Integrating Reliability, Availability and Maintainability (RAM) in Conceptual Process Design

An Optimization Approach

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Proefschrift

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Preface

This thesis presents the results of four years of research on integrating reliability and maintainability aspects into the early stages of chemical process design. During the course of my time in Delft, many people have helped me directly as well as indirectly. I would like to convey my gratitude to some of them for their efforts and best wishes.

Let me start with my supervisors Margot Weijnen and Johan Grievink, who, with their different areas of expertise, provided me insight in many topics and guided this research while at the same time allowing me to pursue my own research interests. I would like to thank Margot for inspiring me to take up new challenges and for introducing me to the great worlds of reading and music. I will remain grateful to Johan for our detailed technical discussions and motivating me to take up the challenge of going into new areas of mathematical programming and reliability engineering.

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I had many discussions with people from both the scientific world and everyday practice. I owe them much gratitude for their valuable contribution to the completion of this thesis. I would like to thank Art Westerberg for providing me time for discussion during his short visits to Delft. I would also like to thank Nazim Nathoo for his enthusiasm and interest in my work.

I would like to thank my colleagues from “E&I” group who have made my time as a Ph.D. student at Delft more pleasant. My sincere gratitude goes to Adam Turk for sharing the highs and lows of my Ph.D. work. I also like to thank Laurens for always being helpful to me throughout my stay in Delft. Special thanks to Gerard for introducing me to AIChE NL-BE section. I enjoyed being part of AIChE as Ph.D. student officer. I am very much thankful to Miranda Aldham-Breary for her English support and Ivo for Dutch translation. I would also like to thank Austine for allowing me to use his desk during my often unannounced visits to Delft. I also acknowledge the faculty staff and the secretaries of E&I group for all their constant support during the period of my stay.

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A special credit for this work goes to my parents who always supported me and gave me freedom to choose the path I wanted. I cannot thank them enough for every sacrifice they have done for me. My mother taught me the most valuable lesson of life: *education is the treasure that cannot to be taken away from you.* I would also like to thank the "Goel Parivar" for all their best wishes and blessing. Finally, I would like to thank Lopa for always being there for me to share all my most enjoyable and worst moments. Her constant support and encouragement kept me afloat and motivated me to complete this work.

Harish Goel
Delft, April, 2004

Contents

1

Introduction

A theoretical framework for integrating reliability, availability and maintainability (RAM) aspects during the early stages of the process design is presented in this thesis. The focus of the the thesis is the setting of quantitative RAM targets while simultaneously making crucial design decisions.

1.1 Background

1.1.1 The changing business environment

In the present business environment, where profit margins are becoming slimmer and competition is increasing, the attention of the industry leaders has turned to the reliability engineering paradigm to find ways of saving costs savings and revenue improvement opportunities. According to a recent market forecast (HPI Market data book, 2003), total hydrocarbon processing industry maintenance spending in 2003 is forecasted to reach \$44.9 billion of which \$11.4 in the United States alone, and the majority on the Gulf Coast. Spending for equipment and materials represents 40% of the maintenance budget and will reach almost \$18 billion in 2003. Labor costs account for the other 60% (almost \$27 billion) of the maintenance budget. Although significant these figures do not include the cost of interruption due to unplanned failures. It is generally observed that the revenue lost due to unexpected shutdowns of plant can range from \$500-\$100000 per hour (Tan and Kramer, 1997). For refineries the cost of unplanned shutdowns could come to millions of dollars per day (Nahara, 1993).

According to another estimate (Williams, 2001), typical opportunities for profitability improvement using RAM tools* in the case of petroleum refinery operations range from

*RAM tools include myriad of methods, both qualitative and quantitative, and commercially available software tools to support RAM studies during the plant's life cycle. More information on different methods, approaches and software is provided in chapter 2.

0.10 - 0.20 US$/bbl while in the case of a poor performer the range can increase to 1.0-2.0 US$/bbl range with any capital investment. To get some perspective on the scale of saving, for a typical petroleum refinery with a throughput of about 30000 bbl/day, or roughly 198 m^3/hr, the saving could be in the range of about 1-2 million US$/year while for poor performers it could be in the range of 10-20 million US$/year.

From the aforementioned figures it can be established that significant profits can be squeezed out by implementing different reliability engineering tools to increase the operational effectiveness of existing petrochemical plants and refineries around the world. The opportunities to improve the economic performance of a plant are not limited to the operational stage, they exist throughout its life cycle: design, procurement, construction, start-up, operation and during turnarounds. The cost-effectiveness of the alternatives available to improve plant availability performance however diminishes as the plant passes through the initial of its life cycle, that is, from the design stage to its operational stage.

The reliability engineering discipline provides industry with necessary concepts and tools to improve its economic performance by increasing the effective utilization of its manufacturing assets. The major petrochemical and oil companies around the world have taken aggressive steps towards embracing reliability engineering principles into their decision-making processes. Currently companies have started to invest in different in-house programs or to have external specialized consulting firms to find ways to cut down on their maintenance budget and improve or optimize their asset performance. Table 1.1 lists some of the success stories that can be extracted from companies's internal magazines, corporate websites and their annual reports. These examples point to the growing attention given in industry to using reliability engineering tools to squeeze profit from their existing facilities.

It is very hard to come to conclusions regarding the current status of the application of RAM tools in the process industry when dealing only with the available literature on the subject. Therefore in this work, to get a broader view, interviews were conducted with experts working at the manufacturing companies and at consulting firms specialized in developing commercial softwares. The following general conclusions can be made about the application status of RAM tools in process industries:

- There is a lack of structured and quantitative approach to manage reliability, availability and maintenance measures throughout the life span of plants.

- Most of the ongoing projects in industry are usually done on an *ad hoc* basis focusing mainly on improving a system or a subsystem or a unit level

- The existing quantitative maintenance optimization methods are considered to be too complex and insufficient to handle practical real world conditions in industry. Thus, alternative quantitative tools such as RBI (risk based inspection), RCM (reliability centered maintenance), and TPM (total productive maintenance) are frequently used in industry.

- At the design stage most of the decision variables, such as initial reliability and maintenance characteristics, redundancy level, sparing, maintenance plan etc., that have an impact the overall RAM performance of the plant, are determined based on *experience* or *benchmark* data available about the similar plants.

Table 1.1: Examples

Company	Benefits
Marathon Ashland Petroleum (Matusheski and Andrews, 2002)	Saved $3 million lost opportunity costs in one year by avoiding heat exchanger failures at a total cost of about $500,000
ExxonMobil[1]	The reliability and maintenance system program, since its introduction in 1994, has reduced maintenance costs (about $1 billion) by about 30% while improving mechanical availability by about 2%
Shell's Pulau Bukom refinery [2]	The design and operational modifications made during 1996 turnaround results in a four year run of its long-residue catalytic cracking unit (LRCCU) with only 21 hours of downtime
Toa refinery, Japan[3]	With the help of Shell Global Solutions International BV's maintenance and reliability (Merit) program saved $10 million in its first year and $17 million in the second year
Lima refinery (Paul, 1997)	Over $1.4 million dollars per year were saved in pump repairs by increasing the MTBF (Mean time between failure) of the pumps
Conoco Refinery[4]	Maintenance costs dropped by 21% and unscheduled lost profit opportunities were down 47% ($34 million) due to improved equipment reliability and streamlined maintenance practices

[1] ExxonMobil financial and operating review, 2001
[2] *Impact Magazine* (internal magazine of Shell Global Solutions), Issue 2, 2001
[3] *Impact Magazine* (internal magazine of Shell Global Solutions), Issue 4, 2001
[4] Dupont consulting website (http://www.dupont.com/consulting/solutions/conoco.html)

In order to achieve their true profit potential, companies have to move away from a traditional experience-based paradigm to a new knowledge-based paradigm. Here quantitative models are used at different stages of the life cycle to set RAM targets in the design phase during process and equipment selection, and these are later controlled throughout the asset life cycle (Grievink et al., 1993).

1.1.2 RAM performance measures

A number of performance measures are used in the process industry as indicators to describe the performance of a plant regarding its reliability and maintainability. Commonly used indicators are: onstream factor, onstream factor with slowdown, availability (inherent, achievable or operational), turnaround rate, annualized turnaround index, routine maintenance cost index etc. Clearly most of these indicators are used mainly in the operational stage while a few of them can be used to evaluate different designs at the early stages of design. Plant availability is commonly considered in the design stage for screening different design alternatives.

Availability, in general, is defined as the ability of an item to perform its required function at a stated instant of a time or over a stated period of time (BS4778, 1991). Achieving a high level of availability is important to plant operations and profitable for the manufacturing industry. Plant availability can be divided into several subtypes: operational, achievable and inherent. For a plant, operational availability reflects system availability including unplanned and planned maintenance time and time lost to operational logistics and administration. An achievable availability reflects availability, including unplanned and planed maintenance time. Inherent availability of a plant measures the availability to be expected when only taking into account unscheduled (corrective) maintenance. Operational availability, although the most realistic of the three, is less important in design evaluations as administrative and logistics downtime is outside the control of the designer.

Plant availability is a function of the reliability and maintainability characteristics of a plant. Reliability is the ability of an item to perform a required function, under given environmental and operational conditions and for stated period of time (BS4778, 1991). Maintainability, is the ability of an item, under stated conditions of use, to be retained in, or restored to a state in which it can perform its required functions when maintenance is performed under stated conditions and using prescribed procedures and resources (BS4778, 1991).

It is clear from the definition of availability that a process engineer can improve the plant availability at the design stage by either increasing reliability or maintainability or both. Although it might look simple, the problem of improving plant availability at the design stage is quite complex given that there are number of decisions that can contribute to plant's reliability and maintainability attributes throughout its life cycle.

1.2 Managing plant availability during the plant life cycle

Plant availability is influenced by number of decisions taken at various moments in the total life cycle of a typical chemical plant or system (as shown in Figure 1.1). Opportunities to influence plant availability exist throughout its life cycle. For example, at the conceptual design stage plant availability is fixed by design decisions such as process selection, equipment size and initial reliability characteristics etc. Once the process structure and equipment sizes are fixed plant availability can be further fine tuned by manipulating the different decision variables described in Figure 1.1.

At present current common practices to ensure plant availability in new projects for the process industry are mainly experience-based (Moene, 2000). At the conceptual design stage, the screening of different design alternatives is based on some predefined and assumed plant availability (usually 85-95%). These assumptions are made by the engineer, largely based on his or her personal experience and benchmark data obtained for similar installations. During the basic engineering phase the design selected from the conceptual design is further developed and experience and engineering insight is used by the engineer to select materials and plant layout. Maintenance and inspection plans are developed based largely on experience and vendor recommendations during the detailed engineering phase,

As stated earlier, industry has to move from a traditional experience based paradigm to a knowledge-based paradigm where the quantitative plant availability targets have to

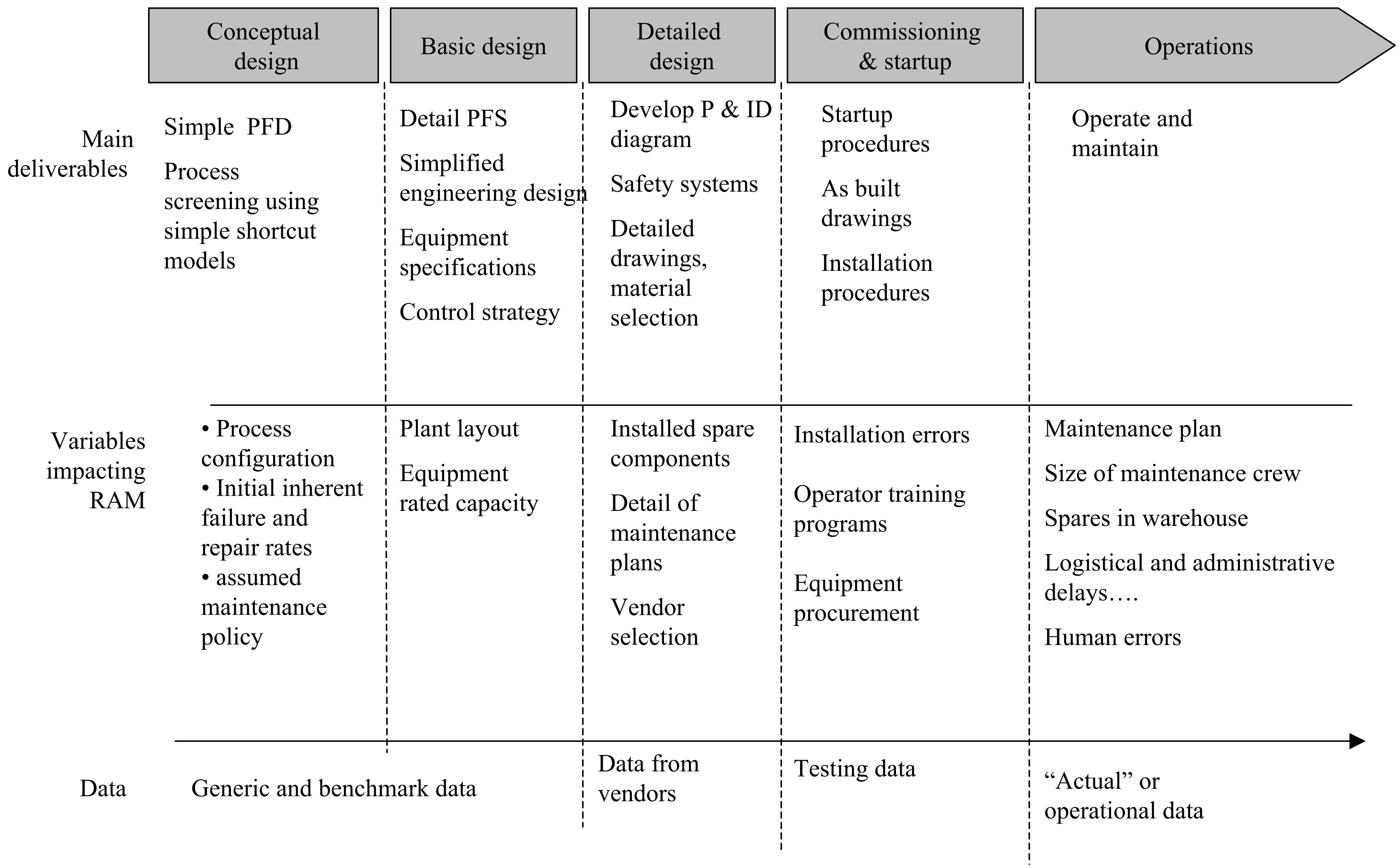


Figure 1.1: Typical plant life cycle

be set in the conceptual stage and these can then serve as a point of reference for later phases in a plant's life cycle. The evolution of a systematic process system design approach can be used as an example to allow us to understand completely the implications of a knowledge-based paradigm. The design of chemical process has evolved over the last century from a unstructured and experience-based activity to a more systematic approach. Currently, design is divided into conceptual, basic engineering and detailed engineering stages. At the conceptual stage, process alternatives are generated and subsequently based on certain predefined criteria (usually specified in Basis of Design (BoD)), the best flowsheet is selected and the optimum design conditions are specified. At this stage simple short-cut process models are commonly used for screening purposes and assumptions are made about the future control strategy, operational logistics and other details. Going from the conceptual stage to the detailed engineering stages extra layers of complexity are added to the process models to relax some of the assumptions.

In the same way as the process model evolves from the conceptual stage to the detailed engineering stage, a simple RAM model can be built at the conceptual stage which can then be defined in more detailed in the later stages. In this work the emphasis is given on the development of a simple RAM model to be used at the conceptual stage and that can be used in conjunction with the process model to provide preliminary conceptual RAM targets that can ne used to support design engineers making crucial conceptual design decisions.

1.2.1 Managing plant availability at the conceptual stage of design

Douglas (1988) defined conceptual process design as the task of finding the best process flowsheet, i.e., selecting the process units and the interconnections among these unit, and estimating the optimum design conditions.

Conceptual process design is a highly complex task due to a large number of possible design alternatives and a large number of criteria usually defined in the BoD. Over the last few decades considerable research effort has been devoted to the development of a systematic approach to the conceptual process design. Two these conceptual design approaches are the hierarchical decomposition approach (Douglas, 1988) and the superstructure optimization based approach (Grossmann, 1997). In a hierarchical decomposition approach the complex design problem is decomposed into a series of design decision sub-levels characterized by increasing amounts of detail as the levels descend. This approach starts with considering the input-output structure of the process in the first levels, in subsequent levels more details are added, finally ending with a complete flowsheet. The design decisions are mainly made using heuristics and shortcut models. While this approach is relatively simple to implement, the sequential nature of the decisions and the heuristics rules that are used often lead to sub-optimal designs. Several other authors deal with the hierarchical design method for chemical plant design. For example, Smith's (Smith, 1995) approach can be compared to Douglas's approach as it follows an hierarchy of decisions from the selection of reactor type to the heat exchanger network design.

In the superstructure optimization based approach, a complex design problem is formulated (and solved) as an combinatorial optimization problem. The design alternatives are embedded into a superstructure and a combinatorial optimization problem is formulated where continuous design variables like sizes, temperatures, pressure and flowrates, and discrete (usually binary) design variables are used to indicate the structure of the process and discrete choices. The advantage of mathematical programming strategies for process synthesis is that they can simultaneous optimize the process structure and operating conditions. The drawback is that global optimality conditions cannot be guaranteed for non-linear models unless specific global optimization methods are used. Another drawback of the superstructure approach is that the designer needs to define *a priori* all the alternatives that are to be embedded in the superstructure.

Conceptual process design and different approaches are discussed in more detail in (Grossmann, 1997; Herder, 1999; Meeuse, 2003). Currently, to get the best of both approaches they have been used in a complementary manner . The vast number of design alternatives are first screened, based on heuristics using a decomposition approach and then the remaining alternatives are embedded into a form of superstructure and can then be solved using gradient based, mixed integer non linear programming (MINLP) techniques (Daichendt and Grossmann, 1998).

Traditionally, neither of the approaches mentioned above contained requirements regarding RAM characteristics. It starts with the BoD definition where commonly requirements regarding operational plant availability are not included. Therefore, when design options are evaluated, assumptions are made regarding future operational plant availability (usually between 85-95%). These assumptions are made by designers, largely based on their personal experience and benchmark data from similar installations; and as a result, crucial design decisions such as process selection and equipment sizes are made based on assumptions that have been made about the future RAM characteristics of the plant. Once the design is fixed in the conceptual stage a firm is left with fewer and more expensive degrees of freedom for improving plant availability. Further limitations of the traditional optimization based approach are discussed in section 3.2.

In the last two decades two approaches have appeared in literature that complement the traditional conceptual design paradigm: the sequential and the simultaneous approach. A detailed discussion of these approaches is presented in the following chapter. In brief, the sequential approach separates the process design activity from the reliability analysis to find improvements in plant availability. In the first step, for a certain plant availability, a flowsheet is selected with traditional hierarchical or optimization based method which is then analyzed by a reliability expert to determine the quantitative plant availability and design improvements that should increase plant availability. The information is sent back to the design step to update assumed plant availability data and to process the recommendation of the reliability experts with regard to their feasibility. Clearly, this approach results in costly design iterations.

To circumvent the limitations of the sequential approach, a new optimization based approach using system effectiveness as a criterion has been proposed by a number of researchers (Grievink et al., 1993; VanRijn, 1987; Vassiliadis and Pistikopoulos, 2001). The idea is to combine the process model and RAM model to form an integrated unified optimization model that captures the interactions between the design variables and RAM measures. The existing optimization frameworks in this category mostly assume a fixed system structure and initial reliability of the process components. *Thus, with existing frameworks, the possibility to set RAM targets while making crucial structural decisions and selecting equipment is missing.*

1.3 Research Objective

The problem of integrating RAM performance measures in the conceptual design process is addressed in this thesis. As Grievink et al. (1993) have pointed out, the problem of addressing the integration of RAM into design has two sides: a management side and an engineering side. The management side of the problem concerns practical issues related to the transition required in an organization that wishes to embrace the use of RAM tools in the conceptual design process. Although this seems straightforward, bringing change in to an organization's business and work processes may prove to be a formidable task. In his book, Lamb (1995) describes in detail how to embed RAM activities into different stages of design and operation. More recently, Moene (2000) has explored the challenges a major oil company had to deal with when it is incorporated reliability goals into the project development phase.

The engineering side of the problem focuses on the development of reliability engineering tools that can be used to improve system effectiveness. As stated earlier, existing reliability analysis tools and existing system effectiveness optimization approaches fall short when it comes to providing a systematic framework to integrate RAM measures quantitatively into the conceptual process design. The focus of the work to engineering side of the problem and the overall objective can be formulated as

> "to develop a systematic theoretical framework for integrating the reliability, availability and maintainability attributes of the plant into the conceptual design stage to obtain quantitative optimal RAM targets together with other optimal design parameters"

The following two points set this work apart from other existing works:

- Most of the existing rigorous optimization models have been criticized for being too detailed or complex, in this work special attention has been given on the complexity of the resulting problem formulation. The approaches developed in this work provide a basis to solve large-scale problems by coupling the optimization approach with simple models used at the conceptual stage.

- This work acknowledges the great incentives that can be obtained by including reliability engineering tools from the start of the conceptual design process especially where crucial decisions about process structure and equipment selection are made. Most of the existing work in the literature starts with assumption regarding system structure and given reliabilities for underlying components and hence the opportunity to optimize RAM during these decisions is lost.

1.4 Outline of the Thesis

A brief review on RAM applications in process design is presented in chapter 2 . The theoretical background provided in this chapter serves as the foundation for the theoretical development described in the remaining chapters.

The development of new simultaneous optimization approaches to integrate reliability optimization into process design are discussed in chapters 3 and 4. These new approaches allow the designer to select optimal initial reliabilities while selecting the process configuration and other optimum design parameters such as equipment size, flowrates etc. In chapter 3, the focus is on the grassroots design problem for a general process system. A Benchmark HDA (hydrodealkylation process to produce benzene) design case study is used to demonstrate the usefulness and effectiveness of the proposed new approach. In chapter 4, the focus is on the special case of process synthesis where a retrofit design problem of multiproduct batch plant is considered.

The development of new optimization models where maintenance optimization models are integrated into the combined reliability optimization and process design frameworks to provide a unified approach to optimize reliability and maintenance schedules with the design decisions in chapters 5 and 6. The problem of optimizing reliability and maintainability simultaneously with the selection of a process configuration and production schedule for multipurpose process plants at the design stage is addressed in chapter 5. A case of imperfect preventive maintenance actions is considered in chapter 6. Finally, conclusions from this work and recommendation for future work are described in chapter 7.

2

RAM in process design: a literature review

A brief review on different reliability engineering tools is provided in this chapter. The review is by no means exhaustive but it serves to illustrate the state-of-the-art on the penetration of reliability engineering tools in the process system engineering area, especially at the conceptual design stage. The current approaches to the integration of RAM into process design are divided into two types sequential and simultaneous. A brief overview is provided of both approaches.

2.1 Introduction

Various degrees of freedom to improve the RAM measures were listed in Figure 1.1. Considering the overwhelming number of factors that influence overall plant availability, it is not surprising that there is a myriad of methods, both qualitative and quantitative, and software tools that are available today to support RAM studies during plant's life cycle. In literature a number of review papers have appeared in the last few decades that provide a detailed survey of topics that include reliability-availability analysis methods (Dhillon and Rayapati, 1988; Lie et al., 1977; Sathaye et al., 2000), reliability optimization (Kuo and Prassad, 2000) and, maintenance optimization (Dekker, 1996; Dekker and Scarf, 1998). More detailed information on these topics can be found in standard reliability engineering textbooks such as Henley and Kumamoto (1992), Billinton and Allan (1992), and Kuo et al. (2001).

The conceptual design process tasks are commonly undertaken by chemical engineers who are usually not trained in reliability engineering principles. The purpose of this chapter is therefore to give a brief overview of reliability engineering methods and the tools that are available for the process engineer to use during the conceptual stage of design. An attempt is also made to answers to such questions as: How are these seemingly

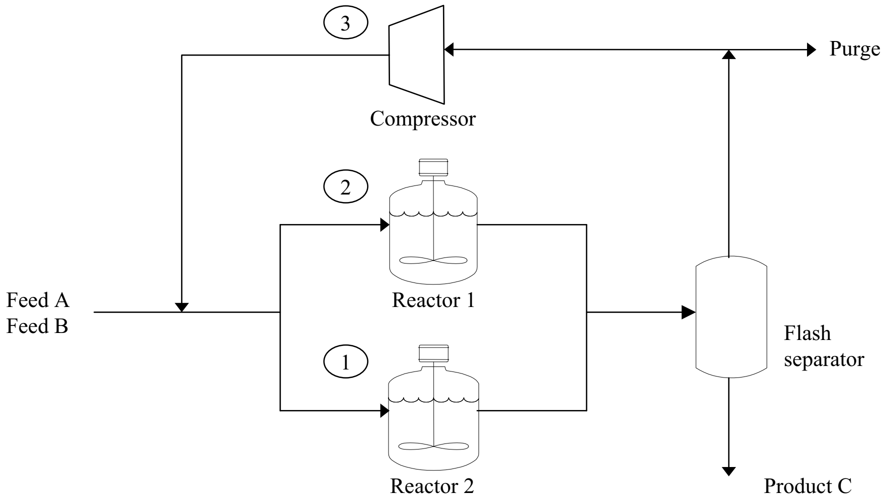


Figure 2.1: Process flow diagram for an illustrative example

different topics connected? How can different methods or tools be used to support system effectiveness approaches in process design? Do we need new tools?

A simple process system is used as an example throughout this chapter to illustrate various methods and approaches. The example involves the production of product C from reactants A and B. The process flow diagram for the example is given in Figure 2.1. The main reaction is as follows:

$$A + 2B \rightarrow C$$

The process comprises two reactors in parallel, i.e. built-in redundancy, a flash separator, and a compressor. A small purge stream is allowed to avoid build up of the impurities that come with the feed. The equipment in the flowsheet is numbered so that it is easy to cite them in the following sections. It should be noted that in the following discussion, the flash separator is left out as is assumed that it has an insignificant failure rate.

2.2 Reliability-availability analysis methods

Numerous reliability-availability techniques exist that can be used to provide quantitative performance measures such as system reliability, availability, throughput etc. Reliability-availability methods may be used at the design stage for assessing various designs options and/or deriving effective inspection and maintenance policies at the operational stage for any given system configuration, failure and repair data for components, and the interrelationship between them, the . The various reliability-availability methods can be broadly classified as measurement based and model based methods (Sathaye et al., 2000). Measurement based methods are expensive as they require building a real system or its prototype and taking measurements and then analyzing the data statistically. In the context of process systems, at the design stage where the system or its prototype is not yet been built, the use of measurement technique is not feasible. While at the operational stage it

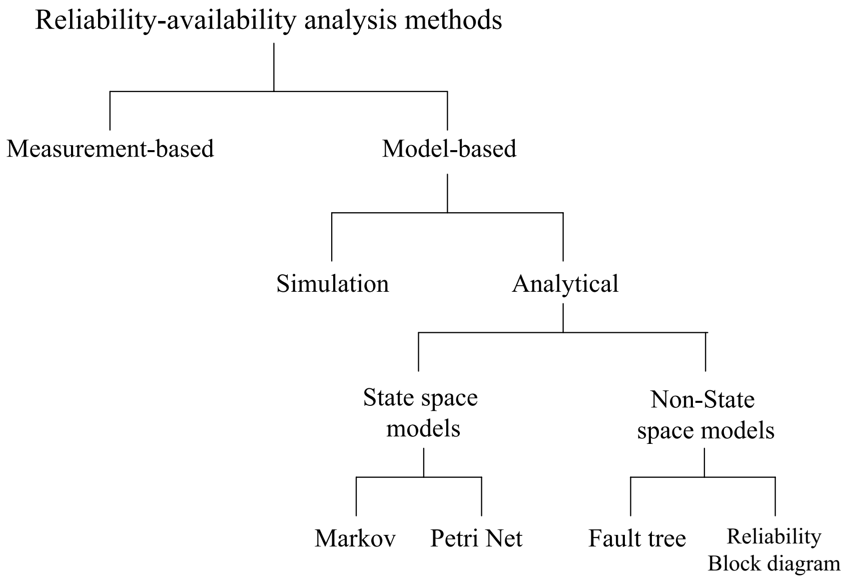


Figure 2.2: Classification of reliability-availability analysis methods

can prove to be very expensive to inject faults into a real system to measure data. Model-based methods are much easier to use and are particularly useful at the design stage to screen lots of design alternatives without building the actual system. It is important to mention here that the model-based methods are also subjected to model uncertainty which propagates into RAM performance.

Model-based methods can be further categorized into simulation methods and analytical methods, both require a system model to be constructed in terms of random variables for the state of the underlying units (Dekker, 1996). The simulation method uses a probability distribution function for equipment failure and repair actions and uses a simulation engine (usually a Monte Carlo simulation engine) to simulate the detailed dynamic behavior of the system and evaluate the required measures. Analytical methods use analytical models that consist of sets of equations describing the system behavior. For simple systems it is possible to obtain a closed-form solution of the analytical model, but more often numerical methods are used to solve the underlying set of equations. A classification of reliability-availability analysis methods is given in figure 2.2.

2.2.1 Analytical methods

Analytical methods are used to calculate the reliability and the availability measures of a system by using structural results from applied probability theory. A number of analytical methods have been developed which can be broadly categorized into state space or non-state space modelling techniques (Sathaye et al., 2000). The choice of an appropriate modelling technique to describe the system behavior depends on factors such as

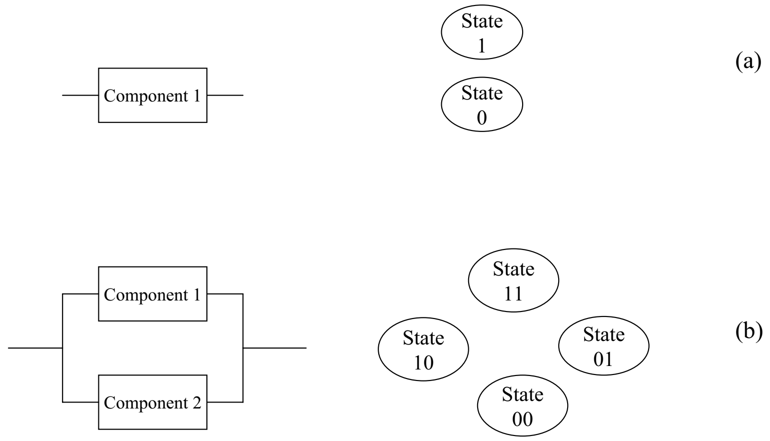


Figure 2.3: Component and system states

- measures of interest (steady-state or time-dependent, reliability, availability etc.)
- level of detail and complexity of the given system (size, structure etc.)
- available tools to specify and solve the model
- availability and the quality of data

Before going into details of the different analytical methods, it is useful to understand the meaning of the term "state". The term "state" can be used in reference to a component or a system. For example, in Figure 2.3(a) two possible failure modes for component 1 are described by the "up" and "down" states. Now for a system, e.g. a two-component parallel system, as shown in Figure 2.3(b), there are four possible states. The number of total states for a system depends on the total number of components and on the possible failure modes for the underlying components. For instance, considering three failure modes for a component ("up", "degraded" and "down"), a two-component system will have $2^3 = 8$ possible states.

Non-state space methods

As the name suggests, non-state space models can be solved without generating the underlying state space. These models can be easily used for solving systems with hundreds of components. These models can be applied to fairly large systems to provide performance measures such as a system's steady-state availability, reliability and the mean time between failure (MTBF). The key assumptions used in non-state space models are statistically independent failures and independent repair for components. Two prominent non-state modeling techniques used to evaluate system availability are the fault tree (FT) and reliability block diagrams (RBD).

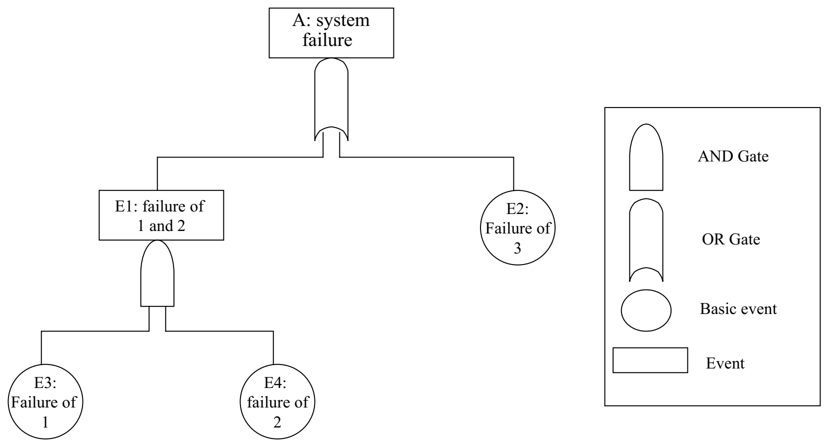


Figure 2.4: Fault tree for an illustrative example

Fault tree (FT)

Fault tree analysis techniques, first developed in 1962 at Bell Telephone Laboratory, have long been used by a wide range of engineering disciplines as one of the primary methods of predicting system reliability and availability parameters. A fault tree is a pictorial representation of logical relationships between events and it can be used to represent a combination of events that will lead to system failure, called as top event. The fault tree model for the illustrative example is shown in Figure 2.4. In Figure 2.4, the top event A represents total system failure which would occur if either event E_1 (failure of reactor1 (E_3) and failure of reactor2 (E_4)) or event E_2 (failure of compressor) occurs.

One key limitation of a traditional fault tree when used as a reliability-availability analysis tool is its capacity for handling complicated maintenance procedures which are best handled by state-space methods (discussed later in this chapter). However, some of recent developments such as dynamic fault trees (Dugan et al., 1997) which are able to model sequence dependent events have enhanced the capabilities of fault trees. Another limitation is that a manual construction of a fault tree can be time consuming and susceptible to human error. This limitation has been addressed with the development of new sophisticated algorithmic and computational tools for the evaluation and the synthesis of fault trees (Wang et al., 2002). Several examples exist in the literature of the successful application of fault tree analysis to industrial process systems (Dhillon and Rayapati, 1988). For example, fault tree analysis has frequently been used for reliability analysis of RO desalination plant (Hajeeh and Chaudhuri, 2000; Kutbi et al., 1981, 1982; Unione et al., 1980b).

Reliability block diagram (RBD)

A reliability block diagram is a graphical representation of how the components of a system are connected reliability-wise. The simplest and most elementary configurations of an RBD are the series and parallel configurations. In a reliability block diagram each component of the system is represented as a block that is connected in series, and/or

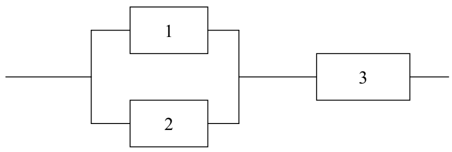


Figure 2.5: Reliability block diagram for an illustrative example

parallel, based on the operational dependency between the components. The reliability block diagram for the illustrative example is shown in Figure 2.5. It is worth noting here that the compressor is considered to be in series with the reactors in Figure 2.5 as its failure will result in total system failure.

The reliability block diagram is by far the most popular modelling technique used in availability analysis of process systems. This can be explained by the fact that it is relatively easy to derive a high-level reliability block diagram from a process flow diagram. For small and simple systems such block diagrams provide a quick estimation of average measures such as steady-state reliability and availability. An availability study of an ammonia plant provides an example of the application of RBD for a industrial process system (Khan and Kabir, 1995).

State-space methods

The non-state models described above cannot easily handle more complex situations such as failure/repair dependencies, shared repair facilities, different types of maintenance for different units with different effects and different resource requirements. In such cases, more detailed models such as the Markov chain model and Petri net models can be used.

Markov model
The Markov model provides a powerful modelling and analysis technique with strong applications in time-based reliability and availability analysis. The reliability/availability behavior of a system is represented using a state-transition diagram, which consists of a set of discrete states that the system can be in, and defines the speed at which transitions between these states take place. The transition from one state to the next state depends only on the current state irrespective of how the system has arrived in that state. The Markov models can be classified into continuous time Markov chain (CTMC) and Discrete Time Markov Chain (DTMC). In case of CMTC, the rate of transition between different states is described by ordinary differential equations (ODEs). While in case of DTMC, they are described using a set of algebraic equations. Markov models provide greater modelling flexibility with some of the following advance features

- an ability to model component dependency issue such as cold or warm standby
- an ability to model sequence dependent behavior

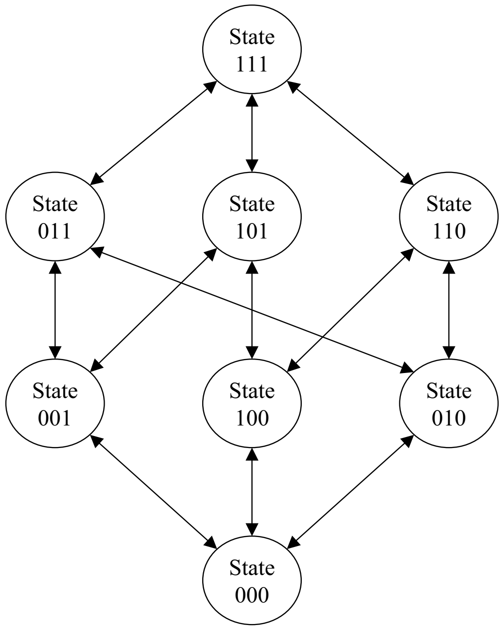


Figure 2.6: Markov state-transition model for an illustrative example

- an ability to handle different types of maintenance

The state-transition diagram for the illustrative example is shown in figure 2.6. The states are described in the example by combination of 0 and 1, where 1 denotes the "up" state and 0 denotes the "down". For example, state (101) describes the system state where reactor 2 is down.

The major disadvantage of Markov modelling is an explosion of the number of states even when dealing with relatively small systems. However, recently, Knegtering and Brombacher (2000) have proposed a new technique to reduce the of the number of Markov states by combining the practical benefits of a reliability block diagram. The published work (Kumar et al., 1991, 1996; Singh et al., 1990) on the availability analysis of a urea fertilizer plant provides an example of the application of Markov modelling in a process system design.

Petri net
Petri net of different types can be used to evaluate reliability and availability measures for a system at the design stage. A Petri net is a directed-graph (digraph) consisting of places, transitions, arcs and tokens. Tokens are stored in places and moves from one place to another along arcs through transitions. A marking is an assignment of tokens to the places and these may change during the execution of a Petri net. If the transition firing times are stochastically timed, the Petri net is called a stochastic Petri net (SPN). If the transition firing is distributed exponentially , it is possible to make a statistical approximation of the same availabilities as those of homogeneous continuous Markov chains models. The Petri net diagram for the illustrative example is shown in Figure 2.7 which shows the initial state of the system (i.e, all tokens are in up-state places).

