Integrated electricity demand-side management and scheduling of energy-intensive plants

Application to stainless-steel and thermo-mechanical pulping industry

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- Chapter 4.2, 4.3

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- Chapter 2.2, 2.3, 2.4

ABSTRACT

Energy is a critical resource for industry as new environmental policies drive changes. Industrial Demand-side Management (iDSM) has been recognized as a promising concept that incentivizes active shaping of the industrial load in response to energy market conditions in order to achieve bilateral benefits, i.e. the industrial plant reduces the energy bill while the energy supplier reduces peak generation hours and increases grid's reliability. For energy-intensive processing industries, such as stainless steel and pulp production the concept appears to be appealing, especially for the plants with high level of process flexibility.

One supporting technology to realize the iDSM strategy is energy-aware scheduling of daily operations by the industrial consumers. In this work, the monolithic formulations are developed for a batch process, of stainless-steel production and a continuous process of Thermo-Mechanical Pulping. For both, an energy-cost optimization is formulated as a generalized Minimum-Cost Flow Network model to find the optimal structure of multiple time-sensitive electricity contracts including base load, Time-of-Use, day-ahead spot market and onsite power generation, and opportunity to sell electricity back to the grid. The scheduling part of the model comprises all process constraints and also the minimization of deviation penalties as a result of the committed load problem. For the steel problem, general precedence using continuous-time formulation is used; for the pulping problem discrete-time Resource-Task Network approach is exploited. All models are formulated using Mixed Integer Linear Programming (MILP) and solved using realistic data instances from literature and industrial practice. In addition, due to large-scale nature of the steel problem, a bi-level heuristic is developed to obtain satisfactory solutions in reasonable times.

From monolithic models, a novel approach with functionally separated problems of energy-aware production scheduling and energy-cost optimization is developed. Such separation is beneficial for industrial environments as it increases modularity of the solutions and reduces the effort for energy-aspects integration into scheduling. Due to the special problem structure it is possible to use the Mean Value Cross Decomposition (MVCD) for solving the total problem as separated models of the energy-aware production scheduling problem and energy-cost optimization problem. The two optimizers can be modified such that they are a part of the sub-problem of the Benders' decomposition (energy-cost optimizer) and a part of the sub-problem of the Dantzig-Wolfe decomposition (energy-aware scheduler). The models exchange two signals: dual information of the complicating constraint from the energy-cost optimizer, and the load curve of the scheduler. The strategy is investigated in industrial case studies on processes of the steel-making and pulping industries. In addition, since the steel scheduling problem is not tractable due to its large size, the bi-level heuristic is integrated into the functional decomposition concept.

The results show that the new approach obtains either optimal or close-to-optimal solutions in case of the pulping, or similar solutions as the original bi-level heuristic applied on the monolithic formulation for the steel case. The existing limitation of the concept is the lack of convergence properties for One-sided Weighted MVCD. However, for industrial use, the approach builds upon existing models and obtains very good quality solutions. This fact will contribute to fostering of industrial implementations of the both monolithic and functional decomposition strategies.

PREFACE

The work in this dissertation is a contribution to the ITN Energy-SmartOps research project funded by the European Union. The work has been carried out at ABB Corporate Research Germany. This report is a final dissertation for the Doctor of Philosophy degree awarded by Technical University of Dortmund in Germany, Faculty of Bio- and Chemical Engineering.

I would like to thank Prof. Sebastian Engell for the supervision and giving me the opportunity to seek the degree at the Faculty. I also thank Prof. Ignacio Grossmann for contributions and hosting me for my secondment at Carnegie Mellon University.

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LIST OF ABBREVIATIONS AND ACRONYMS

(i)DSR	(Industrial) Demand-side Response
AOD	Argon oxygen decarburization
BF	Blast Furnace
CC	Continuous Caster
CD	Cross Decomposition
CPAS	Collaborative Process Automation Systems
DSM	Demand-side Management
EAF	Electric Arc Furnace
EU	European Union
HRM	Hot Rolling Mill
IEA	International Energy Agency
LF	Ladle Furnace
LNG	Liquefied Natural Gas
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MVCD	Mean Value Cross Decomposition
NLP	Non-linear Programming
OMVCD	One-sided Mean Value Cross Decomposition
OSWMVCD	One-sided Weighted Mean Value Cross Decomposition
PMS	Power Management Solutions
PSE	Process Systems Engineering
RTN	Resource-Task Network
STN	State-Task Network
TMP	Thermo-Mechanical Pulping
WMVCD	Weighted Mean Value Cross Decomposition

1 INTRODUCTION

The work done for this dissertation was carried out at ABB Corporate Research Center in Ladenburg, within the Process and Production Optimization Research Group (I4). The ABB Group is one of the largest engineering conglomerates in the world with primary businesses in power and automation. The research group supports the R&D activities of the company in the broad field of advanced decision-making support for process industries.

For the period between October 2011 and October 2014 the research group employed the author as a Marie Curie Fellow to contribute to the European Union funded research project ITN Energy-SmartOps. The project was aiming at augmenting existing automation systems to enable energy-intensive industries to take advantage of Demand-side Response (DSR) concepts. For process plants, one of the approaches to realize the DSR potential benefits is intelligent scheduling of daily operations in response to market conditions and incentives given by the volatile energy markets. Active shaping of the industrial load brings benefits to both market actors, for example energy bill savings on the energy-user side and operational (peak) cost savings on the energy-supplier side.

