights on robustness in ecologic networks, seems favorable for MSs. Drawing an analogy between mutualistic networks and MSs, the relationship between robustness and nestedness as a form of functional redundancy is thus analyzed within MSs in the following.

In the first section 4.1 of this chapter, the concept of nestedness is explained in more detail, and different metrics to measure it are reviewed. Subsequently, an overview on the main findings concerning nestedness in mutualistic and non-ecological networks is presented in section 4.2. In the following section 4.3, an analogy is drawn to model MSs as mutualistic networks, which enables the calculation of nestedness metrics in MSs. Nestedness is then analyzed in an exemplary data set of a real MS in section 4.4, showing that a general application of the modeling and calculation approach is feasible. In the last section of this chapter, 4.5, nestedness is measured in the MS configurations created in the previous chapter 3 and linked to the robustness of the respective MSs. The results of a correlation analysis show that a significant positive correlation between robustness and one of the nestedness metrics exists in a MS context.
4 Analyzing nestedness of the part-resources network in manufacturing systems

4.1 Nestedness concept and metrics

The concept of nestedness originates from an analysis of species extinction in the Rocky Mountain area, where a pattern in the distribution of different montane mammal species among the different mountain ranges, termed nested subset pattern or nestedness, was identified (Patterson 1984). Nestedness in this ecological context means that the species that constitute a small fauna are proper subsets of the species that constitute richer faunas. This pattern was shown to be also present in mammalian fauna on different island groups, where smaller islands contain only a proper subset of the species found on all larger islands (Patterson and Atmar 1986). This is conceptually depicted in figure 4.1, where a nested and a non-nested island group are shown. The circles represent biotas within the island groups and the circle size indicates species size of the biotas. In the nested island group, the species that are present in the small biota C are also present in the larger biotas B and A. In the non-nested island group, the small biota C is comprised of species which do not exist in all richer biotas.

![Schematic representation of nestedness](image)

Figure 4.1: Schematic representation of the nestedness (Patterson 1987)

When depicting a mutualistic system as a bipartite graph (see also section 2.3.3), the nested pattern of the network is also visible in the adjacency matrix of the interaction graph. An exemplary depiction of a nested bipartite mutualistic network and its corresponding adjacency matrix is given in figure 4.2. The perfectly nested structure of the adjacency matrix is indicated by the characteristic core of interactions in the top left corner of the matrix, with the upper half of the matrix completely filled and the lower half completely empty. The line that separates the areas filled with ones of the matrix from the area filled with zeros is called the extinction threshold: species are ordered such that in all habitats, the species most susceptible to extinction is the rightmost.

Already in the early works on nestedness it was argued by many authors that the nested subset structure of biotas has important implications for their biological conservation, i.e. their robustness to extinction (Patterson 1987; Atmar and Patterson 1993; Cutler 1994). Since species in smaller biotas are not only random draws of all species in the source pool, but are due to the subsets also included in all the larger biotas, species might vanish from a small biota, but are still very likely to be present in larger biotas and thus not become extinct. This hypothesis was later confirmed in works such as Memmott et al. (2004), Fortuna and Bascompte (2006), or Burgos et al. (2007) (see also section 4.2).

3Parts of this section have been published in similar form in (Meyer et al. 2014).
4.1 Nestedness concept and metrics

Thus nestedness, which can also be seen as a form of species or functional redundancy, is seen as an indicator for the likelihood of biological conservation (i.e. robustness) of an ecologic system.

In order to evaluate the extent to which a system exhibits the characteristic of nestedness described above, different metrics to measure nestedness have been suggested. The metrics used within this thesis are introduced in detail in the following. An early metric called temperature ($T$) was initially introduced by Atmar and Patterson (1993) to measure the order or disorder in the distribution of species in fragmented habitats. $T$ is calculated based on the adjacency matrix of a bipartite graph of the mutualistic network, which is also referred to as presence-absence matrix of species and their habitats, as an entry of one in the matrix marks a species presence in a habitat and an entry of zero marks a species absence in a habitat. An example of a presence-absence matrix from an observed ecological system is given in figure 4.3a. Here, the observed data from ecological systems is not ordered, and the nested pattern is not immediately visible. To see the nested pattern, rows and columns need to be rearranged from highest to lowest value respectively, as done in figure 4.3b. In the approach of Atmar and Patterson (1993) to calculate $T$, this process is referred to as packing or shuffling of the presence-absence matrix, and is done by an algorithm developed by the authors. After the observed incidence matrix has been packed, $T$ is calculated based on how likely the occurrence or absence of an entry in the left or right part of the extinction threshold is. The absence of a matrix element in the area above the threshold or the presence of a matrix element below the threshold are unexpected in a scenario of complete nestedness. The unexpectedness of such an element depends on how far it is away from the threshold, thus unexpectedness $u_{ij}$ is calculated as

$$u_{ij} = \left( \frac{d_{ij}}{D_{ij}} \right)^2 \quad (4.1)$$

where $D_{ij}$ is the length of a full line with a slope of $-1$ running through the $j$th species in the $i$th habitat and where $d_{ij}$ is the distance from the $j$th species in the $i$th habitat to the threshold along this line (Atmar and Patterson 1993; Rodriguez-Girones and Santamaria 2006). This is also conceptually depicted in 4.4, where point $X$ represents an unexpected presence of a species, and point $Y$ represents the point where a line with the slope of -1 that runs through point $X$ meets the threshold. The total unexpectedness ($U$)
4 Analyzing nestedness of the part-resources network in manufacturing systems

\[
U = \frac{1}{m \cdot n} \sum_{i} \sum_{j} u_{ij}
\]  
(4.2)

where \( m \) is the total number of habitats and \( n \) is the total number of species (Atmar and Patterson 1993).

This measure is then normalized to receive the nestedness metric temperature \( T \), which is calculated as the ratio between the total unexpectedness of species extinction \( U \) and the maximum unexpectedness \( U_{\text{max}} \), which is a constant derived from a matrix of maximum unexpectedness (Atmar and Patterson 1993).

\[
T = \frac{100 \cdot U}{U_{\text{max}}}
\]  
(4.3)
4.1 Nestedness concept and metrics

\( T \) can range between 0 and 100°, with values around 0° indicating perfect nestedness and values close to 100° indicating completely random matrices. Note that the presence-incidence matrix does not need to be square for this measure to be applicable. For the calculation of the temperature as presented here, Atmar and Patterson (1993) created a freely available software called Nestedness Temperature Calculator (NTC).

Over the years, several extensions and variations of this initially proposed nestedness measure have been established (Guimaraes Jr. and Guimaraes 2006; Rodriguez-Girones and Santamaria 2006; Almeida-Neto et al. 2008; Araujo et al. 2010), of which the most frequently used ones are introduced in the following. Guimaraes Jr. and Guimaraes (2006) developed an improved algorithm to calculate \( T \), which allows calculating the temperature in several matrices at the same time. They implemented this algorithm in their freely available software called Aninhado. In Rodriguez-Girones and Santamaria (2006), a new algorithm for the shuffling of the incidence matrix is developed and implemented into a software called binary nestedness temperature calculator (BIN-MATNEST). It outperforms the initially proposed algorithm by Atmar and Patterson (1993) for specific matrix layouts (e.g. checkerboard patterned matrices). Almeida-Neto et al. (2008) introduced a new metric to measure nestedness, called the nestedness metric based on overlap and decreasing fill (NODF). While \( T \) is calculated based on the distances of an expected or unexpected occurrence of a fill in the matrix from an isocline, NODF is calculated using a pairwise comparison of the fills in the matrix rows and columns and the rows and column overlap. In comparison to \( T \), NODF is less affected by species number (number of rows/columns in the matrix) (Almeida-Neto et al. 2008), thus it more accurately depicts the conceptual idea of nestedness and has become increasingly popular among ecologists in the recent past. As both measures, \( T \) and NODF, will be used in the following section, the calculation of NODF is introduced in detail in the upcoming paragraph.

NODF is, as \( T \), calculated from an incidence matrix with \( m \) rows and \( n \) columns. Rows that are further "up" \( i \) are compared to rows "below" \( j \), and columns that are located further "left" \( k \) are compared to columns further to the "right" \( l \) (Almeida-Neto et al. 2008). The decreasing fill (DF) does a pairwise comparison whether a row that is further up or a column that is further left has more entries of 1’s than a row further down or a column further to the right. The decreasing fill in a pair of rows \( i \) and \( j \) (\( DF_{ij} \)) is equal to 100 if the marginal total (MT), which is the sum of 1's in a row or column, in MT\(_j\) is smaller than in MT\(_i\). If the sum of 1’s in MT\(_j\) is larger or equal to MT\(_i\), then DF\(_{ij}\) is equal to 0. The same holds for the pairwise comparison of the columns: DF\(_{kl}\) is 100 if MT\(_l\) < MT\(_k\) and 0 if MT\(_l\) ≥ MT\(_k\). The paired overlap (PO) compares for a pair of rows or columns how many 1’s in a row or column are located at the same location than in the other row or column of the pair (in percent). The paired overlap of a pair of rows \( i \) and \( j \) (PO\(_{ij}\)) is the percentage of 1’s in row \( j \) that are located at the identical column position in row \( i \). Likewise, the paired overlap of a pair of columns \( k \) and \( l \) (PO\(_{kl}\)) is the percentage of 1’s in column \( l \) that are located at the identical row position in column \( k \). The degree of paired nestedness (N\(_{paired}\)), either for a pair of rows or columns, will take the value 0 if the DF of this pair is equal to 0. If the DF of the pair is 100, N\(_{paired}\) will take the value of PO. The measure for nestedness for the whole matrix (NODF) is then calculated as the sum of all N\(_{paired}\) (of rows and columns), averaged by number of rows \((m)\) and columns \((n)\) as shown in equation 4.4. In figure 4.5, the calculation of NODF for an exemplary matrix is
To calculate NODF, Almeida-Neto et al. (2008) also created a freely available calculation software called *Aninhado*. Further metrics to measure nestedness have been proposed, for example by Araújo et al. (2010) who measure nestedness as the sum of distances of the occupied elements in an incidence matrix, but the focus of this thesis will be on T and NODF. However, T and NODF are measured on different scales: while T ranges between 0 and 100, where 0 signifies perfect nestedness and 100 stands for a completely random matrix, NODF like most other nestedness measures ranges between 0 and 1, with 0 being equal to no nestedness in the matrix and 1 meaning that the matrix is fully nested. To
make both measures comparable, the normalized $T_n$ will be used in the following analysis, which is calculated as

$$T_n = \frac{(100 - T)}{100}$$

(4.5)

The general procedure of a nestedness analysis first requires that a metric to quantify the pattern of nestedness in a matrix is calculated, and then the metrics are compared with an appropriate null model or randomization test to assess the statistical significance of the metric (ULRICH et al. 2009).