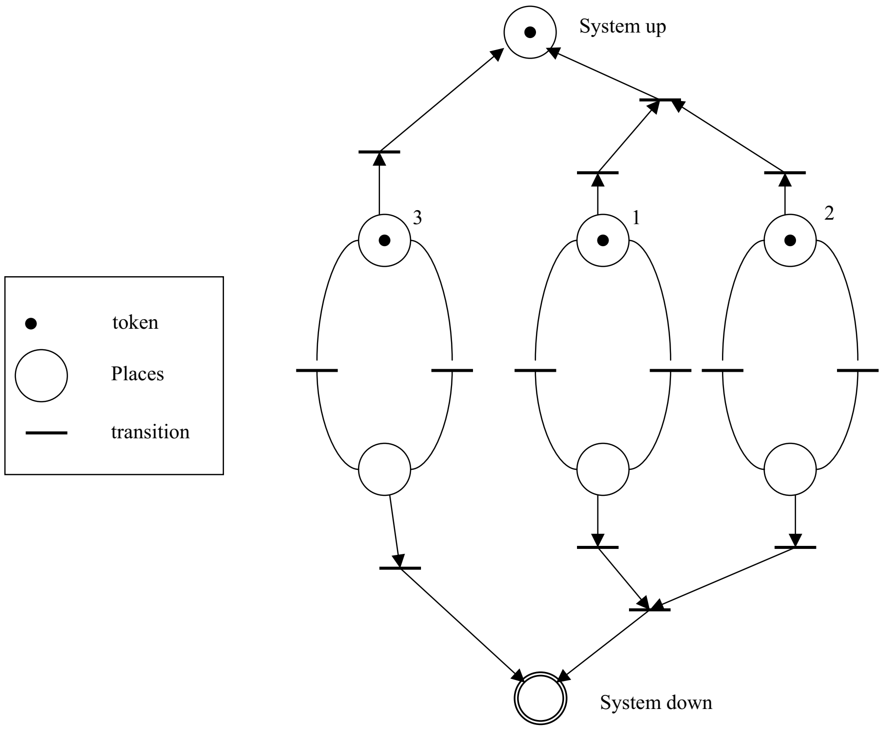


Figure 2.7: Petri net model for an illustrative example

2.2.2 Simulation methods

It is hard (or sometimes impossible) to obtain reliability and availability measures analytically, for modern large and complex chemical plants with equipment that follows different failure and repair distributions. Simulation is used in these cases as an approximation to remedy the limitations of analytical methods. The first step in the simulation method is to construct a system model (FTA, RBD, Markov state-space diagram etc.) describing the interrelations between underlying components. Equipment failures and maintenance actions are treated in the model as random discrete events for which the data is usually described in the form of probability distribution functions. A computer program generates random draws from these distributions to simulate when the system is up and down, stores tables of failure, failure effects, etc. in a log and tracks system or function capability over the considered time horizon. A variety of relevant parameters can then be derived from the log. The number of simulation runs required for accurate availability measure results will depend on the variation in the output measure at each run.

Simulation methods are very flexible and can provide accurate predictions for system perform measures. In particular, they overcome the limitations of the analytical methods and provide time-dependent availability, number of failures and other time dependent measures (cost, throughput etc.) even in cases where non-exponential distributions are used to describe equipment failure and maintenance actions. Therefore, they are well suited for commercially the available software used for RAM studies.

In the last decade, a numbers of authors have published papers have on the successful application of simulation methods for availability analysis of industrial systems. Thangamani et al. (1995) assessed the availability of the fluid catalytic cracking unit (FCCU) of a refinery by using fault tree to model the system and Monte Carlo simulation to simulate the results. Recently, Cochran et al. (2001) have provide availability simulation results for the FCCU unit using Petri net and generic Markov chain models for the system analysis. Khan and Kabir (1995) reported the results of an availability simulation of an ammonia plant. They used a reliability block diagram to represent the system model. Cordier et al. (1997) used a stochastic Petri net to describe the interdependencies between various components of a gas terminal and performed the availability simulation using a Monte Carlo simulation engine.

The major drawback of using a simulation method is that a lot of effort (time and cost) is required to perform the analysis and that there is always some degree of statistical error incurred. Carrying out a "what if" analysis also requires rerunning the model for different input parameters.

2.3 Reliability and maintenance optimization

The reliability-availability analysis methods described above are used to calculate availability related parameters for a *given* system configuration with predetermined failure and repair characteristics of components, maintenance resources and the interdependencies between various components. However, in practice, even for a simple process system a large number of design alternatives can be generated by creating simple "what if" scenarios. For example, for a system described in the illustrative example, the following alternatives can be proposed to improve system availability.

Reliability related decisions

- Increasing the reliability of a compressor/ reactor 1/ reactor2
- Considering active redundancy for the compressor (i.e., considering two compressors in parallel)
- Considering a storage tank before the separator to reduce the impact of failure of both reactors
- ...

Maintenance related decisions

- Increasing the number of preventive maintenance actions on a compressor/reactor 1/reactor 2
- Increasing the number of spares held for a compressor/reactor1/reactor 2 in the warehouse
- ...

The alternatives listed above differ in performance (system availability) and required cost. Analyzing each alternative using the analysis methods described above could be very time consuming.

In recent years, a wide range of optimization methods has been developed in literature to remedy the problem of considering a large number of system alternatives in RAM studies at the design and the operational stage. The methods used well-established combinatorial optimization algorithms such integer programming (Alkamis and Yellen, 1995), genetic algorithms (Painton and Campbell, 1995) etc. Two kinds of optimization approaches that are predominant in the literature are: reliability optimization and maintenance optimization. It is important to recognize the difference between the two optimization frameworks. In reliability optimization, the focus is only on those alternatives that improve the system availability by increasing its inherent reliability, i.e., by increasing the reliability of the system's components and/or add redundancy. The maintenance policy for components in the reliability optimization problem is considered to be fixed (usually a minimal repair policy). Maintenance optimization in contrast takes into account the structure and inherent reliability features of the fixed system and focuses mainly on deriving optimal maintenance policies, or in some cases spares, number of maintenance crew etc., for components by balancing the benefits of maintenance actions against costs.

2.3.1 Reliability optimization

The reliability optimization process begins with the development of a model that represents the entire system and interrelations between underlying components. This is usually accomplished with the construction of a system reliability block diagram. Using a reliability block diagram model, the system reliability impact of different component modifications and system's configuration modifications can be estimated and considered alongside the costs that would be incurred in the process of making those modifications. Depending on the modifications such as creating redundancy (adding parallel units), increasing component's reliability or both, the reliability optimization problem can be formulated as a redundancy allocation, a reliability allocation or a mixed optimal problem, respectively.

The optimal reliability allocation problem addresses the problem of maximizing the reliability of a given system through the selection of component reliabilities subject to resource constraints. The reliability block diagram for a reliability allocation problem for the illustrative example described in the introduction is shown in Figure 2.8(a). The diagram contains only the option to increase the reliability of the compressor (three options are considered). The relation between the reliability and investment costs for the compressor can be described by a continuous function as shown in Figure 2.8(b).

The redundancy allocation problem can be defined as the problem of finding redundancy levels for maximizing system reliability subject to resource constraints. The reliability-redundancy allocation problem is defined as the problem of finding simultaneously optimal redundancy levels and optimal component reliabilities that maximize system reliability subject to resource constraints. More detailed information on different formulations and solution procedures can be found in Kuo et al. (2001).

It is essential to obtain the relation between the reliability and investment cost of the various components for the successful application of reliability optimization at the design stage. In the context of the chemical process design, the existing cost models currently used at conceptual stage are a function of size and kind of the equipment and are not capable, in their present forms, of providing a relationship between the investment cost and their reliability. There are two alternatives to describe the cost-reliability function of equipment in an objective function of a reliability allocation problem. The alternatives

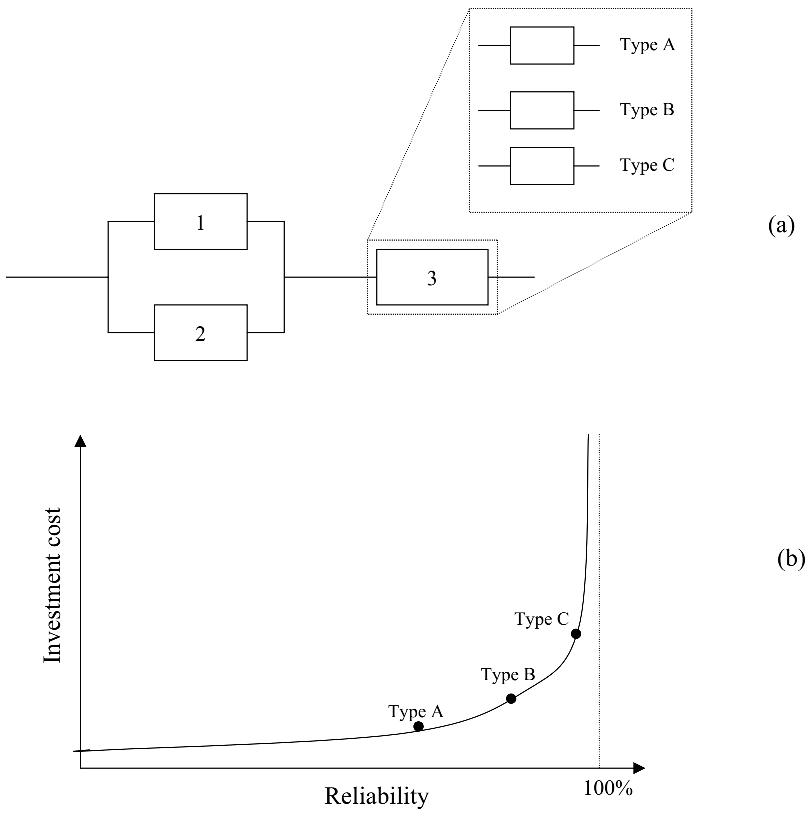


Figure 2.8: Reliability optimization (a) reliability allocation problem considering option of increasing reliability of compressor (b) function of cost-reliability of compressor

are:

1. using exponentially increasing closed-form functions to relate cost and reliability/availability of the equipment (Ishii et al., 1997; Mettas, 2000)

2. using directly the discrete set of cost and reliability data of a piece of equipment in the design problem (Jin et al., 2003; Majety et al., 1999).

Detailed discussions on the development of both kinds of cost estimation models are provided in subsequent chapters. It is important to mention here that the choice of describing the relation between cost and reliability using continuous function or by discrete sets has a significant impact on the complexity and computational burden of the resulting problem.

In the context of chemical process systems, Ishii et al. (1997) first applied the reliability optimization (allocation) as the last step in their 6-step heuristic procedure. In their work, they introduced new extended Lang factor cost estimation models and a maintenance cost estimation model that are a function of equipment availability. The resulting problem was solved as non-linear programming problem. More recently, Jin et al. (2003) have applied reliability allocation method to a cooling system of a jacketed reactor to select equipment from a discrete set of alternatives that have different failure rates and initial investment costs, to reach a certain required level of unavailability. Due to the discrete function between cost and failure rate of a piece of equipment, the resulting problem was solved as an integer programming problem.

2.3.2 Maintenance optimization

Maintenance optimization models provide a structured and a quantitative approach to identify the maintenance policy that maximizes the balance between the benefits and the cost of maintenance. For a given system with failure rate profiles of its components and the available maintenance resources, the maintenance optimization model provides the answer to questions like: “What is the optimal number of maintenance tasks required on this piece of equipment for a given time horizon?” or “When is the appropriate time to execute this maintenance action?” In more complicated cases the optimization model also includes decisions about the sparing policy for components and estimating the number of maintenance crews required in a given shift.

Returning to our illustrative example, consider a case where the compressor failure rate is best characterized by the wear-out phase of the famous bathtub curve. We could think of two situations here. In the first situation, only corrective maintenance is done on the compressor and no preventive action is taken. The failure profile of the compressor will remain unchanged (as shown in Figure 2.9(a)), while in the second case we assume that two preventive actions of an AGAN (as good as new) type are taken on the compressor in a given time period and the failure profile is as shown in Figure 2.9(b). It is interesting to note in Figures 2.9(a) and (b). That in the first case, the average failure rate (λ_{ave}) is higher than then the second i.e., the average availability of the compressor in the first case would be lower. However, in the second case maintenance costs are increased. Therefore, it can be seen that there is a natural trade-off between the benefits (increased uptime) and the costs.

Maintenance optimization is a well-established area and there are several reviews that provide an excellent overview of this area. Valdez-Flores and Feldman (1989) reviewed research work on the maintenance optimization of a single unit system from 1976 through 1989. Dekker (1996) provides a review of applications of maintenance optimization models. Later, Dekker and Scarf (1998) describe in detail some of the applications and discuss the status of application in several application areas. They observed that the maintenance optimization modelling is economically attractive and progressing in many areas. In the context of process systems, Tan and Kramer (1997) developed an analytic approach to consider scheduling of opportunistic and corrective and preventive maintenance in process plants. Due to the complexity of the problem, they applied a genetic algorithm to solve the resulting optimization problem. Monte-Carlo simulations were used to evaluate the cost rate function in their model. Alkamis and Yellen (1995) studied the problem of preventive maintenance scheduling for refinery units and posed the resulting problem as an integer-programming problem. Vatn et al. (1996) present a methodology for maintenance optimization of process systems.

2.4 Software tools

An essential part of performing a RAM study at the design stage is finding a simple, user-friendly tool to apply it. A number of software tools have recently become avail-

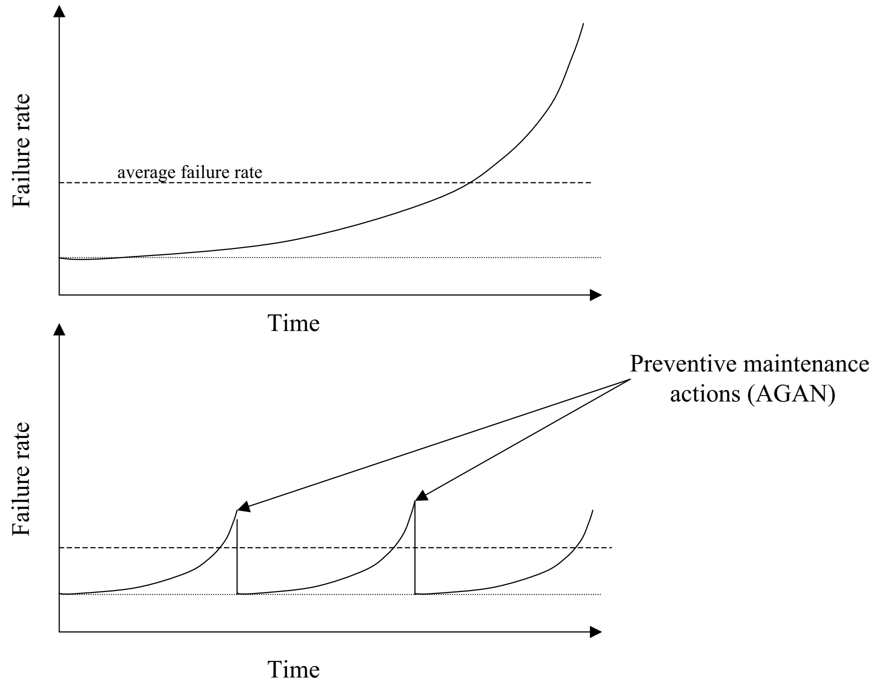


Figure 2.9: Maintenance optimization (a) failure rate profile of the compressor with only minimal repair (b) failure rate profile of the compressor with minimal repair and two preventive maintenance actions in a given time period

able for use by reliability/process engineers. There are large numbers of software tools (commonly called decision support tools) available which can be used to support simple problems like data collection/analysis and more complex problems such as spare optimization, preventive maintenance scheduling etc. Like any other engineering support software, these tools can be expensive and will probably require a significant investment in learning how to use them with confidence. Many big companies, recognizing the importance of these tools, are now either developing them in-house (for example, SPARC developed in Shell) or buying licenses from external vendors.

Dekker (1996) reported three aspects of software that are interesting to the user namely: the user interface and results explanation, the analysis tools and finally the databases. The attractive user-interface is nowadays almost an essential feature of all commercially available software (see Table 2.1). On the reliability databases side, software companies are increasingly either investing in making their own databases for reliability and maintainability data drawn from a wide range of customers or collaborating with others in ongoing projects to develop huge generic databases such as the OREDA (OREDA, 1984) project. The features that essentially differentiate the available software tools are the analysis tools they use. These software tools can be classified broadly as simulation based, or analytical based, or hybrid.

Six commercially available computer programs are evaluated in Table 2.1 against a set of common features important in RAM studies. The objective of this comparison is to give reliability or process engineers a quick way to identify capabilities that distinguish tools, it does not indicate the superiority of one simulator over another. It can be observed from Table 2.1 that all software based on simulation methods provides almost similar kinds of capabilities with only few exceptions. Only SPAR and TITAN allow the user to program several real world situations into the simulation program. Another important development is found in BlockSim, where analytical methods are now used to provide designers with the opportunity to perform reliability allocation optimization for cases where the component's reliability and cost data are given.

2.5 Data Sources

Failure and repair data are the backbone of RAM studies. The availability of appropriate and quality data for performing RAM studies has always been a problem. The sources of reliability data are relatively sparse and collecting appropriate data can be a time consuming effort. The different data sources are listed below.

- Company in-house data
- Data from equipment suppliers
- Generic data sources

Big companies such as Shell, Dow, and BP are investing in efforts to standardize the collection and storage of data from their manufacturing sites. This is evident by the growing use of plant wide or enterprise wide maintenance software such as computerized maintenance management systems (CMMS) that tracks the operational and maintenance activities.

Data can also be obtained from the equipment suppliers for complete systems such as compressor stations, pumps etc. In some cases where the equipment design is proprietary the reliability and maintenance data can only be obtained from a company log book (if they have similar equipment) or from the equipment supplier. It should be noted that the supplier-guaranteed data are usually conservative and should therefore be used with care (Koolen, 2001).

In cases where there is not enough data available in-house or it is difficult to obtain from suppliers, there are several generic data sources available. The degree of quality of data derived from these data sources differs considerably. In best cases, generic databases such as CCPS (CCPS, 1989) and OREDA (OREDA, 1984) provide data that also include engineering and functional characteristics (system boundaries definitions) to complement the estimation of failure rate in the principal failure mode. In other cases, the information could be very restricted, probably confined to an overall failure rate estimate for general classes of equipment. Some of the generic databases and textbooks that include most or a substantial number of process equipments are shown in Table 2.2. More detailed information on different generic databases can be found in Moss and Strutt (1993).

Some detailed reliability/availability analysis studies have been published in journals and industrial magazines for a limited number of process plants, . This includes an ammonia plant (Khan and Kabir, 1995), an RO desalination plant(Hajeeh and Chaudhuri, 2000; Kutbi et al., 1981, 1982; Unione et al., 1980b) , an MSF desalination plant(Unione et al., 1980a), and a Fluid Catalytic Cracking Unit (FCCU) (Cochran et al., 2001; Thangamani et al., 1995).

Table 2.1: Commercial softwares

			BlockSim[1]	AvSim[2]	TITAN[3]	MAROS[4]	SPAR[5]	SPARC[6]
Type	Simulation/Analytical		Hybrid	Simulation	Simulation	Simulation	Simulation	Analytical
Model	RBD/FT/Markov/Petri Net		RBD	RBD/FT	RBD	RBD	RBD	RBD
GUI			+[7]	+	+	+	+	+
Input data	Failure rate	Constant	+	+	+	+	+	+
		Time varying	+	+	+	+	+	
		Different modes	+	+	+	+	+	+
	Maintenance data	Corrective	+	+	+	+	+	+
		Preventive	+	+	+	+	+	+
Modeling capability	redundancy	Active parallel	+	+	+	+	+	+
		Standby	+	+	+	+	+	
	Intermediate storage		+	+	+	+	+	
	Spares		+	+	+	+	+	
	Cost analysis		+	+	+	+	+	+
	User defined logical restrictions				+		+	
Output	Average and point reliability/availability		+	+	+	+	+	+
	Spare and stocks optimization		+	+	+	+	+	
	Reliability optimization		+					

1 ReliaSoft Corporation, 115 S. Sherwood Village Drive, Suite 103, Tucson, AZ 85710
2 Item Software, Inc., 2030 Main Street, Suite 1130, Irvine, CA 92614
3 Fidelis Group, 4545 Post Oak Place STE 347 Houston, TX 77027
4 Jardine and Associates Ltd, Nine Holyrood Street, London SE1 2EL, United Kingdom
5 Clockwork Designs, Inc., 3432 Greystone Drive, Suite 202, Austin, TX 78731
6 IES Products 2811 NV Reeuwijk Reeuwijkse Poort 301 The Netherlands
7 '+' denotes YES

Table 2.2: Generic data sources

Data Source	Title	Publisher and date
CCPS	Guidelines for process equipment	American Institute of Chemical Engineers, 1989
OREDA 97	Offshore reliability data (OREDA) handbook	DnV Technica, Norway, 1997
EIReDA	European Industry Reliability Data Bank	A joint publication of the European Commission and Electricite de France Crete university Press, 1998
ENI data book	ENI reliability data bank - component reliability handbook	Ente Nazionale Indocarburi (ENI), Milan, 1982
Bloch, Heinz P. and Fred K. Geitner	Appendix A, Practical Machinery Management for Process Plants, Volume 2: Machinery Failure Analysis and Troubleshooting	Gulf Publishing Company, Houston, TX, 1994
ANSI/IEEE	Reliability Data for Pumps and Drives, valve Actuators, and Valves	John Wiley & Sons, New York, 1986
NPRD-95	Nonelectronic Parts Reliability Data (NPRD-95) databook	Reliability Analysis Center, Rome, NY, 1995
	Reliability Data for Control and safety systems	SINTEF industrial management, Trondheim, Norway, 1998
PERD	Process Equipment Reliability Database	American Institute of Chemical Engineers
FARADIP	FAilure RAte Data In Perspective	Maintenance 2000
COREDAT	Component Reliability Data Bank	Serco Assurance, UK

2.6 Current approaches to integrate RAM in the process design

In this section we look at the big picture of the role of different reliability-availability analysis methods and frameworks in the conceptual process design. The objective of the conceptual design is to find the best process flowsheet (i.e., to select the process units and the interconnections among these units) and to estimate the optimal design conditions. Although in this definition the terms reliability or availability are not mentioned explicitly, they are considered implicitly during the the conceptual stage. In the implicit mode, the designer freezes the reliability and maintainability dimensions of the design problem by

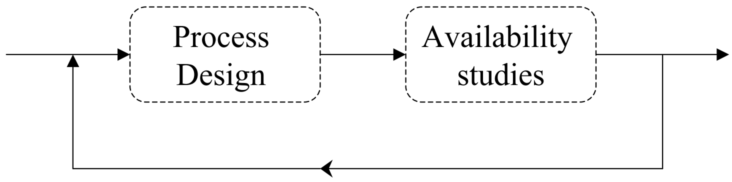


Figure 2.10: Sequential approach of integrating RAM in the conceptual design

fixing the availability of the plant based on their own experience or the historical data given to him or her. The plant capacity and other design decisions are based on the assumed plant availability.

Given the significance of explicitly considering reliability and maintainability in the design problem, it is necessary to set RAM targets more explicitly by building a RAM model at the conceptual stage. The current approaches described in the literature regarding using RAM modelling techniques (described in the previous sections) in the conceptual design process can be categorized into the sequential approach and the simultaneous approach.

2.6.1 Sequential approach

As the name suggest, the design activities and RAM studies are done sequentially during the conceptual design stage. First, the design is selected in the process design step based on some predefined reliability and availability Figures for the installation that will be designed. Then the selected design(s) is(are) analyzed by constructing a detailed reliability -availability analysis model, or in some cases using a reliability/maintenance optimization model, on the selected design to validate the assumptions made in the design step and/or to find those modifications that provide reliability or availability improvement in the selected design(s).

The results of the availability studies provide useful qualitative and quantitative information that may be used to improve the design, i.e. the feedback loop as shown in Figure 2.10. The key advantage of this approach is that due to the separation of tasks, both the process engineers and the reliability experts can focus in their specialized area and can use commercially available tools, such as ASPEN Plus for process simulation and SPAR for reliability simulation, to support their activities.

Although simple in application this approach leads to expensive design iterations, and as the number of possible design alternatives increases with this approach, it becomes almost impractical to analyze all possible alternatives. Another major limitation of this approach is that in most of the cases the availability studies are done after the major design decisions, i.e., determining the flowsheet structure and equipment size, in the design step. In practice, once the process flowsheet is fixed at the design step, it may be very expensive to accommodate the results of availability studies, if structural changes are required. Most

Figure 2.11: Simultaneous approach of integrating RAM in the conceptual design

of the examples stated in the previous sections fall into this category.

To understand the sequential approach, let us go back to our illustrative example. Consider a situation where a process engineer obtains the optimal capacities of various components based on the predefined plant availability of 95%. The design is then passed on to a reliability engineer who, after performing detailed availability analysis*, finds the compressor to be critical equipment and recommends an increase in its reliability by either buying more reliable equipment or adding a parallel compressor, either as a cold or active standby, to the base design. With the new modification plant availability is predicted to go as high as 98%. Now, there are two things that the process engineer has to take into account when processing these recommendations. First, considering a fixed demand, any increment in plant availability (due to modification) should be translated into corresponding adjustment (such as down-sizing) in the capacities of the components. Second, in the case where the compressor is added as an active standby, the process engineer has to make changes in the process model to consider two compressors in the flowsheet (with a perfect switching mechanism). After taking into consideration these two things, the process engineer will run the simulation again and perform an economic evaluation now taking into account the additional cost of adding a compressor and also the reduction in cost due to the reduced size of the equipment.

It is clear from the above illustration that there is a clear benefit to be gained from combining the detailed process models with existing reliability and maintenance model to get a unified integrated framework to obtain process related, and availability related optimal parameters simultaneously in one step.

2.6.2 Simultaneous approach

In the last decade, a new simultaneous approach has become prominent, this avoids expensive design iterations and allows all possible design alternatives to be evaluated . The approach is focused on maximizing system effectiveness measure by making reliability and maintenance decisions in conjunction with the process design/synthesis decisions at the conceptual design stage (as shown in Figure 2.11).

The major advantage of this approach is that it allows process engineers to embed the maintenance and reliability dimensions of the design into the early design problem by incorporating detailed reliability and maintenance models. Thus allowing him or her to obtain optimal values for RAM targets together with other optimal design parame-

*In this case we consider availability analysis however if appropriate data is available, the reliability engineer can also perform reliability allocation or maintenance optimization on a fixed process structure.

ters. These optimal RAM targets can then be used throughout plant life cycle to monitor system-effectiveness.

Pistikopoulos and co-workers at Imperial College, London have made significant progress over the last few years in this direction by proposing different optimization frameworks for simultaneously doing maintenance optimization and design optimization to determine the optimal design together with a detailed maintenance schedule. In their earlier work, Pistikopoulos and Thomaidis (Pistikopoulos et al., 1996; Thomaidis and Pistikopoulos, 1994, 1995, 1998) introduced a combined flexibility-availability index, which is optimized within the overall design optimization framework to obtain optimal design decisions while considering continuous uncertainty, equipment failures and corrective maintenance policy. This initial work was extended by Pistikopoulos and Vassiliadis (Vassiliadis and Pistikopoulos, 1998, 1999, 2001) to incorporate rigorous maintenance models to obtain a detailed preventive maintenance schedule together with optimal design parameters.

In the aforementioned works, Pistikopoulos and his co-workers used examples of a simple multiproduct batch plant and two small continuous process systems. The case of a multipurpose process plant requires a little more attention as an added strong interaction exists between production scheduling and maintenance scheduling. Dedopoulos and Shah (1995a) address the problem of simultaneous production and maintenance planning for multipurpose process plants. They adopted the two-step approach where, in the first step, they identify optimal production and a maintenance and maintenance plan over a long-time horizon of operation (Dedopoulos and Shah, 1995a). Subsequently they used the results of the first step as input for a more detailed maintenance and production schedules over a short time horizon of operation (Dedopoulos and Shah, 1995b). In a separate work, Sanmarti et al. (1997) also address the problem of simultaneous production and maintenance scheduling. Sanmarti et al. (1997) defined the reliability index to assess the robustness of a production schedule depending on (1) the reliability of the equipment units assigned to production tasks and (2) the possibility of finding alternative unit in the case of equipment failure (reliability of a scheduled task). They used robustness as an optimization criterion in their optimization model to identify production and maintenance policies.

In both works mentioned above, the emphasis is on simultaneously obtaining the production schedule and maintenance schedule while considering the other design variables to be fixed. Pistikopoulos et al. (2001) extended the work of Dedopoulos and Shah (1995a) and proposed a system effectiveness optimization framework for the simultaneous acquirement of design, production and maintenance planning of multipurpose process plants.

Although the work of Pistikopoulos and his co-workers is a big step in the direction of integrating RAM in to conceptual design in a systematic and more quantitative way, it has following the limitations.

- In major parts of their work, they used state-space based Markov models to represent the system and its states and to derive very rigorous maintenance models. The resulting integrated combined design and maintenance optimization becomes complex and proves to be computationally challenging as the number of components in a system increases.

- As their optimization frameworks assumes a fixed system structure† and initial reliability of process components, the possibility to consider alternatives to improve initial reliability and redundancy of components is not considered in their work.

2.7 Summary and refined problem formulation

In this chapter a brief overview is provided of various methods and tools that can be used by a designer at the conceptual stage. The reliability-availability methods described in section 2.2. are the building blocks for more advanced optimization frameworks. These reliability and maintenance optimization models can be seen as an extension of analytical reliability-availability analysis models where optimization capability is built around these to perform trade-offs between the costs, of modifying the base case, and the benefits.

The current approaches to integrating RAM in chemical process design are categorized into the sequential and the simultaneous approaches. Although simple, the sequential approach is found to be limited in its application to maximize the system-effectiveness at the conceptual design stage.

To maximize system effectiveness at the conceptual design stage, a new optimization approach of making reliability and maintenance decisions conjunction with the process design/synthesis decisions is gaining momentum in academia. Recent work in the simultaneous approach, however, have been found to focus only on deriving optimal maintenance schedules together with design decisions, while opportunities to optimize the inherent reliability during process and equipment selection are not considered.

The purpose of this work is to propose a unified and quantitative optimization framework where both the reliability and maintainability dimensions of availability are optimized with design parameters to maximize the system effectiveness of the process system at the conceptual stage of design. In particular, the reliability and/or maintenance optimization models are incorporated in conventional process design/synthesis optimization problem to obtain quantitative RAM targets together with optimal design parameters.

In in its simplest form, the new integrated optimization problem addressed here in this work can be stated as:
Given

- the process superstructure describing different design alternatives.
- the process model describing material and energy balance, technical and regulatory specification, relation between system availability and production capacity etc. In cases of multipurpose plants it also includes production scheduling constraints.
- a reliability allocation model that create the connection between the allocation of initial reliability (targets) to units and its reliability and the initial investment costs.
- a maintenance model that describes the impact and costs of different types and the number of maintenance actions required for an equipment in a given time horizon;
- an availability model (derived from reliability and maintenance model).

†Except in the case of multipurpose process plants (Pistikopoulos et al., 2001)

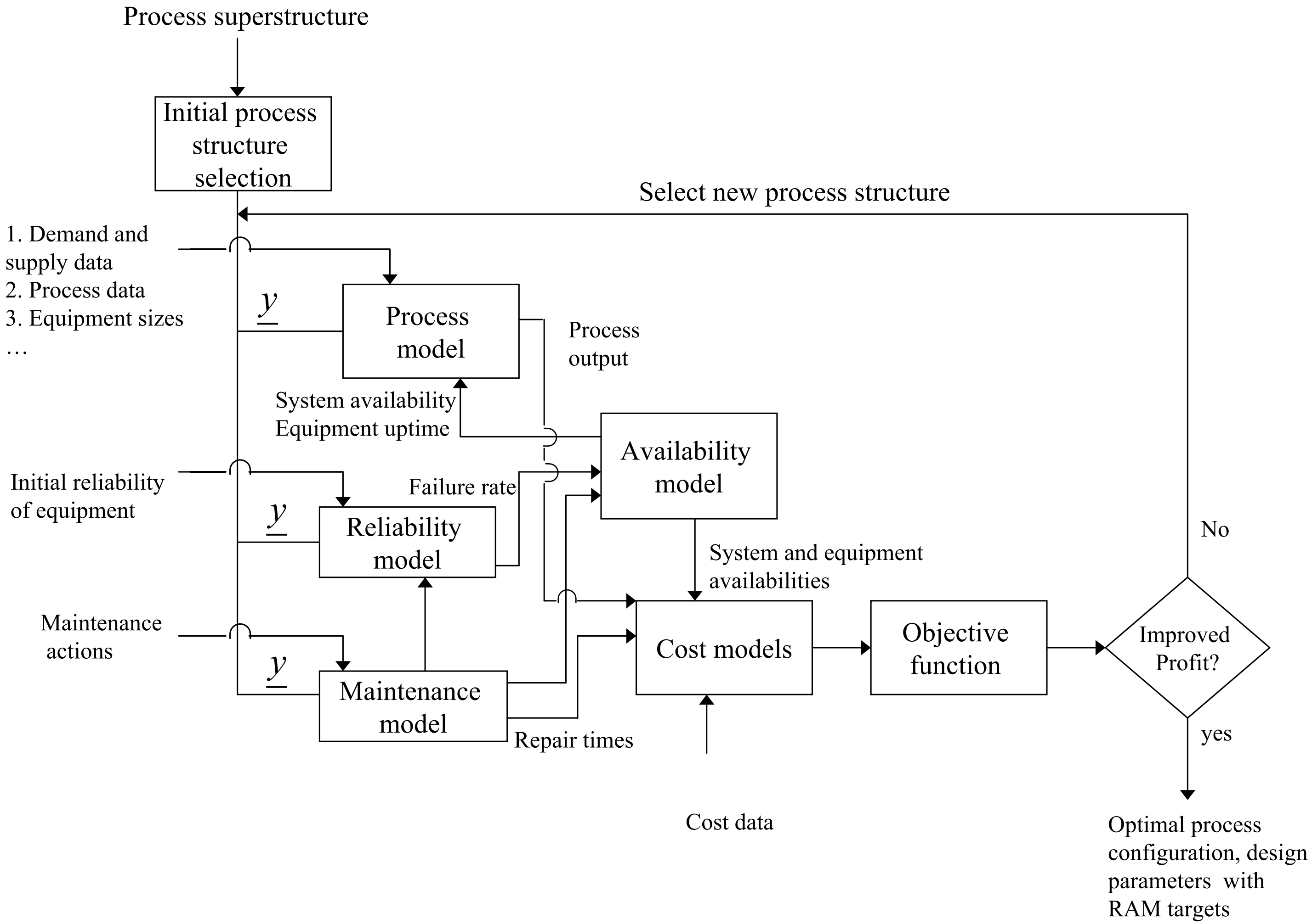


Figure 2.12: Models interactions: joint integrated process synthesis and availability optimization problem

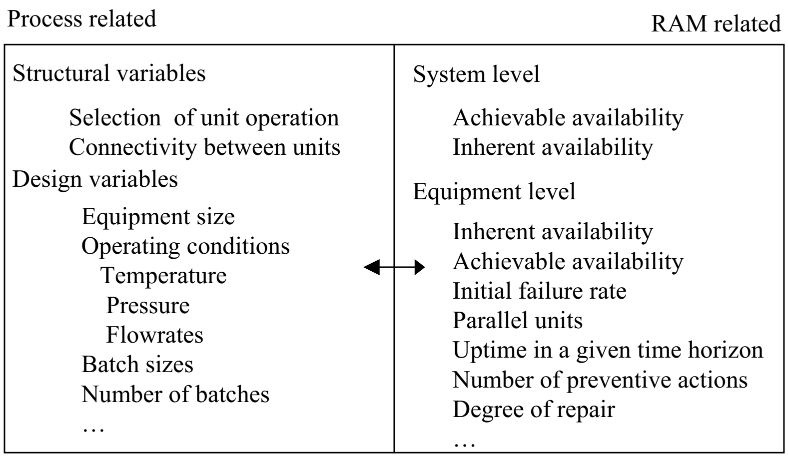


Figure 2.13: Decision variables space: joint integrated process synthesis and availability optimization problem

- cost models including initial capital investment models and maintenance cost models made function of intrinsic reliability or availability characteristics of equipments units.

- an objective function, that provides a trade-off between increased revenues due to extra equipment availability and two additional costs a) increased capital costs for improving unit's initial reliability (reliability allocation) and/or b) increased operational costs for preventive maintenance actions (maintenance optimization).

- data about capital cost, failure and repair rate, corrective and preventive maintenance cost for different types of equipment, other costs such as raw material, products costs, energy costs etc.

Determine

The optimal process configuration with optimal design parameters and optimal RAM targets for critical equipment.

The important thing to be noted from the problem definition described above is the interplay of different elements such as the process model, the reliability and maintenance models etc. A picture of interactions between different elements of the new integrated framework is provided in Figure 2.12, the $\underline{\mathbf{y}}$ denotes the fixing as $\mathbf{y}$ vector at each major iteration.

It is also clear from Figure 2.12 that the integrated approach developed in this work to set RAM targets together with the structural and design decisions at the conceptual results in a much larger set of decision variables than the decision space in any of the main sub-disciplines, process engineering and reliability engineering. The total decision space for the integrated optimization problem with important decision variables is shown in Figure 2.13.

The decision space described in Figure 2.13 also indicates the boundaries of different models used in the this work. For instance, the process models used are ”short-cut” models describing the process at higher abstract level often focusing on key design attributes such as equipment sizes, flowrates, and in cases of batch processes, batch size and number of batches. In some cases, the variables defining the operating conditions of the equipment such as temperature and pressure can also be included. As for the RAM model, it is clear from Figure 2.13, some design variables such as storage tanks and some complex operational variables such as number of spares present in the warehouse, number of maintenance crew available etc. are not considered. This could be explained by a) the amount of limited resources at such a time, people and money available at the conceptual stage and b) amount of detailed data available for the process.

At the conceptual stage, the designer is often confronted with wide range of problems, differing in attributes such as batch vs continuous, multiproduct vs multipurpose, grassroot vs retrofit, etc. Further, depending upon situation, the designer might have limited reliability and maintenance data. The optimization framework defined above is generic in nature and can be applied to wide range of design situations. To illustrate its general applicability, a number of optimization frameworks will be developed in thesis that will cover a wide range of design problems. The number of examples used for the frameworks by no mean covers the entire range, however, they do demonstrate how, by changing the process model, the reliability model and the maintenance model, the generic formulation as described in Figure 2.12 can be applied to different situations. For example, in chapters 3 and 4 the emphasis will be on the optimization of “inherent availability” by combining reliability optimization and process synthesis problems while assuming a fixed maintenance policy for each alternative. In chapter 5 and 6, the emphasis will be on optimizing “achievable availability” taking into account reliability and maintenance optimization using process synthesis.

3

Integrating reliability optimization in process design/synthesis†

A new optimization framework is developed in this chapter by combining the reliability optimization and process synthesis. The combined optimization problem is posed as a mixed integer nonlinear programming (MINLP) optimization problem. The proposed optimization framework features an expected profit objective function, which takes into account the trade-off between initial capital investment and the annual operational costs by supporting the appropriate estimation of revenues, investment costs, costs of raw material and utilities costa, and maintenance costa as a function of the system and its component availability. The effectiveness and usefulness of the proposed optimization framework is demonstrated using two examples: a small illustrative example and a medium scale example of synthesis of the hydrodealkylation process (HDA) process.

3.1 Introduction

An overview of different methods on integration of reliability and maintainability into design stage was presented in the previous chapter. Further, the approaches for integrating RAM in the conceptual process design were categorized into a sequential and simultaneous approaches.