The research work has been carried out under scientific supervision of Prof. Dr. Ing. Sebastian Engell who is leading the Chair of Process Dynamics and Operations at Technical University of Dortmund. At ABB in Ladenburg Corporate Fellow Dr. Iiro Harjunkoski and I4 Group Leader Dr. Ing. Guido Sand mentored the technical work.

1.1 Research motivation

The topic of electricity demand-side management has been increasingly recognized as an important cross-disciplinary aspect of industrial production. It can be considered as one of the tools within the umbrella term of “smart grids”. It involves both the electricity supply systems and markets, and large-industrial electricity consumers in a more efficient exchange of information that would lead to bi-literal benefits. It deals with different time-scales, ranging from Power Management Solutions (PMS) supporting very fast demand-response such as direct load control on second- and minute-wise basis within ancillary reserves markets, to production process planning and scheduling in response to e.g. spot markets, covering a period of hours to months. In this work, as it is explained later, the focus is on the latter aspect.

Large-scale energy users might account for the electricity cost even up to 60% of the total raw material cost, e.g. as for air separation processes or for stainless-steel production with 20-40% (Ali et al. 2007). In developed countries, the reduction of operating costs for process plants is presently appealing due to high competitiveness (e.g. from Asian plants) and reduced orders due to the changing economic situation (e.g. 2008 global financial crisis). On the other hand, the energy suppliers have different motivations to establish a link with their consumers. Namely, in many countries there is increasing importance of environmentally-friendly policies, introduction of distributed generation and increased overall energy demand. An important trend of market liberalization and tendency to express the true volatile price of electricity generation on the customer side also opens up new opportunities. All of these aspects pose new challenges to the old electricity grid infrastructure for which operators need to seek new solutions supporting the grid's reliable operation. Involvement of the energy-intensive customers in active shaping of their load can provide another means for the Grid Management actors in securing stable and reasonably-priced delivery of energy. More reasoning for the motivation and benefits of the DSR is described in Chapter 2.

Electricity-demand side management is one of the technologies identified to have the potential to support the aforementioned challenges. However, how exactly the industrial plants should realize the response to energy-market incentives and who should provide that technology are still open questions. The former question is tackled in this work to some extent (see goal and scope in Chapter 1.2). For the latter question, among the traditional technology vendors is ABB. The Group provides solutions to the power generation and grid management side. At the same time, the company also reported many activities in the field of Collaborative Process Automation Systems (CPAS) which supports various industries, including energy-intensive process plants (Hollender, 2010).

From the industrial plant's point of view the DSR technology is concerned with a decision-making process that supports optimal production shifting in response to the energy-market conditions. Therefore, it has to be connected to the planning and scheduling of the daily operations. The solutions for large-scale processes are difficult to develop and implement, therefore received significant attention from academia over the last decades, e.g. from the Chemical Engineering and Process Systems Engineering (PSE) community. Recent advancements in mathematical modeling and optimization enable the development of more sophisticated and holistic solutions. However, inclusion of more and more aspects to the problem formulation which would satisfy the industrial needs give rise to the new scientific challenges – computational limitations, applicability to different processes and integration with plant systems. The challenges identified within the scope of this work are explained in more details in the beginning of each research chapter, i.e. Chapter 3 and 4. The industrial DSR technology is still in its early phase of development, however due to its potential benefits and interest from both academia and industry (Harjunkoski et al. 2015) it is foreseen by many to have noticeable impact on the industrial landscape (Scholtz 2013) in the coming decades.

1.2 Goal, scope and methodology

To answer the industrial needs of bridging production and energy management at the scheduling level, there are two primary goals of the dissertation. They are related to solving challenging problems as follows:

- find a strategy to solve a large-scale steel plant scheduling problem in a reasonable time, while optimizing both energy and production cost (system-wide optimal solution) using a general precedence continuous-time scheduling approach;
- develop and test a framework for solving the production scheduling problem separately from the electricity purchase and sale optimization – functional decomposition, however

still allowing to reach a system-wide optimal (or close to optimal) solution in a reasonable time.

A more detailed description of these goals is given in the introduction section of the corresponding chapters 3 and 4 respectively. The first goal translates into the development and testing on real-world problem examples with the following methodology and contributions:

- extend the continuous-time scheduling formulation with energy-awareness which enables energy-resource use accounting – three different strategies are developed and tested to find the best performing one (Hadera et al. 2015);
- embed optimization of various time-sensitive energy price tariffs into scheduling –a generic strategy based on a Minimum-cost Flow Problem (e.g. Ahuja, Magnanti and Orlin, 1993; Bertsekas, 1991) is developed and tested;
- overcome computational intractability to solve instances of industrial size – here bi-level heuristic approach are developed and tested.