### 4.2 Application of nestedness analysis in ecological and non-ecological systems

Nestedness has been extensively analyzed in various ecological systems, using a variety of different metrics. In a large-scale study by BASCOMPTe et al. (2003), 52 different plant-animal mutualistic networks were analyzed using $T$ as a nestedness measure, and nearly all of the analyzed pollination or seed dispersal networks were found to be significantly nested. It was further shown that nestedness increases with complexity (number of interactions) of the network (BASCOMPTe et al. 2003). GUIMARAES Jr. et al. (2006) analyzed four mutualistic networks of ants and extrafloral nectary-bearing plants also using $T$ as a nestedness measure, and found that three out of the four networks are highly nested. In OLLERTON et al. (2007), it was shown that a marine mutualistic network of anemone fish and sea anemones is also strongly nested, using also $T$ as a nestedness measure. A further study analyzed three mutualistic networks of cleaning symbiosis in reefs using $T$ as a nestedness measures, and revealed that all investigated networks are strongly nested (GUIMARAES Jr. et al. 2007). KONDOH et al. (2010) analyzed nestedness in 31 trophic food webs by transforming the usually unipartite food networks into bipartite networks. They used $T$ and NODF as measures for nestedness and showed that 65% of the analyzed food webs were nested. In JAMES et al. (2012), 59 different plant-pollinator networks are studied with regard to nestedness (measured by NODF) and it was found that the different ecologic networks exhibit strongly varying nestedness values, ranging from close to 0 to 0.8.

In addition to the several studies that examine the nestedness values ecologic systems display, a further stream of research is also dedicated to studying the relation of nestedness to robustness of ecologic systems. MEMMOTT et al. (2004) studied two large mutualistic networks of plants and flower visitors to gain insight on their biological conservation abilities (i.e. their robustness to extinction of either plants or flowers). For this they simulated species extinction by removing pollinators from the network using three different algorithm, and analyzed which and how many plants were left non-pollinated after removal. Their results show that both mutualistic systems studied are relatively robust against removal of pollinators, and they conclude that the robustness of mutualistic networks "derives from redundancy in pollinators per plant and from nested topology of the networks" (MEMMOTT et al. 2004). In the approach by FORTUNA and BASCOMPTe (2006), the robustness of two real ecologic networks is compared to randomized versions of the real networks. The authors find that the real networks are more robust to higher destruction levels: although

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4Parts of this section have been published in similar form in (MEYER et al. 2014).
species start to decay sooner when habitat is lost in the real networks, the threshold at which all species go extinct is significantly higher in the real networks than in the randomized networks. They argue that this behavior stems from the nested structure of the real networks, where the dense core of generalist animals and plants "is very robust to habitat loss" (Fortuna and Bascompte 2006). Burgos et al. (2007) measure robustness of a mutualistic system, similar to Memmott et al. (2004), as the tolerance to the removal of species. They analyze several different mutualistic networks and conclude that a "close positive relationship" (Burgos et al. 2007) exists between nestedness and robustness in mutualistic networks.

A variety of different real-world and man-made networks have also been found to exhibit nested characteristics. Saavedra et al. (2009) analyzed ecological and organizational networks and found that a network of manufacturer-contractor interactions exhibits similar, i.e. nested, structural patterns as mutualistic plant-animal pollination networks. The analysis of nested structures has further been applied to data of countries and their trade products by Ermann and Shepelyansky (2013), who discovered that the network of countries and their trade products exhibits analogous features to plant-pollinators networks, i.e. they are highly nested. It has also been shown for two large-scale automotive supply chains (Toyota and Ford) that they exhibit highly nested patterns in their supplier-product relations (Kito and Ueda 2014). Similarly, Brintrup et al. (2015) also discover nested patterns in data on supplier-product and supplier-manufacturer relations from automotive supply chains.

However, the concept of nestedness and its measures are also discussed critically by several authors, for example by James et al. (2012) or Staniczenko et al. (2013), who claim that the largest drawback of most nestedness measures is that they ignore interaction frequencies between the two bipartite types of nodes that are connected in the network. This means all links are always regarded as equally important, even if for example some of the plants or pollinators exist in significantly larger volumes than others.

### 4.3 Modeling manufacturing systems as mutualistic networks

Similar to the question of biological conservation and system robustness in ecological systems, MSs need to be designed in a way that their performance stays robust against different fluctuations and disturbances (see section 2.1.4). In ecological systems, nestedness is used as an indicator for system robustness, as it gives an insight on how the removal of habitats or the extinction of species affects the system. To apply the concept of nestedness and its measures to MSs, analogies between the previously introduced ecological systems (see section 2.3.3) and MSs are drawn in this section. The bipartite, mutualistic networks that are subject to nestedness analysis in ecology usually consist of relations between plants and their seed dispersers or between habitats and the species that live in them (exemplary conceptual depiction in figure 4.6a). To measure nestedness in a manufacturing context, relations between resources and the parts that are processed on the resources are depicted as a bipartite network, where nodes are either resources or parts and the links between the nodes signify that a part is processed by the linked resource (exemplary conceptual depiction in figure 4.6b). A removal of a species (species extinction) is then analogous

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5Parts of this section have been published in similar form in (Meyer et al. 2014).
4.3 Modeling manufacturing systems as mutualistic networks

to the removal of a certain part (e.g., if a part/product is removed from the product portfolio), while the destruction of a habitat is analogous to the removal of a resource (e.g., machine breakdown). In such a bipartite depiction, each MS exhibits a specific nestedness value.

(a) exemplary bipartite species-habitat graph  (b) exemplary bipartite part-resource graph

Figure 4.6: Exemplary depictions of bipartite ecological, mutualistic network and bipartite manufacturing network

The data necessary to calculate nestedness in the parts-resources network is either available from the design or process planning department or can easily be derived from the operations or route sheets of the parts or final products (see section 2.1.1). It can also be derived from feedback data, which can be obtained from the manufacturing execution system of a MS. An exemplary derivation of a parts-resources matrix (analogous to the species-habitat matrix) from a route sheet of exemplary parts that together form a product is depicted in figure 4.7. Note that if more than one resource per part is given in the route sheet (figure 4.7a), these are alternative resources, meaning that the part can be treated on either of them.

(a) route sheet for exemplary parts  (b) the part-resource matrix derived from 4.7a

Figure 4.7: Deriving the part-resource matrix from an exemplary route sheet, modified from (MEYER et al. 2014)
In a bipartite parts-resources network, a change in parts or products (e.g., the discontinuation of a product), directly affects the composition of the network and matrix representation, meaning that it will have lesser columns and thus also a different nestedness value. Likewise, the removal of a resource also results in a change in the amount of columns of the matrix. Similar to analyses in ecology, conclusions can be drawn from this parts-resources matrix as to whether certain parts have alternative routes through the system. By linking this nestedness value to the robustness of MSP (as defined in section 3.1), it can be analyzed whether nestedness can also be used as a suitable predictor for MSP robustness. The analogy thus allows to evaluate, how performance robustness is affected by the structural aspects, i.e. parts and the corresponding resources, of the MS. The idea of analyzing the effect of changes in the part-resources relations on the manufacturing performance is similar to recent investigations of the blocking effect that the product structure can impose on the manufacturing process flow (Martínez-Olvera 2012). Martínez-Olvera (2012) argues that as products are made up of various parts, conflicts in the use of resources can arise as different parts might need to undergo the same operations on the same resources. This notation is also similar to the part-machine matrices used in group technology or design of cellular MSs, which aim at grouping machines according to the process combinations that occur in families of parts (Askin 2013). However, in this thesis, the part-resource matrix is used for a different purpose, namely to study the performance robustness of the system in relation to operational redundancy.

4.4 Application of nestedness analysis to a case study manufacturing system

4.4.1 Description of the analyzed system

In this section, the structure of the part-resource network in a real job shop environment is analyzed with regards to nested characteristics. The part-resource network is derived from an actual manufacturing facility, which is organized as a job shop and produces large press-tools. The production process includes the manufacturing of different metal components, which are later assembled into a press-tool. The assembly step is not part of the analysis of the network of parts and machines. The job shop consists of 32 machines, which are grouped according to the operation that they are able to perform. Figure 4.8 shows the number of machines per machine group as well as the material flows between the machines. Similar to ecological systems, there is a certain amount of redundancy inherent in the manufacturing system, as for the treatment of some of the parts, several resources are available. 241 unique parts were identified from 7 months of production feedback data, which was collected from the job shop’s production planning and control software. With 32 machines as resources, this results in a 241 x 32 parts-resources matrix.

Parts of this section have been published in similar form in (Meyer et al. 2014).
4.4 Application of nestedness analysis to a case study manufacturing system

4.4.2 Nestedness calculation and discussion of results

The previously introduced nestedness measures $T_n$ (see equation 4.5) and $\text{NODF}$ (see equation 4.4) are used to calculate nestedness of the parts-resources matrix. To calculate $T_n$ of the parts-resources matrix, several free programs are available, for example the Nestedness Temperature Calculator by Atmar and Patterson (1993), the Binmatnest calculator by Rodriguez-Girones and Santamaria (2006), or the Aninhado calculator by Guimaraes Jr. and Guimaraes (2006). The difference between these calculators is that the resulting temperature values usually differ from each other, as Binmatnest and Aninhado use slightly improved algorithms to generate the nested matrix, thus they represent extensions of the Nestedness Temperature Calculator. For this case study, the Aninhado calculator is chosen, as it is also able to calculate $\text{NODF}$. The calculation results in a $T_n$ value of 0.77 and a $\text{NODF}$ value of 0.00 for the parts-resources matrix. The relatively high $T_n$ value indicates that the analyzed matrix is nested. In mutualistic networks, the term highly, at which networks are considered to be highly nested, ranges between 0.75 and 1 (Bascompte et al. 2003). As $T_n$ of the part-resources matrix is within this range, the network can be described as highly nested. However, the low $\text{NODF}$ value indicates that the matrix is not nested at all. The fact that the results for both metrics differ so strongly is not surprising for the analyzed network: it is strongly compartmented and has a low fill (percentage of 1’s in the matrix), which can be seen in figure 4.9, and it was shown by Almeida-Neto et al. (2008) that $\text{NODF}$ yields values of zero for such compartmented matrices or matrices with beta-diversity. However, $\text{NODF}$ will still be analyzed in the following section as it has been shown to be superior to $T_n$ in many ecological contexts (see for example Ulrich et al. (2009)). Figure 4.9 is a plot of the analyzed matrix after shuffling which clearly shows that the matrix is compartmented and also minimally filled (11%).
4 Analyzing nestedness of the part-resources network in manufacturing systems

Similar to ecological systems, the nested matrix of the analyzed parts-resources network exhibits a central core of machines in the top left corner. As opposed to the findings in ecological systems, a completely nested structure with nestedness values close to one will most likely seldom be found in a parts-resources network, as this would require some of the resources in the network to be able to conduct all manufacturing processes present in the system (comparable to the most stable species in the ecological systems, which can be found in all habitats). This is only possible if the process variety within the MS is not high and if some of the machines are flexible machining centers that can conduct all possible manufacturing processes. As this case study has shown that the general concept and calculation of nestedness are applicable to real manufacturing data, the following section analyzes the general relation between nestedness as a redundancy indicator and MSP robustness in MSs, using the 81 MS configurations created in chapter 3.