Due to the limitations (described in section 2.6) of a sequential approach, the focus of this work is put on the simultaneous approach. In a simultaneous approach, reliability and maintenance decisions are made in conjunction with the process design/synthesis decisions at the synthesis step. As pointed out earlier, Pistikopoulos and co-workers have made significant progress over the last few years in this direction by proposing an optimization framework for simultaneously doing maintenance optimization and design optimization to determine the optimal design together with a detailed maintenance schedule.

†Parts of this chapter have been published by Goel et al. (2002) and Goel et al. (2003a)

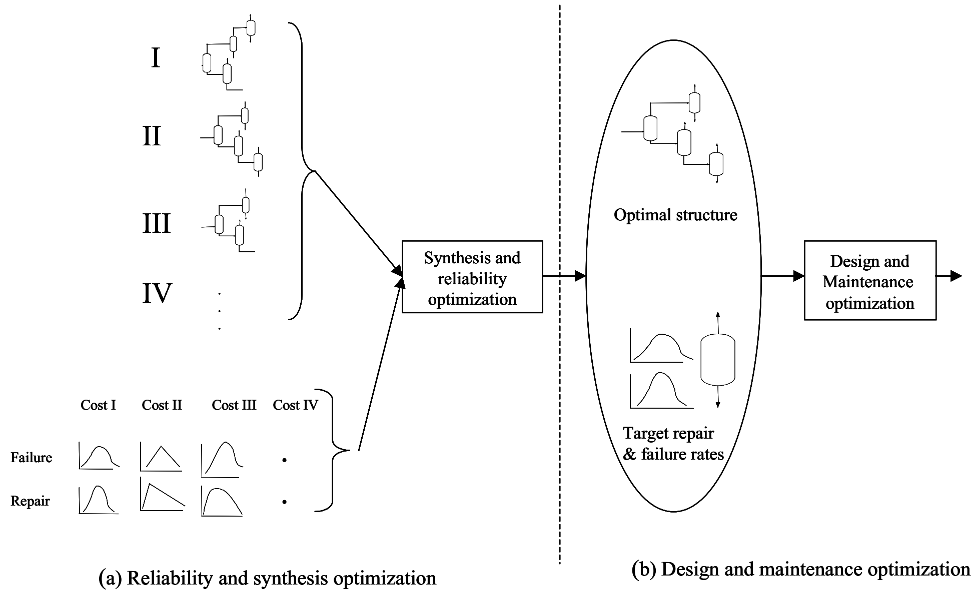


Figure 3.1: Decomposition strategy to maximize the availability at design stage

In their optimization frameworks they assume a fixed system structure (except in their recent work on multipurpose process plants (Pistikopoulos et al., 2001)) and a given initial reliability of process components. As a result, it can be concluded that the degree(s) of freedom to improve initial reliability in design decisions are not considered in their work.

As discussed earlier plant availability is a function of reliability and maintainability attributes of the plant. To incorporate the degrees of freedom required to improve initial reliability at the design stage, the reliability optimization model should be included in existing simultaneous frameworks.

Integrating reliability optimization formulation into a existing framework will lead to one integrated design, reliability and maintenance optimization framework which in some cases could be computationally expensive. In this work, a decomposition strategy is adopted to decompose the large synthesis, reliability and maintenance optimization problem into manageable sub-problems: reliability optimization and process synthesis, and maintenance and design optimization problems, see Figure 3.1. In chapters 5 and 6, we focus on the development of an integrated design, reliability and maintenance optimization framework.

In the first sub-problem, efforts are focused on optimizing inherent availability and obtaining the optimal structure and optimal level of inherent availability required for equipment in the final optimal structure. Once the optimal structure and optimal availability of components have been obtained, detailed process models together with detailed maintenance models using time dependent reliability functions, can be used to obtain the optimal design parameters and a detailed maintenance schedule. It is worth noting here that in the first sub-problem the initial reliability is considered to be a degree of freedom whereas the degree of freedom with respect to choosing maintenance type and schedule is frozen when considering minimal repair policy. In the second sub-problem the focus is only shifted on the degrees of freedom with respect to improving maintainability.

In this chapter, an optimization framework is developed by combining reliability optimization and process synthesis challenges. The proposed optimization framework provides the designer with the flexibility to configure a process or select initial reliabilities of equipment in a way that maximizes the inherent plant availability at the design stage. The key elements of the proposed approach are (1) a process model that describes the process-related characteristics and capture the interactions between system availability and design parameters; (2) an availability model that describes the availability of the components and the system availability as a function of components availability; and (3) an expected profit objective function, which takes into account the trade-off between initial capital investment and the annual operational costs by supporting appropriate estimation of revenues, investment cost, raw material and utilities cost, and maintenance cost as a function of the system and its component availability. The application of the proposed framework is illustrated using the synthesis example of a toluene hydrodealkylation process.

3.2 Background

3.2.1 Reliability optimization at the design stage

Reliability optimization problems were discussed in the previous chapter. One can identify the following limitations of these approaches when attempting to apply reliability optimization approaches at the synthesis step of a chemical process system:

- in the conventional reliability optimization formulation, the basic system structure, N-stages in series, is rigidly defined with the option of increasing the unit reliability and or adding redundancy at each stage. In the context of a process system, it is equivalent to assuming a situation where the main process units (as stages) in the process flowsheet have already been fixed and the decision variables are the number of parallel units that can be added to each stage and/or the options of increasing the unit reliability. However, at the synthesis stage, one of the key design decisions is the selection of the basic skeleton of the flowsheet structure, N stages of the system, from the different process flowsheet alternatives that are available.

- in the conventional reliability optimization problem formulation, only reliability characteristics of the components are used in a system reliability model aimed at maximizing the system reliability without considering the process models used to capture detailed process interactions. Consequently, the reliability optimization problem is solved independently without considering the impact of improved reliability on the design such as improved revenues, reduced capacity requirement etc.

3.2.2 Process Synthesis

The conventional process synthesis problem involves selecting an optimal flowsheet structure, from a given superstructure and setting parameters that describe the operation of the desired process (Kocis and Grossmann, 1989). The superstructure is postulated based on preliminary screening and is used to define the search space of candidate flowsheet alternatives. The process synthesis problem, with a given superstructure can be formulated as a MINLP problem (**P1**) of the form :

$$
\begin{aligned}
\max_{x,y} \quad & \mathrm{P}(x,y) \\
s.t. \quad & h(x,y) = 0 \\
& g(x,y) \leq 0 \\
& x \in X \subseteq R^n \\
& y \in Y \subseteq [0,1]^m
\end{aligned}
$$

Where **x** is a vector of continuous variables specified in the compact set **X** and **y** is a vector of discrete, mostly binary 0-1 variables, used to represent discrete choices such as, existence or non-existence of units, P(**x**,**y**) is a scalar economic objective function, in this case annual profit, $\mathbf{h}(x,y)$ is a vector of equality constraints that corresponds to process models, covering mass and energy balances, equilibrium relationships, and $\mathbf{g}(x,y)$ is a vector of inequality constraints that correspond to process design and operational specifications. In the conventional process synthesis problem **P1** above, the reliability and maintainability of the equipment are not considered explicitly as decision variables. They are, however, fixed implicitly by making assumptions in the economic objective function P(**x**,**y**) such as assuming certain fixed operational availability (about 95%) while estimating revenues, raw material and utilities costs and estimating annual maintenance costs as a fraction of fixed capital costs (about 4%), which should be estimated as a function of the reliability of the equipment. As a result, with formulation **P1**, it is not possible to make certain critical economic trade-offs at the design stage such as justifying the extra initial investment required to acquire more reliable components or different kinds of components to improve system reliability which would lead to a reduction in production loss and lower maintenance costs in the operational phase. In other words, it is not possible to make decisions aimed at reducing total life cycle cost, by making a trade-off between acquisition costs and operational costs.

Traditional reliability optimization and process synthesis formulations, as described above, therefore optimize either hardware performance or process performance at the design stage. As a result, the solution obtained by solving these optimization formulations separately provides a sub-optimal solution with respect to the overall system performance criterion.

3.3 Model Development

In this section, we describe the mathematical foundations and assumptions made during the development of an optimization framework for integrating reliability optimization and process synthesis at the conceptual stage of design. In its general form, the optimization problem can be represented as:

Max Objective Function (Expected Profit)
s.t. Process model
Availability model

It should be noted that technical, regulatory and logical constraints on the system are accounted for in the process and availability models described in the following subsections.

3.3.1 Process model

The equalities and inequalities, $h(x, y) = 0$ and $g(x, y) \leq 0$ in problem formulation **P1**, which describes the process-characteristics, include mass and energy balance equations, equipment sizing equations, and operational specifications. These design equations and guidelines for process specification are well established in the process design paradigm and can be found in standard textbooks such as Douglas (1988) and Biegler et al. (1997).

In the conventional problem formulation **P1**, the inherent equipment and the system availabilities (approximately 0.95 time the operational availability) are considered to be unity. In other words, the system is designed with a broad assumption that the equipment or subsystem will always be available to perform its pre-described function. In practice, however, unplanned shutdowns occur that result in production losses and therefore should be considered when deciding the size of a plant. In this work, therefore, an equation describing the interaction between system availability and process design parameters such as equipment sizes is also added into the process model. More detailed information on the kind of process models used in process synthesis will be given in section 4, where two process examples are used to demonstrate the application of the optimization framework developed in this chapter.

3.3.2 Availability model

In this section we develop an availability model to estimate the system and its components availability, which is used in the development of the objective function and the process model. Availability is determined by the reliability and maintainability of an item. As further stated in the chapter 1, plant availability is classified into three types: inherent, achievable and operational. As per the decomposition strategy (see Figure 3.1) adopted this chapter, the inherent availability of the components and the overall system are considered to be decision variables in the overall optimization framework.

The inherent availability of the component j is described by A_j, and is assumed to be bounded as $A_{o,j} \leq A_j \leq A_{\max,j}$. The maximum inherent availability $A_{max,j}$ is dictated by the capital and the technical limitations for the component j.

The overall system availability, A_{sys}, is estimated from the underlying components availabilities (A_j) by constructing a reliability block diagram. For a given process flowsheet, a reliability block diagram can be derived that would reflect the consequence of equipment failure(s) in the process system. From a reliability viewpoint, most of the process systems tend to be very simple, often consisting of parallel trains of units, possibly with standby units and can therefore be modelled as a series or series-parallel reliability block diagram.

In the process synthesis optimization problem, challenge arises due to the fact that the process structure is not known *a priori*, it is one of the outcomes of the synthesis problem. Therefore, for a case, where all possible alternative process flowsheets are embedded into one process superstructure, the number, type and the connectivity between different units

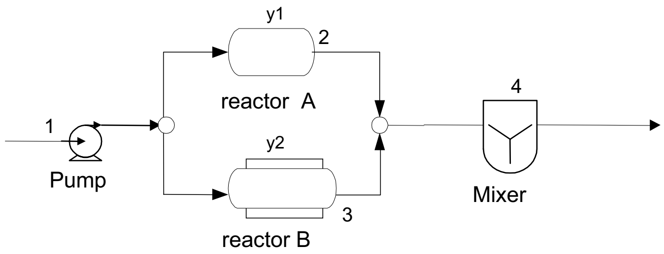


Figure 3.2: Illustrative example

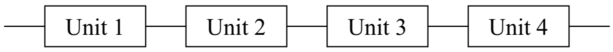


Figure 3.3: Reliability block diagram superstructure: Illustrative example

are not yet fixed and hence, a single reliability block diagram cannot be derived to obtain the system availability expression. It is, however, possible to construct a reliability block diagram superstructure similar to a process superstructure, which embeds all possible reliability block diagrams corresponding to the process flowsheets embedded in the process superstructure. The mapping of a process flowsheet in the process superstructure to a corresponding reliability block diagram from a reliability block diagram superstructure is achieved by using same structural y variables to construct process and availability models. As a result, while solving the combined integrated reliability optimization and process synthesis problem, at each major iteration where y variables are fixed to obtain a process flowsheet, a corresponding reliability diagram would be constructed and solved to obtain the system availability. This is further explained with the help of the following illustrative example.

Consider the simple illustrative example shown in Figure 3.2. The process superstructure in Figure 3.3 embeds two process alternatives: process with reactor type reactor1 or reactor2. Each of the possible alternative process structure is governed by the values of **y** variables. Constraint $y_1 + y_2 = 1$ restricts the selection of only one kind of reactor; therefore it is not possible to have both kinds of reactors in the optimal process flowsheet. The corresponding reliability block diagram superstructure for this illustration is also shown in Figure 3.3. It should be noted that two reactors are shown in series. This is because only one reactor is to be chosen in the solution. The system availability expression for this illustrative example can be derived as

$$
\begin{aligned}
&A_{sys} = A_1 \cdot A_2 \cdot A_3 \cdot A_4 \\
&(1 - y1)\,(1 - A_{o,2}) + A_{o.2} \leq A_2 \leq (1 - y1)\,(1 - A_{\max,2}) + A_{\max,2} \\
&(1 - y2)\,(1 - A_{o,3}) + A_{o,3} \leq A_3 \leq (1 - y2)\,(1 - A_{\max,3}) + A_{\max,3}
\end{aligned}
\tag{3.1}
$$

At each major iteration, for instance, if $y_1 = 0$, A_2 becomes unity (it has no impact on the system availability calculations), and if, $y_1 = 1$ then the variable A_2 is bounded as $A_{o,2} \leq A_2 \leq A_{\max,2}$. In this way, the special structural property of the process and reliability block diagram superstructures is exploited in the solution strategy to solve the combined process synthesis and reliability optimization problem.

3.3.3 Objective function

In most of the process synthesis problems, the objective function is taken to be the maximization of annual profit, which can be defined as

Annual profit = Revenue - Annualized investment costs - Maintenance costs
- Operating costs i.e. raw material and utilities

Revenue

It is generally observed that revenue lost due to the unavailability of plant can range from $500 to 100,000 per hour (Tan and Kramer, 1997). At the conceptual design stage, revenues are estimated as the product of total annual production rate and the sales price of products and by-products, assuming some fixed plant availability, in the range of 70-95% availability. Operational plant availability, however, is a function of reliability and the maintainability of the system and its components. Therefore, in this work revenue (Rev) is estimated as:

$$Rev = SOT \cdot A_{sys} \cdot \sum_{i \in \mathbf{PR}} x_i \cdot \xi_i \tag{3.2}$$

Where, SOT is defined as the standard scheduled operating time per year, A_{sys} is the system inherent availability, **PR** is the set of product and by-product streams in the process superstructure, x_i is a continuous variable describing, in this case, the flowrate of process i^{th} stream and ξ_i is the cost/price of i^{th} process stream. The SOT defined in the equation (3.2) is similar to plant production time as defined by Grievink et al. (1993) which is:

SOT = total time available (365 days a year) - time lost through operational logistics and administration - planned maintenance downtime

Investment costs

Investment costs at the design stage are generally estimated by well-known shortcut methods such as Guthrie's cost models (Guthrie, 1969), Lang factors (Lang, 1948), simple linear cost-charge models (Kocis and Grossmann, 1989) or simple cost models developed within companies. Although these cost models are very simple and useful for quick estimates, they do not take into account the reliability and maintenance aspects of process units while estimating the initial investment cost of equipment. Generally, at the design stage it is possible to select more reliable equipment (with extra cost), or a different kind of equipment for the same duty. For example, we can purchase different kinds of compressors, such as reciprocating or axial centrifugal, having different acquisition costs and reliability features. Although these choices are discrete in nature in a simplified form they can be represented as a continuous cost relation between investment costs and reliability performance measure for the component. Ishii et al. (1997) introduce an availability factor in the existing cost models to represent a simple exponential relationship between investment cost and availability of equipment. Ishii et al. (1997) assumed similar exponential relations for each piece of equipment, which can be expected to differ significantly between types of equipment in practice. Therefore, we introduced a parameter ϕ in Ishii et al's availability factor. The resulting cost model for a piece of equipment can be represented as:

$$CI_j = CI_{o,j} \cdot \exp\left[\phi_j\left(\frac{A_j}{A_{o,j}} - 1\right)\right] \tag{3.3}$$

Where, CI_j is the investment cost for equipment j and $CI_{o,j}$ is the investment cost estimated using the conventional cost model, ϕ_j is an equipment constant, and A_j and $A_{o,j}$ are equipment availability and its base value.

Using a linear cost-charge model as described in (Kocis and Grossmann, 1989) as a conventional cost model, the annual investment cost for equipment can be estimated as

$$CI_j = K_j^0 y_j + K_j^1 x_j \exp\left[\phi_j\left(\frac{A_j}{A_{o,j}} - 1\right)\right] \tag{3.4}$$

The fixed charge parameter K_j^0 denotes the fixed investment of unit j incurred only when the associated binary variable y_j is set to 1, while K_j^1 is the variable cost. The variable x_j describes here the capacity or some other physical parameter of unit j. In equation (3.4), when a piece of equipment does not exist (y_j = 0), the variable x_j also becomes 0. Therefore, only the investment cost of existing equipment is considered at each iteration.

Maintenance costs

Annual maintenance costs are usually estimated at the conceptual design stage as 4% of the initial fixed capital investment (Douglas, 1988). Although small compared to initial costs, maintenance costs can climb to about 30% of total operating costs(VanRijn, 1987). Preventive maintenance costs are dictated mainly by the kind of maintenance policy applied at the operational stage. Since only inherent availability is considered in this work, preventive maintenance costs are not considered in the objective function. Corrective maintenance cost are dictated by the inherent reliability of each unit j and can be estimated as

$$C_j^{c,total} = SOT \cdot C_j^c \cdot \left(\frac{1 - A_j}{A_j}\right) \tag{3.5}$$

Where, $C_j^{c,total}$ is the annual corrective maintenance cost for unit j, and C_j^c is the cost of corrective maintenance per hour on unit j.

Raw material costs

Similar to revenues, the annual raw material cost in an objective function is estimated as

$$C_{raw} = SOT \cdot A_{sys} \cdot \sum_{i \in \mathbf{RM}} x_i \cdot \xi_i \tag{3.6}$$

Where, **RM** is the set of raw material streams in the process superstructure.

Other operational costs

Utilities costs are estimated from the energy balance equations specified in the process model.

3.3.4 Problem formulation

The process synthesis problem can be now defined as follows: Given

- a process superstructure, imbedding all process alternatives
- a process model describing mass and energy balances, equilibrium relationships, design and operational specifications, and relation between production and system availability
- an availability model describing system availability as a function of availability of underlying equipment
- cost data, reliability data, a cost function describing the relation between capital investment and the inherent availability of each unit

Determine :

- an optimal system configuration
- optimal inherent availability targets for each process unit
- optimum design parameters such as capacity of each unit with optimal flowrates etc.

Mathematically, it can be formulated as an MINLP problem of the form (problem **P2**):

$$\begin{aligned}
\max_{x,y,A} \quad & P(x, y, A) \\
s.t. \quad & h(x, y, A) = 0 \\
& g_1(x, y, A) \leq 0 \\
& g_2(y, A) \leq 0 \\
& x \in X \subseteq R^n \quad y \in \mathbf{Y} \subseteq [0, 1] \quad A_o \leq A \leq A_{\max}
\end{aligned}$$

Where **A** is a vector of continuous variables describing the availability of a system and its components. The solution to the above MINLP optimization problem **P2** can be obtained using different solvers available in the GAMS modeling language such as the

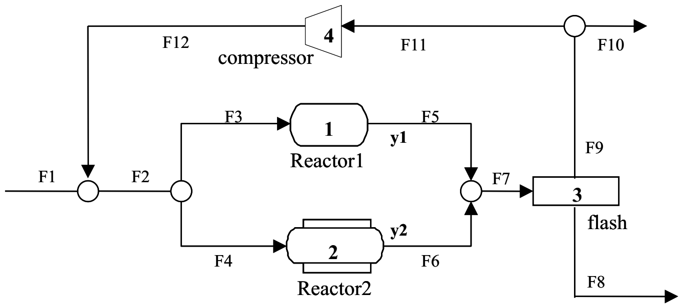


Figure 3.4: Process superstructure: Example 1

SBB or the DICOPT solver. The SBB solver uses the branch and bound approach, which start by solving the continuous relaxation (NLP) of the MINLP and subsequently perform an implicit enumeration where a subset of the 0-1 variables is fixed at each node. The DICOPT solver uses the Outer approximation (OA) algorithm where the continuous optimization (NLP sub-problem) and the discrete optimization (MILP master problem) are performed separately and repetitively till convergence. The selection of the more suitable MINLP solver to solve problem **P2** depends largely on the problem structure. Overall, DICOPT perform better on models that have a significant and difficult combinatorial part, while SBB may perform better on models that have fewer discrete variables but more difficult non-linearities. However it should be added here that the presence of bilinear terms, e.g. equation 3.2, brings non-convexity to the overall MINLP problem and hence tends to have multiple solutions. Neither SBB nor DICOPT solvers guarantee a global optimum solution to such problems. To ensure the global optimality, one has to either convexify the problem or use existing global optimization solvers such as BARON or QPNLP.

3.4 Process synthesis examples

The proposed strategy for integrating reliability optimization in process synthesis is illustrated using two examples.

3.4.1 Example 1

Consider a simple process synthesis problem, as described in Figure 3.4, for the production of chemical C from reactants A and B. The main reaction is as follows:

$$A + 2B \rightarrow C$$

The process alternatives shown in Figure 3.4 involve the selection of reactor type, reactor1 and reactor2. The process comprised a reactor, a flash separator, and a compressor. It is important to mention here that this example is different from the one shown in Figure 2.1 where the both reactors are considered in parallel (fixed) in the flowsheet. The process model, mass balance, specifications and objective function, used to describe the process is given in Table 3.1. Index k denotes components (A, B and C). Parameters $\gamma 1_k$ and $\gamma 2_k$

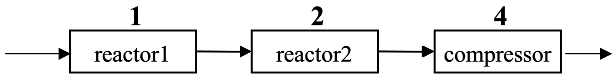


Figure 3.5: Reliability block diagram superstructure: Example 1

are separation ratios for a flash and purge splitter respectively. Their value together with values for supply (S_k) and demand (D_k) and conversion data for reactor1 and reactor2 in this example are given in Table 3.2. The cost data (K_j^0 and K_j^1) and minimum and maximum values for inherent availabilities of equipments are given in Table 3.3. The data for standard operating time (SOT) and C_j^c are also given in Table 3.3.

The reliability block diagram superstructure is given Figure 3.5. The availability model is described in equation 3.7 as

$$\begin{aligned}
&A_{sys} = A_3 \cdot A_4 \cdot A_8 \\
&(1 - y_3)\,(1 - A_{o,3}) + A_{o.3} \leq A_3 \leq (1 - y_3)\,(1 - A_{\max,3}) + A_{\max,3} \\
&(1 - y_4)\,(1 - A_{o,4}) + A_{o,4} \leq A_4 \leq (1 - y_4)\,(1 - A_{\max,4}) + A_{\max,4}
\end{aligned} \tag{3.7}$$

where A_3, A_4 and A_8 are the inherent availabilities of reatcor1, reactor2, and compressor respectively.

The objective function for this example is described in equation 3.8 as

$$\begin{aligned}
\text{Profit} = {} & SOT \cdot A_{sys}.(F8_C \cdot 17 - F1_A \cdot 5 - F1_B \cdot 2.5) \\
& -y_3 \cdot K_3^0 - K_3^1 \cdot \sum_k F5_k \cdot \exp\left(\phi_3\left(\tfrac{A_3}{A_{o,3}} - 1\right)\right) - y_4 \cdot K_4^0 \\
& -K_4^1 \cdot \sum_k F6_k \exp\left(\phi_2\left(\tfrac{A_4}{A_{o,4}} - 1\right)\right) - K_6^0 - K_6^1 \cdot \sum_k F8_k \\
& -K_8^0 - K_8^1 \cdot \sum_k F12_k \cdot \exp\left(\phi_8\left(\tfrac{A_8}{A_{o,8}} - 1\right)\right) - \text{maintenance costs}
\end{aligned} \tag{3.8}$$

The overall process synthesis problem is posed as an MINLP problem. The problem is solved using both SBB and DICOPT solvers which provide the optimal configuration, shown in Figure 3.6 and optimal availability given in Table 3.4. Neither SBB nor DICOPT solvers provide global optimum. Nowadays, different commercial global optimizers such as BARON, and OQNLP are available with a standard modelling package GAMS, that can be used to obtain a global optimum. For instance, for this simple example, BARON solver provided similar optimal results. It must be added here that these solvers are still in their development phase and lots of modelling expertise is necessary to identify correct bounds on continuous variables.

The results obtained for the combined case, process synthesis + reliability optimization, are further compared with the conventional process synthesis approach. The optimal solutions obtained with both formulations are given in Table 3.5. It is interesting to note that the profit obtained in the process synthesis case is higher than the one obtained in the combined case. However, it should be noted that unplanned shutdown (1 - 0.940) is

Table 3.1: Process model: Example 1

Species balance for mixer (node 1)	Species balance for mixer (node 5)
$F2_k = F1_k + F12_k \quad \forall k$	$F7_k = F5_k + F6_k \quad \forall k$
Species balance for splitter (node 2)	Species balance for flash (node 6)
$F2_k = F3_k + F4_k \quad \forall k$	$F8_k = \gamma 1_k \cdot F7_k \quad \forall k$
Species balance for reactor1 (node 3)	Species balance for splitter (node 7)
$F5_A = F3_A - \alpha_1 \cdot F3_A$ $F5_B = F3_B - 2 \cdot \alpha_1 \cdot F3_A$ $F5_C = F3_C + \alpha_1 \cdot F3_A$	$F10_k = \gamma 2_k \cdot F9_k \quad \forall k$ $F11_k = (1 - \gamma 2_k) \cdot F9_k \quad \forall k$
Species balance for reactor2 (node 4)	Species balance for compressor (node 8)
$F6_A = F4_A - \alpha_2 \cdot F4_A$ $F6_B = F4_B - 2 \cdot \alpha_2 \cdot F4_A$ $F6_C = F4_C + \alpha_2 \cdot F4_A$	$F12_k = F11_k \quad \forall k$
Supply rate constraints $F1_k \leq S_k \quad \forall k$	Demand constraint $F8_C \cdot A_{sys} = D_C$
Logical constraints $\sum_k F5_k \leq 30y_3$,$\sum_k F6_k \leq 30y_4$ $y_3 + y_4 = 1$	

Table 3.2: Data: Example 1

Reactants	$\gamma 1_k$	$\gamma 2_k$	S_k	D_k
A	0.1	0.02	30.0	0.0
B	0.1	0.02	30.0	0.0
C	0.99	0.02	0.0	15.0
Conversion factors				
α_1	0.6			
α_2	0.62			

Table 3.3: Cost models and reliability data for example 1

Units	K_j^0	K_j^1	$A_{o,j}$	$A_{max,j}$	ϕ_j
Reactor1	150	0.2 $\times$ outlet flowrate	0.970	0.990	40
Reactor2	175	0.3 $\times$ outlet flowrate	0.975	0.995	20
Flash	114	0.5 $\times$ outlet flowrate			
Compressor	160	0.4 $\times$ outlet flowrate	0.965	0.985	40
SOT	8500				
C_j^c ($/hr/unit)	50				

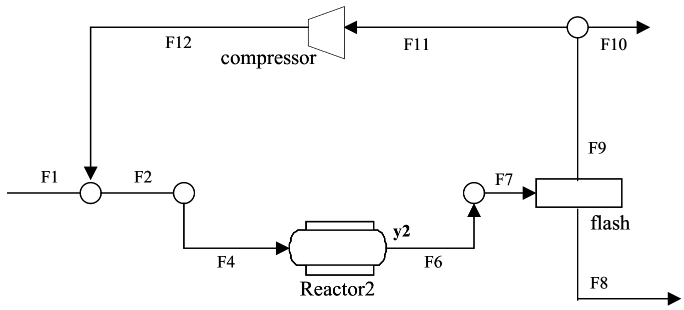


Figure 3.6: Optimal configuration : Example 1

Table 3.4: Results obtained for example 1

Unit	$A_{o,j}$	A_j
Reactor2	0.975	0.995
Compressor	0.965	0.992
System	0.940	0.987

not considered while estimating the annual revenues and raw material costs. Thus the annual profit in the conventional process synthesis provides an overestimate of the expected annual profit. Considering the unplanned shutdown due to equipment inherent reliability characteristics as given in Table 3.3 while estimating the revenues and raw material costs would lead to a new expected annual profit of \$358139 yr^{-1} (842082×0.940 - 433418) for the conventional synthesis formulation, which is lower than the expected profit obtained in the case of the proposed combined formulation.

3.4.2 Example 2: HDA process synthesis

The problem addressed here is the selection of the flowsheet structure, operating conditions and optimal availability requirements for selected equipment in the final flowsheet structure.

Table 3.5: Comparison of results : Example 1

Formulation	y_3	y_4	Maintenance (\$/yr)	CAPEX (\$/yr)	Revenues - Raw material (\$/yr)	Profit (\$/yr)
Process Synthesis	1	0		433418	842082	408660
Combined	0	1	5373	472151	864269	386740

Process description

The HDA process has been described extensively in Douglas (1988) . The superstructure used for this problem is shown in Figure 3.7. The desired reaction in the HDA process is

$$C_6H_5CH_3 + H_2 \longrightarrow C_6H_6 + CH_4$$

In addition to this desired reaction, an undesired reversible reaction occurs to produce diphenyl

$$2C_6H_6 \longleftrightarrow C_12H_10 + H_2$$

The conditions for these gas phase reactions are a pressure of 3.4 MPa (500 psia) and a temperature between 895 K and 980 K. At lower temperatures, the toluene reaction is too slow and at high temperatures, hydrocracking takes place. A ratio of at least 5:1 moles of hydrogen to moles of aromatics is required at the reactor inlet to prevent coking. The hydrogen feed stream (95 % H_2 and 5 % CH_4) is mixed with a fresh inlet stream of toluene, and a hydrogen and toluene recycle. A membrane separator, membrane separator 1, can be used to remove methane from the hydrogen feed stream. The feed mixture is heated in a furnace before being fed to a reactor, adiabatic (reactor #1) or isothermal (reactor #2). The reactor effluent contains unreacted hydrogen and toluene, benzene (the desired product), diphenyl and methane. The effluent is quenched and subsequently cooled in a flash separator, flash 1, to condense the aromatics from the non-condensable hydrogen and methane. The vapor stream coming out of the flash separator contains unreacted hydrogen and methane which can either be recycled back with a small purge, to prevent methane build up, or alternatively, a membrane separator, membrane separator2, can be used to recover valuable hydrogen from the purge stream. Another alternative, as imbedded in the superstructure, is to treat the vapor stream in an absorber to recover benzene lost in the flash separator. The toluene feed can be used as the liquid stream in this absorber. The liquid stream from the flash containing dissolved hydrogen and methane, can either be sent directly to the stabilizer column (dist #1) where lights can be separated from the aromatics, or to another flash separator, flash2, operating at a lower pressure than the first flash. The liquid stream from the stabilizing column, or from flash2, containing benzene, toluene and diphenyl, is fed to a benzene column (dist #2) to get benzene of specified purity (99.97%).

The bottom stream leaving the benzene column contains primarily toluene, with a small amount of biphenyl. Prior to recycling the unreacted toluene, diphenyl should be removed using a flash separator, flash 3, or a toluene column (dist #3).

The objective function selected is the maximization of annualized expected profit. Revenue is based on the sales of benzene, the main product, and fuel values assigned to purge streams. Fixed-charge linear cost estimation models are used as in equation 3.4 to estimate the annualized capital cost of equipment as a function of their inherent availability. A summary of cost data and cost model co-efficients used in this example is given in Tables 3.6 and 3.7 (Kocis and Grossmann, 1989). The corrective maintenance cost, per hour for each piece of equipment, and the SOT considered in this synthesis example are also included in Table 3.6.

Simplified models such as Raoult's law for phase equilibrium and the Fenske-Underwood

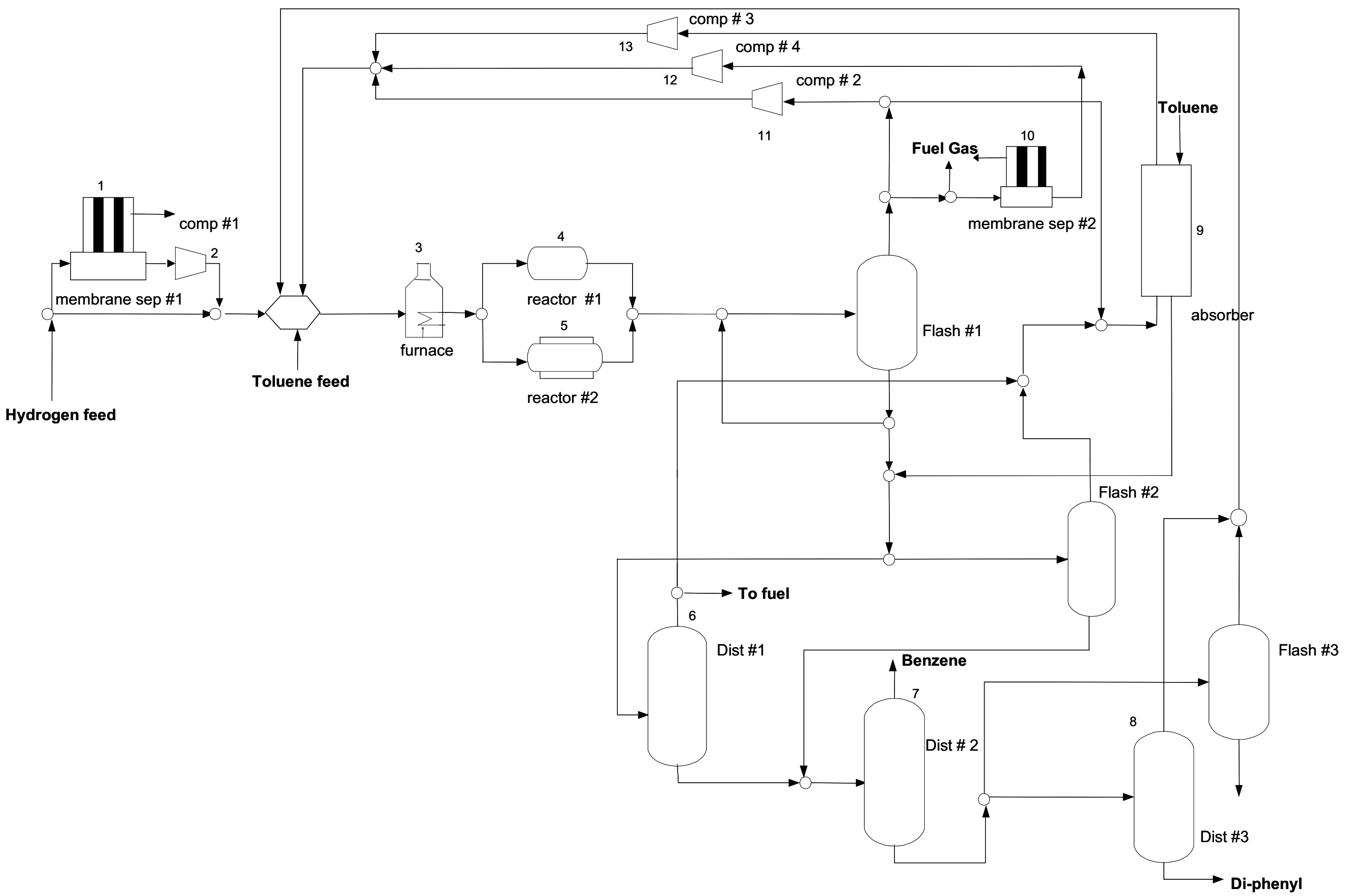


Figure 3.7: Process superstructure: HDA process synthesis example

Table 3.6: Cost Data: HDA example

Feedstock/Product		Costs/price($kg-mol)
Hydrogen feed	95% hydrogen 5% methane	2.5
Toluene feed	100% toluene	14.00
Benzene product	99.97% benzene	19.90
Diphenyl product		11.84
Hydrogen purge	(Heating value)	1.08
Methane purge	(Heating value)	3.37
Utilities	Costs	
Electricity	$0.04 $\times$ kWh^{-1}	
Heating (steam)	$8.0 $\cdot$ 10^{6}kJ^{-1}	
Cooling (water)	$0.7 $\cdot$ 10^{6}kJ^{-1}	
Fuel	$4.0 $\cdot$ 10^{6}kJ^{-1}	
SOT	8500 hrs	
C_j^c	$0.175 $\cdot$ 10^{3}hr^{-1}	

Table 3.7: Fixed charge cost estimation models : HDA example

Investment costs($10^{3}yr^{-1})	Fixed-Charge	Cost Linear Coefficient
Absorber	13.0	1.2 $\times$number of trays 3.0 $\times$vapor flowrate
Compressor	7.155	0.815 $\times$brake horsepower (kw)
Stabilizing column	1.126	0.375 $\times$number of trays
Benzene column	16.3	1.55 $\times$number of trays
Toluene column	3.90	1.12 $\times$number of trays
Furnace	6.20	1.172 $\times$heat duty(10^9kJ yr^{-1})
Membrane separator	43.24	49 $\times$inlet flowrate
Reactor (adiabatic)	74.3	1.257 $\times$reactor volume (m^3)
Reactor (isothermal)	92.875	1.571 $\times$reactor volume(m^3)

equation for distillation columns are used to model process units in the superstructure. A summary of models used for various units is given in Table 3.8. More detailed information can be found in the cited references. These models are sufficiently accurate for the preliminary synthesis stage. A proper correction is made by considering the system availability in the mass balance equation

$$x_p \cdot A_{sys} = D_p \tag{3.9}$$

where x_p and D_p are variables specifying production rate and given demand of main product (benzene). As a result, the production rate is adjusted to compensate for expected

Table 3.8: Models used for different equipment in HDA process synthesis example

Equipment	Model
Absorber	Kremser equation neglect heat effects assume pure solvent 33% tray efficiency fixed recoveries for hydrogen, methane, diphenyl
Compressors	Isentropic compression of ideal gas compressor coefficient 0.3665 compressor efficiency 0.750
Distillation	Minimum reflux (rmin) from Underwood equation reflux reflux (r) $= 1.2 \times$ rmin (heuristic) minimum trays (nmin) from Fenske equation theoretical trays (Gilliland‘s approximation) actual trays(n) $=$ nt/efficiency column tray efficiency 0.500
Expansion valve	Isentropic expansion of ideal gas
Flash	Ideal flash (Raoult‘s law)
Furnace	50% efficiency
Membrane separator	Shortcut method (driving force approximated as arithmetic mean)
Mixers (single inlet stream)	Linear model for heat and mass balances
Mixers	Nonlinear heat balance
Pump	Pressure Out(Pout)$>$ Pressure In (Pin)
Reactor	Plug flow reactor 1. isothermal 2. adiabatic - use average temp
Splitters (single outlet stream)	Linear model for heat and mass balances
Splitters	Split fraction model

production loss due to an inability to meet the same given deterministic demand for the main product.