The second goal translates into the development and assessment on real-world examples of the following contributions:

- show the potential of convergence to optimality of the developed functional decomposition and indicate its theoretical limitations – different variations of Mean Value Cross Decomposition will be explored (Holmberg 1992);
- identify an industrially-relevant framework structure for the exploitation of existing state-of-the-art approaches – One-sided Mean Value Cross Decomposition is identified as promising and tested on various problem instances (Hadera et al. 2015b);
- apply the developed concept on different scheduling problem formulations to show its flexibility and assess its usefulness – two different time-representation strategies as well two different scheduling modeling principles are investigated.

The scope of the work presented here covers the development of monolithic models for handling real-world scheduling and energy-cost optimization problems. These serve as a basis for further functional decompositions for the separation of energy contracts optimization from the scheduling as shown in Figure 1-1.

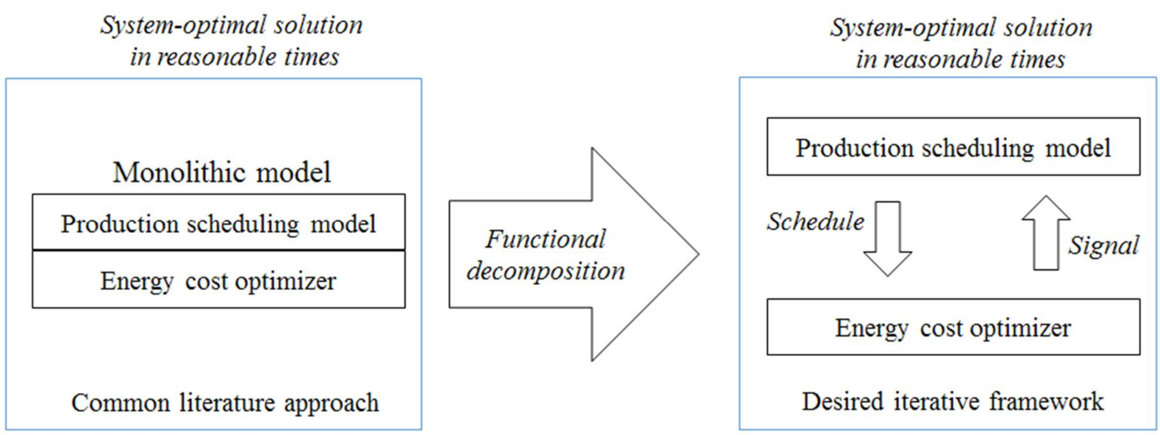


Figure 1-1 Dissertation goal and scope

The decomposition needs to follow certain requirements dictated by the industrial practice as discussed in Chapter 4.1. It is important to note that the goal of the work is also to test the developed approaches on real-world industrial example processes. Outside of the scope is a comparison of the industrial approach (explained in Chapter 4.1) with the concepts developed in this work. Also assessing the financial benefits of iDSR (see Chapter 2.4 for literature positions assessing the benefits) is not within the scope of this dissertation.

In this work, standard approaches for tackling scheduling problems using Mathematical Programing are utilized, as they provide a powerful framework that has been exploited in Process Systems Engineering (e.g. Grossmann 2002) in the past years. A real-world problem is formulated as mathematical optimization model and solved using specialized algorithms. The optimization problem can be modeled using different state-of-the-art approaches. In this work, a standard rigorous approach of Mixed Integer Linear Programing (MILP) is utilized for this purpose (e.g. see Nemhauser and Wolsey, 1988; Schrijver, 1998), in contrast to such other techniques such as Constrained Programming (CP) or Timed Automata (TA) (e.g. see Hentenryck, 1989; Subbiah, 2012 respectively). In MILP approaches, problem constraints are represented by equations and inequalities. In addition, discrete decisions are represented using binary and integer variables, while the continuous degrees of freedom are modeled as variables which can take real values. The objective of the optimization problem is modeled as a function that depends on the decision variables which are a subject of optimization.

In the course of the dissertation, monolithic MILP models are developed which theoretically can be solved to optimality. However, due to the combinatorial complexity of the large-scale industrial scheduling problems considered, the practical performance is limited due to computational inefficiency. For this reason, heuristic methods are developed which do not guarantee that one obtains the optimal solution. In addition, to achieve the goal of the work, several decomposition approaches for mathematical optimization are used, such as Benders' (Benders 1962) and Dantzig-Wolfe (Dantzig and Wolfe 1960).

The concepts developed are tested on real-world scheduling problems from industry. Since the solution schemes are meant to support the energy-intensive process plants in decision-making, the scope of the numerical experiments includes energy-intensive example processes: stainless-steel production and Thermo-Mechanical Pulping (TMP). These represent different types of processes. The steel plant operates in a batch mode where products are subsequently processed on a number of production stages (multistage plants in a Flexible Flowshop environment, see e.g. Pinedo 2012). Pulping is a continuous process where certain inputs are transformed into the final product which is extracted at a given rate.

In addition, the scheduling problems of the two industrial processes are developed using two major modeling principles (Méndez et al. 2006). The steel process is modeled by a general precedence concept which is a rather classical approach where model variables and constraints are matched to real process entities with processing units at different production stages using a sequencing concept (e.g. Harjunkoski and Grossmann 2001). In contrast, the pulping process is modeled using Resource-Task Network (Pantelides 1994) strategy which transforms the real process into variable and constraints by representing them in a generic network model with materials, tasks, units and utilities. Moreover, the time representations of the two scheduling approaches are also fundamentally different. As shown in Figure 1-2, the steel process utilizes the exact continuous-time approach as opposed to the discrete-time approach of the pulping process. The reasons for the choice of the two approaches and the two industrial processes characteristics are discussed in Chapter 4.1.