4.5 Application of nestedness analysis to the test manufacturing system configurations

4.5.1 Nestedness calculation and discussion of results

To study the general relationship of robustness and nestedness in MSs, the 81 MS configurations that were established in the previous section 3.4 are used in this section. In a first step, the two different nestedness measures used in the previous section 4.4 ($T_n$ and $NODF$) are calculated for each of the 81 MS configurations. For the calculation of $T_n$ and $NODF$
4.5 Application of nestedness analysis to the test manufacturing system configurations

In each configuration, the freely available Matlab library BiMat was used. Contrary to the previously used Aninhado calculator which can only calculate nestedness in one matrix at a time, it is possible to analyze several matrices at once with BiMat. Within BiMat, $T_n$ is calculated using the algorithm suggested by (Atmar and Patterson 1993), whereas $NODF$ is calculated using the algorithm by (Almeida-Neto et al. 2008). Figure 4.10 compares both nestedness measures per MS configuration. The resulting nestedness values for each configuration can be found in Appendix D.

![Nestedness values for the 81 MS configurations](image1)

(a) $T_n$ values for the 81 MS configurations

![NODF values for the 81 MS configurations](image2)

(b) $NODF$ values for the 81 MS configurations

Figure 4.10: Nestedness values of the 81 MS configurations

Similar to the results for the redundancy metrics $mr$ and $mfr$ in section 3.4.2, MS configurations with high and low values for both $T_n$ and $NODF$ exist. This is in coherence with findings from ecological networks, which also exhibit a wide range of different nestedness values between 0 and 1 (see for example (James et al. 2012)). The average of $T_n$ over all MS configurations lies at 0.57 which is a lot higher than the average of 0.31 for $NODF$ over all MS configurations. Values for $NODF$ also vary slightly stronger (standard deviation of 0.2) than those for $T_n$ (standard deviation of 0.13). This can easily be explained with the many values of 0.0 that $NODF$ takes for 17 MS configurations. This behavior is also in line with what was found in the analysis of the case study of real MS system data, where
4 Analyzing nestedness of the part-resources network in manufacturing systems

$T_n$ indicated a rather strong nestedness (0.75) while NODF indicated no nestedness (0.0). The fact that both metrics can differ strongly for the same network and that NODF even indicates non-existing nestedness while $T_n$ shows rather strong nestedness is also common in mutualistic networks, due to the substantially different measurement logic both metrics use (as explained in section 4.1). Overall, both measures do not indicate as high nestedness measures (on average) as in the analysis for mutualistic networks (the average nestedness of 52 mutualistic networks in Bascompte et al. (2003) lies at 0.82). Thus it can be concluded that MS configurations in general are not as strongly nested as mutualistic networks. An explanation for this was already given in the small case study of real manufacturing data: a completely nested structure with nestedness values close to one will most likely seldom be found in a parts-resources network of a MS, as this would require some of the resources in the network to be able to conduct all manufacturing processes present in the system.

4.5.2 Correlating robustness and nestedness

In order to analyze the relation between robustness and nestedness in MS, the nestedness values are correlated to the robustness values of the 65 MS configurations, which were calculated in section 3.1. Figure 4.11 shows the relation between robustness ($r$) and the nestedness values $T_n$ and NODF in the 65 MS configurations.

The linear correlation between $r$ and $T_n$ is positive, with an extremely low Pearson’s correlation coefficient of $c_p = 0.07$ and a $p$-value of 0.5, indicating no significant correlation. The rank correlation between $r$ and NODF is also positive, with a rather weak correlation coefficient of $c_r = 0.22$ at a significant $p$-value of 0.05. From this it is concluded that with a higher NODF value, robustness of the MSP measure lateness against machine breakdowns also increases slightly. The reason why the scatter plots show the values for $T_n$ more in the right and for NODF more to the left side of the axis lies in the different values ranges for $T_n$ and NODF, explained also in the previous figure 4.10.
4.6 Summary of intermediary results

The aim of this chapter was to analyze the relationship between nestedness, a robustness indicator used in the analysis of ecologic systems, and robustness of MS performance. To calculate nestedness in MSs, an approach for modeling MSs as mutualistic networks was introduced first. Nestedness was then calculated both in an exemplary real world case study data set of a job shop MS, and in the 81 MS configurations generated in section 3.4.2, showing the general applicability of the concept to MS data. The calculation of nestedness further revealed that both the case study data set and the MS configurations exhibit high nestedness values for $T_n$ and $NODF$, two classical nestedness measures that were introduced in this chapter. However, the average nestedness values found for the MSs are significantly lower than those usually found in mutualistic networks (see for example Bascompte et al. (2003)). As discussed in detail in section 4.4.2, this might be the case since true generalists, i.e. machines that can conduct every manufacturing step found in a job shop, usually do not exist in a manufacturing context. Thus a completely nested matrix is highly unlikely.
to exist in the case of a parts-resource network of a MS. Moreover, the correlations of both
nestedness measures $T_n$ and $NODF$ to robustness $r$ of MSs are rather weak and only one
of them is significant. Consequently, it is concluded that for the analyzed configurations,
nestedness does not serve as an equally good indicator for robustness in MSs as it does in
mutualistic networks. Compared to the findings from the previous chapter, the correlation
found between machine functional redundancy ($mfr$) and robustness ($r$) of MSs exhibited
a strikingly larger significance.
5 Analyzing elementary flux modes in the resources-material flow network in manufacturing systems

In the fifth chapter, *EFMs*, which were introduced as a robustness indicator in metabolic networks in section 2.3.3, are analyzed in MSs. Similar to one of the redundancy metrics used in chapter 3 and the nestedness metrics used in chapter 4, EFMs can be seen as a form of functional redundancy. An EFM is a non-decomposable chemical reaction path in a metabolic network that allows for autonomous function of the underlying organism (Schuster and Hilgetag 1994). While EFMs can be defined for arbitrary (categories of) start and end points, they are mostly used to analyze paths from nutrients (i.e. external resources) to biomass components (i.e. final products) (Schuster and Hilgetag 1994; Schuster et al. 1999). If several paths in a metabolic network lead to the production of the same component, this is also referred to as *pathway redundancy* (Papin et al. 2002; Price et al. 2002). In systems biology, EFMs are used for example as an indicator for robustness of a metabolic network, as it was shown that the number of EFMs in a metabolic network directly relates to the robustness of the network against gene deletion (Stelling et al. 2002; Wilhelm et al. 2004). Moreover, EFMs were shown to be a better predictor for system robustness in metabolic networks than for example standard metrics from complex networks science (Stelling et al. 2002). As explained in section 2.3.3, metabolic systems share a lot of strong commonalities with MSs, such as the internal and external fluctuations both systems are faced with (see also figure 2.18). An application of EFMs, which are used to relate network structure to function in metabolic networks, is therefore suitable to link the purely structural aspects of redundancy in MSs to a system function such as robustness of a performance measure. Similar to the previous chapter on nestedness in MSs, the relation between the structural indicator EFMs and robustness in MSs is analyzed in the following.

To transfer EFM analysis to a MS context, a description of how EFMs are calculated in a systems biology context is given as a first step in section 5.1. It is further explained there how insights on cell metabolism were gained using EFM analysis and in which aspects this method has been shown to be superior to similar approaches. As already introduced in section 2.3.3, striking structural similarities exist between manufacturing and metabolic systems. Building on these similarities, an analogy is drawn how a MS network can be modeled as a metabolic network to be able to calculate EFMs in MSs in section 5.2. In order to show the applicability of EFM analysis to a real world MSs, EFMs are calculated for an exemplary case study data set of a real world MS in section 5.3. Within this case study, EFMs are compared to a classical measure for machine significance from a manufacturing context and to two classical measures from complex-network science. It is shown that EFMs can be used as an equally good or even better predictor for MSs robustness of the performance measures lateness than the other analyzed measures. As the
case study indicates that a relation between EFMs and MS robustness exists, this relation is analyzed on a broader level in section 5.4, where the EFMs of the MS configurations created in section 3.4 are first calculated, and then correlated to the robustness of the respective MS configurations.

5.1 Elementary flux mode analysis in metabolic networks

As introduced in section 2.3.3, a metabolic system is the complete set of chemical reactions within a cell, and is referred to as a metabolic network when depicted in a graph-theoretical representation (Pålsson 2015). An exemplary metabolic reaction network is depicted in figure 5.1a. A chemical reaction between enzymes and metabolites usually contains the metabolites and their concentrations, given as stoichiometric coefficients in chemical reaction equations (Pålsson 2015). As a metabolic system consists of several chemical reactions taking place, an entire system of chemical reaction equations exists per metabolic systems. These chemical reactions - including the stoichiometric coefficients - of a metabolic network can be depicted as a stoichiometric matrix (Pålsson 2015). The stoichiometric matrix of a metabolic network is the data basis for EFM calculation. Every column of a stoichiometric matrix corresponds to a reaction and every row to a metabolite of a metabolic reaction network. The stoichiometric coefficients entered in the matrix are integers. This is also depicted in figure 5.1b, which shows the stoichiometric matrix corresponding to the exemplary metabolic reaction network in figure 5.1a.

![Exemplary metabolic reaction network](image)

(a) exemplary metabolic reaction network

![Stoichiometric matrix for 5.1a](image)

(b) stoichiometric matrix for 5.1a

Figure 5.1: Metabolic network modeling, modified from (Meyer et al. 2016)

As mentioned in the beginning of this chapter, EFMs of a metabolic network are the set of vectors that form the smallest sub-network of the original metabolic network which still allows a metabolic network to function in steady state (Schuster and Hilgetag 1994; Klamt and Stelling 2003; Papin et al. 2003). They can be defined for arbitrary start (corresponds to external metabolites ext1 and ext2 in figure 5.1a) and end points (corresponds to external metabolite ext3 in figure 5.1a) in a metabolic system, which are mostly chosen to be paths from specific nutrients (inputs) to biomass components (outputs) (Schuster and Hilgetag 1994; Schuster et al. 1999). As shown in figure 5.2, an EFM is defined by a vector, which is composed of elements that each describe the net

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7 Parts of this section have been published in similar form in (Meyer et al. 2016).
rate of the corresponding reaction from the stoichiometric matrix (i.e. such a vector or EFM is a flux distribution) (Klamt and Stelling 2003).

$$\begin{align*}
\text{EFM}_1 &= \begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 0 & 1 \\
\end{pmatrix} \\
\text{EFM}_2 &= \begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 1 \\
\end{pmatrix} \\
\text{EFM}_3 &= \begin{pmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 0 & 1 \\
\end{pmatrix}
\end{align*}$$

$$r = \text{reaction, EFM = elementary flux mode}$$

Figure 5.2: EFM s of the metabolic reaction network shown in figure 5.1a, modified from (Meyer et al. 2016)

A pathway through the metabolic system is thus identified by the utilized chemical reactions. One of the first mathematical definitions of EFMs, which has been given by Schuster and Hilgetag (1994), states that, in case all fluxes have fixed signs, all EFMs of a metabolic network are given by the set of generating vectors of a convex polyhedral cone. Such polyhedral cones are a well-studied convex set in computational geometry, thus calculating the EFMs of a metabolic network can be said to be equivalent to extreme ray enumeration of polyhedral cones (Terzer and Stelling 2008). Different algorithms for computing the generating vectors of convex polyhedral cones were then suggested, for example by Schuster and Hilgetag (1994) or Terzer and Stelling (2008), and many of them were implemented into software that is freely available for computation of EFMs.