The corresponding reliability block diagram superstructure is given in Figure 3.8 for the HDA process superstructure. It should be noted that in the reliability block diagram superstructure the complete system is represented on a unit-level such as a distillation column unit and not at an equipment's component level (for example, valves, controllers, etc.). Furthermore, the reliability of small pieces of equipment such as pumps, which contribute significantly to total system reliability but are generally ignored in the conceptual design stage, is considered explicitly while defining the system boundary of the

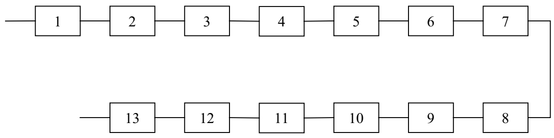


Figure 3.8: Reliability block diagram superstructure: HDA process synthesis example

main equipment unit. The level of aggregation for units used in this work is in line with the limited information and resources generally available at the synthesis stage. Since no redundancy is considered in the process superstructure, the reliability block diagram superstructure is represented as a series system. The availability of simple static units in the main superstructure such as splitters, mixers, flash separators etc. are considered to be unity and are left out. The availability of remaining equipment such as compressors, membrane separators, distillation columns, furnace, absorber and reactor are considered in the estimation of total system availability.

The system availability expression for HDA process can be derived as

$$\begin{aligned} &A_{sys} = \prod A_j \\ &(1 - y_j)(1 - A_{o,j}) + A_{o,j} \leq A_j \leq (1 - y_j)(1 - A_{\max,j}) + A_{\max,j} \qquad \forall j \in J' \end{aligned} \tag{3.10}$$

where is A_j a continuous variable, bounded as $A_{o,j} \leq A_j \leq A_{\max,j}$, specifying the availability of units used for the reliability block diagram. The logical constraints described in equation 3.10 determines the bounds on the availabilities of units in set J', which is the set of units described as discrete choices in the process and reliability block diagram superstructure. The ($A_{0,j}$ and $A_{max,j}$ data and assumed ϕ_j values for major equipment are given in Table 3.9.

The resulting MINLP optimization involved 764 constraints, 769 continuous and 13 binary variables and was solved using the SBB and DICOPT solvers from the GAMS modeling package. Both solvers provided similar results. The global optimality of the results for the HDA process however can not be guaranteed as the BARON global solver is currently not capable to handle a MINLP problem of this scale. The design, as described in Douglas (1988) and base case design was chosen in the initialization step as shown in Figure 3.9. The optimal solution of the HDA process synthesis example was obtained without any convergence problem with an expected annual profit of $\$5434 \times 10^3$ yr^{-1} and is shown in Figure 3.10. The only structural difference in Figures 3.9 and 3.10 is that the membrane separator has been placed on the methane purge stream.

The optimal values for equipment availability and total system availability are provided in Table 3.10. It should be noted that the availabilities of the furnace, membrane separator and reactor remain at their initial availability level, which is explained by the large investment required to improve their availability level. From Table 3.10 it follows that reliability is primarily allocated to the stabilizer and toluene columns, where the optimal required availability equals the maximum availability, with significant improvements

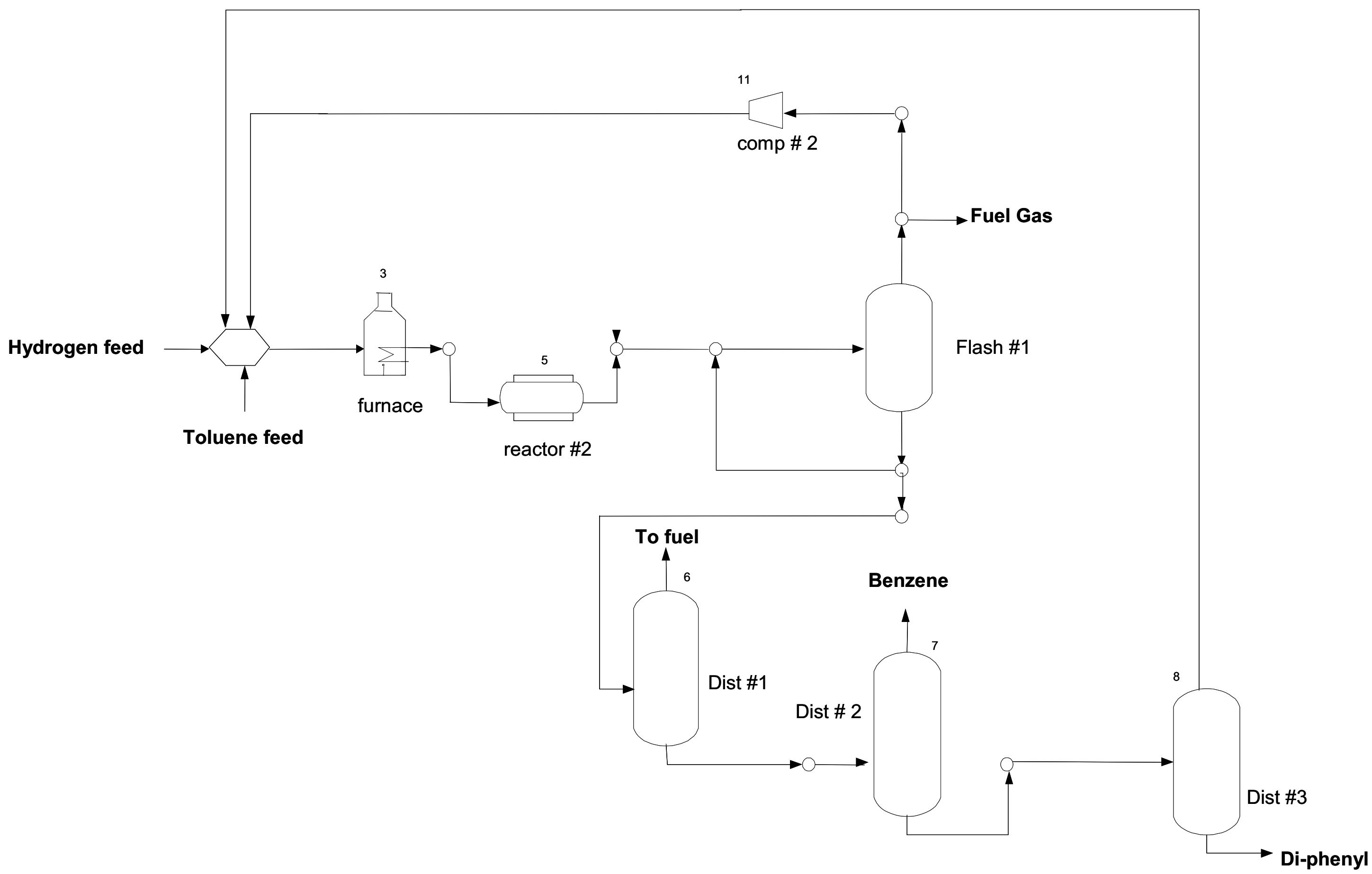


Figure 3.9: Flowsheet structure selected as initial point for HDA process

for compressors 2 and 4, and the benzene column. These optimal availabilities for each unit can then be used as target values during the basic and detailed engineering stage.

The optimal solution obtained in the present work is further compared with the optimal solution obtained by solving the conventional process synthesis model where the inherent availability of a plant is considered to be unity, that is, no unplanned shutdown is considered. Although, the process structure in the optimal solution of conventional process synthesis formulation is the same as the one that is obtained in the proposed formulation, the profits and the optimal design and operating parameters, e.g. sizes, temperatures, pressures etc., differ significantly in both cases. The annual profit obtained in the conventional process synthesis problem formulation is $\$5785 \times 10^3$ yr^{-1}, which is higher than the expected profit obtained solving proposed optimization problem. However, it should noted that since unplanned shutdown is not considered while estimating the annual revenues and raw material costs, the annual profit in the conventional process synthesis provides an overestimated the expected annual profit. Considering unplanned shutdown (1- 0.837) due to equipment inherent reliability characteristics as given in Table 3.9 while estimating the revenues and raw material costs would lead to a new expected annual profit of $\$4650 \times 10^3$ yr^{-1} for the conventional synthesis formulation, which is lower than the expected profit obtained in the case of proposed formulation.

Different optimal design and operating parameters obtained in both cases are shown in Table 3.11. Note that only the design parameters that are used in cost estimation models are included in Table 3.11. The difference in the optimal design parameters can be explained by the fact that for compensating for the production losses that occur in unplanned shutdown (1- 0.884), the hourly production rate of the main product is increased by approximately 11% in the optimal solution of the proposed optimization formulation and hence, other optimal design parameters such as flowrates, temperature, pressures and capacities are changed accordingly. It is worth noting that the productive capacity required to compensate for the unplanned loss was obtained by increasing the size of the equipment or increasing its availability or both, depending on which one was more cost effective.

Finally, the problem statistics and computational times are compared in Table 3.12 and it shows that, compared to the traditional process synthesis problem, the proposed combined optimization problem requires the same order of magnitude computational resources. This can be explained by the equal number of binary variables in both formulations. It is important to emphasize here that although in terms of computational efficiency the two optimization problems, the conventional and the combined one, are comparable the extra efforts is required in the combined case to obtain required reliability and cost for different equipment at the conceptual stage.

3.5 Summary

In this chapter, a new optimization framework was presented that can used to identify an optimal process flowsheet structure and optimal equipment availability requirements at the conceptual design stage. The key feature of this framework is the development of an expected annual profit objective function, which considers the trade-off between initial capital investment and the annual operational costs by appropriately estimating revenues, investment cost, raw material and utilities costs, and maintenance costs as a function of

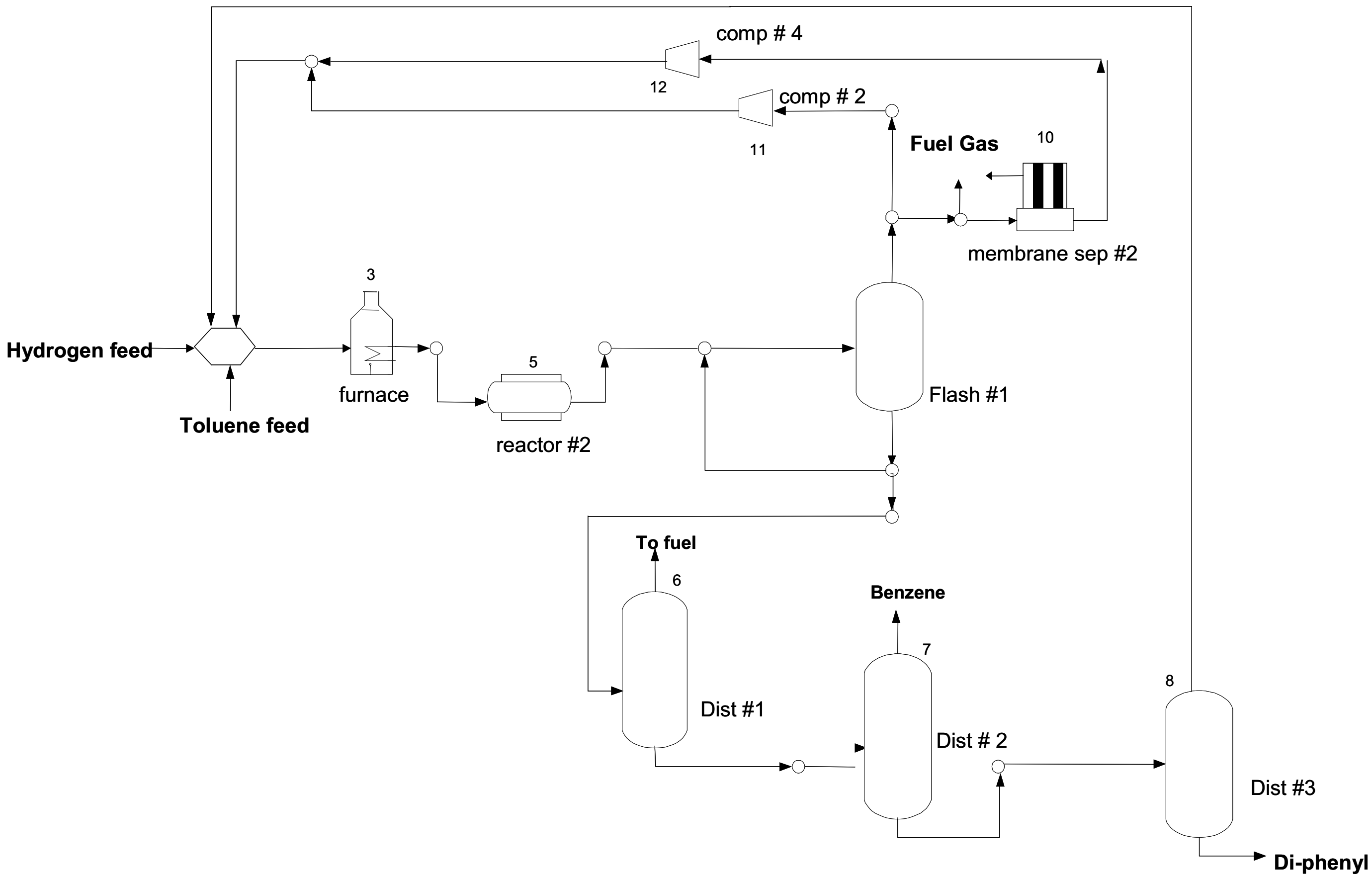


Figure 3.10: Optimal solution: HDA process synthesis example

Table 3.9: Reliability and maintainability data and ϕ value for major equipments: HDA example

	$A_{o,j}$	$A_{max,j}$	ϕ value
Absorber	0.985	0.999	35
Compressors	0.97	0.985	60
Stabilizing column	0.985	0.999	30
Benzene column	0.985	0.999	30
Toluene column	0.985	0.999	30
Furnace	0.975	0.990	30
Membrane separator	0.980	0.985	40
Reactors	0.975	0.989	30

Table 3.10: Results obtained for HDA process synthesis example

Equipment	Initial Availability (A_0)	Optimal Availability (A_i)
Compressor 2	0.970	0.985
Compressor 4	0.970	0.978
Stabilizing column	0.985	0.999
Benzene column	0.985	0.986
Toluene column	0.985	0.999
Furnace	0.975	0.975
Membrane separator	0.980	0.980
Reactor (adiabatic)	0.975	0.975
Total system availability	0.837	0.884

system and component availabilities. In particular, while estimating the initial investment costs of various components, general exponential cost functions are developed to capture the behavior of the component's cost as a function of a component's inherent availability. In addition to this, a proper correction has been made in the process model to account for any loss of production due to unavailability by appropriately increasing the capacity in the final design. The effectiveness and usefulness of the proposed optimization framework is demonstrated for the synthesis example of an HDA process. The results obtained clearly show the trade-off between the initial investment and annual operating cost by converging to an optimum level of availability required for compressors and distillation columns in the final HDA process flowsheet. The practical relevance for obtaining the availability requirement for equipment in the final flowsheet is that once they are estimated at the conceptual stage, one can set these value as a target value to be achieved in the basic engineering and detailed engineering stages of design. The success of the proposed framework hinges on the quality of the cost function used to describe the relationship between component costs and its reliability.

Table 3.11: Comparison of results

Equipment	Conventional approach	This work
Compressor 2 (brake horsepower (kw))	12.398	13.502
Compressor 4 (brake horsepower (kw))	28.251	30.166
Stabilizing column (number of trays)	13.305	13.448
Benzene column (number of trays)	52.199	52.430
Toluene column (number of trays) hline Furnace (heat duty (10^9 kJ yr^{-1}))	10.688 510.0	10.233 570.0
Membrane separator (inlet flowrate kgmol hr^{-1})	289.2	331.98
Reactor (reactor volume (m^3))	98.651	108.821
Revenues - Raw materials ($\times 10^3$\$ yr^{-1})	6965.00	6956.00
Investment cost ($\times 10^3$\$ yr^{-1})	1179.00	1337.00
Maintenance cost ($\times 10^3$\$ yr^{-1})	.	184.6
Profit ($\times 10^3$\$ yr^{-1})	5785.00	5434.745

Table 3.12: Model statistics and computational results for HDA process synthesis example

Model type	Number of Equations	Number of Continuous variables	Number of discrete variables	CPU time (sec.)	NLPs solved
Conventional Process Synthesis	719	723	13	26.5	16
This work	764	769	13	43.6	19

Nomenclature of chapter 3

Index

i	process streams
j	units
k	components in a process stream
p	product

Sets

PR	set of product and by-product streams in the process superstructure
RM	set of raw material streams in the process superstructure

Parameters

SOT	the standard scheduled operating time per year
$\gamma 1_k$	separation ratio for flash in example 1
$\gamma 2_k$	separation ratios for purge splitter in example 1
S_k	supply of component k
D_k	demand of component k
D_p	demand of product p
ϕ_j	constant for equipment j
K_j^0	the annualized fixed charge of a unit j
K_j^1	the annualized variable cost constant of a unit j
C_j^c	cost of corrective maintenance for unit j
$A_{o,j}$	base value for inherent availability of equipment j
$MTBF$	Mean Time Between Failure
$MTTR$	Mean Time To Repair

Variables

Continuous variables

x_j	describing flowrate capacity etc. for equipment j
CI_j	investment cost for equipment j
$CI_{o,j}$	investment cost estimated using the conventional cost model
A_j	inherent availability of equipment j
A_{sys}	total system inherent availability
$C_j^{c,total}$	annual corrective maintenance cost for equipment j
C_{raw}	annual raw material costs
z	hazard rate

Binary variables

y_j	discrete variable describing the existing or non-existing of equipment j

4

Optimal reliable retrofit design of multiproduct batch plants †

A retrofit design problem for a multiproduct batch plant is considered in this chapter using a new perspective that involves explicit consideration of the inherent reliability and maintainability characteristics of existing and new equipment. Todate in multiproduct batch plant retrofitting formulations production capacity is specified by limiting batch size and limiting cycle time. We propose a more robust retrofit solution that is obtained by defining effective production capacity using three parameters: limiting batch size, limiting cycle time and overall plant availability. The novel simultaneous optimization framework, developed in this work, combines a process model and an availability model to obtain optimal size, optimal operating mode and optimal allocation of inherent availability for new equipment during the retrofit stage. The overall problem is formulated as a mixed integer non-linear programming (MINLP) model, and its applicability is demonstrated by solving a number of examples. This framework provides the designer with the opportunity to select the initial inherent availability of new equipment during a retrofit by balancing the cost of design investments against costs of downtime.

4.1 Introduction

it was shown in chapter 3 how reliability optimization can be integrated into the process synthesis problem to obtain target availabilities for components while selecting the process structure. In this chapter, we extend this framework to a special case of process synthesis: a retrofit design problem.

Multiproduct batch plants are designed to produce a number of related products using the same equipment operated in the same sequence. The retrofit design problem for a multiproduct batch plant arises e.g. when new production targets and market selling prices

†Parts of this chapter have been published by Goel et al. (2004a).

have been specified for one or more products or when there is a need to improve the overall effectiveness of the existing plant by improving its reliability and maintainability characteristics. The retrofitting problem consists of finding those plant modifications that involve the removal of existing equipment, i.e. selling old units for salvage value, and/or the purchase of new equipment for the existing plant to maximize net profit.

Vaselenak et al. (1987) have formulated the retrofit design of a multiproduct batch plant as an MINLP problem, where the new equipment is added to the existing plant and is operated either in-phase or out-of-phase with the existing units at each stage. Fletcher et al. (1991) extended Vaselenak et al.'s formulation by removing the restriction that any new equipment must be operated in the same manner for all the products. Yoo et al. (1999) generalize Fletcher et al's formulation by removing the difference between existing and new units and introducing the *group* concept. They define a group as a set of units, which are operated in phase, but those in different groups are operated out of phase. Their model also allows the designer to sell old units with some salvage value. More recently, Montagna (2003) has extended Yoo et al.'s work to include the possibility of installing storage tanks in between the stages. Besides these MINLP formulations, Lee et al. (1993) and Lee and Lee (1996) have presented a heuristic procedure to determine first the positions of new equipment to be added and then subsequently solve the resulting NLP problem to obtain their optimal sizes.

In all these aforementioned problem formulations, the production capacity of a multiproduct batch plant is specified by only two parameters: limiting batch size and limiting cycle time. The retrofitting strategy considered in these approaches focuses on adding new equipment to either increase the limiting batch size or decrease the limiting cycle time for each product or both. The availability of the existing plant and that of the new retrofitted plant is not considered in these approaches.

Due to the inherent failure characteristics of equipment, the occurrence of some unplanned shutdowns is unavoidable which may lead to significant production losses and accordingly reduced profitability. Therefore, it is critical to include information about existing plant availability and the possibility to improve it while adding new equipment during retrofit design to obtain more robust design parameters and profitability projections.

Until now, approaches that consider reliability and maintainability simultaneously with other design parameters have focused primarily on grassroots designs and have been applied mainly to continuous plants. In this chapter, the framework developed in chapter 3 is extended to a case of multiproduct batch plant retrofitting and we develop a new simultaneous optimization framework, which combines a process model and an availability model to obtain optimal size, operating mode and optimal allocation of reliability for new equipment during retrofitting. The existing retrofitting formulation of Yoo et al. (1999) is extended to account for production losses due to unplanned shutdown and maintenance costs and is used as a process model in our work.

4.2 Illustrative example

A small retrofit design problem for an existing two-stage multiproduct batch plant, producing products A and B, is chosen for illustration. For a given new product demand, the retrofit strategy of Yoo et al. (1999) can be used to add new equipment to the existing

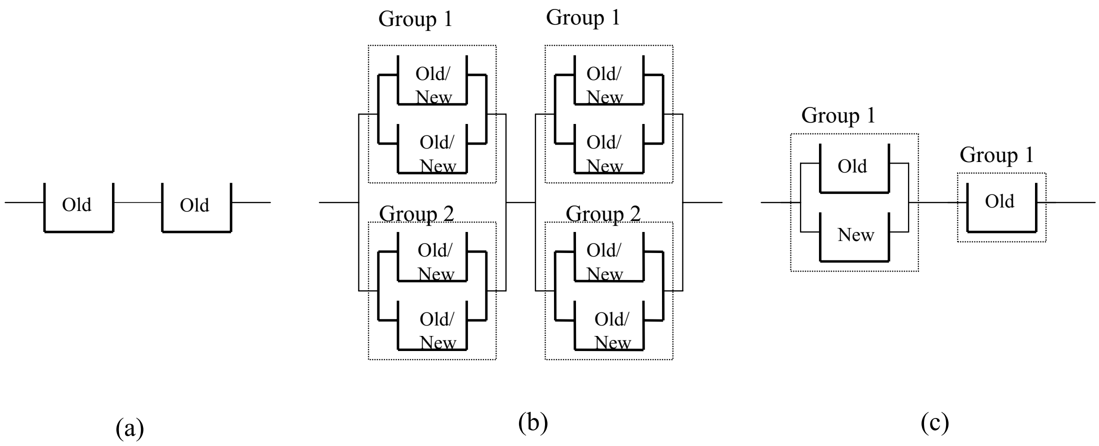


Figure 4.1: Illustrative example: (a) Existing plant, (b) Generalized superstructure and (c) Optimal solution

plant. For the case where only one piece of equipment can be added at each stage of an existing plant, Figure 4.1(a)-(c) shows the existing plant, the generalized superstructure, as described in Yoo et al. (1999)) and an (assumed) optimal solution respectively, for this example.

Consider a case where the reliability and maintainability data for existing equipment and that of new equipment items are given. For simplicity, let us assume the inherent availability, obtained from given reliability and maintainability data, for both existing and new equipment items is 97 %. The overall plant availability of the existing and the new retrofitted plant can be estimated by constructing a reliability block diagram (RBD) (as shown in Figure 4.2). Using a simple analytical expression (described in equation (4.26)) to estimate the system availability for series configurations, the plant availability for both existing and retrofitted plants is estimated to be 94.09 %, and 91.26 %, respectively.

It is important to explain the choice to use a series configuration to represent the reliability block diagram superstructure derived from the process superstructure. As pointed out by Dekker and Groenendijk (1995), the reliability block diagram derived from the process flow diagram should reflect the consequences of failures of the equipment. The consequences of failures are dictated by the process interaction between equipment as defined in the process model. Further, the reliability block diagram should be constructed based on a specific product. In the case of the multiproduct batch plant, different products are manufactured using the same equipment operated in the same number of stages. The optimal production values for each product obtained with the Yoo et al. (1999) process model, is only for the system state where all the underlying equipment (both existing and new) is working. Therefore, in this work, a series configuration is used to represent the reliability block diagram superstructure.

The consequence of assuming a series reliability block diagram superstructure in the present work is that a conservative set of optimal values of design parameters such as batch size, number of batches for each product, capacity of new equipment etc will be obtained. For example, in our illustrative example, the inherent availability of a retrofitted batch plant is estimated to be 91.26 %. The 91.26 % availability means that the retrofit plant will run 91.26 % of the time with ”all” equipment running. In practice, the plant can run at reduced capacity (in the event of equipment failure). For instance, at the second stage of the retrofitted plant, we have two pieces of equipment and in the event of one equipment failure in the second stage, depending on the type of product, the plant can still be operational. Thus, by using a series system, we assume that the combined production of all reduced states is negligible. This could be true for cases where the inherent availabilities of underlying equipments are quite high or not many of the possible reduced states are operational but in other cases the optimal solution obtained with the present formulation will be on the conservative side.

The alternative approach is to enumerate every single possible operational state and assign probabilities for each state and then use a Markovian model to estimate effective production. This approach however can only be applied to a given system configuration and in the present work, the system structure has to be determined. Further, as the number of pieces of equipment increases, it becomes a formidable task to assign probabilities and production capacities to each state. Therefore, for those cases where it is important to consider production due to reduced states, a two-step approach can be undertaken. In the first step, a conservative design should be found using the present formulation and then for a selected structure, a Markovian model can be applied to fine-tune the design parameters.

It is apparent that the addition of new equipment with series to the existing equipment results in the reduction of overall plant availability. Overall plant availability can be improved during retrofitting by procuring more reliable new equipment. For example, let us consider the case where the new equipment is also available in a different type with an inherent availability of 99 %. The overall plant availability of the retrofitted plant would then be 93.14 %. In light of this new information gained from the separate availability analysis of both existing and new retrofitted plants, one can observe the following:

- conventional retrofitting formulations, in this case Yoo et al. (1999), obtain optimal design parameters, size and operating mode, for new equipment without considering production losses due to the unavailability of the existing plant (5.91 %) and the new retrofitted plant (8.74 %). These production losses due to unplanned downtime directly result revenue loss.

- plant availability also impacts the maintenance costs, which are a significant part of the total operating costs. In previous formulations, the maintenance costs are not considered in the objective function. Hence, an opportunity to trade-off maintenance costs and design costs during retrofit strategy is lacking these formulations.

The shortcomings of previous formulations are addressed in our new retrofit problem formulation. The production losses due to unavailability are compensated by a more robust strategy, derived by combining the process model with the availability model. The strategy, described in Figure 4.3, is to match the effective throughput with the projected demand for each product during the retrofit.

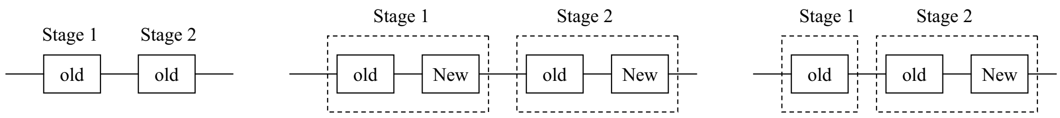


Figure 4.2: Reliability block diagram for illustrative example

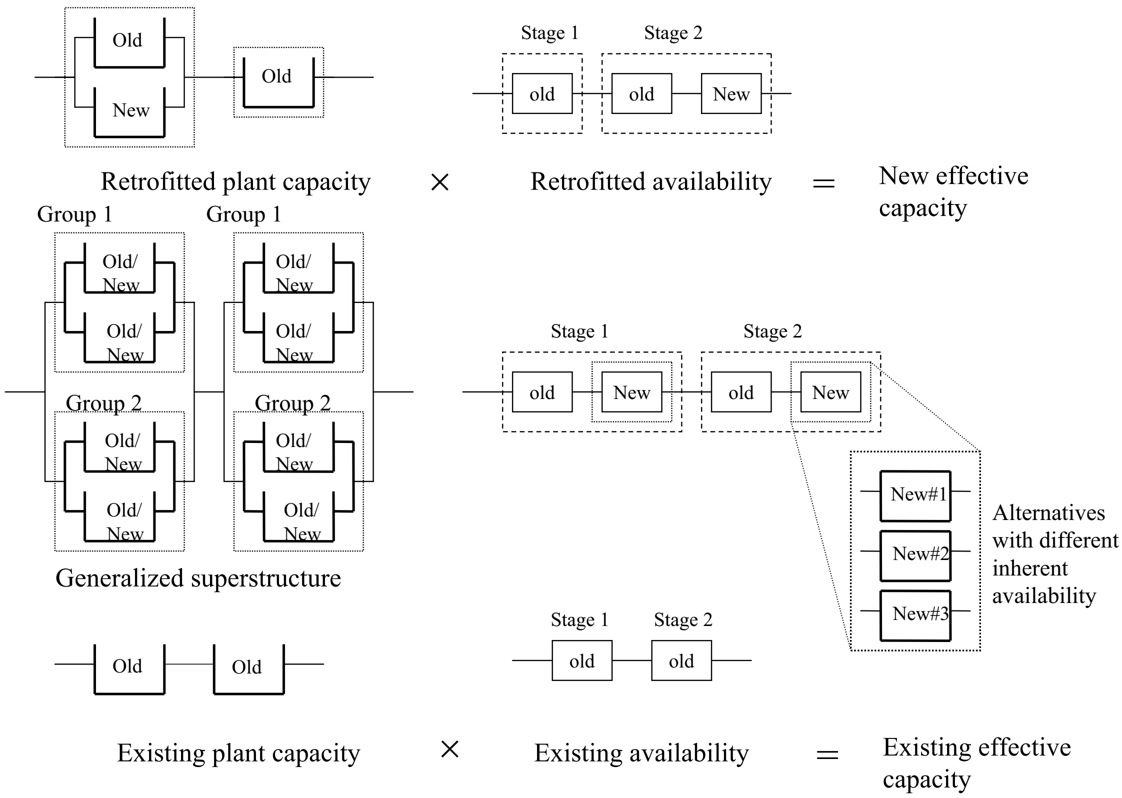


Figure 4.3: New retrofitting strategy

4.3 Modelling framework

In this chapter the effective production capacity of a multiproduct batch plant is defined using three parameters: limiting batch size, limiting cycle time, and overall plant availability in a given time horizon. The first two parameters can be optimized in the retrofit problem by varying the size and the operating mode (in-phase or out-of-phase) of new equipment, whereas plant availability can only be improved by selecting the appropriate plant configurations and levels of initial reliability for new equipment. The key elements of the proposed approach are as follows:

- a process model as described in Yoo et al. (1999), which is extended here to include a) the impact of overall system availability on the overall production , b) the estimation of maintenance costs as a function of equipment availability and c) the estimation of additional capital investment needed for availability improvement of new equipment;

- an availability model that describes the availability of the equipment, both existing and new, and the plant availability as a function of equipment availability
- an expected profit objective function, which takes into account the tradeoff between initial capital investment and the annual operational costs.

The retrofit design problem for multiproduct batch plants can be defined as follows.
Given :

- a new production target, selling price, unit cycle times, and size factors for each product
- the existing plant configuration, including the size, cost, reliability, and maintainability data for existing units
- the number, size, reliability, and maintenance characteristics and costs of new equipment available.

Determine :

- the net expected profit and the revised plant configuration
- the method of grouping parallel units and various processing parameters for each production campaign
- the optimal inherent availability for selected new equipment.

4.4 Problem formulation

In this section, we describe the mathematical foundations and assumptions made in the development of an optimization framework for formulating the retrofit design problem for multiproduct batch plants.

4.4.1 Process model

The process model described in Yoo et al. (1999) is extended in this section. In particular, the model is extended to include the impact of overall system availability on the overall production by considering HA_{sys} to be the maximum time available for production. Second, the capital cost estimation model is extended to become a function of the inherent availability of the equipment. Finally, the maintenance cost estimation model is adapted to include the estimated maintenance cost as a function of the inherent reliability of the equipment.

The products are identified by index i and N represents the total number of products. The batch processing stages are identified by index j, and the total number of stages in the plant is represented by the parameter M. Each stage is assumed to consist of a number of pieces of equipment or units, and the total number of the existing units in a stage j is

N_j^{old}. The total number of new units that can be added during retrofiting in stage j is Z_j . The parallel units (both existing and new) in each stage are identified by index k, and the total number of existing and the new units is given by $N_j^{total}(= N_j^{old} + Z_j)$. Index l is used to indicate the level of inherent availability of new equipment available at the retrofit stage. The N_j^{total} parallel units of stage j can be grouped arbitrarily into groups, identified by index g .

The retrofit strategy is determined by the value of the binary variable y_{ijkg} representing unit-to-group assignments, a pseudo-binary/real variable y_{ijg} indicating whether group g exists or not in stage j, and y_{jkl} indicating the level of inherent availability chosen for new equipment at the design stage. It should be noted that the pseudo-binary/real variable y_{ijg} , as explained in Yoo et al. (1999), is actually a real variable.

For product i in a unit of stage j, the unit cycle time,T_{ij} , is conventionally expressed as

$$T_{ij} = t_{ij} + c_{ij}B_i^{\gamma_j} \qquad \forall i = 1, ..., N, \qquad j = 1, ..., M \tag{4.1}$$

wherec_{ij},t_{ij} and γ_j are fixed parameters and B_i is the limiting batch size for product i . For an overlapping mode, the limiting cycle time for product i is given by

$$T_{Li} = \max_{j=1,...,M}\left(\frac{T_{ij}}{G_{ij}}\right) \qquad \forall i = 1, ..., N \tag{4.2}$$

where

$$G_{ij} = \sum_{g=1}^{G_j^{total}} y_{ijg} \qquad \forall i = 1, ..., N, \qquad j = 1, ..., M \tag{4.3}$$

The limitation on production of each product i is given by constraint

$$n_iB_i \leq Q_i \qquad \forall i = 1, ..., N \tag{4.4}$$

where Q_i is the upper bound on production of product i. The time available for the production of each product within the given time horizon (H) is given by constraint

$$\sum_{i=1}^{N} n_iT_{Li} \leq HA_{sys} \tag{4.5}$$

where A_{sys} is the overall plant availability during the given time horizon.

Combining equations (4.1)-(4.3) yields the constraint

$$\frac{t_{ij} + c_{ij}B_i^{\gamma_j}}{T_{Li}} \geq \sum_{g=1}^{G_j^{total}} y_{ijg} \qquad \forall i = 1, ..., N, \qquad j = 1, ..., M \tag{4.6}$$

The lower and upper bounds on the volume of new units are ensured by the following constraint

$$\begin{aligned} &V_j^L y_{jk} \geq V_{jk} \geq V_j^U y_{jk} \\ &\forall j = 1, .., M, \qquad k = N_j^{old} + 1, ..., N_j^{total} \end{aligned} \tag{4.7}$$

where V_{jk} is the volume of the new unit k in stage j while V_j^L and V_j^U, respectively, are lower and upper limits on the volume for chosen new unit. To ensure the distinct assignment for new units, the following constraints are included

$$y_{jk} \geq y_{j,k+1} \qquad \forall j = 1,..,M, \qquad k = N_j^{old}+1,...,N_j^{total}-1 \tag{4.8}$$

$$V_{jk} \geq V_{j,k+1} \qquad \forall j = 1,..,M, \qquad k = N_j^{old}+1,...,N_j^{total}-1 \tag{4.9}$$

The requirement that the volume is sufficient to process the batch size yields the following constraint

$$\begin{gathered}\left[\sum_{k=1}^{N_j^{old}} V_{jk} + Z_j V_j^U\right](1-y_{ijg}) + \sum_{k=1}^{N_j^{total}} V_{jk} y_{ijkg} \geq S_{ij} B_i \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad g = 1,...,G_j^{total}\end{gathered} \tag{4.10}$$

This constraint contains the product of a real variable V_{jk} and a binary variable y_{ijkg}, which adds difficulty to the convergence. Introducing a continuous positive variable V_{ijkg} linearizes the nonlinearities of the form,$V_{jk}y_{ijkg}$ in equation (4.10) by replacing it with the following set of constraints

$$\begin{gathered}\left[\sum_{k=1}^{N_j^{old}} V_{jk} + Z_j V_j^U\right](1-y_{ijg}) + \sum_{k=1}^{N_j^{total}} V_{ijkg} \geq S_{ij} B_i \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad g = 1,...,G_j^{total}\end{gathered} \tag{4.11}$$

$$\begin{gathered}V_{ijkg} \leq V_j^U y_{ijkg}, \qquad V_{ijkg} \leq V_{jk} \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad k = 1,...,N_j^{total}, \\ g = 1,...,G_j^{total}\end{gathered} \tag{4.12}$$

Each unit k at the stage j can be assigned at most to one group for product i

$$\begin{gathered}\sum_{g=1}^{G_j^{total}} y_{ijkg} \leq 1 \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad k = 1,...,N_j^{total}\end{gathered} \tag{4.13}$$

For unit k to be assigned to group g in stage j for product i , the unit must be installed and the group g must exist

$$\begin{gathered}y_{ijkg} \leq y_{jk} \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad k = 1,...,N_j^{total}, \\ g = 1,...,G_j^{total}\end{gathered} \tag{4.14}$$

$$\begin{gathered}y_{ijkg} \leq y_{ijg} \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad k = 1,...,N_j^{total}, \\ g = 1,...,G_j^{total}\end{gathered} \tag{4.15}$$

Group g can exist in stage j for product i only if unit is assigned to the group g

$$\begin{gathered}y_{ijg} \leq \sum_{k=1}^{N_j^{total}} y_{ijkg} \\ \forall i = 1,..,N, \qquad j = 1,...,M, \qquad g = 1,...,G_j^{total}\end{gathered} \tag{4.16}$$

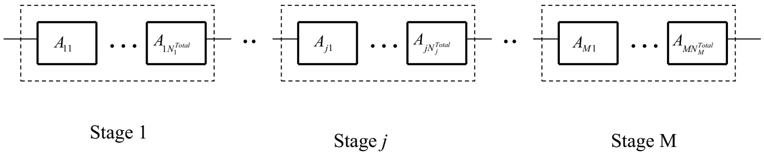


Figure 4.4: Reliability block diagram superstructure

The upper bound of the variable y_{ijg} is one:

$$
\begin{aligned}
&y_{ijg} \leq 1 \\
&\forall i = 1, .., N, \qquad j = 1, ..., M, \qquad g = 1, ..., G_j^{total}
\end{aligned} \tag{4.17}
$$

Redundant assignment to a group with the same value for the objective function can be avoided by introducing the following constraint (Yoo et al. (1999))

$$
\begin{aligned}
&\sum_{k=1}^{N_j^{total}} 2^{N_j^{total}-k} y_{ijkg} \geq \sum_{k=1}^{N_j^{total}} 2^{N_j^{total}-k} y_{ijk,g+1} \\
&\forall i = 1, .., N, \qquad j = 1, ..., M, \qquad g = 1, ..., G_j^{total} - 1
\end{aligned} \tag{4.18}
$$

The cost of new unit k in stage j in the previous formulation is expressed by a function of the volume V_{jk} of the form

$$
f(V_{jk}) = K^0 + K_j^1 V_{jk}^{r_j} \tag{4.19}
$$

where K^0 is the annualized fixed charge and K_j^1 is the annualized proportionality constant of a new unit in stage j, and r_j is the exponential constant of a new unit in stage j, which is considered to be equal to 1 in this work. In this work, to estimate the extra investment needed to improve availability of new equipment, we need to extend the conventional cost model (4.19) to make it a function of the inherent availability of equipment. The new extended model used in this work is given as

$$
f_1(V_{jk}, A_{jk}) = K^0 + K_j^1 V_{jk}^{r_j} + K_{jl}^2 y_{jkl} \tag{4.20}
$$

where K_{jl}^2 is the annualized fixed charge associated with the selection of alternative l for new unit in stage j . The maintenance costs constitute a significant portion of total operating costs. In the previous formulation it is not included into the objective function. The maintenance costs consist of corrective and preventive maintenance costs. Since only inherent availability is considered in this work, preventive maintenance costs are not considered in the objective function. The corrective maintenance cost is dictated by the inherent reliability of each unit j and can be estimated as function of A_{jk}

$$
f_2(A_{jk}) = C_j^c H(1 - A_{jk})/\Delta_j^c \tag{4.21}
$$

where C_j^c and Δ_j^c are the cost and duration of corrective maintenance for unit in stage j .