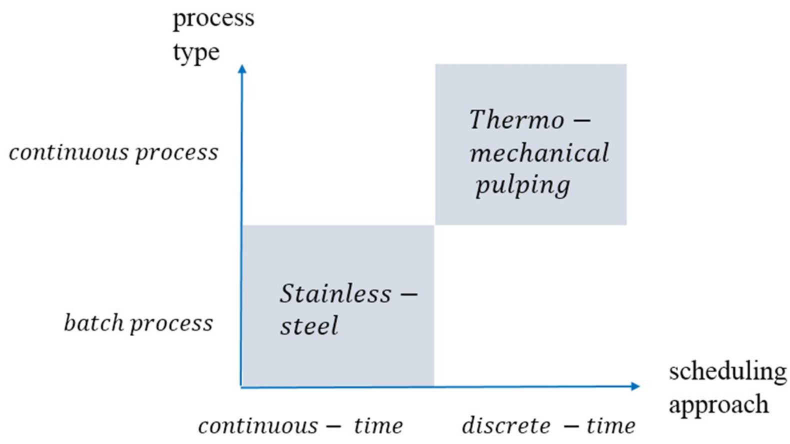


Figure 1-2 Types of scheduling formulations and use case processes

1.3 Dissertation outline

This thesis consists of five main chapters. Every chapter begins with a short summary and explanation of its relation to the goal and scope.

The second chapter describes the motivation and scope of this dissertation. It explains the main drivers for this work which are a part of the challenges related to energy-supply systems and the role of industrial consumers. In addition, a part of the literature review related to energy-aware scheduling is presented to give a first motivation regarding the scientific research challenge.

The third and fourth chapters are the core of the research. For both chapters, the related scientific challenge is explained in the beginning. In Chapter 3, the first goal of the dissertation is addressed. The monolithic model of the stainless-steel case problem is formulated and solved using a heuristic strategy. The chapter also explains the energy-cost optimization problem and the solution approach using the flow network formulation. The description of these aspects at this point introduces the reader into the topic and gives a background for the understanding of the functional decomposition concepts developed in the fourth chapter. Chapter 4 starts by explaining the motivation and scope of the second goal of the dissertation. Next, a generic conceptual strategy for functional decomposition is developed. Furthermore, for testing purposes, the monolithic model of the Thermo-Mechanical Pulping process is formulated and solved. The model together with the heuristic developed for the steel case are then applied on the functional decomposition concept to assess the functional decomposition scheme and its performance and limitations.

The last chapter summarizes the main conclusions that can be drawn from the research part. The limitations of the study and recommendations for future work are discussed at the end.

2 CONCEPT MOTIVATION AND BACKGROUND

This part of the dissertation is a rather general explanation of the main concept related to the goal and scope of the research. The purpose of this chapter is as follows:

- give the reader the context to understand challenges and the motivation that call for new technologies (Chapter 2.1);
- explain one of the supporting solution strategies to answer the challenges in the motivation part (Chapter 2.2);
- describe enablers on the process side for realizing the solution strategy and motivation for use cases chosen in the research part of the dissertation (Chapter 2.3)
- give an overview of the technical challenges that are tackled by the scientific community in the area of energy-aware scheduling (2.4).

The chapter gives the reader a general background related to the research part of the dissertation. It begins with a description of challenges on the energy-supply side which serves industrial electricity consumers. It continues with an explanation concerning one of the strategies to support better balancing between energy supply and demand which is seen to have potential to support answering the challenges. Next, the important factors on the consumer side that enable the energy intensive industries to realize the demand-side response are explained. The last section explains that on the plant level the demand-response can be realized with energy-aware production scheduling methods. Therefore, a review of approaches for scheduling under energy constraints is presented to give the reader an initial perspective on the technical details which follow in the next two research chapters.

2.1 Challenges in energy supply systems

In many regions, renewable energy sources contribute a significant share to the overall electric power consumption, and due to the volatility of their availability and their privileged role on the market, this may cause high fluctuations of the energy cost for the final user. On the grid level, the demand should always match the supply, otherwise the grid infrastructure is stressed, possibly causing expensive failures. Therefore it is of interest to the supply side of the grid to achieve flexibility of the demand, which traditionally was assumed to be inelastic in the short-term. This is largely because the consumer of electricity was not getting any incentive signals, which could trigger a change of the consumption pattern when shortages or oversupply occur. In recent times, smart grid technologies and the liberalization of the energy markets have provided new ways of communicating the signals, both for dispatchable (the user is given direct signals to change the load) and non-dispatchable (the user decides whether to change the load) strategies (NERC 2007). The latter signals are considered in this work in the form of financial incentives and different pricing contracts. It has been recognized that both small consumers and retailers should be provided with technical tools to actively and effectively participate in the electricity markets (Kirschen, 2003).