In systems biology, EFMs are used to investigate the stoichiometry and structural properties of metabolic networks (Schuster et al. 1999; Schuster et al. 2000). Additionally, they have been extraordinarily successful, compared to other structural network measures, as a predictor for system robustness of metabolic systems (Stelling et al. 2002; Wilhelm et al. 2004; Behre et al. 2008), specifically for robustness against mutations. The prediction of lethal mutations (i.e. mutations that render the metabolic system nonviable) in systems biology had previously been addressed using a huge range of predictors derived from complex network science. Jeong et al. (2000) modeled metabolic systems as networks in which the degree of a node is a measure of the node’s importance and the broad degree distribution implements a high robustness against random failures (at the expense of a high vulnerability of targeted attacks against the high-degree nodes). In Wunderlich and Mirny (2006), the change of synthetic accessibility (which is a variant of the network diameter) has been employed for this task. Comparing their synthetic accessibility measure to other topology-based characteristics, such as node degree, graph diameter, or node usage, they show that these classical measures fail as a predictor for lethal mutations. In accordance with this, it was shown by Stelling et al. (2002) that the graph theoretical measure of the network diameter (defined as the average minimal path length between any two nodes), which is typically used as an indicator whether a network is invariant to random removal of nodes, did not indicate functionality of the metabolism under study, while the number of EFMs clearly did. This questions of robustness against is lethal mutations is
5 Analyzing elementary flux modes in the resources-material flow network in MSs

otherwise also tackled in systems biology by applying FBA, which is an operations research method formulated for the prediction of metabolic fluxes. However, since FBA uses a real mathematical optimization model and thus requires a set of constraints imposed on the fluxes as well as an objective function derived from experiment (VARMA and PALSSON 1994; ORTH et al. 2010), it also needs more information, data input, and modeling effort than EFM analysis.

The largest drawback of the calculation of EFMs is the combinatorial explosion of possible routes for larger metabolic systems, and the resulting computational challenges (KLAMT and STELLING 2002). KLAMT and STELLING (2002) demonstrate with an exemplary case study how long the calculation of EFMs in different metabolic systems needs and in how many modes it results. They also point out that the number of resulting modes cannot be estimated solely by considering the amount of reactions and metabolites (i.e. the size of the stoichiometric matrix) in the system, but that it also depends on how strongly certain metabolites are connected. Strategies for overcoming these computational limitations are subject to current research. MACHADO et al. (2012) for example suggest to calculate random samples of EFMs instead of the whole set for large-scale metabolic systems.

5.2 Modeling manufacturing systems as metabolic networks

As stated in the motivation (section 1) and the section on interdisciplinary research between biology and manufacturing (section 2.3.3), this thesis builds on the commonalities between metabolic and MSs, such as that both systems have inputs, both transform material, and both have outputs. In order to calculate metrics from metabolic systems such as EFMs in MSs, the available MS data needs to be transformed in a way that it corresponds to the input data necessary for calculating metabolic network measures. As presented in the previous section, the input necessary for EFM calculation in metabolic networks is a stoichiometric matrix. In section 5.1, it was explained that the stoichiometric matrix contains the external inputs and outputs of a metabolic system (metabolites and biomass), as well as the chemical transformation processes that connect them (reactions). In job shop MSs, several data sources concern the transformation processes of material. For one, information about raw materials and parts that are necessary to manufacture the products can be found in the BOM of a product. In addition to that, the information about which manufacturing processes are necessary to manufacture a part or product is contained in the route sheet, which also lists the resources that correspond to the manufacturing processes (see also section 2.1.1). Figure 5.3a shows the BOM (in form of a product structure) for an exemplary product F, while in figure 5.3b the route sheets for the parts and product used for the exemplary product F are depicted.

The following analogies are drawn from this: raw materials, parts, and products in a MS correspond to metabolites in metabolic systems, manufacturing processes correspond to metabolic reactions, and enzymes that facilitate the reactions correspond to resources (see figure 5.4a). These analogies make it possible to depict the exemplary product from figure 5.4a as a metabolic reaction system (see figure 5.4b) and thus as a stoichiometric matrix (see figure 5.4c). The exemplary stoichiometric matrix in figure 5.4c exhibits exactly one EFM, which is $EFM_1 = [2111111]$.

8Parts of this section have been published in similar form in (MEYER et al. 2016).
5.2 Modeling manufacturing systems as metabolic networks

(a) Analogies between manufacturing and metabolic systems for a MS that produces the exemplary product F

(b) Reaction network of the exemplary manufacturing system

(c) Stoichiometric matrix of the reaction network from 5.4b

Figure 5.4: Modeling machine-material flow networks as metabolic networks, modified from (MEYER et al. 2016)
5.3 Application of elementary flux mode analysis to a case study manufacturing system

5.3.1 Description of the analyzed system

In this section, EFMs will be calculated for the MS of a company that produces gearboxes and their accessories in a job shop MS. The resources in this MS are 51 machines used for different metal forming and machining processes. Although three of the 51 machines are actually workstations for quality control and three are assembly stations, they will in the following also be referred to as machines. The analyzed data set is one year worth of feedback data which was extracted from the company’s central production control software. The central production control software monitors the flows of material through the MS, recording for each operation on each machine the planned and actual start and end times as well as the set-up times and work content. Every operation on a machine is uniquely identifiable and can be traced back to the final product it belongs to through the product’s BOM and route sheet, which were also extracted from the software.

In figure 5.5a, the material flows that took place between all machines in an exemplary time span (week 10 of the analyzed year) are depicted as a network, with machines as nodes and material flows between the machines as links. Figure 5.5b gives an overview on some of the characteristics and manufacturing performance values of the MS under study.

![Exemplary network of machines (nodes) and material flows (links) in week 10](image)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of different products produced in one year</td>
<td>544</td>
</tr>
<tr>
<td>Average number of different products per week</td>
<td>61</td>
</tr>
<tr>
<td>Number of operations executed in one year</td>
<td>32.120</td>
</tr>
<tr>
<td>Average planned operation time (in days)</td>
<td>3.12</td>
</tr>
<tr>
<td>Average actual operation time (in days)</td>
<td>7.8</td>
</tr>
<tr>
<td>Average lateness of an operation (in days)</td>
<td>24</td>
</tr>
</tbody>
</table>

(a) Exemplary network of machines (nodes) and material flows (links) in week 10
(b) Characteristics and performance values of the analyzed manufacturing system

Figure 5.5: Analyzed real case data, modified from (MEYER et al. 2016)

Although the possibility of taking alternative routes exists for certain products (some machines are able to perform the same manufacturing processes), the company in the case study only attributes one route sheet with one fixed route to each product.

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9Parts of this section have been published in similar form in (MEYER et al. 2016).
5.3.2 Elementary flux mode calculation and discussion of results

Using 3131 BOMs and route sheets extracted from the company's production control software, a stoichiometric matrix for the real case data was created according to the analogies introduced in section 5.2. Computation of the EFMs was done using the freely available *efmatool* in MATLAB (Terzer and Stelling 2008). As a result of the large amount of different products being manufactured per year (see figure 5.5b), the calculation of EFMs based on the manufacturing network that results from a year's worth of feedback data is computationally challenging, with the stoichiometric matrix reaching a size of about 3000 columns x 3000 rows for one entire year. Moreover, the demand for product types and amounts significantly varies from week to week, so that an analysis on a yearly basis would conceal these fluctuations. Additionally, planning and scheduling in the MS is carried out daily to weekly (which is also the time span range for planned and actual operation times, see figure 5.5b), so that performance effects should be measured on this basis. The yearly data was therefore divided into weekly *time bins*. For each time bin, the products that were manufactured and the corresponding operations and material flows between the machines were extracted. Then all the manufacturing operations necessary to manufacture the products were derived from the feedback data and thus a weekly material flow network for every time bin was created, following the analogy described in section 5.2. An exemplary material flow network for week ten is given in 5.5a. The number of EFMs per time bin $t$ ($e_t$) was then calculated using the stoichiometric matrices of the weekly material flow networks. Figure 5.6 gives an overview on the different amounts of EFMs per time bin.

![Number of EFMs per time bin](image)

Figure 5.6: Number of EFMs per time bin ($e_t$), modified from (Meyer et al. 2016)

As assumed, the value of $e_t$ does not stay the same in every time bin, as the product mix is different from time bin to time bin. In case no alternative work plans or materials and thus no alternative routes exist in the system, the number of EFMs in each time bin corresponds to the number of different products produced in that time bin. For each product there is exactly one possible way that leads from one or more raw materials to the final product.
5 Analyzing elementary flux modes in the resources-material flow network in MSs

As an example, 39 different products are being produced in time bin one, while in time bin eleven, 79 different products are being produced (see figure 5.6). Comparing this finding to biological systems, the number of EFMs to be found for example in the metabolism of bacteria is a lot higher for most biomass components produced (Stelling et al. 2002). This is primarily caused by the fact that in metabolic systems, many of the occurring reactions are reversible, that the same final product can be produced via different paths, and that final products can be produced from different types of substrates which through different reactions yield the same product in the end. The case that a product in a MS can either be manufactured from one type of raw material (e.g. steel) or from a different type of raw material (e.g. plastic) does not occur in our analyzed dataset, and is hardly occurring in any industrial production system. Therefore the number of EFMs found in MSs is generally lower than in biological systems.

5.3.3 Machine knock-out study and discussion of results

In metabolic systems, the disturbance of a gene deletion can occur due to a multitude of reasons and can have different effects on the production of biomass of the metabolic system. Following the methodology of Stelling et al. (2002) and the analogies drawn between metabolic and MS, the effects a removal of a machine (e.g. a machine breakdown) has on the MS and whether EFMs can serve as a predictor for this are analyzed in the following. To pretend that a machine is not available in a time bin, all reactions that a machine is part of are removed from the stoichiometric matrix, then the number of EFMs that are left in time bin $t$ when machine $i$ is unavailable ($\bar{e}_t(i)$) is calculated. The average number of EFMs that are removed if machine $i$ is under breakdown in time bin $t$ ($\Delta e_t(i)$) is calculated as

$$\Delta e_t(i) = e_t - \bar{e}_t(i)$$  \hspace{1cm} (5.1)

Based on this, the average percentage of EFMs that are left under knock-out of a machine $i$ over all time bins $t$ ($p_e(i)$) can be calculated as

$$p_e(i) = \left\langle \frac{\Delta e_t(i)}{e_t} \right\rangle_t$$  \hspace{1cm} (5.2)

where the brackets denote the average over all time bins $t$. Figure 5.7 shows $p_e(i)$; error bars in this figure arise from the standard deviation corresponding to the average over all time bins $t$ (see equation 5.2).

The number of EFMs that is deleted when a machine is not available indicates how many different products cannot be produced any more. As the sheer number of products alone does not allow conclusions as to the importance of the product and thus the severity of its unavailability, the average amounts of products that are affected by the breakdown of a machine were also analyzed. The product amounts are affected by machine unavailability in a similar way as the product numbers: both values correlate with an average Pearson’s linear correlation coefficient of 0.93 and a standard deviation of 0.08, with a significance
5.3 Application of elementary flux mode analysis to a case study manufacturing system

Figure 5.7: Average percentage of EFMs that are deleted if a machine is not available \((p_{e}(i))\); error bars denote the standard deviation from the average, modified from (MEYER et al. 2016)

...on the 0.1 percent level. Thus the conclusion is drawn that the number of EFMs can serve as an indicator of a machine’s significance. However, as the company only attributes one route per product (also more would be technically possible) the full potential of EFM analysis has not been completely demonstrated yet: if products were produced via different raw materials, if reactions were reversible, or if alternative production paths (route sheets) existed, this would result in a differently structured stoichiometric matrix. In case of a resource breakdown, the number of EFMs would not change as drastically as it is changing now, since many more alternative production paths would be possible.