4.4.2 Availability model

In this section we develop an availability model to estimate the total plant availability (A_{sys}) and equipment availability (A_{jk}), which is used in the development of equations (4.5) and (4.21) in the process model described earlier.
The inherent availability (A_{jk}) of new unit k in stage j, is given by

$$A_{jk} = \sum_{l=1}^{P} \overline{A}_{jl} y_{jkl} \\ \forall j = 1, ..., M, \qquad k = N_j^{old} + 1, ..., N_j^{total} \tag{4.22}$$

where parameter $\overline{A}_{jl}$ describes the inherent availability of alternative l available for new unit in stage j. The following constraint ensures that only one alternative is selected if new unit k is selected in stage j during retrofitting process

$$\sum_{l=1}^{P} y_{jkl} = y_{jk} \qquad \forall j = 1, ..., M, \qquad k = N_j^{old} + 1, ..., N_j^{total} \tag{4.23}$$

The inherent availability for existing units is given by

$$A_{jk} = y_{jk} A_{jk}^{old} \qquad \forall j = 1, ..., M, \qquad k = 1, ..., N_j^{old} \tag{4.24}$$

where A_{jk}^{old} is the parameter describing the inherent availability of existing units. The parameters $\overline{A}_{jl}$ and A_{jk}^{old} can be estimated from historic reliability and maintainability data. For instance, for given constant failure rate λ_{jk}^{old} and repair rate μ_{jk}^{old} for existing unit k in stage j, A_{jk}^{old} can be estimated from

$$A_{jk}^{old} = \frac{\mu_{jk}^{old}}{\mu_{jk}^{old} + \lambda_{jk}^{old}} \qquad \forall j = 1, ..., M, \qquad k = 1, ..., N_j^{old} \tag{4.25}$$

The total plant availability is estimated from the inherent availabilities of units by using a reliability block diagram (RBD). The generic reliability block diagram superstructure is described in Figure 4.4. The total plant availability can be expressed as

$$A_{sys} = \prod_{j=1}^{M} \prod_{k=1}^{N_j^{total}} A'_{jk} \tag{4.26}$$

$$A'_{jk} = A_{jk} y_{jk} + (1 - y_{jk}) \qquad \forall j = 1, ..., M, \qquad k = 1, ..., N_j^{Total} \tag{4.27}$$

where variable A'_{jk} in equations 4.26 and 4.27 is a dummy variable, which is described by relation explained in equation 4.27. Constraint 4.27 makes sure that only the availabilities of equipment selected at each iteration are considered in the estimation of overall system availability (A_{sys}) while the availability of non-existing equipment becomes unity. Constraint 4.27 contains the product of a real variable A_{jk} and a binary variable y_{jk}, which adds difficulty to the convergence. Introducing a continuous positive variable, A''_{jk}, linearizes the nonlinearities of the form, in equation 4.27 by replacing it with the following set of constraints

$$A'_{jk} = A''_{jk} + (1 - y_{jk}) \qquad \forall j = 1, ..., M, \qquad k = 1, ..., N_j^{Total} \tag{4.28}$$

$$\begin{aligned} &A''_{jk} \le \max_l\{\overline{A}_{jl}\} y_{jk}, \qquad A_{jk} - \max_l\{\overline{A}_{jl}\}(1 - y_{jk}) \le A''_{jk} \le A_{jk} \\ &j = 1, ..., M, \qquad k = 1, ..., N_j^{total} \end{aligned} \tag{4.29}$$

Equations (4.22)-(4.24) and (4.29) describe the availability model.

4.4.3 Objective function

The objective function of the problem, which will be maximized, is the expected annualized net profit. Expected net profit is defined here as the net income minus the annualized investment and operating costs. The objective function can be represented as

$$\begin{aligned} \max \quad & \sum_{i=1}^{N} p_i n_i B_i + \sum_{j=1}^{M} \sum_{k=1}^{N_j^{old}} R_{jk}(1 - y_{jk}) \\ & - \sum_{j=1}^{M} \sum_{k=N_j^{old}+1}^{N_j^{total}} (K_j^0 y_{jk} + K_j^1 V_{jk}) - \sum_{j=1}^{M} \sum_{l=1}^{P} \sum_{k=N_j^{old}+1}^{N_j^{total}} K_{jl}^2 y_{jkl} \\ & - \sum_{j=1}^{M} \sum_{k=1}^{N_j^{total}} C_j^c H (1 - A_{jk}) / \Delta_j^c \end{aligned} \tag{4.30}$$

The first term of the objective function is the revenue from product sales. The second term corresponds to the income from disposed batch units while the third and fourth terms correspond to investment costs and the costs of increasing the inherent availability of new batch units, respectively. The last term corresponds to the accumulated corrective maintenance costs.

The problem described by equations (4.1) -(4.30) corresponds to an MINLP problem and can be solved by the outer approximation (OA) algorithm of Duran and Grossmann (Duran and Grossmann, 1986). The MINLP problem described above contains several non-convex terms in constraints and in the objective function. The exponential transformation of non-convex terms, as described in Vaselenak et al. (1987), is used to remove non-convexities. The resulting set of transformed equations is given in appendix B.

4.5 Examples

Three examples are presented to demonstrate that the new retrofit strategy gives greater flexibility and more robust solutions as compared to the conventional formulations. The first two examples are taken from previous works, Vaselenak et al. (1987) and Yoo et al. (1999), respectively. In order to compare with the previously published results, these two examples are solved first for the case where maintenance costs are not considered in the objective function and second for the case where they are included in the objective function. The third example is added to demonstrate the sensitivity of the results with respect to new cost parameters (K_{jl}^2, and C_j^C) introduced in the formulation presented in this work. The examples are solved using the DICOPT++ solver in the GAMS environment on an AMD athlon processor.

Table 4.1: Data input for example 1

	Stage 1	Stage 2
Product	t_{ij}	
A	4.0	6.0
B	5.0	3.0
	S_{ij}	
A	2.0	1.0
B	1.5	2.25
N_{jk}^{old}	1	1
V_{jk}^{old}	4000	3000
A_{jk}^{old}	0.97	0.97
Z_j	2	2
V_j^L	0	0
V_j^U	4000	3000
K_j^0	30560	30560
K_j^1	32.54	32.54
Δ_j^c	10	10
C_j^c	250	250
K_{jl}^2	0, 1000, 2100	0, 1000, 2100
$\overline{A}_{jl}$	0.97, 0.98, 0.99	0.97, 0.98, 0.99
Product	p_i	Q_i
A	1.0	1200000
B	2.0	1000000

4.5.1 Example 1

An existing multiproduct batch plant consisting of two stages produces products A and B. The process data for this example is taken from Vaselenak et al. (1987) and is given in Table 4.1. Table 4.2 also includes three potential alternatives for new equipment with different inherent availabilities and capital costs considered available at the retrofitting stage. The relationship between inherent availability and costs reflects the commonly used exponential relationship between reliability and capital cost.

The example is solved for two different cases: formulation where the maintenance cost model is excluded (case 1) and a formulation where it is included (case 2). The optimal structure and grouping for products A and B for the new retrofitted plant obtained for both cases with the present formulation is similar to that obtained by Yoo et al. (1999). Table 4.2 shows the results obtained using the model of Yoo et al. (1999) and the results obtained using the model developed in this work. It is interesting to note the following from Table 2.

- The proposed formulation results (in both cases) in a lower net profit than reported

Table 4.2: Results for example 1

	Yoo et al. (1999)		This work			
			Case 1		Case 2	
Product	A	B	A	B	A	B
T_{Li}	6	3	6	3	6	3
B_i	2679	905	2779	1039	2755	1007
n_i	448	1104	431	961	435	992
$n_i B_i$	1200000	1000000	1200000	1000000	1200000	1000000
New units	V_{jk}	A_{jk}	V_{jk}	A_{jk}	V_{jk}	A_{jk}
Stage 1	1358		1559	0.97	1511	0.99
Stage 2						
Overall Availability			0.913		0.931	
maintenance costs($)					9300	
Profit($)	3125236		3118698		3108843	

by Yoo et al. (1999). This can be explained by the fact that Yoo et al. (1999) do not account for the revenue loss caused by unplanned downtime and the maintenance costs (in case 2).

- In case 2, the extra capacity needed due to the unavailability of the existing and retrofitted plant is compensated for partly by increasing the volume of new equipment and partly by selecting new equipment with a better inherent availability (option 3). The choice between increasing volume versus increasing inherent availability of new equipment is dictated by marginal cost for capacity (K_j^1) and inherent availability (K_{jl}^2), and the maintenance data (Δ_j^c and C_j^c). Thus it is important to note that the optimal solution is sensitive to the values chosen for K_j^1, K_{jl}^2, Δ_j^c and C_j^c.

- Further it is important to compare case 1 and case 2 results. In case 2, new equipment with a better inherent availability (option 3) and reduced size is chosen as compared to case 1. This could be explained by the fact that maintenance costs are a function of inherent availability only and therefore to reduce maintenance costs, more reliable equipment is chosen for an optimal solution with corresponding compensation in the capacity.

4.5.2 Example 2

This example is taken from Yoo et al. (1999) and it illustrates the disposal of the existing unit. The input data for this example is given in Table 4.3. Figures 4.5 and 4.6 show the optimal plant structure and grouping for products A and B. As shown in Figure 4.6 (for

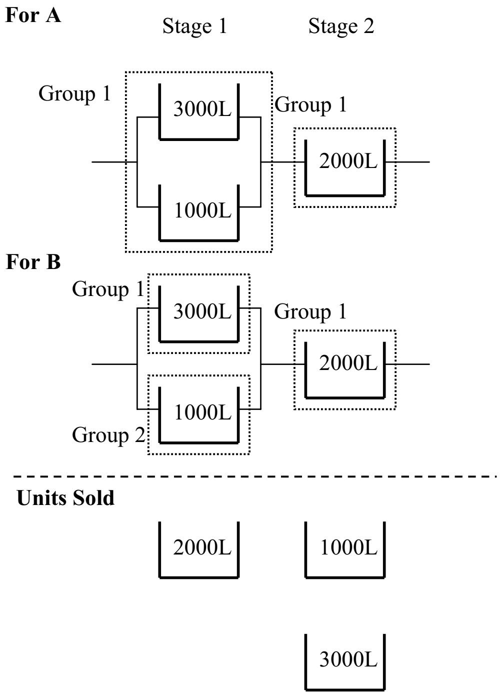


Figure 4.5: The optimal structure for example 2 obtained with Yoo et al. (1999)

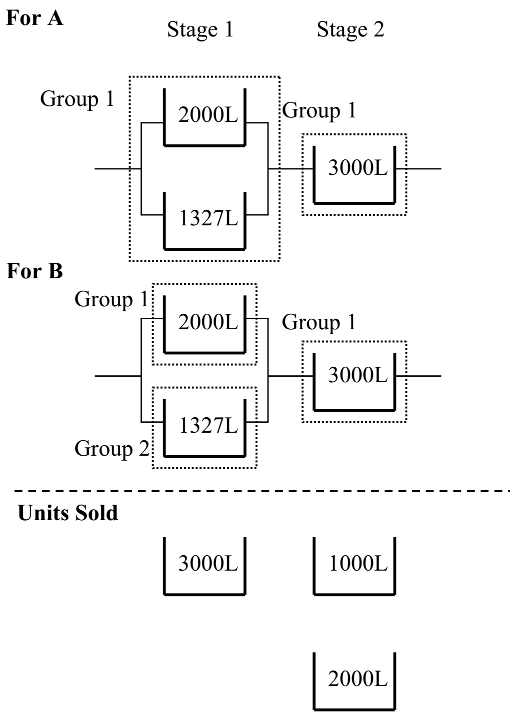


Figure 4.6: The optimal structure for example 2 obtained with the proposed formulation (case 1)

Table 4.3: Data input for example 2

	Stage 1	Stage 2
Product	t_{ij}	
A	1.0	1.0
B	2.0	1.0
	S_{ij}	
A	4.0	2.0
B	1.0	2.0
N_{jk}^{old}	2	3
V_{jk}^{old}	2000, 3000	1000, 2000, 3000
A_{jk}^{old}	0.96, 0.96	0.96, 0.96, 0.96
Z_j	3	2
V_j^L	1000	1000
V_j^U	3000	3000
R_{jk}^{old}	24000, 34000	16000, 24000, 32000
K_j^0	10000	10000
K_j^1	10	10
Δ_j^c	10	10
C_j^c	100	120
K_{jl}^2	0, 300, 800	0, 300, 800
$\overline{A}_{jl}$	0.96, 0.98, 0.99	0.96, 0.98, 0.99
Product	p_i	Q_i
A	0.15	2000000
B	0.10	4000000

case 1), the revised plant obtained by the proposed formulation disposes of the existing equipment unit of volume 3000 L in stage 1, and 1000 L and 2000 L in stage 2, while adding a new unit of 1327 L with inherent availability of 98 % in stage 1. Other optimal design parameters such as batch size, number of batches, limiting cycle time etc. for each product are summarized in Table 4.4. The extra capacity needed due to unavailability of existing and retrofitted plant in example 2 is compensated for partly by increasing the volume of new equipment and partly by increasing total plant availability. In Table 4.4, for case 2, new equipment with a better inherent availability (option 3) and reduced size is chosen compared to case 1.

4.5.3 Example 3

In the previous two examples, it is shown that adding maintenance costs in the objective function mainly influences the inherent availability and capacity of the new equipment. This example is devised to show the sensitivity of the optimal solution with respect to the

Table 4.4: Results for example 2

	Yoo et al. (1999)		This work			
			Case 1		Case 2	
Product	A	B	A	B	A	B
T_{Li}	1	1	1	1	1	1
B_i	1000	1000	831	1326	827	1308
n_i	2000	4000	2404	3014	2417	3056
n_iB_i	2000000	4000000	2000000	4000000	2000000	4000000
New units	V_{jk}	A_{jk}	V_{jk}	A_{jk}	V_{jk}	A_{jk}
Stage 1	1358		1327	0.98	1308	0.99
Stage 2						
New units						
Stage 1	2000		3000		3000	
Stage 2	1000,3000		1000,2000		1000,2000	
Overall Availability			0.903		0.912	
maintenance costs($)					5312	
Profit($)	752000		748430		742512	

new cost parameters K_{jl}^2 and C_j^c . The example 3 considers the retrofitting of an existing plant that produces two products to be processed in three stages. The input data for this example are given in Table 4.5. The example is solved first for the values of K_{jl}^2 and C_j^c given in the Table 4.5, and then solved for two different scenarios. In the first scenario, K_{jl}^2 remains the same but the value of C_j^c is increased by 50 %. Similarly, in the second scenario, C_j^c remains the same but the value of K_{jl}^2 is increased by 50 %. Figures 4.7 and 4.8 show the revised plant obtained for different cases. As shown in Figure 4.7, for nominal and scenario 1 cases, the existing equipment unit of volume 2000 L in stage 1, and 2500 L stage 2 are disposed of while new units of volume 2500 L and 1875 L are added in stages 1 and 2, respectively in the new retrofitted configuration. For scenario 2, the optimal structure is shown in Figure 4.8 where the existing equipment unit of volume 2000 L in stage 1, and 2000 L stage 2 are disposed of while new units of volume 2500 L and 1875 L are added in stages 1 and 2, respectively in the new retrofitted configuration. It is interesting to note here that in all of three cases, the same number of groups is obtained for products A and B and two new pieces of equipment of similar capacities are added.

The result for the nominal case and for the two scenarios are summarized in Table 4.6, note the sensitivity of the optimal results to the values K_{jl}^2 and C_j^c . The points of deviations are different profit projections in each case, and in the case of scenario 2 different existing equipment is disposed. The difference in profitability in nominal case, and scenario 1 can be explained by the increment in the maintenance cost and similarly the selection of lower inherent availability in case 2 is dictated by increased incremental costs K_{jl}^2. It can be observed in table 4.6 that the optimal design parameters are sensitive

Table 4.5: Data input for example 3

	Stage 1	Stage 2	Stage 3
Product		t_{ij}	
A	8	20	8
B	16	4	4
		S_{ij}	
A	2	3	4
B	4	6	3
N_{jk}^{old}	2	2	1
V_{jk}^{old}	2500,2000	2000,2500	2500
A_{jk}^{old}	0.96, 0.96	0.96, 0.96	0.96
Z_j	1	1	2
V_j^L	500	500	500
V_j^U	2500	2500	2500
R_{jk}^{old}	75000, 85000	80000, 95000	90000
K_j^0	35000	35000	40000
K_j^1	30	35	40
Δ_j^c	15	10	15
C_j^c	100	100	150
K_{jl}^2	0, 3000, 6000	0, 3000, 6000	0, 3000, 6000
$\overline{A}_{jl}$	0.96, 0.98, 0.99	0.96, 0.98, 0.99	0.96, 0.98, 0.99
Product	p_i	Q_i	
A	5.5	250000	
B	7.0	250000	

to in this particular example and therefore uncertainty in this data should be minimized by requesting cost and reliability data for different equipment types from suppliers.

The computational statistics are summarized in Table 4.7. The number of binary variables in the third column also include the binary variables needed to represent piecewise linearization of the negative exponential term in the objective function. It should be noted that the computational burden of the proposed formulation is in the same order of magnitude as the computational burden of Yoo et al.'s formulation. In Table 4.7, only the computational details of one of the cases are reported, as there is very little difference in the computational burden for the different cases for the same example.

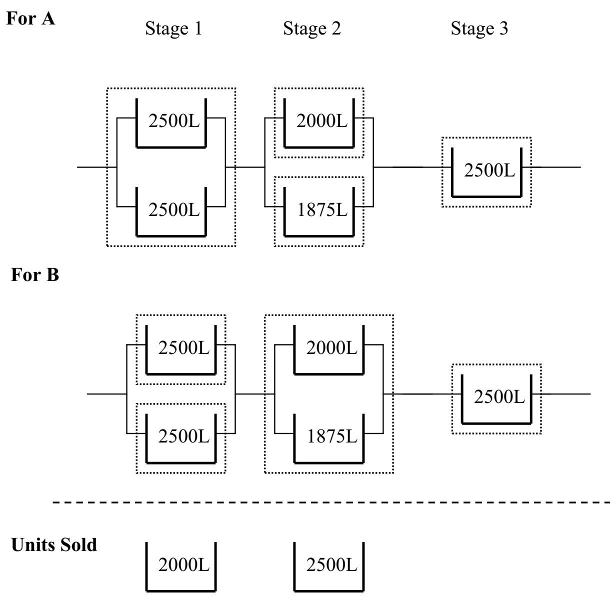


Figure 4.7: The optimal structure for example 3 for Nominal case and Scenario 1

Table 4.6: Results for example 3

	This work					
	Nominal		Scenario 1		Scenario 2	
Product	A	B	A	B	A	B
T_{Li}	10	8	10	8	10	8
B_i	625	635	625	635	625	635
n_i	229	364	229	364	224	356
n_iB_i	194700	240700	194700	240700	192600	238700
New units	V_{jk}	A_{jk}	V_{jk}	A_{jk}	V_{jk}	A_{jk}
Stage 1	2500	0.99	2500	0.99	2500	0.98
Stage 2	1875	0.99	1875	0.99	1875	0.98
Stage 3						
Sold units						
Stage 1	2000		2000		2000	
Stage 2	2500		2500		2000	
Stage 3						
Overall Availability	0.867		0.867		0.850	
maintenance costs($)	7400		11100		8400	
Profit($)	2705810		2702110		2667663	

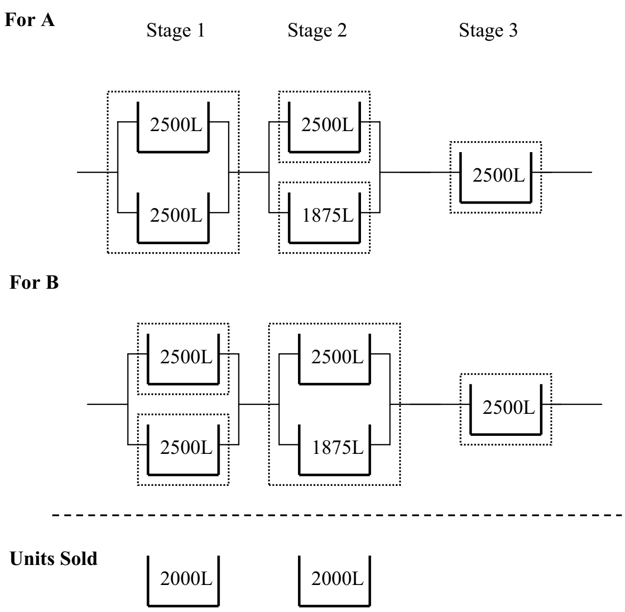


Figure 4.8: The optimal structure for example 3 for Scenario 2

Table 4.7: Computational performance

Example	Formulation	Number of binary variables	Total number of variables	Number of constraints	CPU time
1	Yoo et al. (1999)	60	151	280	1.2
	This work	80	188	317	2.0
2	Yoo et al. (1999)	130	295	592	7.9
	This work	160	356	653	14.2
3	This work	110	257	451	11.6

4.6 Summary

A new optimal retrofit method is presented for multiproduct batch plant design. The key improvements of this method over previous methods are:

- the approach considers the reliability and maintainability of existing and new equipment units and uses this information to quantify the costs of unavailability (revenue loss due to production loss and maintenance costs due to increased unplanned shutdowns)

- it gives a tradeoff between cost of unavailability and the extra capital investment needed to increase the size and/or inherent availability of new equipment while maximizing the overall expected net profit, and thus providing a more robust retrofit solution.

Compared to previous formulations, the proposed new method requires additional data to be specified such as the values of $\overline{A}_{jl}$,A_{jk}^{old}, K_{jl}^2 , C_j^c, and Δ_j^c. It was found that these data can be easily obtained from internal sources such as the company log book, the purchase department, maintenance department, etc. or they can be requested from external sources such as vendors. In cases where the data are not readily available, the cost of obtaining these data can be included in the objective function. The effectiveness of the proposed method was demonstrated using three examples. These examples clearly demonstrate that the new method provides greater flexibility to the designer and allow him or her to obtain a more robust and reliable retrofit strategy for only a moderate increase in computational time.

Nomenclature for chapter 4

Index

i	products
j	stages
k	units
g	groups
l	design alternatives for inherent availability improvement

Parameters

N	number of products manufactured
M	number of batch processing stages in the process
P	number of available design alternatives for inherent availability improvement
G_j^{total}	total number of groups in stage j
H	operating time period
S_{ij}	size factor of product i in stage j
T_{ij}	operation time for product i in stage j
c_{ij}	parameter in the expression for T_{ij}
γ_j	parameter in the expression for T_{ij}
t_{ij}	processing time of product i in stage j
Z_j	number of new units that can be added to stage j
N_j^{old}	number of existing units in stage j
N_j^{total}	total number of parallel units in stage j
V_j^U	maximum volume of new units in stage j
V_j^L	minimum volume of new units in stage$j$
Q_i	upper bound on the production of product i
p_i	expected net profit per unit of product i
$\overline{A}_{jl}$	inherent availability of design alternative l for a unit in stage j
A_{jk}^{old}	inherent availability of existing units
R_{jk}^{old}	annualized capital cost returned when the existing unit k in stage j is sold
r_j	exponential constant for a new unit in stage j
K_j^0	annualized fixed charge for a new unit in stage j
K_j^1	annualized proportionality constant for a new unit in stage j

K_{jl}^2 annualized fixed charge associated with the selection of alternative l for a new unit in stage j
C_j^c cost of corrective maintenance for unit in stage j
Δ_j^c duration of corrective maintenance for a unit in stage j
λ_{jk} constant failure rate of unit k in stage j
μ_{jk} constant repair rate of unit k in stage j

Variables

Continuous variables

n_i number of batches of product i
B_i batch size of product i
T_{Li} limiting cycle time of product i
V_{jk} volume of new unit k in stage j
V_{ijkg} volume of unit k in stage j for product i to be used in group g
A_{jk} inherent availability of unit k in stage j
A_{sys} total plant availability
A'_{jk} dummy variable used in equation 4.26
A''_{jk} dummy variable used in equation 4.28
y_{ijg} indicating whether group g exists or not on stage j

Binary variables

y_{jk} binary variable for unit k in stage j
y_{jkl} binary variable for the selection of availability improvement alternative l of unit k in stage j
y_{ijkg} binary variable for the inclusion of unit k in stage j for the use of product i in group g

5

Reliability and maintainability in process design: multipurpose plants[†]

A combined design, production and maintenance planning formulation for multipurpose process batch plants is extended to incorporate the reliability allocation problem at the design stage in this chapter. A simultaneous optimization framework is presented that addresses the problem of optimal allocation of reliability among equipment in conjunction with the selection of process configuration, production and maintenance planning for multipurpose process plants at the design stage. This new framework provides the designer with the opportunity to select the initial reliability of equipment at the design stage by balancing the associated costs with their impact on the design and availability in the operational stage. The overall problem is formulated as a mixed integer linear programming (MILP)[*] model, and its applicability is demonstrated using a number of examples.

5.1 Introduction

The new optimization frameworks developed in chapters 3 and 4, consider the degrees of freedom available when selecting the initial reliability of components during process design while assuming a fixed minimal repair policy. As a result, the focus of these chapters was on optimizing "inherent" availabilities together with other design parameters. As described in chapter 2, for components with varying failure rate, it is essential to consider the maintenance model describing the impact of various types of maintenance tasks on the availability of equipment. In considering reliability allocation and maintenance planning, the focus of this chapter is on optimizing the "achievable" availabilities of the units (equipment) and overall system. An extended simultaneous optimization framework is

[†]Parts of this chapter have been published by Goel et al. (2003b), and Goel and Weijnen (2004).

[*]In case where non-linearities are present in the process model, the formulation will result in MINLP problem.

presented in this chapter that addresses the problem of optimal, simultaneous allocation of reliability among equipment in conjunction with selecting a process configuration and production and maintenance planning for multipurpose process plants at the design stage.

Multipurpose process plants are used extensively to provide a flexible production platform for the production of many types of chemicals. Different products can be produced in these plants by sharing the available resources, equipment, raw materials, man-power, and utilities, over the planning time horizon. The inherent operational flexibility offered by these plants, however, poses considerable complexity in the design and operation of these plants. For instance, the flexibility obtained by sharing equipment can be affected by unplanned equipment shutdowns due to equipment failure. Thus to achieve timely production of products at a minimum cost, it is crucial to consider plant availability during the design process and operation of multipurpose plants. Plant availability, as described in the preceding chapters is determined by inherent equipment reliability characteristics, and the implemented maintenance policy.

As stated earlier, the initial reliability characteristics of a plant are decided at the design stage where decisions about the process system configuration (e.g. redundancy, buffer storage) and the initial equipment reliabilities are made and can be improved by increasing the reliability of equipment and/or adding redundancy. Once the design has been fixed, high process availability during the operational stage can be achieved by effective maintenance. In general, the problems of determining the optimal reliable design and maintenance policy are interdependent (see Figure 5.1). Therefore, the challenge to achieve high process availability at the operational stage can be formulated as having the following key elements.

- A reliability model aimed at identifying the optimal process structure and reliability of process equipment units at the design stage

- A maintenance model aimed at identifying the optimal maintenance policy to be implemented at the operational stage

- Appropriate linking variables that provide the mechanism for quantifying the interactions between process model, and maintenance and reliability models within an optimization framework.

Several detailed formulations have been proposed in the past decade for multipurpose plants to address the problem of achieving high process availability by introducing reliability and maintenance characteristics of units in the design, planning and scheduling formulations (Dedopoulos and Shah, 1995a; Pistikopoulos et al., 2001; Sanmarti et al., 1997). In most of the aforementioned approaches an important element is left out - *the reliability optimization problem at the design level*. Maintenance can restore degraded performance to initial levels but cannot significantly improve it. Significant improvement would require the selection of different and better equipment at the design stage. Therefore, the initial reliability of each process unit should be considered as another *degree of freedom* in the design problem.

In this chapter we address this gap and present a mathematical formulation for integrated optimal reliable design, production and maintenance planning for multipurpose process plants. The existing formulation of simultaneous design, production and maintenance planning of multipurpose plants (Pistikopoulos et al., 2001) is extended to include

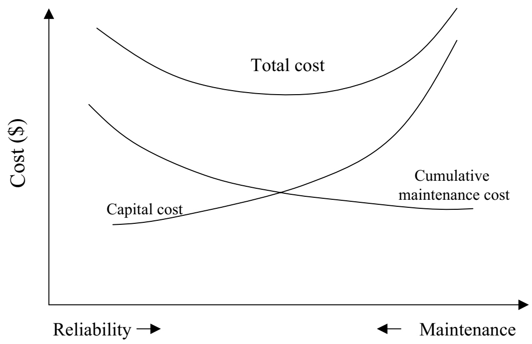


Figure 5.1: Reliability vs. maintenance costs to achieve a high availability

the decisions that must be made when selecting the initial reliability of equipment units at the design stage. The overall problem is formulated as a mixed integer linear programming (MILP) model. The resulting MILP problem employs the same rigorous maintenance and production planning models used in the earlier formulation of Pistikopoulos et al. (2001) with the addition of a reliability allocation model, which is the contribution of this work. It should be noted that the application of the proposed framework requires additional data about different reliability improvement options that are available at the design stage, with their associated additional costs. These data can usually be obtained from company in-house purchase and maintenance departments or from external equipment suppliers. In cases where the data for a particular unit are not readily available, the cost of additional resources required to generate these data can be included in the total additional costs.

5.2 Modeling Framework

Pistikopoulos et al. (2001) recently proposed a system effectiveness optimization framework for a simultaneous approach towards design, production and maintenance planning of multipurpose process plants. In their model they use a piecewise-constant increasing equipment failure rate for all equipment and develop an analytical preventive maintenance optimization model to reflect the effect of a high failure rate on equipment uptime in each period, see Figure 5.2. Pistikopoulos et al. (2001) propose an objective function, which balances additional maintenance costs with increased profit. The initial failure rate $(t = 0)$ of each process unit, however, is considered fixed in their model, i.e. the initial reliability characteristics of equipment are considered to be fixed.

As outlined in the introduction, the availability of equipment is a function of its reliability and the implemented maintenance policy. Therefore, for fixed target availability, equipment with different initial failure rates $(t', t = 0)$ (see Figure 5.3), the design decisions such as volume, and the implemented maintenance policy are expected to be different. We have, therefore, extended their formulation to include a reliability optimization

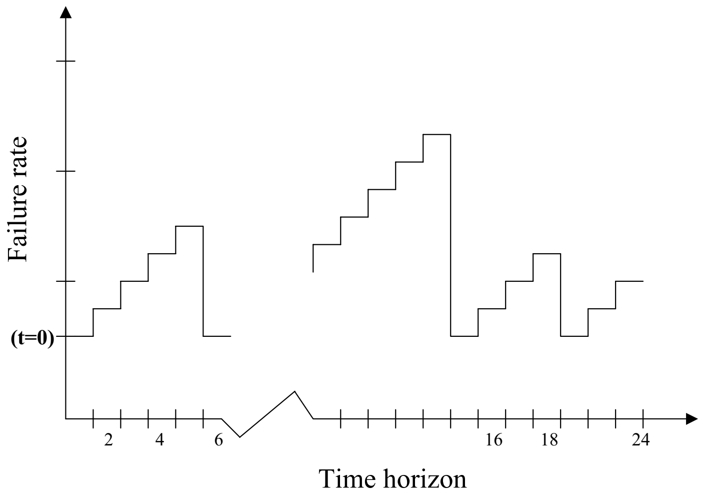


Figure 5.2: Failure rate profile without considering reliability optimization at design stage

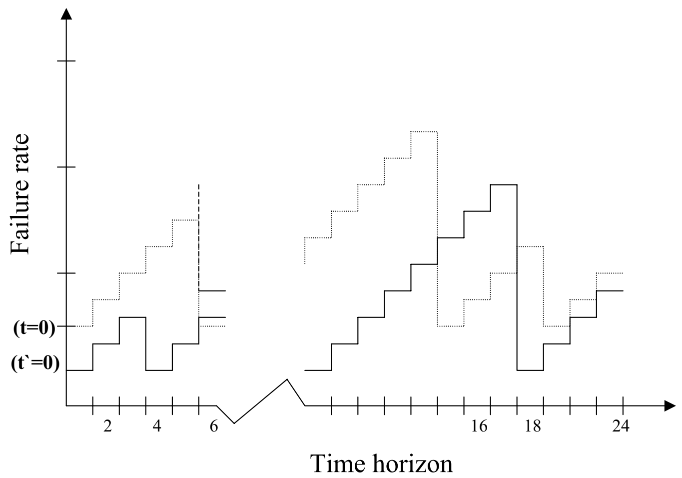


Figure 5.3: Failure rate profile with reliability optimization at design stage

model where the initial reliability of equipment is considered to be a decision variable and the initial reliability of equipment is identified at the design stage.

Different reliability optimization formulations exist in reliability engineering literature, and are described in chapter 2. Depending on the choice of decision variables, whether it is the equipment's reliability or the number of parallel units added to each piece of equipment or both, different reliability optimization formulations can be formulated. In this work, we consider a reliability allocation formulation where, for a specific system configuration, different levels of initial process reliability can be achieved by selecting equipment at different levels of cost and reliability. Using proper mathematical modification the current framework can be extended to cover other formulations. For reliability allocation problems, the relation between the cost and reliability of equipment can be described either as a closed form exponential continuous function (Mettas, 2000) or as discrete cost-reliability data sets (Majety et al., 1999). The amount of information available at the design stage and the level of complexity of the problem considered, influences the choice between discrete and continuous representation (see appendix A for more information). In this chapter, to avoid non-linearities in the final formulation, we consider discrete cost-reliability data sets for the equipment. The key elements in our proposed framework are identified as follows.

1. The simple product state-task network (STN) described by Kondili et al. (1993) for batch transformations are described;

2. A combined aggregate production and maintenance planning model, proposed by Pistikopoulos et al. (2001), which describes the interactions between production and maintenance planning by associating the utilization of process assets and resources with the availability of equipment

3. A reliability allocation model that identifies the initial reliability characteristics of equipment at the design stage by enabling a trade-off between the additional capital costs of the design and the impact of improved reliability on the equipment uptime[†]

4. An objective function, that provides a trade-off between increased revenues due to extra equipment availability and two additional costs a) increased capital costs for improving a unit's initial reliability and b) increased operational costs for preventive actions.

5.3 Problem Definition

The integrated optimal reliable design, production and maintenance planning problem for multipurpose process plants considered in this paper is stated as following:
Given:

- production recipes (STN), i.e. the processing time for each task at the suitable units
- potentially available processing units with available different sizes, cost and reliability
- demand for products in each time period
- the time horizon under consideration
- reliability and maintenance characteristics of units
- the operating and capital cost data involved in the plant process installation and operation;

Determine:

[†]Equipment's uptime is same as equipment's achievable availability. The term "uptime" is used here to maintain consistency with the formulation of Pistikopoulos et al. (2001)

- the units selected and size of each unit
- the optimal initial reliability for each unit at the design stage
- the optimal maintenance plan describing the number and the time of preventive maintenance actions in the operational stage
- optimal production plan.

5.4 Mathematical formulation

The multiperiod planning model adopted in this work, is based on a state-task network (STN) process representation proposed by Kondili et al. (1993). The STN is a directed graph with two types of distinctive nodes, the state nodes denoted by a circle and the task nodes denoted by a rectangle. The time horizon is discretized into a number of time periods, of equal duration, H. The indices j, and k denotes the units and the available sizes for a unit while index l denote the initial failure rate of a selected unit. Tasks are denotes by index i. A complete notation list used in the formulation of the integrated optimal reliable design, production and planning model is provided in the nomenclature.

The following are the basic constraints of the optimal reliable design, production, and maintenance planning model. The main design attributes in the following problem formulation are:

- selection of unit (E_j)
- selection of size (E_{jk}) and initial failure rate (E_{jl}) for a selected unit j
- volume of the unit (V_j)
- expected uptime (U_{jt}) of unit j during period t
- number of batches N_{ijt} of task i processed in unit j over time period t

5.4.1 Design structure constraints

$$E_j = \sum_{k \in \psi_j} E_{jk} \qquad \forall j \tag{5.1}$$

$$V_j = \sum_{k \in \psi_j} \overline{V}_{jk} E_{jk} \qquad \forall j \tag{5.2}$$

The design constraints (5.1) and (5.2) determine the system structure by selecting units and their sizes out of a superstructure of units.

5.4.2 Time resource utilization constraints

$$\sum_{i \in I_j} p_i N_{ijt} \leq U_{jt} \qquad \forall j, t \tag{5.3}$$

The resource utilization constraints state that the total processing time on a unit cannot exceed the expected uptime of the unit.

5.4.3 Capacity Constraints

$$\phi_{ijt}^{\min} \sum_{k \in \psi_j} \overline{V}_{jk} E_{jk} N_{ijt} \leq B_{ijt} \leq \phi_{ijt}^{\max} \sum_{k \in \psi_j} \overline{V}_{jk} E_{jk} N_{ijt} \qquad \forall i, j \in K_i, t \tag{5.4}$$

Capacity constraints (5.4) suggest that batch sizes are allowed to vary between minimum and maximum values.

Introducing a continuous positive variable $\overline{EN}_{ijkt}$ can linearize the nonlinearities of the form $N_{ijt}E_{jk}$, in equation 5.4 (Voudouris and Grossmann, 1992).

$$\overline{EN}_{ijkt} \equiv N_{ijt} E_{jk} \qquad \forall i, j \in K_i, k \in \psi_j, t \tag{5.5}$$

together with the following constraints

$$\overline{EN}_{ijkt} \leq N_{ij}^{\max} E_{jk} \qquad \forall i, j \in K_i, k \in \psi_j, t \tag{5.6}$$

$$N_{ijt} = \sum_{k \in \psi_j} \overline{EN}_{ijkt} \qquad \forall i, j \in K_i, t \tag{5.7}$$

where $N_{ij}^{\max}$ describe the maximum number of batches of task i that can be produced in unit j and is given by

$$N_{ij}^{\max} = \frac{H(1 - \Delta_j^c \max_{l \in \zeta_j} \{\bar{\lambda}_{jl}\})}{p(i)} \qquad \forall i, j \in K_i \tag{5.8}$$

Substituting equation (5.5) into equation (5.4), the capacity constraints are now given as

$$\phi_{ijt}^{\min} \sum_{k \in \psi_j} \overline{V}_{jk} \overline{EN}_{ijkt} \leq B_{ijt} \leq \phi_{ijt}^{\max} \sum_{k \in \psi_j} \overline{V}_{jk} \overline{EN}_{ijkt} \qquad \forall i, j \in K_i, t \tag{5.9}$$

The relevant set of capacity constraints covers (5.6)-(5.9).