2.2 Industrial Demand-side Response

Among the identified technologies for supporting an active shaping of the energy use patterns is Demand-side Management. It consists of two strategies: Energy Efficiency and Demand-Side Response (iDSR) as shown in Figure 2-1. The latter activities involve activities defined as a temporary change in electricity consumption in response to market or reliability conditions (FERC 2006). An overview of the present status, classification of programs and future trends in iDSR is described by Baboli et al. (2011). In non-dispatchable iDSR, a consumer, e.g. a steel plant is allowed to decide whether it wants to react to a changing situation within the grid, potentially gaining financial benefits, or stick to the production plan. This implies the need of proper every-day scheduling and planning of plant operations, and for making use of incentive and price based schemes, such as for example intra-day or day-ahead spot market pricing since changes in the prices of energy might significantly affect the profitability as shown for a stainless-steel production plant in Hadera et al. (2014).

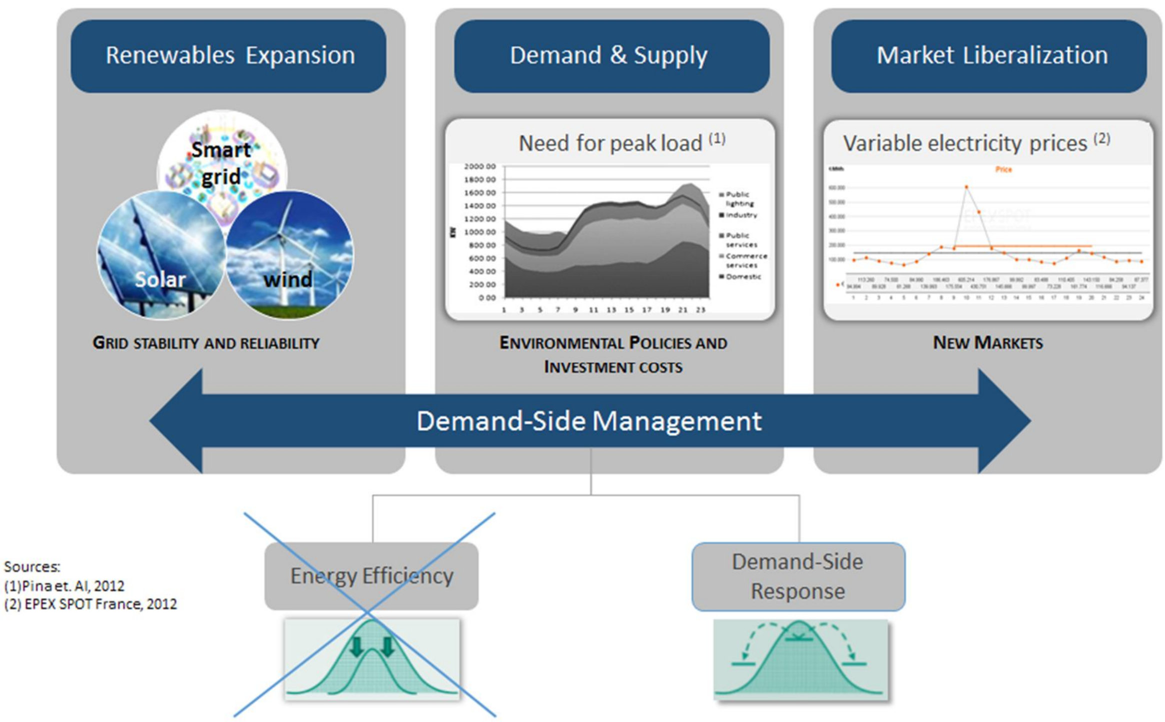


Figure 2-1 Major challenges in energy-supply systems

Demand-response technology on the production scheduling and planning level has an advantage of a potentially low investment cost for the final user, since very often it does not require purchase of new equipment. Other selected positive outcomes of a more flexible Demand-side Response that are reported in the literature are (NECR 2007; CRA 2005; Todd et al. 2009):

- Plant level: direct cost savings on the electricity bill;
- Grid level: increase of reliability, e.g. reduction of outages;
- Grid level: reduction of expensive peak load hours in the short-term;

- Environment: potential emission savings by reducing the grid's peak generation (only for regions with high-emitting peak generation plants);
- Environment: potential emission savings by enabling the installation of larger renewable generation capacities;
- Market: market-wide wholesale electricity price reduction in the long-term;
- Market: market performance benefits, e.g. mitigating the suppliers' ability to raise prices significantly above production costs.

Except for the direct energy bill cost savings at the plant site, quantification of the above benefits is difficult and strongly depends on assumptions; however, industrial and academic studies conclude that the potential exists (DOE 2006; NERC 2007; DENA 2011). When investigating DSR of industrial production, it is important to consider the technical potential of Demand-side Response capabilities and not only the total consumption of the process, as pointed out by Paulus and Borggrefe (2011). Ideal industrial plants should have large consumers of electric power that operate in a preplanned fashion and a degree of process flexibility, both hold true for the steel plant considered in this paper.

Even though the iDSR technology is recognized as beneficial for both the power supplier side and for the energy-intensive industry, it should be noted that it cannot compensate long-term deficits or surplus of electricity generation in regional grids.