5.3.4 Correlation of elementary flux modes and manufacturing performance indicators

In addition to the previously shown relation of EFMs to number and amounts of products manufactured, it should further be demonstrated that the structural measure of EFMs does display a significant relation to dynamic MSP indicators and can thus serve as an indicator of machine significance. Therefore it is analyzed if machines whose deletion results in a deletion of a high number of EFMs are correlated to traditional indicators of MSP. As MSP indicators, lateness and work content were chosen. Lateness is calculated as the average lateness of all operations \(m_t\) that are carried out on a machine \(i\) in time bin \(t\) \((l(i))\)

\[
l(i) = \langle |a_{m}(i) - p_{m}(i)| \rangle_{m_t}\]

(5.3)

where \(a_{m}(i)\) is the actual end date of operation \(m\) on machine \(i\), and \(p_{m}(i)\) is the planned end date of operation \(m\) on machine \(i\). The brackets denote the average over all operations...
Analyzing elementary flux modes in the resources-material flow network in MSs

$m_t$ that take place in time bin $t$. The average work content of operations per machine per time bin ($w_t(i)$) is calculated as

$$w_t(i) = \langle o_{m}(i) \rangle_{m_t}$$ (5.4)

where $o_{m}(i)$ is the work content of operation $m$ on machine $i$ (measured in hours) and $m_t$ is the number of operations on machine $i$ in time bin $t$. The brackets denote the average over all operations $m_t$ that take place in time bin $t$.

Furthermore, the correlation of MSP indicators and EFMs is compared to the correlation between MSP indicators and two indicators that are frequently used as measures in complex network science as well as between MSP indicators and a classical indicator of machine significance from the manufacturing domain. As indicators from complex network science, nodedegree ($nd$) and betweenness centrality of a node ($bc$) (as introduced in section 2.3.2) of the machine-material flow graph are used. In the machine-material flow graph, a node corresponds to a machine, while the links between the nodes correspond to the material flows between the machines. The $nd$ of a node $i$ in time bin $t$ ($nd_t(i)$) is the sum of all incoming and outgoing links of a node in the network of time bin $t$. The $bc$ of a node $i$ in time bin $t$ ($bc_t(i)$) is calculated as suggested by Freeman (1977)

$$bc_t(i) = \sum_{jk} \frac{\sigma_t(j, i, k)}{\sigma_t(j, k)}$$ (5.5)

where $i$ is the number of the node, $\sigma_t(j, i, k)$ is the number of shortest paths between node $j$ and $k$ that pass through node $i$ in time bin $t$, and $\sigma_t(j, k)$ is the total number of shortest paths from node $j$ to $k$ in time bin $t$. As a classical indicator for machine significance, static manufacturing complexity ($mc$) as suggested by Calinescu et al. (1998) was chosen. The $mc$ of a machine $i$ in time bin $t$ ($mc_t(i)$) is calculated as

$$mc_t(i) = -\sum_{s=1}^{N_s} p_{s,t}(i) \log_2 p_{s,t}(i)$$ (5.6)

where $s$ is the state of a machine (either idle, working, or set up), $N_s$ is the number of different states $s$, and $p_{s,t}(i)$ is the probability of machine $i$ being in state $s$ in time bin $t$. Static complexity in MSs serves as a measure of the difficulty to produce the required number and type of products in the required period of time (Calinescu et al. 1998).

To show the relation between the indicators for machine significance ($\Delta e_t(i)$, $nd_t(i)$, $bct_t(i)$, $mc_t(i)$) and the performance of the machines ($l_t(i)$, $w_t(i)$), Pearson’s linear correlation coefficient ($c_p$) between each machine significance indicator and the two performance measures for all machines per time bin (see figure 5.8 and figure 5.9) was calculated. The error bars in the figures represent the mean value and standard deviation of the correlations that resulted from 100 random shuffles of the values of the machine significance indicator and the performance measures for the respective time bin.
While the structural indicators nodal degree per machine ($\text{nd}_i(i)$) and betweenness centrality per machine ($\text{bc}_i(i)$) only exhibit few to no correlation values with work content ($w_i(i)$) that are higher than the correlations of the randomly shuffled $\text{nd}_i(i)$ and $\text{bc}_i(i)$ values, there are clear, non-random correlations between the deleted elementary modes per machine ($\Delta e_i(i)$) and the work content of a machine ($w_i(i)$)(see figure 5.9). Similarly, the correlation values between $w_i(i)$ and $\text{mc}_i(i)$ are for most of the time bins higher than the correlations between $w_i(i)$ and a random shuffle of $\text{mc}_i(i)$, yet this does not seem so surprising as the calculation of $\text{mc}_i(i)$ is based on work content and set-up times (see equation 5.6), and set-up times in the company under study are extremely low.

Even more strikingly, $\Delta e_i(i)$ also shows several correlation values with machine lateness ($l_i(i)$) that are higher than the correlations of the randomly shuffled $\Delta e_i(i)$ values and machine
5 Analyzing elementary flux modes in the resources-material flow network in MSs

Figure 5.9: Correlations of the different indicators ($\Delta e, nd, bc, mc$) with average machine work content ($w$) per time bin ($t$). The error bars denote the average correlation and standard deviation of 100 random permutations of the different indicators and the average machine work content, modified from (Meyer et al. 2016)

lateness ($l(i)$) (see Figure 5.8). None of the other structural based indicators ($nd(i), bc(i)$) exhibit this feature. Note that the correlations between both performance values and $\Delta e(i)$ are predominantly negative, while all other correlations are mostly positive. This means that with a higher number of EFMs that is deleted by the breakdown of a machine, the lateness of this machine becomes lower. For the real world scenario, this means the higher the significance of a machine for the MS, the lower its lateness.

To assess the overall suitability of the indicators for machine importance, a distance measure ($d(h, v)$) that only considers the correlation coefficients ($c$) of those time bins where the correlation coefficient of the significance indicators ($h$) and the performance values ($v$) are outside the random field defined by the 100 random shuffles of the significance indicators, is calculated. The distance measure ($d$) is calculated as
5.3 Application of elementary flux mode analysis to a case study manufacturing system

\[ d(h, v) = (c_u(h, v) - \max_u(h, v))_u \quad (5.7) \]

where the brackets denote a sum over all time bins \( u \), which is the number of time bins in which the correlation coefficient of bin \( u \) (\( ru \)) is higher (for negative correlations lower) than the standard deviation of the average correlation coefficient of the randomly shuffled significance indicator and the performance indicator of time bin \( u \) (\( max_u \)). Figure 5.10 shows the distance measure for the correlations between lateness \( (l(i)) \) and work content \( (w(i)) \) with the machine significance indicators \( \delta_{et}(i), ndt(i), bc_{it}(i), \) and \( mc_{it}(i) \) from figure 5.8 and 5.9.

![Distance measure plots](image)

(a) Distance measure for indicators and lateness \((l)\)  
(b) Distance measure for indicators and work content \((w)\)

Figure 5.10: Distance measure \( (d) \) of the different indicators \( \Delta e, nd, bc, mc \), modified from (MEYER et al. 2016)

The highest absolute distance measure is denoted for the correlation between machine lateness \( (l(i)) \) and the number of elementary flux modes deleted by a machine breakdown \( (\Delta et(i)) \) (see figure 5.10a). The distance measure exhibits positive values for the correlations between \( ndt(i), bc_{it}(i), mc_{it}(i) \), and \( (l(i)) \) since the majority of the significant correlations between them are positive (see figure 5.8). As the majority of significant correlations between the number of deleted EFMs \( (\Delta et(i)) \) and lateness \( (l(i)) \) are negative, the distance measure is also negative, but still exhibits the biggest absolute value and can thus be seen as the most suitable predictor for machine lateness. For work content, \( \Delta et(i) \) shows the second best value of \( d(h) \) and thus suitability, after manufacturing complexity. The indicators based on structural aspects of the underlying machine-material flow graph \( (ndt(i), bc_{it}(i)) \) do not exhibit any significant correlations with machine performance indicators.
5.4 Application of elementary flux mode analysis to the test MS configurations

5.4.1 Elementary flux mode calculation and discussion of results

To demonstrate the applicability of EFM calculation in a larger scale of MSs, the EFMs of each of the 81 MS configurations created in section 3.4 are calculated in the following. Similar to the EFM calculation in the case study (section 5.3), the EFMs are calculated using the Matlab software efntool (Terzer and Stelling 2008). Corresponding to the observations in the case study data set, EFMs cannot be calculated for all of the 81 MS configurations, due to the large size of some of the stoichiometric matrices. This is also a common issue in metabolic systems (see also explanations in section 5.1), and one of the major drawbacks of EFM analysis. The number of EFMs $e$ per MS configuration $g$ ($e_g$) are depicted for 54 of the 81 MS configurations in figure 5.11. A complete list of $e_g$ values can be found in Appendix E.

![Figure 5.11: Number of EFMs per MS configuration ($e_g$) for 54 of the 81 MS configurations](image)

Compared to the case study data analyzed in section 5.3, the average number of EFMs per MS configurations is notably higher in the generated MS configurations, with an average of 386283 EFMs per configuration. However, this value is also subject to a very large standard deviation of 321645, as the number of EFMs ranges between a minimum of 10 and a maximum of 2239928. The reason for this is that within the generated MS configurations - as opposed to the real case study - alternative machines and thus alternative paths for parts and products exist.
5.4.2 Machine knockout study and discussion of results

Similar to the approach for the case study data and the approach by Stelling et al. (2002) in metabolic systems, the impact of machine knockouts on the number of EFMs is analyzed in the following. Compared to the case study data in the previous section, the EFMs are now calculated per MS and not per time bin. This is due to the fact that the MS configurations were artificially created, hence no real data to split into bins exists. To pretend that a machine is not available in a configuration, all reactions that a machine $i$ is part of are removed from the stoichiometric matrix of the configuration $g$ and the residing number of EFMs that are left ($e_g(i)$) is calculated. The average number of EFMs $e$ that are removed under breakdown in a configuration $g$ ($\Delta e_g$) is then calculated as

$$
\Delta e_g = \langle e_g - e_g(i) \rangle_g 
$$

(5.8)

where the brackets denote the average over all configurations $g$. Based on this, the average percentage of EFMs that are left under knock-out of the machines $\rho_e$ per configuration $g$ ($\rho_e(g)$) can be calculated as

$$
\rho_e(g) = \langle \frac{\Delta e_g}{e_g} \rangle_g 
$$

(5.9)

where the brackets denote the average over all configurations $g$. Figure 5.12 shows $\rho_e(g)$; error bars in this figure arise from the standard deviation corresponding to the average over all machines $i$ (see equations 5.8 and 5.9). A complete list of $\rho_e(g)$ values per MS configuration can be found in Appendix E.