5.4.4 Material Balance constraints

$$S_{st} = S_{s,t-1} + \sum_{i \in \overline{T}_s} \sum_{j \in K_i} \overline{\rho}_{is} B_{ijt} - \sum_{i \in T_s} \sum_{j \in K_i} \rho_{is} B_{ijt} - D_{st} \qquad \forall s, t \tag{5.10}$$

The material balance constraints state that the amount of material in state s at the end of period t is the amount in storage at the end of the last period, plus the amount added by producer task, subtracting the amount consumed by consumer tasks and the amount delivered.

5.4.5 Demand Constraints

$$D_{st}^{\min} \leq D_{st} \leq D_{st}^{\max} \qquad \forall s, t \tag{5.11}$$

The demand constraints (5.11) suggest that the demand of state s in each period t fluctuates between lower and upper bounds.

5.4.6 Utility constraints

$$\sum_{i}\sum_{j\in K_i}\sum_{\omega=0}^{p_i-1}(\beta_{uij\omega}N_{ijt}+\delta_{uij\omega}B_{ijt})\leq A_{ut}^{\max}H \qquad \forall u,t \tag{5.12}$$

The utility constraints (5.12) ensure that the utilization level of utilities such as steam, cooling water, manpower etc. does not exceed corresponding availability constraints.

5.4.7 Reliability Allocation Constraints

$$\gamma_{j1}=\sum_{l=1}^{\zeta_j}\bar{\lambda}_{jl}E_{jl} \qquad \forall j \tag{5.13}$$

$$E_j=\sum_{l\in\zeta_j}E_{jl} \qquad \forall j \tag{5.14}$$

$$\gamma_{j\theta}=\gamma_{j\theta-1}+\alpha_j, \qquad \forall j, 2\leq\theta\leq\tau_j \tag{5.15}$$

Reliability allocation constraints (5.13) determine the units' initial failure rate at the design stage. Constraints (5.14) ensure that only one kind of failure rate is selected at the design stage, while constraints (5.15) describe $\gamma_{j\theta}$ transition between periods $2\leq\theta\leq\tau_j$.

5.4.8 Failure Rate Constraints

$$\lambda_{jt}=\sum_{\theta=1}^{\tau_j}\gamma_{j\theta}Z_{jt\theta} \qquad \forall j,t \tag{5.16}$$

$$X_{jt}\leq E_j \qquad \forall j,t \tag{5.17}$$

$$Z_{jt\theta}\leq X_{j,t-\theta} \qquad \forall j,t,\theta=1...\tau_j \tag{5.18}$$

$$\sum_{\theta=1}^{\tau_j}Z_{jt\theta}=E_j\forall j,t \tag{5.19}$$

Constraints (5.16) -(5.19) describe the failure rate of unit λ_{jt} as a function of maintenance policy implemented in the operational stage.

In constraints (5.16), the nonlinearities of the form $\gamma_{j\theta}Z_{jt\theta}$ can be linearized by introducing a continuous variable $h_{jt\theta}$, (Floudas, 1995)

$$h_{jt\theta}\equiv\gamma_{j\theta}Z_{jt\theta} \tag{5.20}$$

together with the constraints

$$\begin{aligned}\gamma_{j\theta}-\gamma_{j\theta}^{\max}(1-Z_{jt\theta})\leq h_{jt\theta}\leq\gamma_{j\theta}-\gamma_{j\theta}^{\min}(1-Z_{jt\theta}) \qquad &\forall j,t,\theta=1...\tau_j\\ \gamma_{j\theta}^{\min}Z_{jt\theta}\leq h_{jt\theta}\leq\gamma_{j\theta}^{\max}Z_{jt\theta} \qquad &\forall j,t,\theta=1...\tau_j\end{aligned} \tag{5.21}$$

where,$\gamma_{j\theta}^{\min}$ and $\gamma_{j\theta}^{\max}$ are lower and upper limit on variable $\gamma_{j\theta}$, respectively and defined by following expressions

$$\gamma_{j\theta}^{\min} = \min_{l\in\zeta_j}\left\{\bar{\lambda}_{jl}\right\} \qquad \forall j \tag{5.22}$$

$$\gamma_{j\theta}^{\max} = \max_{l\in\zeta_j}\left\{\bar{\lambda}_{jl}\right\} + \tau_j\alpha_j \qquad \forall j \tag{5.23}$$

Combining equation (5.20) with (5.16), the equation (5.16) can be replaced by

$$\lambda_{jt} = \sum_{\theta=1}^{\tau_j} h_{jt\theta}\forall j,t \tag{5.24}$$

The relevant set of constraints for failure rate comprises (5.17), (5.18), (5.19), (5.21)-(5.24).

5.4.9 Uptime Definition Constraints

$$U_{jt} = H(E_j - \Delta_j^c\lambda_{jt}) - \Delta_j^p X_{jt} \qquad \forall j,t \tag{5.25}$$

Assuming that equipment can fail both during minimal repair and preventive maintenance, the expected equipment uptime for unit j during period t is given by constraints (5.25) (Dedopoulos and Shah, 1995a).

5.4.10 Objective function

$$\begin{aligned}\max\Phi = &\sum_{st}\eta_{st}D_{st} - \sum_{ut}C_{ut}\sum_{i}\sum_{j\in K_i}\sum_{\omega=0}^{p_i-1}(\beta_{uij\omega}N_{ijt} + \delta_{uij\omega}B_{ijt})\\ &-\sum_{jt}C_{jt}^{p}X_{jt} - \sum_{jt}C_{jt}^{c}(HE_j - U_{jt} - \Delta_j^p X_{jt})/\Delta_j^c\\ &-\sum_{j}\left(K_j^0E_j + K_j^1\sum_{k\in\psi_j}\overline{V}_{jk}E_{jk} + \sum_{l\in\zeta_j}K_{jl}^2E_{jl}\right)\end{aligned} \tag{5.26}$$

In expression (5.26), the first term represents the profit generated by the delivered products, the second term denotes the total cost of utilities, and the third and fourth term correspond to preventive and corrective maintenance costs, respectively. Finally, the fifth term corresponds to design costs as a function of equipment initial failure rate.

5.5 Examples

Two illustrative examples are presented to show the applicability of the model. The problems are modeled and solved within the GAMS (Brooke et al., 1988) modeling environment using the CPLEX MILP optimizer. The computations were carried out on an AMD athlon processor.

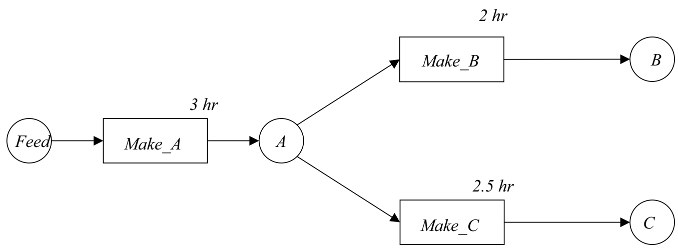


Figure 5.4: STN for example 1

Table 5.1: Design Alternatives: Example 1

unit type	Available unit sizes ($\overline{V}_{jk}$)				Available unit sizes		
					$l = 1$	$l = 2$	$l = 3$
Unit1	150	175	200	250	0.002	0.0015	0.001
Unit2	50	80	150	200	0.004	0.003	0.002
Unit3	60	100	125	200	0.002	0.0015	0.001

5.5.1 Example 1

The first illustrative example is taken from Pistikopoulos et al. (2001) where a multipurpose plant (as described by the STN shown in Figure 5.4) must be designed at a maximum expected profit to produce two main products B and C. Three potential units of different sizes and initial failure rates are considered to be available at the design stage. The available sizes and initial failure rates for different units are given in Table 5.1. Unlimited storage capacity is assumed for feedstock and final products B and C, while no storage facility is considered for intermediate A. Unit 1 is suitable for task Make_A, while units 2 and 3 can perform tasks Make_B and Make_C.

This example assumes an operating horizon of two years, discretized in 24 one-month time periods. The demand for product B and C is assumed to range between 20000 and 50000 units for each month period with a unit price per period of $\eta_{st} = 0.5$ for both B and C. It is furthermore assumed that at least one preventive maintenance action must be performed for each chosen unit every six time periods, i.e. $\tau_j = 6$. The cost and

Table 5.2: Cost Data: Example 1

unit type	Fixed cost (K_j^0)	Size cost factor (K_j^1)	Failure rate cost factor (K_{jl}^2)		
			$l = 1$	$l = 2$	$l = 3$
Unit 1	5000	100	0	2200	6000
Unit 2	20000	300	0	2200	6000
Unit 3	20000	350	0	2200	6000

Table 5.3: Failure Rate and Maintenance Data: Example 1

unit type	α_j	$\Delta_j^c(h)$	C_{jt}^c	$\Delta_j^p(h)$	C_{jt}^p
Unit 1	0.001	24	50	6	1000
Unit 2	0.001	40	100	9	2000
Unit 3	0.001	30	75	7	2000

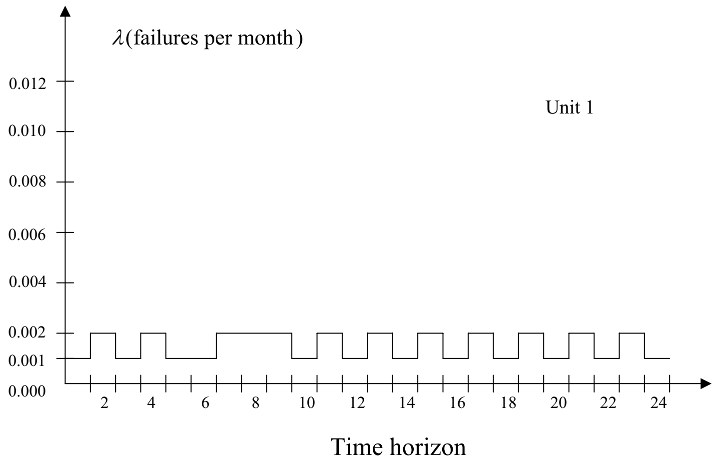


Figure 5.5: Optimal failure rate profile for unit 1: Example 1

maintenance data for all three units are given in Tables 5.2 and 5.3. Note that in Table 5.2, we introduced the additional cost data for improving the initial failure rate of a unit (K_{jl}^2). The assumed additional cost data in the 5.2 reflects the commonly used exponential relationship between initial reliability and capital cost.

The resulting MILP problem involves 480 binary variables, 2042 continuous variables

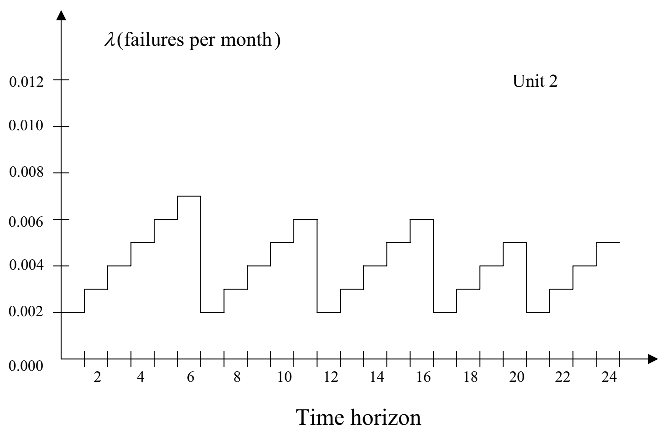


Figure 5.6: Optimal failure rate profile for unit 2: Example 1

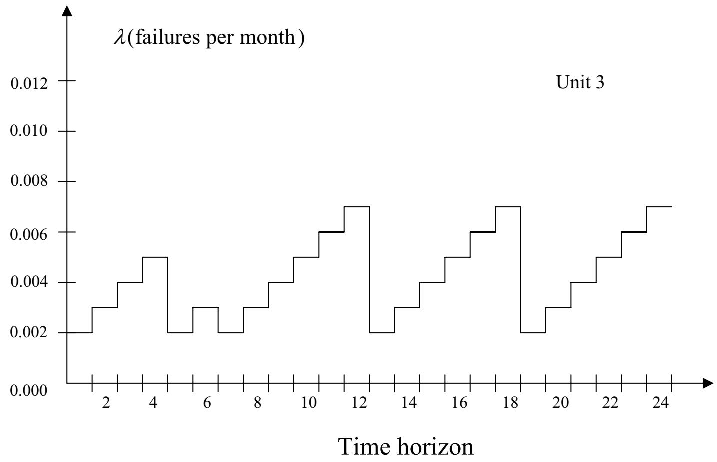


Figure 5.7: Optimal failure rate profile for unit 3: Example 1

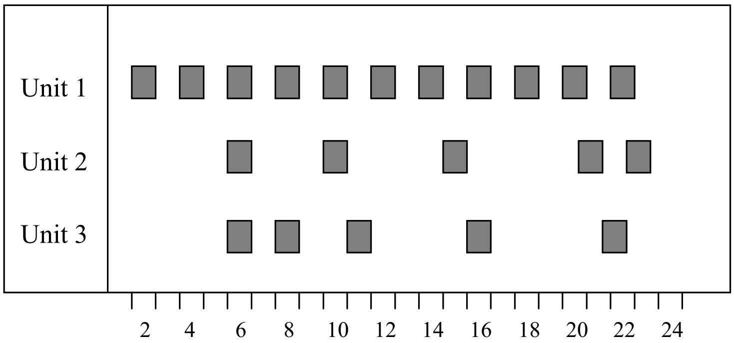
Table 5.4: Results: Example 1

	This work		Pistikopoulos et al (2001)	
unit type	Optimal size	Optimal initial failure rate	Optimal size	Initial failure rate
Unit 1	250	0.001	250	0.002
Unit 2	150	0.002	80	0.004
Unit 3	60	0.002	125	0.002

and 3247 constraints and was solved in 0.33s CPU time with a relative gap of 0.035. The optimal equipment sizes and initial failure rates, obtained from the solution of the proposed model, are depicted in Table 5.4. The corresponding failure rate profiles for the three units are shown in Figures 5.5 ,5.6,5.7, respectively. The corresponding maintenance policy is given in Figure 5.8. A large equipment size was selected for unit 1, this is explained by the importance of unit 1, as it is the only unit that can be used for task Make_A. Furthermore, reduced initial failure rates of 0.001 and 0.002 have been allocated at the design stage for unit 1 and unit 2, respectively.

Table 5.5: Design, Deliveries, and Maintenance Costs: Example 1

	Value of Deliveries	Total preventive maintenance costs	Total corrective maintenance cost	Design cost	Expected Profit
This work	690905	28000	13536	148000	501370
Pistikopoulos et al (2001)	674050	24000	17208	137750	495092



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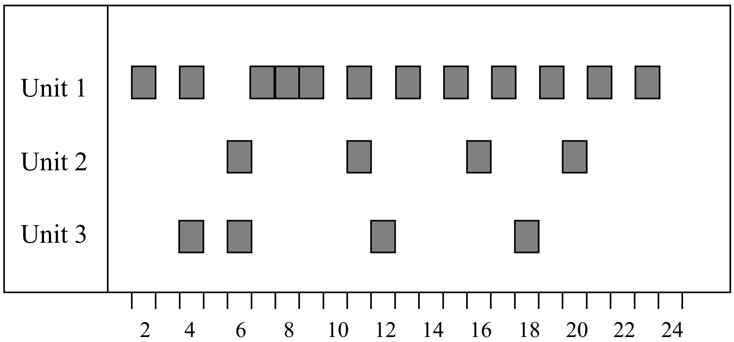


(b)

Figure 5.8: Optimal preventive maintenance schedule: Example 1 (a)with reliability optimization at design stage (b) without reliability optimization at design stage (Pistikopoulos et al. (2001))

The solution obtained is then compared with the results obtained by Pistikopoulos et al. (2001), where the initial reliabilities of units were considered fixed. The optimal sizes for units obtained in their work are given in Table 5.4 with the corresponding maintenance policy schedule shown in Figure 5.8(b). The design costs, maintenance costs, and deliveries costs, obtained from the present model and Pistikopoulos et al.'s model, are compared in Table 5.5. It is interesting to note the trade-off between various costs in Table 5.5. In this work, the increased design and preventive maintenance costs are balanced by a reduction in corrective maintenance costs and increased revenues. This leads to an overall increase in expected profit. It should be noted here that the results obtained are sensitive to the additional data assumed in this work for reliability improvement options and their associated costs. Nevertheless, the results presented in table 5 adequately illustrate the underlying trade-off between capital investment and maintenance costs, which is the purpose of this work. It is furthermore interesting to note from Table 5.4 and Figure 5.8 that considering the initial reliability of process units as a decision variable in a combined design, production and maintenance planning model leads to a different optimal design and

Table 5.6: Details of Processing Resources: Example 2

Unit type	Suitable tasks
Blender	Blending
Reactor	Reaction
Conveyor	Conveying
DryerA	Drying1, Drying2
DryerB	Drying3
PackLine1	Packing1, Packing2, Packing3, Packing4
PackLine2	Packing5, Packing6, Packing7, Packing8
PackLine3	Packing9, Packing10, Packing11, Packing12

Table 5.7: Details of Storage Resources: Example 2

Storage Unit	Capacity	Suitable Tasks
Tank1	250	React Feed
Tank2	100	C1
Tank3	100	C2
Tank4	100	C3
Warehouse	25000	Prod1-prod10

maintenance plan.

5.5.2 Example 2

The second example is an industrial example taken from Dedopoulos and Shah (1995a). The plant concerned uses and semi-continuous operations to produce 10 different products. The process involves five different steps: blending, reaction, conveying, drying and packaging. Blending is a batch operation of three hours creating the initial feedstock to be fed to the reactors. There are two batch reaction types of duration five and six hours, respectively, that produce two different intermediates (R1 and R2). In the conveying step, the reactor products are transferred continuously to intermediate storage via a bucket conveyor. The materials are dried semicontinuously in the drying step. Dried products are fed to packaging lines to produce end products semicontinuously. The process is described by the STN in Figure 5.9. The details of available processing and storage resources are given in Tables 5.6 and 5.7, respectively. The available sizes and initial failure rates for different units are given in Table 5.8.

An operating horizon of four years, discretized into 24 two-month time periods, is considered in this example. The demand and unit price per period for all products are given in Table 5.9. The minimum and maximum capacity utilization factors are assumed to be $\phi_{ij}^{min} = 0.25$ and $\phi_{ij}^{max} = 1$. The cost and maintenance data for all units are given in Tables 5.10 and 5.11 , respectively. It is assumed that at least one preventive maintenance

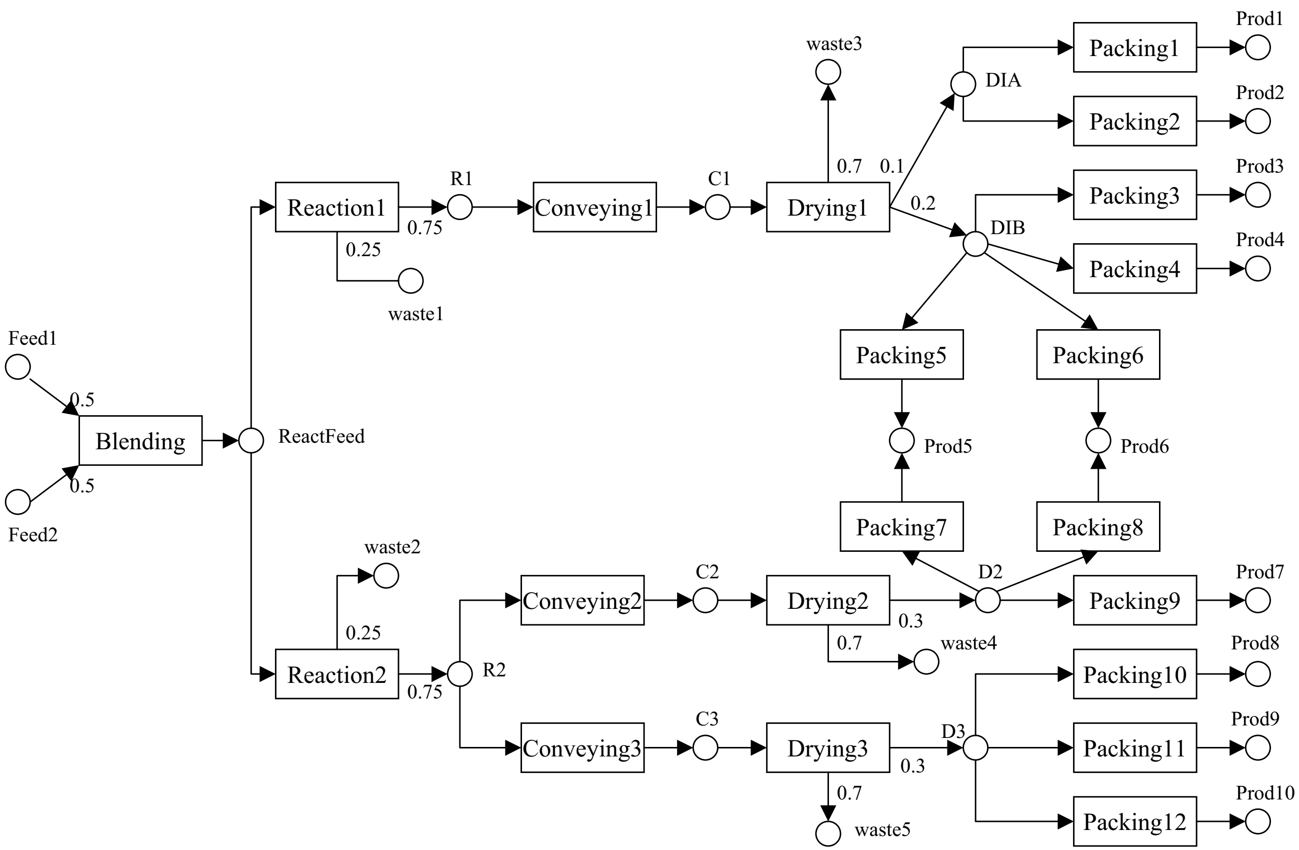


Figure 5.9: STN for example 2

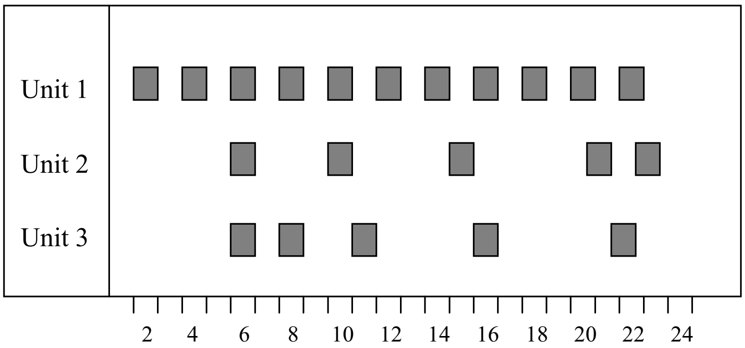
Table 5.8: Design Alternatives: Example 2

	Available unit sizes ($\overline{V}_{jk}$)			Available unit sizes		
	$k = 1$	$k = 2$	$k = 3$	$l = 1$	$l = 2$	$l = 3$
Blender	32.0	36.0	40.0	0.0005	0.0004	0.00035
Reactor	40.0	49.0	56.0	0.0005	0.0004	0.00035
Conveyor	4.5	5.25	6.0	0.0020	0.0019	0.0018
DryerA	5.0	5.5	6.0	0.0020	0.0019	0.0018
DryerB	2.0	2.4	3.0	0.0025	0.0024	0.0023
PackLine1	0.5	0.8	1.2	0.0025	0.0024	0.0023
PackLine2	0.25	0.45	0.65	0.0025	0.0024	0.0023
PackLine3	0.5	0.8	1.2	0.0025	0.0024	0.0023

Table 5.9: Product Demand and price data: Example 2

Product	dmin	dmax	price
Product 1	150	300	500
Product 2	120	360	500
Product 3	150	450	500
Product 4	225	600	500
Product 5	225	510	500
Product 6	165	390	500
Product 7	90	240	500
Product 8	60	180	500
Product 9	75	240	500
Product 10	105	300	500

action must be performed for each chosen unit every nine time periods, i.e. $\tau_j = 9$. The resulting MILP problem involves 1680 binary variables, 8012 continuous variables and 13377 constraints and was solved in 0.95s CPU time with a relative gap of 0.004. The optimal equipment sizes and initial failure rates, obtained from the solution of the proposed model, are depicted in Table 5.12. The optimal preventive maintenance policy obtained for this example is shown in Figure 5.10. Note that the biggest possible size and most reliable option available is selected for the conveyor equipment. This can be explained by its importance for performing conveying 1-3 tasks. In addition, better initial reliability is allocated to the reactor and packingline 1-3; this, in this particular example, can be explained by the marginal cost of increasing the size of equipment and its initial reliability. The solution obtained is also compared with the results obtained with the model formulation of Pistikopoulos et al. (2001) in Tables 5.12 and 5.13. In Table 5.12, it is interesting to note the selection of sizes for pakline2 and 3 in both optimal solutions. Table 5.13 shows the trade-offs between various costs terms used in the objective function



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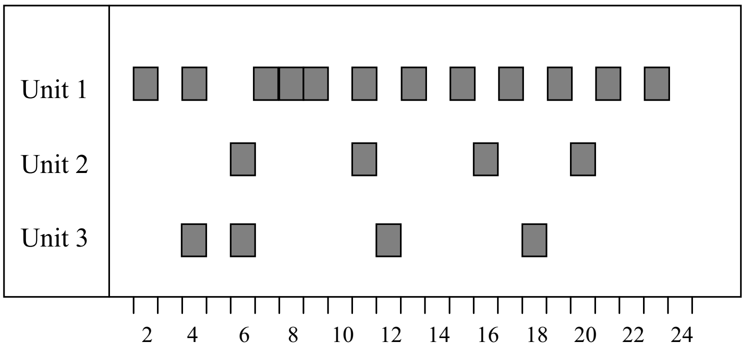

(b)

Figure 5.10: Optimal preventive maintenance schedule: Example 2

for both formulations.

5.6 Summary

A new mathematical formulation is presented in this chapter for integrated optimal reliable design, production and maintenance planning for multipurpose process plants. A reliability allocation model is coupled with an existing design, production, and maintenance optimization framework to allow designer to identify the optimal size and initial reliability for each unit of equipment at the design stage. An explicit objective function is proposed, which balances the additional design and maintenance costs against the benefits obtained due to increased process availability. In contrast to earlier approaches, which focus mainly on deriving an effective maintenance policy at the operational stage, the proposed integrated approach also provides a designer with an opportunity to improve the operational availability at the design stage by selecting better equipment. The resulting optimization problem corresponds to an MILP formulation, which requires modest computational effort. The applicability of the proposed model was demonstrated using

Table 5.10: Cost Data: Example 2

unit type	Fixed cost (K_j^0)	Size cost factor (K_j^1)	Failure rate cost factor (K_{jl}^2)		
			$l = 1$	$l = 2$	$l = 3$
Blender	230000	11000	0	12000	35000
Reactor	230000	11000	0	12000	35000
Conveyor	200000	45250	0	12000	35000
DryerA	230000	45250	0	12000	35000
DryerB	235000	65500	0	12000	35000
PackLine1	235000	100500	0	12000	35000
PackLine2	235000	100750	0	12000	35000
PackLine3	235000	100750	0	12000	35000

Table 5.11: Failure Rate and Maintenance Data: Example 2

unit type	α_j	$\Delta_j^c(h)$	C_{jt}^c	$\Delta_j^p(h)$	C_{jt}^p
Blender	0.0001	48	2000	32	15000
Reactor	0.0001	48	2000	32	20000
Conveyor	0.0005	40	2200	40	30000
DryerA	0.0005	40	2200	32	12000
DryerB	0.0005	40	2200	32	12000
PackLine1-3	0.0001	40	2200	40	30000

Table 5.12: Results: Example 2

unit type	This work		Pistikopoulos et al (2001)	
	Optimal size	Optimal initial failure rate	Optimal size	Initial failure rate
Blender	32.0	0.0005	32.0	0.0005
Reactor	40.0	0.0004	40.0	0.0005
Conveyor	6.0	0.0018	6.0	0.0020
DryerA	5.0	0.0020	5.0	0.0020
DryerB	2.0	0.0025	2.0	0.0025
PackLine1	0.8	0.0024	0.8	0.0025
PackLine2	0.65	0.0024	0.45	0.0025
PackLine3	0.5	0.0024	0.8	0.0025

Table 5.13: Design, Deliveries, and Maintenance Costs: example 2

	Value of Deliveries ($\times 10^3$)	Total preventive maintenance costs ($\times 10^3$)	Total corrective maintenance cost ($\times 10^3$)	Design cost ($\times 10^3$)	Expected Profit ($\times 10^3$)
This work	28157	712	1344	3530	22571
Pistikopoulos et al (2001)	27908	700	1394	3512	22302

two numerical examples. The examples clearly show that the method proposed in this work for including reliability allocation in the design stage leads to a significantly different design (unit sizes, expected profit) and accordingly a different maintenance policy in comparison to existing approaches for combining design, production and maintenance planning.

Nomenclature for chapter 5

Index

$\imath$	processing tasks
$\jmath$	units
s	states of material
u	utilities
t	time periods
k	unit sizes
l	unit initial failure rate
Θ	number of periods elapsed since unit j was last maintained

Sets

$S_i/\overline{S_i}$	sets of states consumed produced by task
$T_s/\overline{T}_s$	set of tasks receiving producing materials in state
I_j	set of tasks for which unit j is suitable
ψ_j	set of unit sizes available for unit
K_i	set of units suitable for task
ζ_j	set of possible initial failure rates for unit

Parameters

$\overline{V}_{jk}$	size for unit
$\overline{\lambda}_{jl}$	initial failure rate for unit
$\rho_{is}/\overline{\rho}_{is}$	proportion of input output of task from state
p_i	set-up and processing time of task
$\beta_{uij\omega}/\delta_{uij\omega}$	fixed variable demand factor for utility u by task i in unit j at the time ω relative

	to the start of the task
$\phi_{ij}^{\min}/\phi_{ij}^{\max}$	minimum maximum utilization factor
$A_{ut}^{\max}$	maximum availability level of utility u during time period t
$N_{ujt}^{\max}$	maximum number of batches when task i is performed in unit j during time period t
H	duration of each period
Δ_j^c	corrective maintenance (repair) duration of unit j
Δ_j^p	preventive maintenance duration of unit j
τ_j	maximum number of consecutive elapsed time periods without maintenance of unit j
$\gamma_{j\theta}$	failure rate value for unit j when the last maintenance action took place θ periods ago
K_j^0	fixed cost for unit j over considered time horizon of planning
K_j^1	variable size factor for unit j over considered time horizon of planning
K_{jl}^2	cost factor for unit j with failure rate l over considered time horizon of planning
η_{st}	unit price of state s during period t
C_{ut}	unit cost of utility during period
C_{jt}^p	preventive maintenance cost of unit j during period
C_{jt}^c	corrective maintenance cost of unit j during period
α_j	constant increment in failure rate

Variables

Binary variables

E_j	1 if unit j is chosen; 0 otherwise
E_{jk}	1 if size k is chosen for unit j ; 0 otherwise
E_{jl}	1 if failure rate l is chosen for unit j ; 0 otherwise
X_{jt}	1 if preventive maintenance is performed on unit j during period t ; 0 otherwise
$Z_{jt\theta}$	1 during period t if unit j was maintained for the last time θ periods ago; 0 otherwise

Continuous variables

N_{ijt}	number of batches of task i processed in unit j over time period t
S_{st}	amount of material in state s in storage at the end of period t
D_{st}	amount of material delivered to external customers from state s over period t
V_j	size of unit j
B_{ijt}	amount of material undergoing task i in unit j during period t
U_{jt}	expected uptime of unit j during period t
λ_{jt}	failure rate of unit j during period t
$\gamma_{j\theta}$	failure rate value for unit j when the last maintenance action took place θ periods ago

6

Reliability and maintainability in process design: continuous plants[†]

A new optimization framework is developed in this chapter where planned downtime due to preventive maintenance actions is explicitly considered in the integrated reliability allocation and process synthesis optimization problem, developed in chapter 3. The aim of this optimization framework is to optimize "achievable" availability of equipment and the overall system together with other design parameters. An illustrative example is used to demonstrate the applicability and the limitations of this formulation.

6.1 Introduction

In the preceding chapters, different new optimization frameworks have been developed to describe the methods that can be implemented for maximizing system effectiveness through design in the conceptual design stage to set optimal RAM targets together with other optimal design parameters. The examples used in these chapters cover a wide range of design situations, e.g., batch or continuous, grassroot or retrofit design project, etc. The complexity of the reliability and maintenance model considered in the development of previously developed optimization frameworks has increased through chapters 3 to 5.

In chapters 3 and 4, where the focus is on optimizing the "inherent" availabilities of the components and the system, a minimal repair policy is assumed in the integrated optimization frameworks. As a result, the optimization frameworks developed in chapters 3 and 4 provide relatively simple and fast ways to set RAM targets while making crucial process synthesis and design decisions during the conceptual stage. Once a process structure is selected, the design parameters can be further tuned by including a more complex reliability and maintenance model.

[†]Parts of this chapter have been submitted as Goel et al. (2004b).

In some cases, business needs dictated the need to include the maintenance-scheduling problem alongside the integrated reliability allocation and design optimization problem developed in the chapters 3 and 4. For example, in the case of multipurpose process plants where the flexibility offered by using the same equipment for different tasks can be jeopardized by unexpected failure, it is critical to take maintenance scheduling together with production planning and design decisions. A detailed maintenance model is required that relates different types of maintenance actions (preventive and corrective) to their impact on the equipment's achievable availability, system achievable availability and total maintenance costs to consider maintenance scheduling, .

A novel simultaneous optimization framework is presented in chapter 5 that addresses the problem of optimal allocation of reliability among equipment in conjunction with the selection of process configuration and production and maintenance planning for multipurpose process plants at the design stage. Some of the following issues were raised while applying the total integrated optimization framework developed in chapter 5 to a more general process system.

- In the case of multipurpose process plants, the discretization of the time horizon is in line with the need to approximate the dynamics of the interactions between production planning and maintenance scheduling decisions. However, for continuous and multiproduct batch plants with a single product campaign, the need to discretize the time horizon is not critical relative to the case for multipurpose plants.

- The increasing equipment failure rate over total time horizon is approximated in chapter 5 as a piecewise-constant failure rate in each time period. Although, the approximation simplifies significantly the complexity of the resulting integrated optimization problem it also increases the number of the total binary variables used to describe the preventive maintenance actions in each period. For non-linear process models, the resulting integrated MINLP optimization problem (with same number of binary variables) may prove to be prohibitively expensive to solve.

The aim of this chapter is to address the aforementioned issues while developing an integrated maintenance planning, reliability allocation and design optimization model for a general process system.

There are numerous maintenance models available in the literature that can be used to describe the impact of preventive and corrective maintenance actions on the average reliability and availability features of equipment and the total maintenance costs in the given time horizon. Some of the maintenance models are outlined in section 2.3.2. It must be stressed here that the existing models differ quite substantially in terms of mathematical complexity, data requirements etc. and there is no single generic "one-size-fit-for-all" maintenance model in the literature.

Pistikopoulos and his coworkers (Vassiliadis and Pistikopoulos, 1999, 2001) have developed one of the most mathematically rigorous maintenance models with their application in the process design domain. Their models provide detailed schedules for providing information such as the optimal number of preventive maintenance actions required on a piece of equipment with their time instants in a given time horizon. The complexity of their model also brings some inflexibility with respect to its integration into the integrated reliability allocation and design optimization framework, as in their maintenance model it is necessary to define the structure of the process system a priori. Further, they used state-space analytical method that for a reasonably size process system can prove to be very expensive computationally.

A simple maintenance model is developed in this chapter based on two key assumptions: a) periodicity of preventive maintenance actions and b) corrective maintenance (CR) actions will be of the as-good-as-old (AGAO) type and the preventive maintenance (PM) actions will be of the as-good-as-new (AGAN) type. It should be stressed here that the object of using a simple maintenance model is simply to obtain the approximate number of PM and CR actions required in the operational stage for the equipment while no attempt is made to obtain the detailed sequence and time instants for these actions.

The key elements in the proposed framework discussed in this chapter are identified below.

- The process model describing material and energy balance, technical and regulatory specification, relation between system availability and production capacity etc.
- An availability model that consists of
  - a reliability allocation model that relates the initial reliability characteristics of equipment at the design stage to the additional capital costs of the design and the impact of improved reliability on equipment availability
  - a maintenance model as that identifies the number of preventive maintenance actions required in a give time horizon for components and the overall system, by enabling the designer to find the balance between maintenance costs and the impact of different types of maintenance actions on equipment failure rates
- An objective function, that provides a trade-off between increased revenues due to extra equipment availability and two additional costs a) increased capital costs for improving a unit's initial reliability, i.e. reliability allocation and b) increased operational costs for preventive maintenance actions, maintenance optimization.

6.2 Model development

In this section, the mathematical foundations and assumptions are described that are made in the development of an integrated optimization framework for integrating maintenance planning into a reliability optimization and the process synthesis at the conceptual stage of design. In its general form, the optimization problem can be represented as:

Max Objective Function (Expected Profit)
s.t. Process model
Availability model

6.2.1 Process model

As described in previous chapters, the process model describes the process-characteristics including mass and energy balance equations, equipment sizing equations and operational specifications. Usually at the conceptual stage short-cut "behavioral" process models are used that are well established in the process design paradigm and can be found in standard textbooks such as Douglas (1988) and Biegler et al. (1997).

One important thing that is added to the conventional process models in this work is the linkage between process capacity and overall system availability. For instance, in the illustrative example discussed in the following section, the demand of the product C is given as an hourly production rate, which is estimated using the assumption that the plant is going to be available during the considered time horizon. However, the plant is not available for production for 100% of the time in a given time horizon: some unplanned (planned) downtime due to corrective (preventive) actions always results in some time when the system is not available for production. One way to avoid production loss during maintenance is to use a factor of safety and over-design the system to increase the capacities of the units. This qualitative approach depends very much on the accuracy of the benchmark data and the designers experience to choose a factor of safety.

In this work, a more systematic and quantitative approach is used where in order to satisfy a fixed demand for product C over a time horizon, the hourly production rate of product C is adjusted to link the total system inherent (achievable) availability with production capacity in the process model (see demand constraint in process model described in Table 6.3).

6.2.2 Availability model

Expressions for the average achievable availabilities (A'_j) of the units and the overall system (A'_{sys}) are developed in this section. As pointed out earlier, achievable availability (A'_j) is estimated by intrinsic, i.e. initial failure rate etc., and operational variables, such as number of preventive and corrective maintenance actions. Similar to chapter 5, let us assume that unit j can be chosen from different types, identified by index l, differing both in its initial failure rate (λ_{jl}) and investment costs. Further, binary variable (y_{jl}) is used to describe the selection of the initial failure rate for unit j.