2.3 Energy-intensive process industry

For many years now the industrial sector has been accounting for the most energy use globally. According to International Energy Agency (IEA) projection, in 2014 industrial delivered global energy end-use will account to more than 50% , with transportation, residential and commercial sharing the rest (IEA 2013). Among the industrial users are the processes of steel- and pulp-making. They are considered later in the dissertation as a result of specific interest of the industrial research community, but also have their motivation in the identified iDSR potential of these processes. According to the German Energy Agency (DENA 2011) the biggest electricity users in Germany are steel and paper industry (Figure 2-2). In some regions it is the paper industry which uses the most energy among all, such as for example in the case of Sweden, with total energy use around 45% (Swedish Energy Agency 2013).

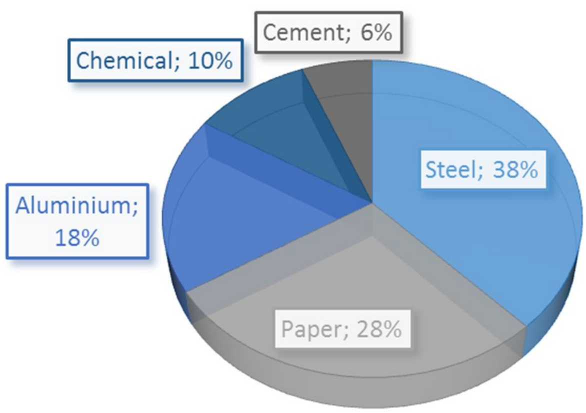


Figure 2-2 Electricity consumption share by industrial sector for Germany (DENA 2011)

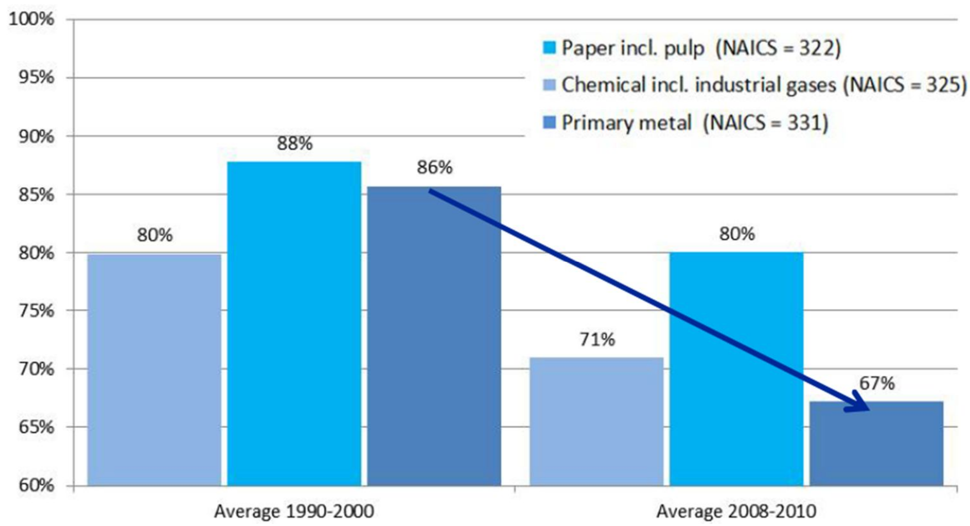


Figure 2-3 Capacity utilization of US Energy-Intensive Industries (based on BGFRS 2013)

Such energy-intensive industries are potential candidates for realizing iDSR strategies. If it is assumed that the goal of the plant managers is to deliver the same amount of final products over a certain time horizon, the production schedule can be modified in favor of a lower cost of energy procurement, but only when the process-specific constraints are always satisfied, and when at the same time the plant faces a certain under-utilization of its production capacity. As shown in Figure 2-3 the capacity utilization of the US-based energy-intensive primary metal sector has gone down by nearly 20% in recent years compared to 1990's (BGFRS 2013).

This creates a potential to optimally shift production to times when the consumption of electricity is cheaper. This is especially valid for energy-intensive process industries, where the raw material and energy cost can account for up to 60% of the total production cost. For the stainless-steel manufacturing process, the electricity accounts for about 20-40% of the total raw material cost in some countries (Ali et al. 2007). Therefore, for such processes more efficient raw material use has a potential to bring significant overall cost reductions. Even if in relative terms the reduction is only a few percent, the quantitative amount can be hundred thousands of dollars on a monthly basis (see e.g. Hadera and Harjunkoski 2013; Castro et al. 2013).

Among the energy users accounted as industrial loads there are production processes which are recognized to have potential for iDSR implementation as investigated in the studies by Paulus and Borggrefe (2011) and Klobasa et al. (2006). The selected processes are shown in Table 2-1. The stainless-steel making process is recognized as a suitable candidate for iDSR (Gajic et al. 2014) since it has a very energy-intensive EAF production stage (around 85 MW for one furnace as noted by Hadera and Harjunkoski 2013) which operates in a batch mode. The pulping process usually includes several pulp refiners each of which consumes about 10-30 MW. If the process includes the paper machine the load is even more significant. However, the paper machine itself does not have much flexibility in load shifting as it should operate with high utilization, thus at this stage the main flexibility is the waiting time between production campaigns. In contrast, the pulping process itself contains storage tanks which serve as a buffer between the pulping and paper making. This can be very advantageous when implementing iDSR principles (Paulus and Borggrefe 2011). Additional motivation for choosing the stainless-steel and TMP process is given later in this chapter as well as in the scheduling literature review in Chapter 2.4 and also in the introductory Chapter 3.1.1 for the steel and 4.3.1 for the TMP case.