Figure 5.12: Average percentage of EFMs that are deleted per configuration with a machine knockout ($\rho_e(g)$); error bars denote the standard deviation from the average
Compared to the EFM analysis on the case study data, the average percentage of EFMs that are deleted by machine knockouts per configuration is strikingly higher (73%) than the average percentage of EFMs that are deleted by machine knockouts per bin in the real case data set (35%). However, while a deletion of an EFM in the real case data is equal to the 'loss' of a product, the deletion of an EFM in the MS configurations does not automatically signify a product loss, as alternative routes for product manufacture exist. As it cannot be concluded from this number alone whether a MS can be classified as more or less robust against machine breakdowns, the number of EFMs per MS configuration ($e_g$) and the average percentage of EFMs that are deleted by machine knockout ($p_e(g)$) are correlated to the robustness ($r$) of the MS configurations in the following section.

5.4.3 Correlation of robustness and elementary flux modes

In order to analyze the relation between robustness of a MS and EFMs, the calculated EFM values $e_g$ and $p_e(g)$ are correlated to MSP robustness $r$ (as defined in 3.1). Figure 5.13 shows the relation between robustness ($r$) and the EFM values $e_g$ and $p_e(g)$ of the 54 MS configurations.

The linear correlation between $r$ and $e_g$ is positive, with a Pearson’s correlation coefficient of $c_P = 0.27$ and a $p$-value of 0.07, indicating no strongly significant correlation, yet compared to the correlations of some of the complex networks measures and nestedness indicators being one of the more significant correlations found within the analysis presented in this thesis. The linear correlation between $r$ and $p_e(g)$ is also positive, exhibiting the yet highest linear correlation coefficient of all analysis - $c_P = 0.39$ - with a strong significance of $p = 0.007$. The rank correlation between $r$ and $e_g$ is also positive, showing the highest rank correlation coefficient of all conducted analysis which lies at $c_S = 0.51$, with an extremely significant $p$-value of 0.00. The rank correlation between $r$ and $p_e(g)$ is as well positive, with a correlation coefficient of $c_S = 0.39$ and highly significant $p$-value of 0.007. From these results it is concluded that the higher the $e_g$ or $p_e(g)$ values of a MS configuration are, the higher is their robustness of the MSP measure lateness against machine breakdowns in the respective MS configuration. The high significance levels (compared to the results for the previous indicators) renders both values the most suitable indicators for MS robustness.
5.5 Summary of intermediary results

In this chapter, an approach for modeling MSs as metabolic networks was introduced, to enable the calculation of EFMs, a robustness measure used in metabolic systems. A first application of EFM analysis in a single case study MS revealed that the number of EFMs that are deleted under machine knockout is more strongly correlated to the MS performance measure average machine lateness than other indicators from complex networks science or from a classical manufacturing research background. Moreover, the larger-scale analysis of EFMs in the MS configurations generated in section 3 showed that the number of EFMs and the percentage of EFMs that are deleted if a machine is under breakdown are both significantly correlated with the robustness of the MSP measure lateness. Out of all redundancy measures that are analyzed in this thesis (machine functional redundancy, complex network indicators, nestedness, EFMs), both EFM indicators yield the highest correlation coefficients and significance levels when correlated to robustness in MSs.

Figure 5.13: Relation of robustness and EFMs
For structural indices of complexity measurement, it has been argued that they show potential to be utilized to evaluate MS designs in the design or re-design phase of MSs (Kuzgunkaya and ElMaraghy 2006; Chryssolouris et al. 2013). Likewise, as EFMs are significantly correlated to robustness, it is concluded that they denote a topological measure that gives an indication of how important a resource is for MSP robustness against machine breakdowns. Similar to the suggestions in Li et al. (2009) or Li (2009), where bottlenecks are detected using a data-driven method, EFMs could serve as a measure to detect resources that are crucial for the performance and functioning of the MS. As also argued in Zhao and Wallace (2016), redundant resources could then be added for those resources that were identified as crucial resources by EFM analysis. In the following chapter, it is thus elaborated on how structural indicators such as the suggested machine functional redundancy (see chapter 3) or EFMs can be integrated in methods for MSD to create RMSD methods.
6 Designing robust manufacturing systems with redundancy considerations

In the previous three chapters, it was analyzed how different structural indicators measuring redundancy in MSs are related to robustness. It was shown that some of the redundancy indicators are significantly correlated to robustness in MSs and can thus be regarded as suitable predictors for the robustness of lateness to machine breakdowns in MS. As stated in the motivation section, this thesis focuses on how the long term adequate amount of resources in job shop MSs can be designed to achieve a high MS robustness. It is thus presented in this chapter how the previously analyzed structural redundancy indicators can be used for RMSD. Existing methods for designing MSs, and in particular determining the adequate amount of resources in job shop MSs, have been presented in section 2.1.3, while approaches for RMSD have been introduced in section 2.2.3. In the first section 6.1 of this chapter, possibilities for integrating structural redundancy indicators into the presented methods for resource determination in job shop MSs are pointed out. Furthermore, as the requirements for initial MSD differ from the re-design of a MS, a concept for assessing robustness of an existing MS in case of re-design is suggested. It was also emphasized in section 2.1.3 that the consideration of trade-offs plays an important role in MSD. As introduced in section 1, a potential trade-off exists between robustness - if it is caused by redundancy - and efficiency. Resources cannot just be added infinitely to a MS, as each of them incurs costs. Section 6.2 gives a more detailed description of this potential trade-off, both in biological systems and MSs, and conceptually describes how it can be considered in MSD. The last section 6.3 of this chapter discusses the advantages and disadvantages of the use of structural indicators for MSD, with a focus on the redundancy indicators analyzed within this thesis.

6.1 Potential use of structural redundancy measures in manufacturing system design procedures

As introduced in section 2.1.3, the main methods for determining the adequate amount of resources when designing job shop MSs are simple analytical, mathematical optimization, queuing, and simulation models. In the presented simple analytical models, a structural indicator such as number of EFMs in the MS configuration or nestedness of the parts-resource network cannot be integrated directly as a part of the model. These approaches are based on the simplified assumptions that the number of resources can be determined by multiplying operation time per product and number of products needed (compare also table 2.1). Similarly, structural indicators such as EFMs cannot be directly integrated into queuing models of MSs, as these consist of the characteristics mentioned in section 2.1.3.

Parts of this section have been published in similar form in (Becker and Meyer 2014).
If such design approaches are chosen, structural indicators can be used to evaluate the configurations created with the approaches, e.g. a high number of EFMs per configuration indicating high robustness and a low number of EFMs indicating low robustness towards machine breakdowns. This approach is conceptually depicted in figure 6.1, where variables used to create alternative MS configurations with analytical, queuing, or simulations models are suggested. The created alternative configurations are then evaluated regarding the amount of EFMs they feature. The MS with the highest amount of EFMs can then be chosen as the most robust system.

Mathematical optimization models however offer the possibility of incorporating structural indicators into the models themselves. In the introduced mathematical optimization approaches for resource dimensioning in job shop MSs (see section 2.1.3), mostly cost functions are used as targets for the mathematical optimization models, which means that the models determine the amount of resources in a way that the overall costs for the MS configuration (e.g. investment costs) are lowest. This usually creates MS configurations with just as many resources as needed to fulfill a given demand, and no excess resources as this would not deliver the most cost-efficient MS configuration solution according to the target function of the optimization model. Integrating structural indicators into the target functions of optimization models would directly allow optimizing a configuration for the desired structural measure, i.e. creating configurations with high or low levels of the respective structural indicator. Figure 6.2 gives an exemplary presentation of which inputs and target function variables are required for such a procedure.

The approach described in figure 6.2 is similar to the existing procedures for RMSD, of which all reviewed ones used mathematical optimization models (see section 2.2.3). Two of the introduced RMSD approaches used structural measures to assess the robustness of a MS and integrated them into an optimization model to create a robust MS (Scholz-Reitter et al. 2011; Sharda and Banerjee 2013). However, in these approaches it was not shown that the utilized structural indicators are actually linked to the robustness of the performance of the MSs, which is the case for EFMs and MS performance measured by lateness. Moreover, none of the existing approaches for RMSD considered the MS performance indicator lateness as a robustness criterion.
6.1 Potential use of structural redundancy measures in MSD procedures

The above described potential usage of structural indicators for the design of MS differs from re-design of MSs. The previous considerations for the use of structural indicators for MS design are based on a robustness measure that requires the comparison of MS performance in perturbed and unperturbed conditions of a MS. This is easily applicable if a model of a MS exists, like in section 3.4.3, where robustness was measured as the ratio of the performance measures lateness in perturbed and unperturbed scenarios. But if robustness should be measured in existing MSs of which no model exists to simulate perturbed and unperturbed conditions, the approach for measuring robustness has to be changed. Figure 6.3 gives a conceptual description of how robustness of existing MSs can be assessed. Similar to the definition of robustness in a modeling state (see section 3.1), for assessing robustness of an existing MS the system under study is the MS of a manufacturing organization. The property or function that should be robust in the face of perturbations is MSP, which varies over time (t) (see figure 6.3). Yet the fact that MSP varies slightly over time does not necessarily imply that the MS is not robust. A slight change in MSP should not directly lead to the system being classified as not robust, it should rather be possible for the performance to slightly fluctuate in a defined invariance or tolerance corridor around a mean value tavg. However, if the MSP is constantly below a target value, the system cannot be described to be robust. Therefore the invariance measure should also include a time-related component, which is the time span for which the performance is allowed to deviate below the average value, depicted as tavg in figure 6.3. The behavior of the MSP with regard to the set invariance measures (t1, t2) determines whether a MS is regarded as robust or not. In figure 6.3, the first perturbation (p1) causes a decrease of the MSP, which is still within tavg, and MSP reaches the average again within tavg. Yet for the second perturbation (p2), MSP is decreased below the average for longer than tavg. If p1 and p2 belong to the set of defined perturbations, the system in the conceptual depiction does not classify as a robust system.

This assessment method has to be tailored to a MS and its conditions, thus it is not possible to compare existing systems with regard to their robustness with this approach.
6 Designing robust manufacturing systems with redundancy considerations

6.2 Considering the trade-off between redundancy-induced robustness and cost-efficiency

As introduced in section 2.1.2, a trade-off can exist between the targets of efficiency and robustness in MSs. Such a conflict between robustness and efficiency is also well-known and described in a biological context. In Goerner et al. (2009), a trade-off between sustainability (which is in their definition closely related to the robustness definition used in this thesis) and efficiency in ecosystems is described. As depicted in figure 6.4, Ulanowicz et al. (2009) and Goerner et al. (2009) hypothesize that sustainability in ecosystems, i.e. the survival of species, is in a trade-off relationship with efficiency, where too low diversity in number of species (high efficiency) causes brittleness of the ecosystem, while too high diversity (low efficiency) causes stagnation within the ecosystem. They analyze several data sets of real ecosystems and find that all systems are positioned in an optimal balance between too high and too little efficiency, which they refer to as a window of vitality.