Considering the case when the maintenance actions are performed periodically on each unit selected unit jl (unit j with initial failure characteristics of alternative l) every t_{jl} time units, the availability function of unit jl in the PM cycle m ($m = 1, , np_{jl}$) can be given by the expression (Zhao, 2003)

$$A_{jlm}(t) = \frac{t}{t + \Delta_j^c \int\limits_0^t \lambda_{jl}(t)dt + \Delta_j^p}, \qquad m = 1, ..., np_{jl} \tag{6.1}$$

where, Δ_j^p and Δ_j^c are expected time for PM and CR actions, respectively. The second term, product of expected CR time and the number of failures, describes the total unplanned downtime. Assuming that PM action is taken just at the time a failure occurs, the average availability for unit jl during PM cycle m can be estimated as (Zhao, 2003)

$$A_{jlm}^* = \frac{T_{jl}m}{T_{jl}m + \Delta_j^c m(nf_{jl} - 1) + \Delta_j^p m}, \qquad m = 1, ..., np_{jl} \tag{6.2}$$

where, $T_{jl}m$ is the operational time over the time interval t_{jl} ($= T_{jl}m + \Delta_j^c m(nf_{jl} - 1) + \Delta_j^p m$) between two preventive maintenance cycles and nf_{jl} denotes the total number of failures for unit j in a given PM cycle m and can be estimated as

$$nf_{jl} = \frac{T_{jl}}{mtbf_{jl}} \tag{6.3}$$

where, $mtbf_{jl}$ is the mean time between failure for unit jl. Consider a unit jl with failure characteristics described as a Weibull distribution* with parameters η_{jl} and θ_{jl}, the failure rate ($\lambda_{jl}(t)$) function can be expressed as

$$\lambda_{jl} = \frac{\theta_{jl}}{\eta_{jl}} \left(\frac{t}{\eta_{jl}} \right)^{\theta_{jl}-1} \tag{6.4}$$

where, η_{jl} and θ_{jl} describes the scale and shape parameters of the Weibull distribution, respectively. The $mtbf_{jl}$ for such a unit can be estimated as

$$mtbf_{jl} = \eta_{jl} \cdot \Gamma \left(\frac{1}{\theta_{jl}} + 1 \right) \tag{6.5}$$

where, $\Gamma(x)$ is a gamma function and be estimated as

$$\Gamma(x) = \int_0^\infty e^{-x} t^{x-1} dt \tag{6.6}$$

which can be numerically approximated with an expression with an accuracy of about 0.2-0.3% (Khan and Kabir, 1995)

$$\Gamma(x) = x^x e^{-x} \sqrt{\frac{2\pi}{x}} \left[1 + \frac{1}{12x} + \frac{1}{288x^2} - \frac{139}{51840x^3} - \frac{571}{2488320x^4} \right] \tag{6.7}$$

The total average achievable availability (A_{jl}^{ave}) of a unit jl over time horizon H can be estimated as (using equation 6.3)

$$A_{jl}^{ave} = \frac{nf_{jl} mtbf_{jl} np_{jl}}{nf_{jl} mtbf_{jl} np_{jl} + \Delta_j^c np_{jl}(nf_{jl} - 1) + \Delta_j^p np_{jl}} \tag{6.8}$$

The denominator of equation 6.8 is equal to the total time horizon H.

An example of the failure rate profile and the achievable availability profile for unit jl with 3 PM cycles (2 PM actions) is given in Figure 6.1. The unit jl has 2 CR actions in each PM cycle.

The total system achievable availability (A'_{sys}) can be derived from the achievable availabilities (A'_j) of the underlying units and the binary variables (y_j) defining the system structure. Achievable system availability can be formulated as

$$A'_{sys} = f(A'_j, y_j) \tag{6.9}$$

where, A'_j can be estimated by

$$\begin{aligned} A'_j &= \sum_l A_{jl}^{ave} y_{jl} \\ \sum_j y_{jl} &\leq y_j \end{aligned} \tag{6.10}$$

*A Weibull distribution is chosen here as it is far the most frequently used distribution used in practice to describe the failure rate of a repairable system. It should be added here that any other distribution can be used to describe the failure and repair rate of components.

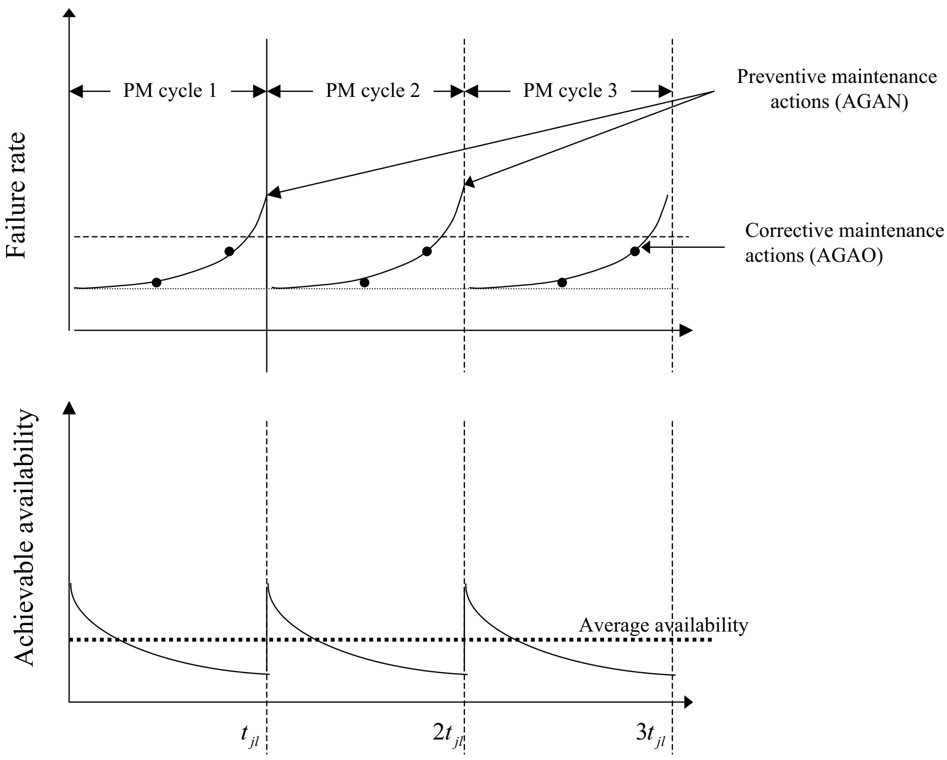

Figure 6.1: Illustration of failure rate and achievable availability profiles for a unit jl

Where y_j and y_{jl} are the binary variables describing the existence or non-existence of the unit j in the reliability block diagram structure and the selection of unit reliability characteristics at the design stage, respectively. It must be noted here equation 6.9 for system availability is a function of y_j and A'_j, which is estimated using expression 6.10, where two elements of achievable availability (as pointed out earlier in this chapter) can be clearly seen: binary variable, y_{jl} describing the selection of intrinsic characteristics, i.e. reliability allocation, and A_{jl}^{ave}, describing the operational characteristics (maintenance schedule described by the variable np_{jl}).

6.2.3 Objective function

As described in chapter 3, the objective function is taken to be a maximization of expected profit, which can be defined as

> Expected profit = revenue - investment costs - maintenance costs - operating costs i.e. raw material and utilities

It must be noted that the various terms such as revenue and investment costs are now defined over a given time planning horizon which is typically considered here as the time between major turnarounds, usually between 2-4 years.

Revenue

The revenue (Rev) and raw material costs (C_{raw}) are estimated as :

$$\mathrm{Re}v = H \cdot A'_{sys} \cdot \sum_{\mathrm{i} \in PR} x_i \xi_i \tag{6.11}$$

$$C_{raw} = H \cdot A'_{sys} \cdot \sum_{\mathrm{i} \in \mathrm{RM}} x_i \xi_i \tag{6.12}$$

Where, H is the time horizon, **PR** is the set of product and by-product streams in the process superstructure and x_i is a continuous variable describing the flowrate of i^{th} process stream and ξ_i is the cost/price of i^{th} process stream.

Investment costs

The capital investment costs of equipment j over the considered time horizon, H, can be estimated as

$$CI_j = K_j^0 y_j + K_j^1 x_{c,j} + \sum_l K_{jl}^2 y_{jl} \tag{6.13}$$

CI_j is the investment cost for equipment j. The fixed charge parameter K_j^0 denotes the fixed investment of unit j incurred only when the associated binary variable y_j is set to 1. The second and third terms are used to estimate the variable costs of increasing capacity and intrinsic reliability characteristics of the equipment, respectively. The variable $x_{c,j}$ describes the capacity of unit j. When a piece of equipment does not exist ($y_j = 0$), the variables $x_{c,j}$ and y_{jl} become 0. Therefore, only the investment cost of existing equipment is considered at each iteration.

Maintenance costs

Since "achievable availability" of the equipment is considered in this formulation, the maintenance costs considered here are made up of preventive and corrective maintenance costs. The overall maintenance costs over the time horizon can be estimated as:

$$MC_j^{tot} = \sum_l \left(C_j^c \Delta_j^c np_{jl}(nf_{jl} - 1) + C_j^p \Delta_j^p (np_{jl} - 1)\right) \cdot y_{jl} \tag{6.14}$$

Where, MC_j^{tot} is the total maintenance cost for unit j over the time horizon H.

6.3 Illustrative example

The example used here is similar to example 1 from chapter 3, which describes a simple continuous process system. The details for this example can be found in section 3.4.1.

Since the emphasis is this chapter is on optimizing "achievable" availability, the following modifications are made to example 1 of chapter 3:

Table 6.1: Cost Data: Illustrative example

unit type	Fixed cost (K_j^0)	Size cost factor (K_j^1)	Failure rate cost factor (K_{jl}^2)		
			$l = 1$	$l = 2$	$l = 3$
Compressor	320000	8000	36000	40000	52000
Reactor1	300000	5000	25000	27000	30000
reactor2	350000	5200	25000	27000	29000
flash	228000	1000			

Table 6.2: Failure Rate and Maintenance Data: Illustrative example

unit type	$\Delta_j^c(h)$	C_{jt}^c	$\Delta_j^p(h)$	C_{jt}^p	θ_{jl}			η_{jl}		
					$l = 1$	2	3	1	2	3
Compressor	25	40	45	30	2.3	2.2	2.1	700	800	850
Reactor1	25	40	45	30	2.5	2.4	2.3	850	950	1100
Reactor2	25	40	45	30	2.5	2.45	2.35	850	1000	1100

1. time horizon: As stated earlier in the introduction while defining different availabilities, the achievable availability is defined over a time horizon with includes planned downtime due to preventive maintenance actions. Therefore, a broader annual time horizon is considered here, say 8600 hrs instead of 8500 hrs. Further, preventive maintenance planning is usually done for the time between the two major turnarounds, which is typically in the range of 2-4 years. Therefore, a time horizon of 2 years (17200 hrs) is considered in this example.

2. investment cost model: unlike chapter 3, where the cost models are made a function of inherent availability, the cost estimation models here cannot be a function of achievable availability as achievable availability is influenced by design, i.e. initial failure rate, and the operational, i.e. number of preventive actions variables. Therefore, similar to the cost estimation model used in chapter 5, the cost function is made a function of the initial failure characteristics that are intrinsic to the equipment. The cost data and reliability data for the units used in the illustrative example are given in Tables 6.1 and 6.2, respectively.

3. maintenance costs: maintenance costs include preventive and corrective maintenance costs.

The process data for this example is given in Table 3.2. The overall process model for this illustrative example is shown in Table 6.3 which is similar to the one described in Table 3.1 in chapter 3 except that here achievable system availability is used instead of inherent availability in the demand constraint and a new time resources constraint is added. It should be further noted that an inequality sign is used in the time resource constraints due to the presence of a product of two discrete variables: nf_{jl} and np_{jl}.

Table 6.3: Process model: Illustrative example

Process Model	
Species balance for mixer (node 1)	Species balance for mixer (node 5)
$F2_k = F1_k + F12_k \quad \forall k$	$F7_k = F5_k + F6_k \quad \forall k$
Species balance for splitter (node 2)	Species balance for flash (node 6)
$F2_k = F3_k + F4_k \quad \forall k$	$F8_k = \gamma 1_k \cdot F7_k \quad \forall k$
Species balance for reactor1 (node 3)	Species balance for splitter (node 7)
$F5_A = F3_A - \alpha_1 \cdot F3_A$ $F5_B = F3_B - 2 \cdot \alpha_1 \cdot F3_A$ $F5_C = F3_C + \alpha_1 \cdot F3_A$	$F10_k = \gamma 2_k \cdot F9_k \quad \forall k$ $F11_k = (1 - \gamma 2_k) \cdot F9_k \quad \forall k$
Species balance for reactor2 (node 4)	Species balance for compressor (node 8)
$F6_A = F4_A - \alpha_2 \cdot F4_A$ $F6_B = F4_B - 2 \cdot \alpha_2 \cdot F4_A$ $F6_C = F4_C + \alpha_2 \cdot F4_A$	$F12_k = F11_k \quad \forall k$
Supply rate constraints $F1_k \leq S_k \quad \forall k$	Demand constraint $F8_C \cdot A'_{sys} = D_C$
Logical constraints $\sum_k F5_k \leq 30y_3$,$\sum_k F6_k \leq 30y_4$ $y_3 + y_4 = 1$	Time resources constraints
Time resources constraints $nf_{jl} \cdot mtbf_{jl} \cdot np_{jl} + \Delta_j^c \cdot np_{jl} \cdot (nf_{jl} - 1) + \Delta_j^p \cdot np_{jl} \leq H$	

The achievable system availability can be estimated by

$$\begin{aligned} &A'_{sys} = A'_3 \cdot A'_4 \cdot A'_8 \\ &(1 - y_3) \cdot (1 - A'_{o,3}) + A'_{o,3} \leq A'_3 \leq 1 \\ &(1 - y_4) \cdot (1 - A'_{o,4}) + A'_{o,4} \leq A'_4 \leq 1 \end{aligned} \tag{6.15}$$

where, A'_3, A'_4 and A'_8 are variables describing the achievable availabilities of reactor1, reactor2, and a compressor, respectively (see Figure 3.4). These variables can be estimated by using equations 6.8 and 6.10. Two constraints are added in equation 6.15 to enforce lower and upper bounds on the variables A'_3 and A'_4. For instance, when the unit 3 (reactor1) is selected in an iteration, the variable A'_3 is bounded as $A'_{0,3} \leq A'_3 \leq 1$ while the variable A'_4 becomes 1. The minimum values $A'_{0,3}$ and $A'_{0,4}$ can be estimated by using the lower bound on the np_{jl} and nf_{jl} variables. In this example, the minimum number of PM cycles for each unit jl is considered to be 3 and with at least 1 failure in each PM cycle ($nf_{jl} = 1$). The minimum values then can be estimated as

$$A'_{o,3} = \min_l \left\{ \frac{mtbf_{3l}}{3mtbf_{jl} + 3\Delta_3^p} \right\} \tag{6.16}$$

$$A'_{o,4} = \min_l \left\{ \frac{mtbf_{4l}}{3mtbf_{4l} + 3\Delta_4^p} \right\} \tag{6.17}$$

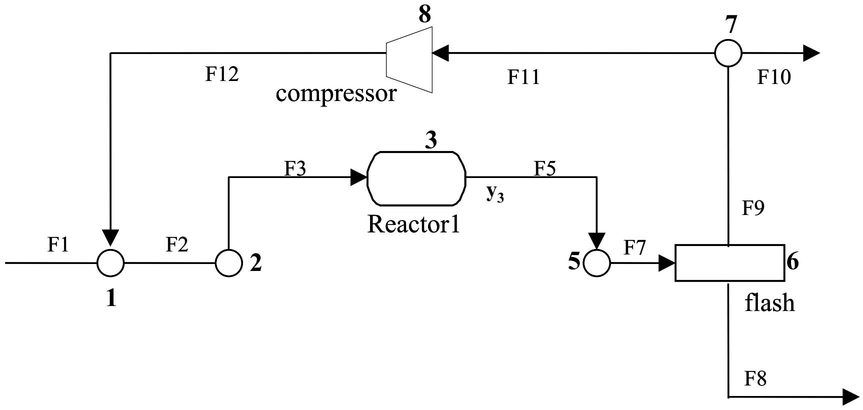

Figure 6.2: Optimal solution for illustrative example

Finally the objective function can be given as

$$\begin{aligned}\text{Profit} = & H \cdot A'_{sys.}(F8_C \cdot 17 - F1_A \cdot 5 - F1_B \cdot 2.5) \\ & -y_3 \cdot K_3^0 - K_3^1 \cdot \sum_k F5_k - y_4 \cdot K_4^0 - K_4^1 \cdot \sum_k F6_k - K_6^0 \\ & -K_6^1 \cdot \sum_k F8_k - K_8^0 - K_8^1 \cdot \sum_k F12_k - \sum_{jl} K_{jl}^2 y_{jl} \\ & - \sum_{jl} \left(C_j^c \Delta_j^c np_{jl}(nf_{jl} - 1) + C_j^p \Delta_j^p (np_{jl} - 1) \right) \cdot y_{jl}\end{aligned} \tag{6.18}$$

The first line in the objective function describes the difference between revenues and the raw material costs. The second and the third lines describes the total investment costs including the added costs of allocating reliability. The last term in the fourth line describes the total maintenance costs over the given time horizon.

The overall optimization problem described above is an MINLP problem with continuous variables (flowrates, availabilities of units and the overall system), binary variables (y_j and y_{jl}), and discrete variables (nf_{jl} and np_{jl}). Similar to chapter 3, due to the presence of bilinear terms, global optimality can only be guaranteed by using any of the present global solver. The problem was solved using the global optimization solver BARON. The resulting MINLP problem for the illustrative example involves 29 discrete variables (including binary variables), 93 continuous variables and 90 constraints and was solved in 1.69s CPU time. The optimal solution involves the selection of reactor1, see Figure 6.2. The selected initial failure rate and achievable availabilities for reactor1 and compressor in the optimal solution are given in Table 6.3 while the value of total revenue, raw material costs, maintenance costs, capital investment costs and expected profit are given in Table 6.5. The corresponding failure rate and achievable availability profiles for the reactor1 and compressor units are shown in Figures 6.3 and 6.4. From Figure 6.3 it can be clearly seen that there are 3 PM actions (4 PM cycles) planned on reactor1 with 3 CR actions in each PM cycle. Similarly, for the compressor, 5 PM cycles with 4 CR actions in each PM cycle are planned over the time horizon H.

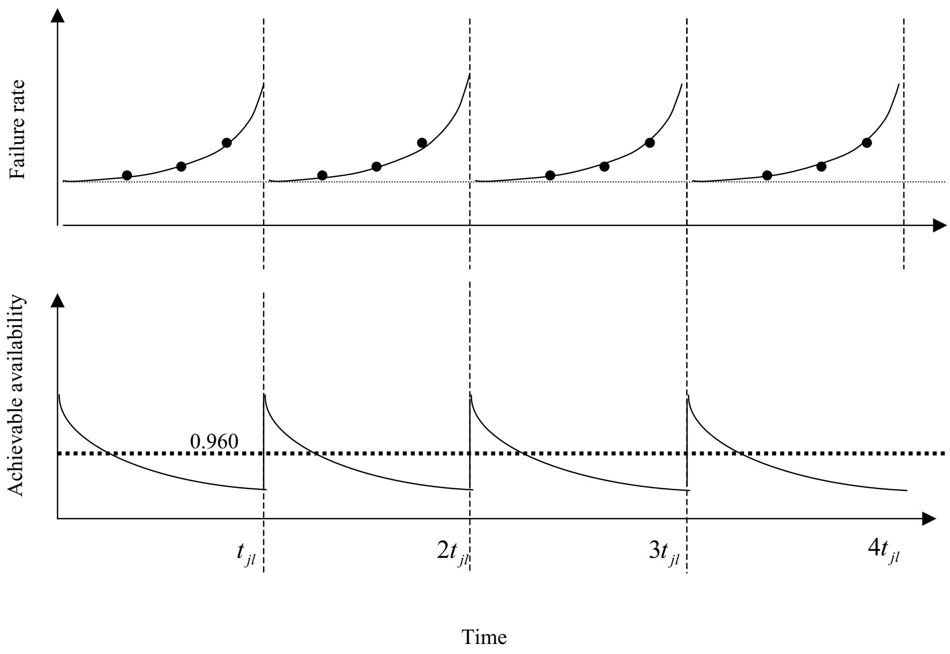

Figure 6.3: Failure rate and achievable availability profiles for unit reactor1

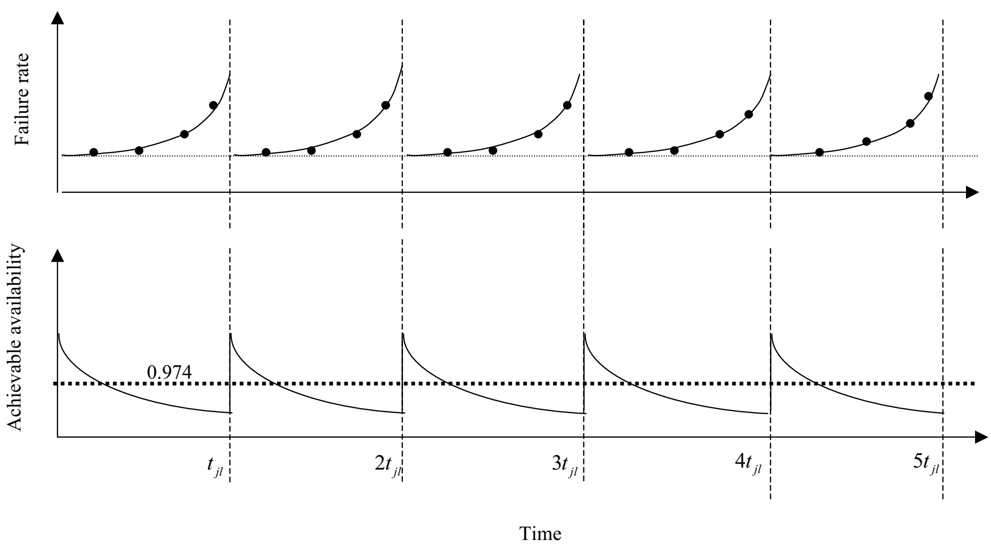

Figure 6.4: Failure rate and achievable availability profiles for compressor

Table 6.4: Results obtained for the illustrative example

Unit	With PM planning			Without PM planning			
	A'_j	θ_{jl}	η_{jl}	A_j	A'^{1}_j	θ_{jl}	η_{jl}
Compressor	0.974	2.3	700	0.976	0.964	2.3	700
Reactor1	0.960	2.3	1100	0.963	0.951	2.3	1100

[1] The achievable availability in this case is estimated by inherent availability × 17000/17200.

The results obtained from the current formulation are further compared with the results obtained from the formulation developed in chapter 3. Before comparing the two cases, it is important to mention that the inherent availabilities for units and the overall system are defined over a time horizon that excludes the fixed planned downtime, say 100 hrs per year for PM actions. As a result, while solving the illustrative example with formulation developed in chapter 3, a time horizon of 17000 hr was considered. The inherent availability of unit jl over the time horizon can be obtained by

$$A_{jl} = \frac{mtbf_{jl}}{mtbf_{jl} + \Delta_j^c} \tag{6.19}$$

where, A_{jl} is the inherent availability of the unit jl. The same cost estimation model as described in equation 6.13 is used here. The total corrective maintenance cost and overall system inherent availability is estimated as described in chapter 3. In addition a total fixed preventive cost is added to the objective function that are estimated for each unit for a fixed 100 hrs. The overall MINLP problem is also solved using the BARON solver. The optimal solution yields the same process structure, i.e., reactor1 is selected and initial failure rates for the units. Investment costs, revenue, raw material costs, maintenance costs obtained from the present model and formulation developed in chapter 3, are compared in Table 6.5.

Although in both cases the optimal structure and initial failure rates are the same, the expected profit obtained differs significantly. This could in part be explained with help of Table 6.3 where one can see the equivalent achievable availabilities of units in the sixth column are lower than the achievable availabilities obtained using the current formulation. The overall achievable system availability therefore in the cases using PM planning and those without PM planning are 0.935 and 0.916, respectively. It should be noted that the results obtained are sensitive to the additional data assumed in this work for reliability improvement options and their associated costs and the fixed planned maintenance period. Nevertheless, the results presented in table 6.5 adequately illustrate the added value of considering preventive maintenance planning when dealing with a reliability allocation and process synthesis problem when the failure rate is not constant.

6.4 Summary

The combined reliability allocation and process synthesis formulation developed in chapter 3, was extended to include the maintenance optimization problem. This new combined

Table 6.5: Comparison of results : Illustrative example

Formulation	Maintenance ($)	CAPEX ($)	Revenues	Raw material ($)	Profit ($)	A'_{sys}
Without PM planning	42504	1075075	4335000	2650835	491580	0.916
With PM planning	44600	1076283	4386000	2682021	517090	0.935

formulation provides a designer with an opportunity to improve the achievable availabilities of the units and the overall system at the design stage by selecting better (reliable) equipment and/or increasing the number of preventive maintenance cycles. The resulting optimization problem corresponds to an MINLP formulation. The applicability of the proposed model was demonstrated using an illustrative example. The results obtained clearly demonstrate the trade-off between the costs of improving the intrinsic, initial failure rate, and the costs of improving the operational, number of preventive maintenance cycles, dimensions of the unit achievable availabilities while maximizing the overall expected profit.

For simplicity, the maintenance model was very simple based on the common assumption of perfect and periodic preventive actions, however, the maintenance model developed in this work can be extended to take into account the degree of preventive maintenance action (Zhao, 2003) and the age degradation of the unit.

Nomenclature of chapter 6

Index

i	process streams
j	units
k	components in a process stream
p	product
l	unit initial failure rate
m	preventive maintenance cycle

Sets

PR	set of product and by-product streams in the process superstructure
RM	set of raw material streams in the process superstructure

Parameters

A_{jl}	inherent availability of the unit jl
λ_{jl}	failure rate for unit jl
η_{jl}	scale parameter in Weibull distribution
θ_{jl}	shape parameters of the Weibull distribution
H	the given time horizon

$\gamma 1_k$	separation ratio for flash in example 1
$\gamma 2_k$	separation ratios for purge splitter in illustrative example
S_k	supply of component k
D_k	demand of component k
K_j^0	the fixed charge of a unit j
K_j^1	the variable cost constant of a unit j
K_{jl}^2	cost factor for unit j with failure rate l over considered time horizon of planning
C_j^c	cost of corrective maintenance for unit j
C_j^p	cost of preventive maintenance for unit j
Δ_j^c	corrective maintenance (repair) duration of unit j
Δ_j^p	preventive maintenance duration of unit j
$A'_{o,j}$	base value for acheivable availability of equipment j
$mtbf$	Mean Time Between Failure

Variables

Continuous variables

A_{jlm}	the availability function of unit jl in the PM cycle m
A^*_{jlm}	average availability for unit jl during PM cycle m
A_{jl}^{ave}	total average achievable availability of a unit jl over time horizon H
x_j	describing flowrate capacity etc. for equipment j
CI_j	investment cost for equipment j
A'_j	achievable availability of equipment j
A'_{sys}	total system achievable availability
CI_j	investment cost of unit j
MC_j^{tot}	the total maintenance cost for unit j over the time horizon H
C_{raw}	raw material costs

Binary variables

y_j	discrete variable describing the existing or non-existing of equipment j
y_{jl}	binary variable of for the selection of failure rate alternative l for unit j

Discrete variables

np_{jl}	total number of PM cycles
nf_{jl}	total number of failures in a PM cycle

7

Conclusions and recommendations

The contributions of this thesis are highlighted in this chapter. In particular, the applications of different optimization frameworks are put into the broader context of achieving system effectiveness in different design situations, such as grassroot or retrofit, focusing on inherent or achievable availability etc., at the conceptual design stage. Further, in section 7.3, recommendations for future work are outlined including an outline for the future development of a prototype of a process-engineering tool using commercially available process and availability simulation software packages such as ASPEN PLUS and SPARC.

7.1 Introduction

The development of new optimization frameworks for integrating reliability, availability and maintainability issues for industrial plants during the early process design stage, where the crucial decisions such process selection, equipment sizing etc are made, is described in this thesis. In this chapter, an attempt is made to highlight the contributions of this thesis.

In summary, it was found that traditional reliability analysis tools and existing system effectiveness optimization approaches fall short when it comes to providing a systematic framework to set quantitative RAM targets during process selection at the conceptual design stage. In particular, most of the existing work focuses on the design stage where the system structure and the failure and repair characteristics of the underlying units is known. As a result, the opportunity to improve the RAM performance during process and equipment selection is lost in existing approaches. The work presented in this thesis acknowledges the great advantages that can be obtained by including reliability engineering tools from the very beginning during the conceptual design process where crucial decisions concerning the process structure and the equipment selection are made. Several optimization frameworks have been developed in this work to provide the designer with an opportunity to measure quantitatively and to use RAM performance measures to select the process structure and optimal design parameters during the conceptual stage.

7.2 Conclusions

The results of an extensive literature survey, and informal interviews with experts drawn from academia and industries were given in the chapters 1 and 2. The following are the general conclusions of the literature survey.

General Conclusions

- Gap between theory and practice: in practice, at the conceptual stage, the process engineer, who is often responsible for the process synthesis, has very little or no knowledge (or training) in reliability engineering methods and tools. As a result, crucial decisions such as process selection, equipment-sizing etc, are made based on assumed RAM performance measures. These are either based on the engineers experience or on data obtained from benchmark studies. The vast amount of knowledge, models and tools, that is available in the reliability engineering paradigm has still to penetrate the conceptual process design stage.

- Lack of a systematic methodology: there is little or no evidence for the existence of a structured and quantitative approach to manage reliability and availability measures throughout the life span of chemical plants. It was found that, at the conceptual stage, an engineer's own experience is often used in place of a more systematic, quantitative RAM analysis to set RAM targets. Quantitative RAM analysis is often done, in best cases, at the basic engineering stage, and in worst cases, at the detailed engineering stage of the process design. Further, at the operational level, ongoing projects in industry are usually done on an *ad hoc* basis focusing on a subsystem or a unit level.

- Limitations of existing models and approaches: as outlined in chapter 2, different tools and approaches have been developed in the last decades that are designed to integrate RAM into process design. These approaches can be divided into sequential and simultaneous approaches. The key disadvantage of the sequential approach is its iterative nature. As the number of design alternatives increases, it becomes impossible to evaluate all of them at each iteration. The simultaneous approach overcomes the limitations of the sequential approach and provides a unified approach to maximize system effectiveness by combining design optimization and RAM optimization. Pistikopoulos and co-workers have significantly contributed to the development of a structured simultaneous approach of combining process design and maintenance optimization problems. Although mathematically rigorous, their approaches have the following limitations:
  - these formulations focus only on the operational dimension, such as selecting the type and frequency of maintenance actions, of availability while fixing its intrinsic dimension (such as selecting initial failure rate etc.)
  - most of their formulations consider the process structure to be fixed. Therefore, the opportunity to fix RAM targets while selecting the structure of the process is lost in their formulations.

The present work recognizes the need for a structured approach whereby quantitative RAM targets are set at the conceptual design stage and used throughout the plant life cycle to control and review the RAM performance.

Four different optimization formulations have been developed that cover a wide range of possible conceptual design problems: retrofit vs. grassroot, multipurpose vs. multiproduct, continuous vs. batch etc. These new optimization frameworks contribute to the existing knowledge regarding conceptual process design and reliability engineering paradigms. The key features of the optimization frameworks are discussed in the following subsections.

Development

The main features of the development of optimization frameworks can be broadly explained based on the type of RAM targets that are optimized together with design parameters.

In chapters 3 and 4, the focus was on the optimization of the "inherent" availabilities of the equipment and the overall system while in chapters 5 and 6, the focus was on the "achievable" availability. In chapters 3 and 4, the combined synthesis, reliability and maintenance optimization problem is decomposed into two sub-problems: reliability optimization and process synthesis, and maintenance and design optimization problems. This decomposition allows a designer to solve two sub-problems independent by using different levels of complexity to represent the process and reliability models. The results of the first problem provide an optimal structure with optimal design parameters and RAM targets which can then be used as input to the second sub-problem where for a fixed design, a complex combined design and maintenance optimization problem can be solved to fine tune the design parameters and to find the optimal maintenance schedule required to achieve the RAM targets found in the former sub-problem.

In chapter 3, a new combined process synthesis and reliability optimization problem formulation was presented to help design to identify an optimal process flowsheet structure and optimal equipment inherent availability requirements during the conceptual design stage. The key features of this framework are:

- the development of an expected annual profit objective function, which takes into account the trade-off between initial capital investment and the annual operational costs by appropriately estimating revenues, investment costs, raw material and utilities cost, and maintenance costs as a function of system and component availabilities

- a correction to the process model to account for any loss of production due to unavailability. This is done by appropriately increasing capacity in the final design.

In chapter 4, the formulation developed in chapter 3 was extended to a special case of a process synthesis problem: a retrofit design problem of multiproduct batch plants. A new optimal retrofit method is presented that a) takes into account reliability and maintainability of existing and new equipment and uses this information to quantify the costs of unavailability, i.e. revenue loss due to production loss and maintenance costs due to increased unplanned shutdowns; and b) performs a trade-off between costs of unavailability and the extra capital investment needed to increase the size and/or inherent availability of new equipment while maximizing the overall expected net profit. Thus gives a more robust retrofit solution.

In chapter 5 and 6, a large synthesis, reliability and maintenance optimization is solved to provide an optimal structure, design parameters and maintenance schedules. The optimization frameworks developed in these chapters are particularly useful in situations where enough reliability, cost, and maintenance data is available at the conceptual stage or where it is necessary to consider synthesis, reliability and maintenance optimization problems simultaneously. For example, in the case of multipurpose batch plants, the flexibility obtained by sharing equipment can be affected by unplanned equipment shutdowns due to equipment failures. Thus, to achieve timely production of products at a minimum cost, it is crucially necessary to consider equipment reliability during the design and maintenance scheduling of multipurpose plants.

A new mathematical formulation for integrated optimal reliable design, production and maintenance planning for multipurpose process plants was presented in chapter 5. A reliability allocation model was coupled to the existing design, production, and maintenance optimization framework to identify the optimal size and initial reliability for each unit of equipment during the design stage. In contrast to earlier approaches, which focus mainly on deriving an effective maintenance policy at the operational stage, the proposed integrated approach provides a designer with an opportunity to improve operational availability at the design stage by selecting better equipment.

In chapter 6, the combined reliability allocation and process synthesis formulation developed in chapter 3, was extended to include the maintenance optimization problem. In contrast to the formulation developed in chapter 5, this formulation was applied to a wide range of process design cases where high non-linearity is present in the process models. This is achieved by using a simple maintenance model that is based on commonly used assumptions regarding periodic and perfect preventive maintenance actions.

Complexity

As most of the existing rigorous optimization models have been criticized for being too detailed or complex, in this work special attention was given on the complexity of the resulting problem formulation. The approaches developed in this work provide a basis for solving large-scale problems by coupling the optimization approach with simple models used at the conceptual stage. Therefore, some design variables such as storage tanks and some complex operational variables such as number of spares present in the warehouse, number of maintenance crew available etc. are not considered. This can be explained by a) the amount of limited resources, such as time, people and money, available at the conceptual stage and b) the amount of detailed data available for the process. Further, by the use of the reliability block diagram method for the evaluation of the system availability, for the optimization models developed in this work means that these models do not share the state-space explosion problem faced by the Markov methods.

Applicability

The designer is often confronted with a wide range of problems at the conceptual stage,. Further, depending upon the situation, the designer might have limited reliability and maintenance data. The optimization framework defined above is generic in nature and can be applied to a wide range of design situations. The number of examples used by no mean covers the entire range, however, they do demonstrate how, by changing the process model, the reliability model and the maintenance model, the generic formulation can be applied to different situations. The optimization formulations discussed in this thesis cover different design problem based on

- type of availability: inherent (chapters 3 and 4) and achievable (chapters 5 and 6)
- type of plant: continuous (chapter 3 and 6), multiproduct batch (chapter 4) or multipurpose plants (chapter 5)
- type of problem: grassroot design (chapters 3, 5 and 6) and retrofit (chapter 4)
- assumed failure rate: constant (chapters 3 and 4) and time varying (chapters 5 and 6)
- type of maintenance: minimal repair (chapters 3 and 4), minimal repair and perfect preventive maintenance actions (chapter 5) and minimal repair and imperfect preventive maintenance actions (chapter 6)

7.3 Recommendations and future work

In the course of this work, a range of possible paths for future work were revealed, these are described briefly below:

Industrial application
In the process system-engineering field, academics have always been criticized for developing academically challenging rigorous models that are either applicable only to small simple process systems or are considered to be too complex and detailed to be implemented in the time-constrained conceptual stage of the process design. The approaches developed in this work provide a basis for solving large-scale problems by coupling the optimization approach with simple models used at the conceptual stage.

In this work, shortcut models were used to build the process model. In industry commercially available sequential modular process simulators such as ASPEN Plus, PRO II etc are commonly used to provide more detailed models for calculating mass and energy balances and for sizing and costing. To exploit the detailed process models readily available in commercially available process simulators, Diwekar et al. (1992) developed a prototype MINLP synthesizer that was built around the sequential modular simulator ASPEN. Diwekar et al. (1992) used the benchmark process synthesis example of HDA to demonstrate the power of building the synthesis capability in the commercial process simulator ASPEN. Their work provided a strong link between the development of optimization based process synthesis work and its potential application in the process industry.

The work of Diwekar et al. (1992) provides a starting point on which to build a powerful new practical process engineering tool based on the optimization frameworks developed in this work. For instance, take the case of the optimization framework developed in chapter 3. It has three interconnected distinct elements: the process model, the availability model and the objective function. The framework can be broadly represented in Figure 7.1. Due to the decoupling of process models and the availability model at the system level, it is very well possible to replace the shortcut process model used in chapter 3 by a relatively detailed black-box model provided by ASPEN and similarly, availability models can be constructed either using a simple spreadsheet software (like Microsoft Excel) or any commercial analytical availability simulation software (such as SPARC).

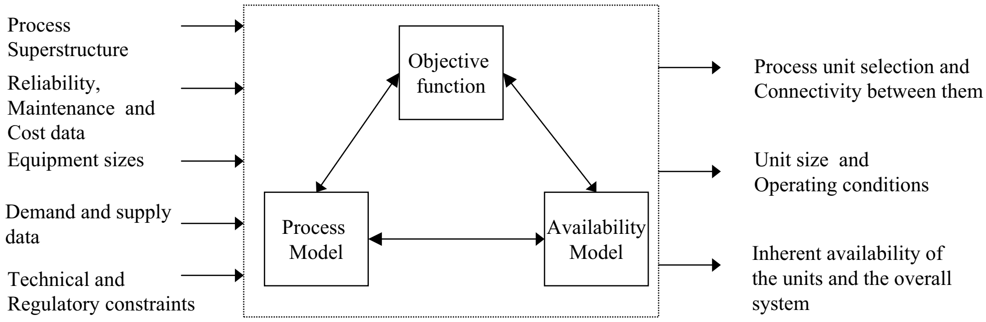

Figure 7.1: optimization framework for integrated reliability optimization and process synthesis problem

When the overall optimization problem (described in Figure 7.1) is solved using the OA algorithm in the DICOPT* solver, the overall solution strategy can be shown in Figure 7.2. The overall algorithm structure consist of solving, at each major iteration, an NLP sub-problem, with all 0-1 variables fixed, and an MILP master problem as shown in Figure 7.2. In the NLP sub-problem, the continuous variables (sizes, flowrates, temperatures, system availability, equipment availability etc.) in both the process model (e.g. ASPEN) and the RAM model (e.g. SPARC) are solved to provide a lower bound (if it is maximization problem) to the optimal MINLP solution. The MILP master problem has the role of predicting an upper bound to the MINLP and new 0-1 variables values for each iteration.