Table 2-1 Selected industrial processes with iDSR potential

Industrial sector	Process	Enabler
Metals	Stainless-steel making	Energy- intensive Electric Arc Furnace stage, batch process
Pulp and paper	Thermo-mechanical pulping (TMP) and paper making	Energy-intensive refiners and paper machines, storage of pulp
Chemicals	Chloralkali electrolysis	Energy-intensive electrolysis, but high capacity utilization
Metals	Aluminum electrolysis	Energy-intensive electrolysis, but high capacity utilization
Metals	Primary steel-making	Energy- intensive Blast Furnace (BF) stage, but high capacity utilization
Cement	Cement milling	Energy-intensive rotary machines
Chemicals	Air separation	Energy-intensive compressors, energy cost is significant raw material cost
Oil and Gas	Liquefied Natural Gas (LNG)	Energy-intensive refrigeration
Mining	Winder systems	Energy-intensive winder motors, intermediate storage of transported material
Mining	Belt conveyor systems	Energy- intensive motors for conveyers
Metals	Hot Rolling Mill (HRM)	Energy-intensive motors for the rolling machine, relatively quick batch process

Apart from the two first processes identified as very good candidates for iDSR there are several others, such as for example the electrolysis process of aluminum and chloralkali. Although they both have very energy-intensive production (15 MWh/t for aluminum and 2,85 MWh/t for chloralkali electrolysis) in order to keep the process efficient high utilization needs to be maintained. Therefore, the potential to shift the energy load in time is decreased. Similarly, in the primary steel making the Blast Furnace (BF) needs to be operated continuously for several years without shut-downs.

The cement production's final phase consists of clinker crushing and grounding with additives. The mills used for this purpose contain large energy-intensive rotary machines. Some recent studies show at least 2% cost reduction by implementation of load shifting strategies (Lidbetter and Liebenberg 2013).

The air separation is an interesting process where the two main raw materials are the air, which is for free and the electricity. The latter is used primarily to run oxygen compressor motors and air compressor motors (Kruger, 2003). As discussed later in Chapter 2.4, the process has been investigated in recent years by a number of studies (e.g. Mitra et al. 2012).

An LNG plant converts the natural gas into liquid for ease of storage and transportation. A typical process consumes around 5,5-6 kWh per kmol of LNG produced (Zargarzadeh et al. 2007) with about 40% of operating cost due to energy in the refrigeration section (Hasan et al. 2009).

In the mining industry the rock winder systems are energy-intensive and possess certain flexibility. The systems are used to transport rock, waste and machinery between the ground surface and the mine's underground levels. The material can be stored temporarily before reaching the surface. A more detailed analysis of the potential of the winder systems is presented in Vosloo (2006).

Another process in the mining industry (and other industries as well) is transportation of material by means of belt conveyor systems. These usually have flexibility and relatively energy-intensive motors are used as shown for example in Marx and Calmeyer (2004). iDSR potential has also been studied as in for example Middelberg et al. (2009), where authors report 66% electricity cost savings by proper scheduling of the operations.

In steel making there is also another energy-intensive stage of Hot Rolling of the steel slabs (AISI 2005). Here, the slab thickness is reduced by applying mechanical pressure on the product. The rolls used to press are driven by energy-intensive motors. The process is carried out in batch campaigns of several slabs, during which the rolling of one slab takes only a few minutes. Unfortunately, this operating mode is in contrast to the need of a large consistent load that could be shifted in time.

2.4 Scheduling under energy constraints

The field of scheduling and planning has grown rapidly in the last decades. Pochet and Wolsey (2006) present an overview of MILP methods used for production planning. A large number of studies have emerged using both time representation approaches: discrete and continuous. For a general overview concerning the scheduling problems there are multiple papers available, such as for example Floudas and Lin (2004), Méndez et al. (2006), Shaik et al. (2006), Maravelias (2012),. Kallrath (2002, 2005) gives an overview of planning and design problems for the process industry which are based on MILP approaches. Harjunkoski et al. (2014) focus especially on the industrial aspects of the scheduling methods.

Scheduling of steel plants under energy constraints

Scheduling of steel plants has been studied quite extensively as well, as it is recognized as one of the most difficult industrial scheduling problems. Tang et al. (2001) give an overview of planning and scheduling systems for integrated steel plants, including Artificial Intelligence, Expert Systems, intelligent search and Constraint Programing methods. In Li et al. (2012) the focus is on the last continuous-casting stage where particular operational features have to be addressed and a rolling horizon was used. For handling complex process constraints and optimizing traditional objectives such as makespan or earliest task completion time, an efficient multi-step decomposition approach for the industrial-size scheduling of the melt shop area of a stainless steel plant is reported by Harjunkoski and Grossmann (2001) based on MILP and LP models. The latter is improved by Harjunkoski and Sand (2008) to extend the flexibility of the formulations.