Figure 6.4: Trade-off between efficiency and resilience in ecologic systems, modified from (Goerner et al. 2009)

Stelling et al. (2002) in their work also conclude that in metabolic networks, a trade-off is found between flexibility - related to robustness - and efficiency. Similarly, Morine et al. (2009) argue that the more efficient metabolic networks are, the less robust they tend to be, which they show in an analysis of 105 real metabolic networks. Apart from biological systems, the trade-off between efficiency and robustness is also known in man-made systems.
6.2 Considering the trade-off between redundancy-induced robustness and cost-efficiency

such as supply chains (Shukla et al. 2011; Ivanov et al. 2014). Shukla et al. (2011) for instance describe, analyze, and optimize the trade-off between robustness of supply chains, caused by built-in risk tolerance, and efficiency of supply chains, represented by operating, transport, and handling costs.

In a manufacturing context, a trade-off that is similar to the ones described above in biological systems was also found and investigated for the capacity planning of MSs, which is a short-term phase of MSD (see section 2.1.3). As capacity requirements can be dynamic (i.e. they change over time when customer demand changes), different planning strategies can be chosen in order to determine the adequate amount of capacity for a MS (Kobylka 2000): capacity can be installed in excess over the peaks of demand, as an average, or exactly corresponding to the demand (see figure 6.5). It was shown by Kobylka (2000) that each of these strategies has a different relation to other performance measures and is suitable for different production environments. Especially the excess capacity strategy stands in a trade-off with investments which can be seen in figure 6.5). This denotes a trade-off between robustness (induced by high excess capacity) and efficiency (low investments).

![Figure 6.5](image)

Figure 6.5: Trade-offs in capacity dimensioning, modified from Kobylka (2000)

The described trade-offs between robustness and efficiency in biology, supply chain, and manufacturing contexts are conceptually similar to the trade-off that arises when designing robust MSP by increasing resource redundancy, which is the underlying assumption of this thesis explained in section 3.3 and conceptually illustrated in figure 3.3. It is described there that the increase of machine redundancy and machine functional redundancy also increases the robustness of the MSP lateness against machine breakdowns. However, the provision of such redundancy requires higher costs, for example for machines with the ability to conduct several manufacturing processes (machine functional redundancy). This redundancy renders the MS more robust, however the cost-efficiency of such MSs with redundancies is lower than the one of systems without redundancy. Similar to the relation between robustness and redundancy, this trade-off between robustness and efficiency can also be conceptually depicted. In figure 6.6, the assumption that efficiency in MSs decreases with increasing robustness and redundancy is graphically depicted. As it was shown in the previous sections of this thesis that robustness increases with redundancy, both values are shown on the y-axis of figure 6.6. Contrary to the complementary relationship between
Designing robust manufacturing systems with redundancy considerations

robustness and redundancy (one increases with the increase of the other), efficiency is assumed to be in a conflicting relationship with both values (one decreases with the increase of the other). However, it is not known how this relationship behaves exactly, hence two different potential curves in figure 6.6 indicate different possible relations.

Figure 6.6: Trade-off between robustness/redundancy and efficiency, modified from (Meyer et al. 2013)

Thus when striving for a robust design of a MS, it should not only be investigated how robustness is influenced by redundancy, but also how increased redundancy affects cost-efficiency of the MS under study. A possibility to consider this trade-off in MSD is the utilization of trade-off curves, which were introduced in section 2.1.3 as an important means of MSD. During the design process, MS configurations with different robustness values can be evaluated with regard to their efficiency, leading to the creation of a trade-off curve, as conceptually depicted in figure 6.7. Here it is shown how for two different MSs, alternative configurations with different amounts of redundancy are created. These alternatives can then be evaluated regarding their cost-efficiency, for example by recording their investment or handling costs. This results in two different curves of which each has a unique fit determined by the behavior of the respective MS.

Figure 6.7: Considering the trade-off between efficiency and robustness in RMSD, modified from (Meyer et al. 2013)
6.3 Discussion of the use of structural redundancy indicators for robust manufacturing system design

The previous section has given an insight on how structural redundancy indicators can be used for RMSD. In this preceding section, it is discussed which advantages and disadvantages the use of structural redundancy indicators bears for RMSD. The discussion considers technical calculation aspects as well as aspects concerning the suitability of the transfer of concepts from a biological context to a manufacturing context. There are several benefits and drawbacks that are shared by all structural redundancy indicators analyzed in this thesis. These will be presented first, followed by a detailed analysis per indicator.

All structural redundancy indicators analyzed in this thesis are calculated based on static information about a MS configuration, such as the number of machines or processes per machine, the BOMs or route sheets. This kind of information is easily accessible within a manufacturing organization from existing databases or software like production planning programs. If a significant correlation between a structural redundancy indicator and robustness exists, it is possible to draw a conclusion about the amount of robustness of a MS configuration from only calculating the level of the structural redundancy indicator. Other standard methods used for determining the amount of robustness, like queuing, optimization, or simulation models (see section 2.1.3), would be more time- and effort-intensive to build and apply. The benefits of such static, structural indicators have also been analyzed and described for assembly systems in a manufacturing context by SAMY and ELMARAGHY (2012). They use a regression analysis and reveal a relationship between part complexity and assembly equipment complexity. Their model shows that the assembly equipment complexity increases as part complexity increases in a nonlinear relation, meaning that in an early design state when only the parts are known, conclusions can already be drawn as to how complex the corresponding assembly system has to be (SAMY and ELMARAGHY 2012).

However, structural indicators in general are also reflected critically by many authors. FOX KELLER (2005) critically discusses the growth and popularity of complex network measures, and in particular the tendency of transferring findings on networks among different disciplines. Similarly, STUMPF and PORTER (2012) argue that many of the findings concerning power laws in complex network research are not backed up enough from a statistical point of view. In LIMA-MENDEZ and HELDEN (2009) it is claimed that many of the complex networks findings in biological networks, such as degree distributions following power laws or metabolic networks being scale-free networks, are not universally true and are sometimes results of sampling artefacts or improper data representation. In ALDERSON (2008), it is further challenged if the application of complex network measures in operations research or engineering domains is beneficial.

Machine and machine functional redundancy

The two indicators machine and machine functional redundancy are both calculated based on static information about a MS configuration, which are the number of machines or the number of processes per machine. As they utilize similar input data as for example measures for flexibility in MSs they are closest to measures from a classical manufacturing
6 Designing robust manufacturing systems with redundancy considerations

background. However, a significant correlation to robustness was only revealed for machine functional redundancy (see chapter 3), which makes this measure a more suitable predictor for the amount of robustness of a MS configuration than machine redundancy.

Nestedness

The two nestedness indicators, $T$ and $NODF$, are also calculated based on static information. As for machine and machine functional redundancy, the required information about the parts and the resources they are treated on is available from the route-sheets of the parts, which can similarly be extracted from existing databases or software. In addition to the already mentioned benefits of structural indicators, a further benefit of $T$ and $NODF$ is that a wide variety of standardized, freely available software implementations are available to calculate them (see for example Atmar and Patterson (1993) or Almeida-Neto et al. (2008)). Moreover, nestedness has gained such high interest in its respective community in recent years that algorithms and software implementations to calculate nestedness measures are being continuously developed and enhanced (see for example Araújo et al. (2010) or Jonhson et al. (2013)). On the other hand, nestedness has also been controversially discussed by several authors. Staniczenko et al. (2013) criticize that nestedness, and in particular the indicator $T$, in the past has been treated only in a binary sense, meaning that species are either absent or present, with no account given to information on abundances and interaction frequencies. This aspect could also hold true for the application of nestedness in MSs, where it might seem that a matrix of part-resource connections is fully nested, however in reality, the majority of the actual material flows are focused on only few of the existing connections. Furthermore, it has been claimed that in the context of ecology and mutualistic networks, indicators such as the number of mutualistic partners of a species, can be a much better predictor of individual species survival and hence ecological system robustness (James et al. 2012).

EFMs

Like the two described indicators, EFMs are calculated based on static information, which is contained in the BOMs and route sheets of products, and can thus be easily calculated. Similar to $T$ and $NODF$, a further benefit of EFMs is that a wide variety of standardized, freely available software for calculating them is available (see for example Pfeiffer et al. (1999), Kamp and Schuster (2006), Terzer and Stelling (2008), and Rocha et al. (2010)). Moreover, as EFMs have gained a high and increasing interest in their respective community in recent years, so that algorithms and software implementations are being continuously developed and enhanced (see for example Terzer and Stelling (2008), Terzer (2009), Hunt et al. (2014), and Gerstl et al. (2015)). Yet a particular drawback of EFMs is that, due to the combinatorial explosion during the calculation, this method is currently not applicable to larger problem sizes (i.e. the size of the stoichiometric matrix used for computation should not be too large) (Klamt and Stelling 2002). As has been shown in the analysis presented in section 5.3, the application of EFM analysis to a small but realistic MS with 51 resources and 544 different products is already feasible, although some limitations became apparent in section 5.4, where EFMs could only be calculated for 54 of the 81 generated MS configurations. However, there is currently a large amount of research in the systems biology community already devoted to solving the problem of

As all of the discussed structural redundancy indicators were analyzed in the same MS configurations that featured small, medium, and large MSs, a general recommendation categorized by the size of the MS, i.e. which method is most suitable for which size of MS, is not possible. However, some methods should for example be restricted to smaller size MSs due to technical computation reasons. Table 6.1 gives a summary of the application potentials and risks that were discussed in this section.

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<th>application risks</th>
<th>application potentials</th>
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<td>no significant correlation to robustness</td>
<td>derived from classical manufacturing background</td>
</tr>
<tr>
<td>mfr</td>
<td>significant correlation to robustness</td>
<td>derived from classical manufacturing background</td>
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<tr>
<td>T</td>
<td>measure is binary and frequencies of usage of a connection are neglected no significant correlation to robustness</td>
<td>significant correlation to robustness</td>
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<tr>
<td>NODF</td>
<td>measure is binary and frequencies of usage of a connection are neglected</td>
<td>significant but weak correlation to robustness</td>
</tr>
<tr>
<td>EFMs</td>
<td>currently only applicable to small to medium size MSs due to computational efforts</td>
<td>significant correlation to robustness</td>
</tr>
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</table>

Table 6.1: Risks and potentials for applying the analyzed structural redundancy indicators in RMSD

Apart from the technical advantages and disadvantages of structural redundancy indicators, the underlying assumption of this thesis that a transfer of methods from a complex network or biological context is feasible and advantageous can also be questioned. Limits to the metaphor between cells and MSs have been pointed out by (Demeester et al. 2004), who for example point out the fact that in metabolic pathways, many reactions are usually reversible, which is not the case in MSs. This is one reason why MSs would - on average - usually also yield a lower number of EFMs than metabolic systems. Even more striking is the difference in control logic that distinguishes both systems: while MSs usually display a central steering entity, e.g. a planner that controls the dynamic behavior of the system, metabolic systems are controlled rather autonomously (Demeester et al. 2004).

6.4 Summary of intermediary results

In this section, it was presented how the structural redundancy indicators that were analyzed in chapters 3, 4, and 5, can be integrated into existing methods for MSD to establish RMSD methods. Further attention was given to a potential trade-off between redundancy and cost-efficiency, an important goal in a MS context. The trade-off was first introduced by comparing similar trade-off examples from a biological and manufacturing context, and then a conceptual description of how it can be integrated when designing MSs
with higher robustness was given. Overall, it can be concluded that the aspect of robustness and cost-efficiency trade-offs should be taken into account by companies when they want to increase their robustness. A thorough discussion on the advantages and disadvantages of the use of structural redundancy indicators in MSD concludes this chapter. In the following conclusion, an overall summary, assumptions and limitations of the presented works, as well as implications for industry and research are presented.
7 Conclusion

The last chapter of this thesis firstly gives a summary of the overall findings, with reference to the initial research questions that were set up in chapter 1. It continues with a summary of the main assumptions and limitations of the chosen methods. Subsequently, implications of the thesis findings on industry are given. The chapter finally concludes with an outlook on future research.