Knowledge base issues at the conceptual stage

There is no doubt that industry acknowledges the need to address RAM issues as early as possible in the conceptual stage of design. However, they also acknowledge that, due to strong competition between different capital projects within a company and in some cases the urgency to be first in the market, the time and other resources available for the conceptual design are becoming increasingly limited. In this situation, it is very hard to make a case to spend more time on undertaking quantitative RAM analysis and spending time on collecting the necessary data. Further, there is a lack of sufficient knowledge with respect to reliability engineering. The conceptual design phase is still is very much dominated by teh chemical engineers.

Regarding the data collection issue, companies such Shell, BP and Exxon are collaborating on projects like OREDA (1984) and CCPS (1989) with the intention of making a large inventory of generic reliability and maintenance data for equipment used in the process industry. The following actions are necessary for issues such as the lack of a knowledge base:

- Real case studies: to enhance the credibility of the ideas presented in this work and the other formulations that are exists in the literature, it is necessary to work

*The solution of the overall optimization framework is not limited to the DICOPT solver. Other solvers such as SBB and BARON can be used as well. DICOPT is used here only to visualize the algorithm.

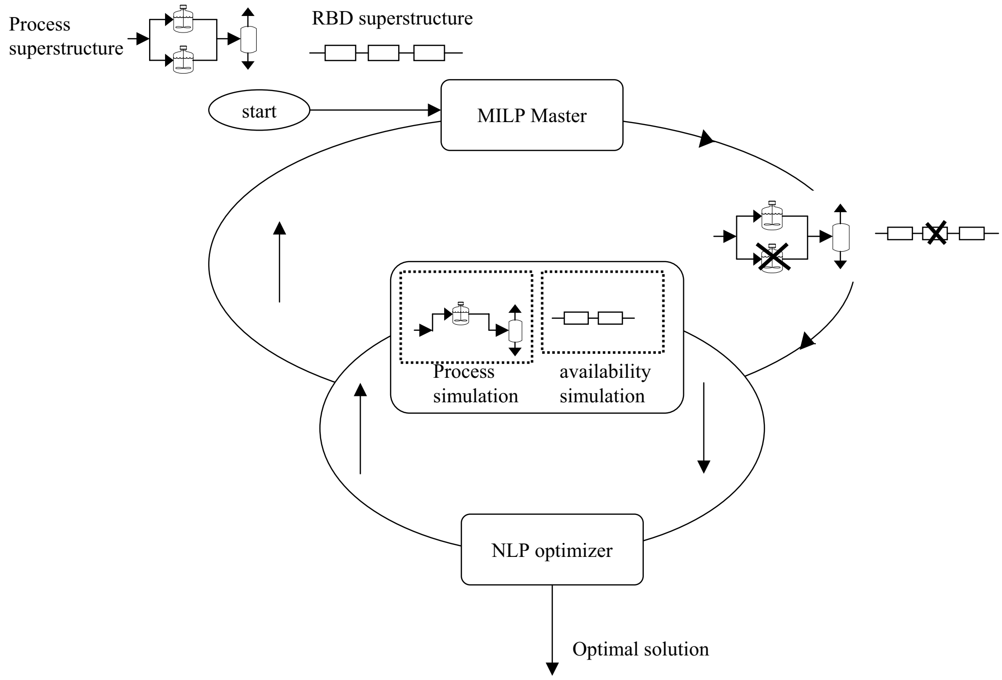

Figure 7.2: Algorithm for solution of the integrated reliability optimization and process synthesis problem

on real case studies. This would in turn would require industry to share some of its operational data with the academics. These case studies would demonstrate the usefulness of the methods and could also be used by process engineers to learn how to apply RAM principles in process design.

- Educating future engineers; i.e., integrating RAM studies into ongoing engineering education: most of the chemical engineers working at the conceptual stage have very limited knowledge of the reliability-engineering domain. This can be explained by the lack of attention given to introducing reliability engineering knowledge in the chemical engineering domain. For instance, most of the prominent design books such as Douglas (1988), and Biegler et al. (1997) do not have a single dedicated chapter or section on reliability issues. It has taken until, for a process engineer, Koolen (2001) to give due emphasis to using RAM performance analysis at the design stage. Engineering schools can play an instrumental role in developing a wide knowledge base in the field by including an introductory course on reliability engineering principles.

Modelling issues

1. The development of robust cost models: different forms of capital investment cost models and maintenance costs models are used throughout this work . Currently, the capital investment models are only a function of the type and the size of the equipment. As explained in the appendix A, the existing cost estimation models can be extended to be a function of an intrinsic RAM measure (such as intrinsic availability, failure rate etc.). However, this requires considerable effort, as large amounts of reliability, maintenance and cost data are needed to develop these models. Therefore, strong collaboration is needed between the modeler, the manufacturer and the equipment supplier.

2. Consideration of process uncertainty and environmental issues: most of the work done in the past on the simultaneous approach to integrate RAM in process design, also focused on simultaneously indulging the flexibility problem by considering the uncertainties present in different parameters such as demand, cost prices (Vassiliadis and Pistikopoulos, 1998, 1999). In their recent paper, Vassiliadis and Pistikopoulos (2001) considered linking RAM performance with the environmental performance. Although flexibility and environmental issues are not addressed in this work, the present optimization formulation can be extended easily to take into account these uncertainties and environmental issues. For example, the tool presented by Chaudhuri and Diwekar (1997) for process synthesis under uncertainty can be extended to included reliability optimization capability.

3. Active redundant system: the optimization frameworks described in chapters 3, 4 and 6 use reliability block diagrams to estimate system availability and share the limitations of the reliability block diagram method. For the case of a process structure with active redundancy or where a piece of equipment can be used for different tasks, such as multipurpose batch plants, effective production for the system cannot be obtained without enumerating all possible feasible and operable states. In these cases, using a series system in RBD provides a conservative estimate of the expected profit. One way to resolve this issue is to use an STN approach to present the process superstructure as explained in chapter 5. More work is required in the development of algorithmic and computational tools if Markov methods are used to estimate the effective production. In particular, the issues of automated procedures to a) identify the number of possible feasible states for a selected process structure at each iteration and b) to evaluate corresponding probabilities and the unique productive capacity of the state.

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Appendix A: capital cost estimation models

For successful application of reliability allocation model at the design stage, it is essential to obtain the relation between the equipment's inherent[†] RAM characteristic (such as inherent reliability/availability, initial failure rate) and its initial capital investment cost. This appendix illustrates different ways to extend the existing shortcut cost estimation model to become a function of a RAM characteristic of a unit, when the appropriate data is available.

In the context of chemical process design, the existing cost estimation models currently used at the conceptual stage are function of the size of the equipment. Most commonly used short cut cost estimation models includes Guthrie's cost models (Guthrie, 1969), Lang factors (Lang, 1948), simple linear cost-charge models (Kocis and Grossmann, 1989) or simple cost models developed within companies. Although these cost models are very simple and useful for quick estimates, they do not take into account the inherent reliability and maintenance aspects of process units while estimating the initial investment cost of equipment.

An example of turbine compressor subsystem is taken here to illustrate different kinds of cost estimation models that can be developed and used at the conceptual stage to estimate its cost as a function of size and any of the above-mentioned inherent RAM characteristics. First, it is important to draw a system boundary around a turbine compressor subsystem. At the conceptual stage, the shortcut cost models do not estimate the cost of a compressor alone but it estimates the cost of entire subsystem which includes the compressor itself and the auxiliary components essential for the smooth running of total compressor subsystem. For turbine compressor subsystem, the system boundary is shown in Figure 1.

Form Figure 1, it is clear that the inherent RAM characteristic of a turbine compressor subsystem can be increased by not only increasing the reliability of the compressor itself but can also be increased by increasing the reliability of the other supporting components. Let us assume for the turbine compressor subsystem different reliability level can be assumed by altering the reliability of the constituent component with extra cost and there are three different alternatives are available at the design stage. The failure and repair rate data with corresponding capital cost for three possible types (lets say type A, B and C) of compressor subsystems, represented here by index l ($l = 1, 2, and 3$), are provided in the Table 1. The failure rate in Table 1 is described by a Weibull distribution with parameters with parameters η_{jl} and θ_{jl}, where, η_{jl} and θ_{jl} describes the scale and shape parameters of

[†]It is very important to recognize the use of word "inherent". The word "inherent" signifies that the property such as inherent reliability/availability or initial failure rate etc of equipment is its initial "built-in" feature and is estimated from the data provided by the equipment supplier. We cannot make cost estimation model as a function of achievable or operational availability as these measure are partly determined by the maintenance policy implemented at the operational stage.

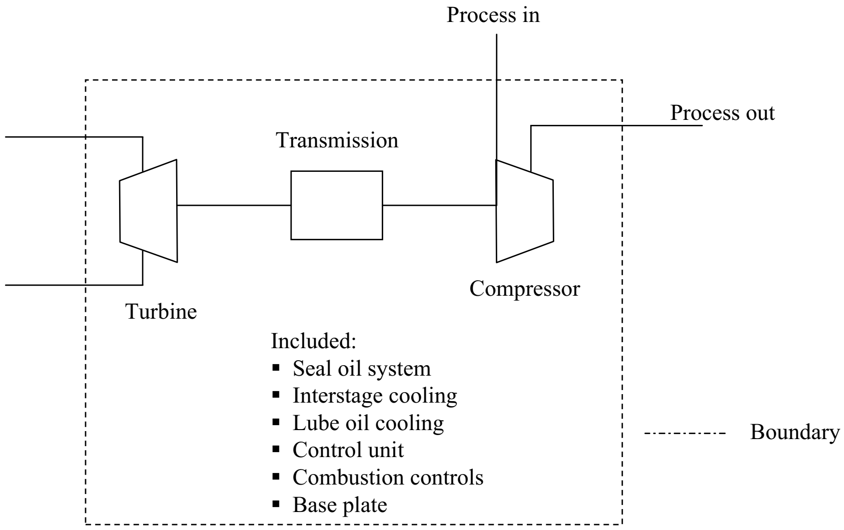

Figure 1: System boundary for a turbine compressor subsystem

Table 1: Failure, Repair and Capital Cost Data

Compressor type	Δ_j^c	θ_{jl}	η_{jl}	A_l	Capital Inv.	K_{jl}^2
Type A ($l = 1$)	25	2.3	1100	0.963	40000	0
Type B ($l = 2$)	25	2.3	700	0.976	55000	15000
Type C ($l = 3$)	25	2.3	500	0.983	80000	40000

the Weibull distribution, respectively.

From the failure and repair data given in Table, the inherent availability A_l for each alternative can be estimated with the help of equations 6.4-6.7 described in chapter 6. The values for inherent availabilities for three alternatives are also provided in Table 1.

There are several conventional shortcut models available to estimate the capital investment of the compressor system. For simplicity, let us take a fixed charge cost model described as

$$CI = K^0 + K^1 \cdot x \tag{1}$$

where CI is the capital cost of compressor with a capability to provide x brake horse power (kw). The parameters K^0 and K^1, respectively, describe the fixed and variable (function of horse power) annualized charge for equipment.

Now this conventional cost estimation model can be extended to include any of the above mentioned inherent RAM characteristics. There are two alternatives to extend the above-mentioned cost model that would describe the cost-reliability function of equipment in an objective function. The alternatives are:

- using exponentially increasing closed-form functions to relate cost and reliability/availability of the equipment
- using directly the discrete set of cost and reliability data of an equipment in the design problem.

In principle either of the above two alternatives can be used in the problem formulation. Actually, the closed form exponentially increasing function for reliability and cost is derived from the discrete sets and is mainly used in problem formulation to minimize the total number of binary variables in the final problem. In industry discrete sets of reliability-cost data can be either gathered in-house from purchase and maintenance departments or requested externally from equipment suppliers. Both alternatives are briefly described below.

Using discrete sets of reliability-cost data

For a turbine compressor subsystem example, the data concerning reliability features with corresponding initial acquisition cost for three types are provided in Table 1. As can be seen from the data sets, the initial capital cost is a strong function of initial RAM characteristic of the equipment. Assuming the first compressor type ($l = 1$) as base case, the incremental cost (K^2_{jl}) for improving inherent availability can be obtained for other two alternatives.

Using fixed charge model described above, the capital investment cost of the equipment over the considered time horizon can be estimated as

$$CI' = K^0 + K^1 \cdot x + \sum_l K^2 \cdot y_l \tag{2}$$

where CI' is the investment cost for the compressor turbine system as a function of intrinsic RAM characteristic. The fixed charge K^0 parameter denotes the fixed investment, whereas, the second and third terms are used to estimate the variable costs of increasing capacity and intrinsic reliability characteristics of the equipment, respectively. The binary variable y_l describes the discrete sets of initial RAM characteristic and the corresponding incremental costs. To ensure that only one pair of reliability-cost data is selected in the final solution, the following constraint must be added to the problem formulation

$$\sum_l y_l = 1 \tag{3}$$

Continuous reliability-cost function

In this type of cost model the capital investment cost is considered a continuous function of a RAM characteristic. The first step in the development is to select an intrinsic characteristic that should be included in the existing cost model. Let us here take inherent availability as an intrinsic characteristic that can be estimated for three alternatives with the help of equation. The inherent availabilities for three alternatives of a turbine subsystem example are given in fifth column of the Table 1. The next step is to plot different data points (availability, cost) on a x-y axis to obtain a continuous correlation (as shown in Figure 2). Usually a closed exponential function is assumed in literature to represent

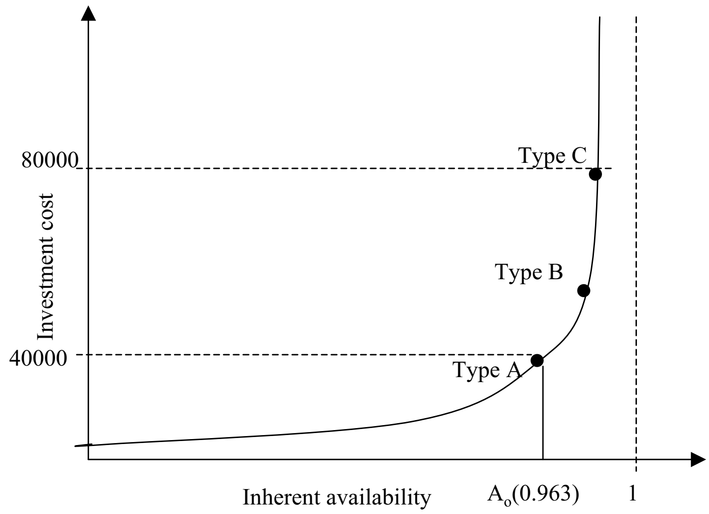

Figure 2: Plot of inherent availability vs initial investment for a turbine compressor subsystem

the correlation between cost and availability. The new extended cost estimation model as used in chapter 3 can be described as

$$CI' = K^0 \cdot y + K^1 \cdot x \cdot exp\left(\phi\left(\frac{A}{A_o} - 1\right)\right) \tag{4}$$

where, A_o is the base inherent availability, which is for the turbine compressor subsystem is the inherent availability of compressor type A ($l = 1$). The parameter ϕ_j is a constant for a compressor describing the slope of the curve shown in Figure 2. As expected, to obtain a robust continuous function, we should have sufficient number of data points. For cases where data collection is difficult, discrete data should used directly.

It is further important to note here that the choice of describing the relation between cost and reliability by continuous function or by discrete sets has significant impact on the complexity and computational burden of the resulting problem. For example, describing the relation as a continuous exponential function introduces non-linearity in the objective function while using discrete sets increases the number of total number of binary variables in the problem.

Appendix B: convexication of the MINLP

To ensure that the global optimum of the MINLP problem described by equations (4.1)-(4.30) is obtained, the following exponential transformations are introduced

$$\begin{aligned} & x_{1i} = \ln n_i, \\ & x_{2i} = \ln B_i, \\ & x_{3i} = \ln T_{Li}, \\ & i = 1, ..., N \end{aligned} \tag{1}$$

Using these transformations, we have the following formulation:

$$\begin{aligned} \min \qquad & -\sum_{i=1}^{N} p_i \exp(x_{1i} + x_{2i}) - \sum_{j=1}^{M} \sum_{k=1}^{N_j^{old}} R_{jk}^{old}(1 - y_{jk}) \\ & + \sum_{j=1}^{M} \sum_{k=N_j^{old}+1}^{N_j^{total}} (K_j^0 y_{jk} + K_j^1 V_{jk}) + \sum_{j=1}^{M} \sum_{l=1}^{P} \sum_{k=N_j^{old}+1}^{N_j^{total}} K_{jl}^2 y_{jkl} \\ & + \sum_{j=1}^{M} \sum_{k=1}^{N_j^{total}} C_j^c H(1 - A_{jk})/\Delta_j^c \end{aligned} \tag{2}$$

Subject to following constraints

$$x_{1i} + x_{2i} \le \ln Q_i \forall i = 1, ..., N \tag{3}$$

$$\begin{aligned} & t_{ij} \exp(-x_{3i}) + c_{ij} \exp(\gamma_j x_{2i} - x_{3i}) \le \sum_{g=1}^{G_j^{total}} y_{ijg} \\ & \forall i = 1, ..., N, \qquad j = 1, ..., M \end{aligned} \tag{4}$$

$$\sum_{i=1}^{N} \exp(x_{1i} + x_{3i}) \le H \cdot A_{sys} \tag{5}$$

$$\exp(x_{2i}) \le B_i, \qquad \forall i = 1, ..., N \tag{6}$$

$$\begin{aligned} & \left[\sum_{k=1}^{N_j^{old}} V_{jk} + Z_j V_j^U \right] (1 - y_{ijg}) + \sum_{k=1}^{N_j^{total}} V_{ijkg} \ge S_{ij} B_i \\ & \forall i = 1, .., N, \qquad j = 1, ..., M, \qquad g = 1, ..., G_j^{total} \end{aligned} \tag{7}$$

$$\begin{aligned} & V_{ijkg} \le V_j^U y_{ijkg}, \qquad V_{ijkg} \le V_{jk} \\ & \forall i = 1, .., N, \qquad j = 1, ..., M, \qquad k = 1, ..., N_j^{total}, \\ & g = 1, ..., G_j^{total} \end{aligned} \tag{8}$$

$$V_j^L y_{jk} \geq V_{jk} \geq V_j^U y_{jk} \quad \forall j = 1,..,M, \quad k = N_j^{old}+1,...,N_j^{total} \tag{9}$$

$$y_{jk} \geq y_{j,k+1} \quad \forall j = 1,..,M, \quad k = N_j^{old}+1,...,N_j^{total}-1 \tag{10}$$

$$V_{jk} \geq V_{j,k+1} \quad \forall j = 1,..,M, \quad k = N_j^{old}+1,...,N_j^{total}-1 \tag{11}$$

$$\sum_{g=1}^{G_j^{total}} y_{ijkg} \leq 1 \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad k = 1,...,N_j^{total} \tag{12}$$

$$y_{ijkg} \leq y_{jk} \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad k = 1,...,N_j^{total}, \quad g = 1,...,G_j^{total} \tag{13}$$

$$y_{ijkg} \leq y_{ijg} \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad k = 1,...,N_j^{total}, \quad g = 1,...,G_j^{total} \tag{14}$$

$$y_{ijg} \leq \sum_{k=1}^{N_j^{total}} y_{ijkg} \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad g = 1,...,G_j^{total} \tag{15}$$

$$y_{ijg} \leq 1 \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad g = 1,...,G_j^{total} \tag{16}$$

$$\sum_{k=1}^{N_j^{total}} 2^{N_j^{total}-k} y_{ijkg} \geq \sum_{k=1}^{N_j^{total}} 2^{N_j^{total}-k} y_{ijk,g+1} \quad \forall i = 1,..,N, \quad j = 1,...,M, \quad g = 1,...,G_j^{total}-1 \tag{17}$$

$$A_{jk} = \sum_{l=1}^{P} \overline{A}_{jl} y_{jkl} \quad \forall j = 1,...,M, \quad k = N_j^{old}+1,...,N_j^{total} \tag{18}$$

$$\sum_{l=1}^{P} y_{jkl} = y_{jk} \quad \forall j = 1,...,M, \quad k = N_j^{old}+1,...,N_j^{total} \tag{19}$$

$$A_{jk} = y_{jk} A_{jk}^{old} \quad \forall j = 1,...,M, \quad k = 1,...,N_j^{old} \tag{20}$$

$$A_{sys} = \prod_{j=1}^{M} \prod_{k=1}^{N_j^{total}} A'_{jk} \tag{21}$$

$$A'_{jk} = A_{jk} y_{jk} + (1 - y_{jk}) \quad \forall j = 1,...,M, \quad k = 1,...,N_j^{Total} \tag{22}$$

$$A'_{jk} = A''_{jk} + (1 - y_{jk}) \quad \forall j = 1,...,M, \quad k = 1,...,N_j^{Total} \tag{23}$$

$$A''_{jk} \leq \max_l \{\overline{A}_{jl}\} y_{jk}, \quad A_{jk} - \max_l \{\overline{A}_{jl}\}(1 - y_{jk}) \leq A''_{jk} \leq A_{jk} \quad j = 1,...,M, \quad k = 1,...,N_j^{total} \tag{24}$$

In addition the following constraints are added by Montagna (2003) to reduce the computational burden.

Equation 25 describes the constraint, where if a unit is selected for one product, it is available for other products without increasing the cost of the solution.

$$\sum_{g=1}^{G_j^{total}} \sum_{k=1}^{N_j^{total}} y_{ijkg} = \sum_{g=1}^{G_j^{total}} \sum_{k=1}^{N_j^{total}} y_{i'jkg} \qquad (25)$$
$$\forall i, i' = 1, ..., N, \qquad i \neq i', \qquad j = 1, ..., M$$

The following constraint determines that is unit k at stage j exists, it must be used at least in one group for one product

$$y_{jk} \leq \sum_{i=1}^{N} \sum_{g=1}^{G_j^{total}} y_{ijkg} \qquad (26)$$
$$\forall j = 1, ..., M, \qquad k = 1, ..., N_j^{total}$$

If the unit j is allocated at the stage k, it can only be included in only one group:

$$\sum_{g=1}^{G_j^{total}} y_{ijkg} \leq y_{jk} \qquad (27)$$
$$\forall i = 1, ..., N, \qquad j = 1, ..., M, \qquad k = 1, ..., N_j^{total}$$

Groups must be generated following an order:

$$y_{ij,g+1} \leq y_{ijg} \qquad (28)$$
$$\forall i = 1, ..., N, \qquad j = 1, ..., M, \qquad g = 1, ..., G_j^{total}$$

For each product, at least one unit must be allocated in one group:

$$\sum_{k=1}^{N_j^{total}} \sum_{g=1}^{G_j^{total}} y_{ijkg} \geq 1 \qquad (29)$$
$$\forall i = 1, ..., N, j = 1, ..., M$$

Summary

INTEGRATING RELIABILITY, AVAILABILITY AND MAINTAINABILITY (RAM) IN CONCEPTUAL PROCESS DESIGN: AN OPTIMIZATION APPROACH

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The key objective of this study is to develop a systematic theoretical framework for integrating reliability and maintainability aspects of industrial plants into the design process at the conceptual stage. This framework will allow designers to specify quantitative targets for RAM and arrive at optimal design parameters.

In chapter 1, the increasing maintenance costs and the cost of unplanned shutdowns are identified as the key driving forces to integrate RAM into the conceptual design process to set quantitative RAM targets, which can subsequently be used in monitoring the RAM performance of the final design throughout its life span. In industry, at the conceptual stage, the benchmark data from similar plants and the designer's own experience often replace the more systematic quantitative RAM analysis for setting RAM targets. In the most favourable cases, the quantitative RAM analysis is performed at the basic engineering stage of the process design; in the worst cases, it is done at the detailed engineering stage. The industry often takes a more 'reactive' approach: improving RAM performance by adjusting the maintenance management, using mostly qualitative tools, such as RCM, at the operational stage. Although this approach does improve the system's RAM performance compared to the status quo, long-term benefits can only be achieved by taking a knowledge-based approach: setting quantitative RAM targets in the design phase that can be controlled throughout the life span of the plant.

This thesis contributes mainly to the development of the knowledge-based approach mentioned above. As outlined in chapter 2, in recent years two different approaches have been developed that address the same issue. These are termed the sequential and the simultaneous approach. In chapter 2, the advantages and the limitations of both approaches are briefly sketched. One of the key disadvantages of the sequential approach is its iterative nature. As the number of design alternatives increases, it becomes impossible to evaluate all of them at each iteration. Therefore, in this work, the simultaneous approach is followed, whereby the design optimization and RAM optimization are connected and posed as a single optimization problem.

In the past decade, several mathematically rigorous simultaneous approaches have been proposed that share some of the common limitations involved in focusing on finding optimal maintenance schedules only, while assuming a fixed system structure and initial reliability characteristics. The present work recognizes the importance of considering both dimensions as well as the need to consider RAM performance as early as during

the selection of the process structure. Four different optimization formulations have been developed that cover a wide range of possible conceptual design problems: retrofit vs. grassroot, multipurpose vs. multiproduct, continuous vs. batch, etc. In addition to the classification according to the above-mentioned differentiation on the basis of plant characteristics, these formulations can be broadly classified on the basis of the type of RAM targets that are obtained together with design parameters.

In chapters 3 and 4, the focus is on the optimization of the inherent availabilities of the equipments and the overall system, while chapters 5 and 6, taking into account maintenance planning, focus on the achievable availability. Chapter 3 presents a new optimization framework to identify an optimal process flowsheet structure and optimal equipment-inherent availability requirements at the conceptual design stage.

The key features of this framework are:

- the development of an expected annual profit objective function, which considers the trade-off between initial capital investment and the annual operational costs by appropriately estimating revenues, investment cost, raw material and utilities cost, and maintenance costs as a function of system and component availabilities;
- the proper correction made in the process model to meet any loss of production due to unavailability by appropriately increasing the capacity in the final design.

The effectiveness and usefulness of the proposed optimization framework are demonstrated for the synthesis example of an HDA process. The results obtained clearly show the trade-off between the initial investment and annual operating cost by converging to an optimum level of availability required for compressors and distillation columns in the final HDA process flowsheet.

In chapter 4, the formulation developed in chapter 3 is extended to a special case of a process synthesis problem: a retrofit design problem of multiproduct batch plants. In the previous formulations addressing the retrofit problem of multiproduct batch plants, the inherent availability of both the existing and the new retrofitted plant are not included in the estimation of the actual production rate. These formulations focus on two design parameters only: limiting cycle time and limiting batch size for each product. In chapter 4, a new optimal retrofit method is presented for multiproduct batch plant design that

- considers reliability and maintainability of existing and new equipment and uses this information to quantify the costs of unavailability (revenue loss due to production loss and maintenance costs due to increased unplanned shutdowns) and
- performs a trade-off between cost of unavailability and extra capital investment needed to increase the size and/or inherent availability of new equipment while maximizing the overall expected net profit and thus gives a more robust retrofit solution.

The effectiveness of the proposed method is demonstrated by means of three examples. These examples clearly show that the new method proposed provides the designer with greater flexibility to obtain a more robust and reliable retrofit strategy with only a moderate increase in computational times.

In chapter 5, a new mathematical formulation is presented for the integrated optimal reliable design, production and maintenance planning for multipurpose process plants. A reliability allocation model is coupled with the existing design, production, and maintenance optimization framework to identify the optimal size and initial reliability for each unit of equipment at the design stage. In contrast to earlier approaches, which focus mainly on deriving an effective maintenance policy at the operational stage, the proposed integrated approach also provides the designer with an opportunity to improve the operational availability at the design stage by means of selecting better equipment. The resulting optimization problem corresponds to an MILP formulation, which requires only a modest computational effort. The applicability of the proposed model is demonstrated in two numerical examples. The examples clearly show that the method proposed in this work for including reliability allocation in the design stage leads to a significantly different design (unit sizes, expected profit) and accordingly to a different maintenance policy in comparison with the existing approaches for combining design, production and maintenance planning.

In chapter 6, the combined reliability allocation and process synthesis formulation developed in chapter 3, is extended to include the maintenance optimization problem. This new combined formulation provides the designer with an opportunity to improve the achievable availabilities of the units and the overall system at the design stage by selecting better (reliable) equipment and/or increasing the number of preventive maintenance cycles. In contrast to the formulation developed in chapter 5, this formulation can be applied to a wide range of process design cases where high non-linearity is present in the process models. This is achieved by using a more simple maintenance model, which is developed on the basis of the usual assumptions of periodic and perfect preventive maintenance action.

Samenvatting

INTEGRATING RELIABILITY, AVAILABILITY AND MAINTAINABILITY (RAM) IN CONCEPTUAL PROCESS DESIGN: AN OPTIMIZATION APPROACH

(INTEGRATIE VAN BETROUWBAARHEID, BESCHIKBAARHEID EN ONDERHOUDBAARHEID (RAM) IN CONCEPTUEEL PROCESONTWERP: EEN OPTIMALISATIEBENADERING)

Harish Devendre Goel
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Het hoofddoel van deze studie is het ontwikkelen van een systematisch theoretisch kader voor de integratie van betrouwbaarheids- en onderhoudbaarheidsaspecten van industrile installaties in de conceptuele fase van het ontwerpproces. Dit kader stelt ontwerpers in staat kwantitatieve RAM-doelen te specificeren en optimale ontwerpparameters te verkrijgen.

In hoofdstuk 1 worden de toenemende onderhoudskosten en de kosten van ongeplande processtops gedentificeerd als de belangrijkste drijfveren voor de integratie van RAM in het conceptuele-ontwerpproces, zodat kwantitatieve RAM-doelen gesteld kunnen worden, die vervolgens kunnen worden gebruikt bij het bewaken van de RAM-prestatie tijdens de gehele levensduur van het definitieve ontwerp. In de industrie nemen in de conceptuele fase de benchmarkgegevens van soortgelijke installaties en de eigen ervaring van de ontwerper vaak de plaats in van de meer systematische kwantitatieve RAM-analyse voor het stellen van RAM-doelen. In het gunstigste geval wordt de kwantitatieve RAM-analyse uitgevoerd in de basic engineering fase van het procesontwerp; in het slechtste geval gebeurt het pas in de detailed engineering fase. De industrie past vaak een meer 'reactieve' benadering toe: verbetering van de RAM-prestatie door bijstelling van het onderhoudsmanagement met gebruik van voornamelijk kwalitatieve methoden, zoals RCM, in de operationele fase. Hoewel deze benadering inderdaad de RAM-prestatie van het systeem verbetert ten opzichte van de bestaande situatie, kunnen langetermijnvoordelen alleen worden bereikt door een op kennis gebaseerde benadering toe te passen: het stellen van kwantitatieve RAM-doelen in de ontwerpfase die gedurende de gehele levensduur van de installatie kunnen worden beheerst.

Dit proefschrift draagt voornamelijk bij aan de ontwikkeling van de bovengenoemde op kennis gebaseerde benadering. Zoals wordt beschreven in hoofdstuk 2, werden de afgelopen jaren twee verschillende benaderingen ontwikkeld die zich toeleggen op dezelfde kwestie. Deze worden de sequentile en de simultane benadering genoemd. In hoofdstuk 2 worden de voordelen en de beperkingen van beide benaderingen kort geschetst. Een van de voornaamste nadelen van de sequentile benadering is de iteratieve aard ervan. Naarmate het aantal ontwerpalternatieven toeneemt, wordt het onmogelijk ze alle te eval-

ueren tijdens elke iteratie. Daarom wordt in deze studie de simultane benadering gevolgd, waarbij ontwerp- en RAM-optimalisatie aan elkaar worden gekoppeld en worden geformuleerd als n optimalisatieprobleem.

In het afgelopen decennium zijn verscheidene mathematisch rigoureuze simultane benaderingen voorgesteld die een aantal van de gebruikelijke beperkingen gemeenschappelijk hebben die vastzitten aan de toespitsing op het bepalen van optimale onderhoudsschema's, terwijl een vaste systeemstructuur en een onveranderlijke betrouwbaarheidskarakteristiek worden verondersteld. De huidige studie erkent zowel het belang van het opnemen van beide dimensies als de noodzaak om de RAM-prestatie reeds tijdens de selectie van de processtructuur in aanmerking te nemen. Er zijn vier verschillende optimalisatieformuleringen ontwikkeld die een grote verscheidenheid aan mogelijke conceptueelontwerpproblemen bestrijken: ontwerp en herontwerp, multipurpose en multiproduct, continu en ladingsgewijs, enz. Naast de indeling volgens de bovengenoemde differentiatie op basis van installatie-eigenschappen, kunnen deze formuleringen ook grofweg worden ingedeeld op basis van het type RAM-doelen die verkregen worden samen met de ontwerpparameters.

In de hoofdstukken 3 en 4 ligt de nadruk op de optimalisatie van de inherente beschikbaarheden van de apparatuur en het gehele systeem, terwijl de hoofdstukken 5 en 6 de haalbare beschikbaarheid centraal stellen, rekening houdend met onderhoudsplanning. Hoofdstuk 3 introduceert een nieuw optimalisatiekader voor het identificeren van een optimale processtructuur en optimale installatiegebonden beschikbaarheidsvereisten in de conceptuele-ontwerpfase.

De belangrijkste kenmerken van dit kader zijn:

- de ontwikkeling van een doelfunctie voor de verwachte jaarwinst, die de afweging tussen initile kapitaalinvesteringen en de jaarlijkse operationele kosten in aanmerking neemt door een juiste inschatting van de opbrengsten, investeringskosten, kosten voor grondstoffen en utilities, en onderhoudskosten als functie van de beschikbaarheid van het systeem en de componenten;

- de juiste correctie aangebracht in het procesmodel, om mogelijke productieverliezen ten gevolge van onbeschikbaarheid te ondervangen door een geschikte vergroting van de capaciteit van het definitieve ontwerp.

De effectiviteit en de bruikbaarheid van het voorgestelde optimalisatiekader worden aangetoond voor het synthesevoorbeeld van een HDA-proces. De verkregen resultaten laten duidelijk de afweging zien tussen de initile investeringskosten en de jaarlijkse operationele kosten, door convergentie naar een optimaal beschikbaarheidsniveau dat vereist is voor compressoren en destillatiekolommen in het definitieve stroomschema van het HDA-proces.

In hoofdstuk 4 wordt de in hoofdstuk 3 ontwikkelde formulering uitgebreid naar een speciale casus van een processyntheseprobleem: een herontwerpprobleem van ladingsgewijze installaties voor meerdere producten. In de eerdere formuleringen gericht op dergelijke herontwerpproblemen, zijn de inherente beschikbaarheid van zowel de bestaande als de nieuwe herontworpen installaties niet opgenomen in de schatting van de werkelijke productie. Deze formuleringen zijn gericht op slechts twee ontwerpparameters: limiterende cyclustijd en limiterende ladingsgrootte voor elk product. In hoofdstuk 4 wordt een nieuwe optimale herontwerpmethode voor ladingsgewijze installaties voor meerdere producten gentroduceerd die

- betrouwbaarheid en onderhoudbaarheid van bestaande en nieuwe apparatuur in aanmerking neemt en deze informatie gebruikt om de kosten van onbeschikbaarheid (opbrengstverlies door productieverlies en onderhoudskosten door toenemende ongeplande processtops) te kwantificeren en

- een afweging maakt tussen kosten van onbeschikbaarheid en extra kapitaalinvesteringen benodigd voor het vergroten van de omvang en/of inherente beschikbaarheid van nieuwe apparatuur, terwijl de totale verwachte nettowinst wordt gemaximaliseerd, en zodoende een robuustere herontwerpoplossing geef.

De effectiviteit van de voorgestelde methode wordt getoond door drie voorbeelden. Deze voorbeelden laten duidelijk zien dat de nieuwe voorgestelde methode de ontwerper meer flexibiliteit biedt om een robuustere en meer betrouwbare herontwerpstrategie te verkrijgen met slechts een geringe toename van rekentijd.

In hoofdstuk 5 wordt een nieuwe wiskundige formulering gepresenteerd voor de gentegreerde optimale betrouwbare wijze van ontwerp, productie en onderhoudsplanning van multipurpose procesinstallaties. Een betrouwbaarheidsallocatiemodel wordt gekoppeld aan het optimalisatiekader voor ontwerp, productie en onderhoud, om in de ontwerpfase de optimale omvang en initile betrouwbaarheid te identificeren voor elke installatie-eenheid. In tegenstelling tot eerdere benaderingen, die zich voornamelijk richten op het afleiden van een effectief onderhoudsbeleid in de operationele fase, biedt de voorgestelde gentegreerde benadering de ontwerper ook een mogelijkheid om de operationele beschikbaarheid te verbeteren in de ontwerpfase, door middel van de selectie van betere apparatuur. Het resulterende optimalisatieprobleem correspondeert met een MILP-formulering, die slechts een bescheiden rekeninspanning vereist. De toepasbaarheid van het voorgestelde model wordt gedemonstreerd met twee numerieke voorbeelden. De voorbeelden tonen duidelijk dat de in deze studie voorgestelde methode voor het opnemen van betrouwbaarheidsallocatie in de ontwerpfase leidt tot een significant afwijkend ontwerp (omvang van de eenheden, verwachte winst) en daardoor tot een ander onderhoudsbeleid in vergelijking tot de bestaande benaderingen voor het combineren van ontwerp, productie en onderhoudsplanning.

In hoofdstuk 6 wordt de in hoofdstuk 3 ontwikkelde combinatie van betrouwbaarheidsallocatie en processyntheseformulering uitgebreid met het onderhoudsoptimalisatieprobleem. Deze nieuwe gecombineerde formulering biedt de ontwerper een mogelijkheid om de haalbare beschikbaarheden van de eenheden en het totale systeem te verbeteren in de ontwerpfase door betere (betrouwbare) apparatuur te kiezen en/of het aantal preventieve onderhoudscycli te verhogen. In tegenstelling tot de formulering ontwikkeld in hoofdstuk 5, kan deze formulering worden toegepast op een grote verscheidenheid aan procesontwerpen, waarin sterke niet-lineariteit bestaat in de procesmodellen. Dit wordt bereikt door het gebruik van een eenvoudiger onderhoudsmodel, dat wordt ontwikkeld op basis van de gebruikelijke aannames van periodieke en ideale preventieve onderhoudsactiviteiten.

Curriculum Vitae

Harish Devendre Goel was born on June 4th, 1975 in New Delhi, India. In 1993, he completed his higher secondary education from LBS Senior Secondary School, New Delhi. After receiving a Bachelor of Chemical Engineering degree (with honours) in 1997 from Mumbai University (India), he joined University Institute of Chemical Technology (formerly known as UDCT), Mumbai University to obtain Master of Chemical Engineering degree. In 1999, he finished his Masters degree (with distinction). The subject of his master's thesis was the Modeling and Simulation of selected Bioreactors.
In September 1999, he joined the faculty of Technology, Policy and Management at the Delft University of Technology as a Ph.D. candidate. The Ph.D. work described in this thesis was executed in the 'Energy and Industry group (E&I)', in close cooperation with the process systems engineering group (PSE) of the faculty of chemical engineering. The research results have been published in various international journals and presented at various refereed conferences in the field of chemical engineering, process system engineering, and reliability engineering, and at various companies. In addition to carrying out the Ph.D. research, he also supervised a Master project for a chemical engineering student.
In October 2003, he joined as a process engineer in process and supply chain design group at Unilever Research and Development Laboratory, Vlaardingen, The Netherlands.