7.1 Summary of results

The overarching aim of this thesis was to investigate the role of redundancies as a means to achieve performance robustness in MSs and to integrate such findings into RMSD methods. The guiding research question was split into several sub-questions that were answered in the different chapters of this thesis, and a summary of each of the findings related to the questions will be given in the following.

Subquestion 1. How can robustness be defined and measured in manufacturing systems?

In the second chapter, a thorough review of robustness definitions in general and in a MS context was given (see sections 2.2.1 and 2.2.2). It was found that the majority of existing approaches concerned with RMSD are so called robust parameter design methods, which are based on Taguchi methods (see section 2.2.3). Only a small amount of approaches for RMSD were identified in literature. As robustness is a well-studied characteristic in disciplines such as biology and complex networks science, robustness definitions from these scientific fields were also included in the review (see sections 2.3.2 and 2.3.3). From these existing approaches in literature, a new indicator to measure robustness in MSs, which is based on the behavior of the MSP measure lateness, was derived to be used within this thesis in section 3.1.

Subquestion 2. How can redundancy be defined and measured in manufacturing systems?

Similar to the approach for the previous subquestion, an extensive literature review was conducted in the second chapter to also collect redundancy definitions in general and with specific relation to a manufacturing context (see section 2.2.5 and 3.2). While different approaches to define redundancy exist in biology or complex network science (see sections 2.3.3), it was concluded that no clear definition of redundancy has been established in the area of MSs research (see sections 2.2.7 and 2.4). Thus a definition and measures for redundancy in MSs based on machine redundancy were derived for further use in this thesis in section 3.2. In addition to this redundancy measure derived from a classical manufacturing background, two indicators for redundancy from a biological background, nestedness and EFMs, were also identified as potential indicators for redundancy in MSs.
Subquestion 3. How is the relationship between robustness of manufacturing system performance and redundancy characterized?

After the definitions for robustness and redundancy in a MS context were established in chapter 2, it was analyzed in chapter 3 whether both constructs exhibit a similar relationship in MSs as they do in other engineered or natural systems, where robustness is usually enhanced by redundancy. To analyze this relationship in a large-scale range of different MSs, firstly a set of realistic MS configurations was created in section 3.4.2. For these MS configurations, robustness of the MSP performance measure lateness was measured as suggested in the definition given in section 3.1, using a discrete-event simulation model (see section 3.4.3). Likewise, redundancy of each MS configuration was calculated using on the one hand the previously established definitions based on machine redundancy and on the other hand indicators from complex network science. Robustness and redundancy were then correlated, revealing a significant correlation between robustness of the MSP measure lateness and machine functional redundancy over all analyzed MS configurations, while no significant correlation could be found between robustness and the indicators derived from complex network science.

To further analyze the relationship between robustness and redundancy in a MS context, two other indicators for redundancy from a biological context were analyzed in chapters 4 and 5. The first indicator, nestedness, is a measure used in mutualistic networks to analyze the relation between structural aspects and robustness of a system. In order to calculate nestedness in MSs, a modeling approach for depicting MSs as mutualistic networks was first established (see section 4.3). Nestedness was then calculated both in an exemplary real world case study data set of a job shop MS (see section 4.4), and in the MS configurations generated in section 3.4.2 (see section 4.5). The average nestedness values found for the MSs were significantly lower than those usually found in mutualistic networks. Due to a low and mostly unsignificant correlation between nestedness and robustness, it was concluded that nestedness is at this stage not as suitable as a robustness indicator in MSs as other measures, such as machine redundancy or EFMIs, that were also analyzed within this thesis.

The second redundancy indicator derived from a biological context, EFMIs, and its relationship to robustness in MSs were analyzed in chapter 5. Firstly the necessary analogies to transfer the concept of EFMIs from metabolic to MSs were drawn in a modeling approach (see section 5.2). EFMIs were then calculated in the resource – material flow network of a real world case study data set of a MS (see section 5.3) and in the MS configurations created in section 3.4.2 (see section 5.4). A correlation analysis conducted in section 5.4 revealed that out of all redundancy indicators analyzed in this thesis (machine redundancy, complex network indicators, nestedness), both EFM indicators exhibit the strongest correlation coefficients and significance levels when correlated to robustness in MS. It was therefore concluded that EFMIs are a suitable predictor for robustness of MS performance and can be used for incorporating robustness into MS designs.

Subquestion 4. How can redundancy be incorporated in the design and reconfiguration of manufacturing systems in order to increase the robustness of manufacturing system performance?
7.2 Assumptions and limitations

As a last step, it was investigated in chapter 6 how the redundancy indicators that exhibited a strong correlation and significance (machine functional redundancy and EFMs) can be applied in practice in order to design robust MSs. It was in particular elaborated on a potential trade-off between robustness caused by redundancy and cost-efficiency, which should be taken into account when trying to increase the robustness of a MS design (see section 6.2).

**Guiding research question.** How can redundancies be integrated in manufacturing systems design so that the manufacturing system performance robustness increases?

To draw an overall summary of the thesis results, the guiding research question can be answered as follows. It was shown in the course of this research that, for a large range of different MS configurations, a significant correlation exists between robustness and different structural redundancy measures. An especially striking correlation was discovered between a redundancy indicator used in systems biology and robustness of MSs, confirming the benefit of applying interdisciplinary methods in MS research. The integration of such structural measures can be accomplished by either integrating the structural indicator as a model variable, or by using it as an assessment criterion of a created MS design. Special attention should however be paid to creating robust designs of MSs, as unfavorable trade-offs between robustness and other MS targets, such as efficiency, potentially exist.

7.2 Assumptions and limitations

In the following, an overall summary of the assumptions and limitations of the methods used within this research work is given, while it is also elaborated on the generalizability of the findings. The overarching aim of this thesis was to analyze the relation between robustness and redundancy in MSs. This research goal can be counted as basic or fundamental research, which is defined as research aimed to improve general knowledge or understanding of phenomena (National Science Foundation 1953). In domains such as biology, phenomena are usually investigated in a large amount of real world data sets, as for example done by Bascompte et al. (2003) for plant-pollinator networks, which ensures a strong statistical significance and generalizability of the findings. However, in a manufacturing context, obtaining large-scale data sets from a different range of real MSs is hardly possible. To ensure that the results of this thesis can still be generalized for a large range of different MSs, the conducted simulation study was thus based on a large-scale amount of different MS configurations. The MS configurations were created using an optimization model that creates cost-optimal layouts, which would be a typical assumption in a manufacturing organization.

The generalizability of the overall results is also influenced by the simulation model utilized in section 3.4.3. In the simulation study, only a single breakdown of one machine at a time is analyzed, meaning that the calculated robustness value only indicates how robust the MS is against single-machine breakdowns. This is sufficient for a first explorative analysis of the matter, but to enhance applicability of the results in practice, a more realistic scenario that depicts robustness against multiple breakdowns would have to be analyzed. Moreover, the underlying dispatching principle used in the simulation model is FIFO, meaning the
results are transferable for MS that operate with this type of dispatching rule, yet they might change for other control principles.

To also ensure that the established analogies and modeling approaches for nestedness and EFM in MSs (see chapters 4 and 5) are not only analyzed in artificially created test instances of MS configurations, it was also shown that the calculations can be applied to two case study MSs with real world data (see section 4.4 and 5.3). Hence the approach in this thesis can be described as a combination of explorative, experimental and case study research.

### 7.3 Implications for industry

As stated in chapter 6, the insights gained on the relationship between robustness and redundancy can be used by manufacturing organizations during their design or re-design process. The structural indicators allow for an easy assessment of the robustness of a company’s MS, and thus can be seen as an aid for decision making. While on a short term scale increased redundancy in a MS could increase the manufacturing costs, redundancy helps to buffer against robustness on a rather long term perspective. Increasing redundancy and thus robustness of MSs can be seen as a way of managing uncertainty in MSs, which is an important aspect in the management of manufacturing organizations for example in the face of risk analysis (Thun et al. 2011). When structural redundancy indicators are implemented in methods to create RMSD as suggested in section 6.1, they can thus help to provide manufacturing managers with a decision-making framework to decide analytically from among various MS configuration alternatives, for example when making long term key decisions such as technology selection.

### 7.4 Outlook on further research

With the analogies and modeling approaches established within this thesis in chapters 4 and 5, a calculation of nestedness and EFM in a manufacturing context was made possible for the first time. Based on the modeling approaches presented, structural indicators like EFM can now be integrated into optimization or simulation models to compare the performance of MSDs that are based on EFM to the performance of designs that were created using standard MSD methods which are usually based on cost-efficiency (see section 2.1.3). The modeling approaches developed here further provide a basis for the application of nestedness and EFM analysis in a MS context also for different research purposes apart from research on robustness. A comparison of the structural nestedness or EFM indicators to other structural indicators such as flexibility or complexity, which are constructs that are of great interest in MS research (see section 2.2.1), is also feasible. Similar to the approach chosen in this thesis, a potential relation between redundancy and other dynamic MSP measures, for example throughput times, is now also possible.

Moreover, the modeling of MSs as metabolic networks also enables the application of further, very promising methods from the domain of systems biology. With the description of how a MS can be modeled as a stoichiometric matrix of a metabolic network given
in section 5.2, other systems biology methods that are based on input data from the
stoichiometric matrix of a metabolic network are potentially applicable to a MS context.
A very interesting example for this is FBA, which was briefly introduced in section 2.3.3.
FBA is an operations research based method formulated for the prediction of metabolic
fluxes and often used to analyze the robustness of metabolic systems (Varma and
Palsson 1994; Edwards and Palsson 2000; Orth et al. 2010). As such a model is
conceptually very close to the traditional methods used for MSD (see section 2.1.3), the
transfer of FBA to further investigate the robustness of MSP seems extremely promising.


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## Appendix

### Appendix A

Table A1: The 81 created manufacturing configurations and their parameters

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## Appendix C

Table C1: Redundancy, complex network, and robustness values of the 81 created manufacturing configurations

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## Appendix D

Table D1: Nestedness values of the 81 created manufacturing configurations

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### Appendix E

Table E1: EFM values of the 81 created manufacturing configurations

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Declaration

I, Mirja Meyer, hereby declare, under penalty of perjury, that I am aware of the consequences of a deliberately or negligently wrongly submitted affidavit, in particular the punitive provisions of § 156 and § 161 of the Criminal Code (up to 1 year imprisonment or a fine at delivering a negligent or 3 years or a fine at a knowingly false affidavit).

Furthermore I declare that I have written this PhD thesis independently, unless where clearly stated otherwise. I have used only the sources, the data and the support that I have clearly mentioned.

This PhD thesis has not been submitted for the conferral of a degree elsewhere.

_____________________________  ______________________________
Place & Date  Signature