In recent years scheduling under energy constraints has gained increasing attention. As suggested by Rudberg et al. (2013) energy management is still not treated strategically by process industry and there is a need for new methods and tools to answer the energy-related issues. Similar conclusions are drawn by Thollander and Ottosson (2010) who particularly investigated foundry and pulp and paper industries. Energy has been also recognized as one of the challenges for industrial implementation of advanced scheduling solutions (Harjunkoski et al. 2014). Merkert et al (2015) present a short overview of the methods and challenges related to industrial scheduling with energy constraints. Thus point out that well formulated models combining production planning and energy management aspects guarantee a more efficient and sustainable production that fits well within the philosophy of Enterprise-Wide Optimization (Grossmann, 2005). In a study by Ashok (2006), a discrete-time formulation is used to schedule a mini steel plant where the operating cost is optimized. The operating cost includes the price of power consumption under different tariffs, charges for registered maximum demand and additional operating cost due to the shifting of loads. Zhang and Tang (2010) introduce a discrete-time scheduling formulation using a Lagrangian relaxation algorithm based on the subgradient method. The model includes constraints concerning power availability and minimization of the energy cost. In recent years, models based on the RTN representation have gained attention as an efficient way to deal with resource consumption. Castro et al. (2009) proposed a new strategy for handling variable electricity cost in continuous plants using a continuous-time formulation. Comparison of both continuous- and discrete-time RTN representations showed that the latter's computational performance is better for handling industrial-size instances. The work has been extended by an efficient rolling horizon algorithm in Castro et al. (2011) using an aggregate model, where time intervals of the same resource cost are aggregated into one interval. A steel plant scheduling problem similar to the one studied in this paper, but with response to a single price curve, has been successfully reported by Castro et al. (2013) for a time granularity of 15 minutes intervals.

Nolde and Morari (2010) propose a strategy for the modeling of electricity consumption with time-dependent prices in continuous-time models based on precedence variables. It was applied to a stainless-steel process with parallel Electric-Arc Furnaces. The formulation uses six different binary variables to capture the relation of a production task to its placement within a grid of uniform time intervals. For these intervals, electricity consumption is individually accounted for, which makes it possible to track the process load and to optimize the deviation from a pre-agreed consumption curve. Haït and Artigues (2011a) propose an improvement to Nolde and Morari's approach replacing the set of six binary variables by binaries indicating whether or not an event takes place before or during a time interval. For the same steel case problem, the resulting continuous-time MILP model introduced fewer number of constraints and binary variables. As a follow up study on scheduling of a foundry, Haït and Artigues (2011b) proposed a hybrid heuristic combining Constraint Programing (CP) for solving the assignment and sequencing problem with an MILP model for solving the remaining energy-cost scheduling problem. In addition, the detailed scheduling of the Electric Arc Furnace stage and human operator availability were taken into consideration. Castro et al. (2014) applies the concept of the six cases of task-time interval relations as in Nolde and Morari (2010) to optimize the maintenance of a gas-fired power plant. Using Generalized Disjunctive Programming, Castro and co-workers finds a tighter formulation for the accounting of electricity consumption. The continuous-time strategy was applied to find a schedule under constraints of operator availability and cost, maximizing profits from electricity sales under time-sensitive demand and pricing. A steel plant is also considered in a study by Boukas et al. (1990), using a hierarchical approach with separation of operation and secondary resource scheduling in two steps. Constraints were subject to a global limitation of the power delivered to the furnaces.

Energy considerations in the pulping industry

In the pulp and paper industry, the traditional major decision regarding scheduling optimization are order allocation, run formation and sequencing, trimming and load planning (Keskinocak et al. 2002). An overview of planning and scheduling methods in the pulp and paper industry is provided for example by Malik and Qiu (2008) and Keskinocak et al. (2002). The energy considerations were always in the scope of interest for this industry since the production process is energy-intensive and in some process types it can generate an energy surplus. Due to this reason, energy integration aspects can be found in the pulp and paper scheduling literature. In a study by Santos and Dourado (1998), a Genetic Algorithms based approach is proposed for an optimal scheduling system for the mass and energy production in a kraft pulp and paper mill. The multi-objective optimization aspects include steam and electricity production to optimize energy cost and production rate changes. More recently, Waldemarsson et al. (2013) include the production of energy related by-products in a broader perspective of the entire supply chain planning of a pulping mill. The work considered the possibility to sell energy products (e.g. black liquor, liquid rosin and bark) and energy carriers (steam and electricity) on the respective markets. The study concluded that with the increasing prices of energy the importance of proper planning that takes energy aspects into consideration increases as well. The uncertainty of energy prices is also addressed for the pulping industry. Using the TMP case example from Pulkkinen and Ritala (2008), the study by Karagiannopoulos et al. (2014) investigates a stand-alone pulp that is a member of a so-called balance group which bind together energy users and suppliers.

A generic energy-cost optimization strategy is presented by Harjunkoski et al. (2012). The model is based on a flow network formulation (see e.g. Ahuja, Magnanti and Orlin, 1993; Bertsekas, 1991) that is able to accommodate different energy sources and sinks. The objective of the model is to minimize the cost under contractual constraints. The approach is used in the steel schedule optimization with regard to electricity by Hadera et al. (2015a) and a pulping process in Hadera et al. (2015c) . Interestingly, related to the latter two, Rebennack et al. (2010) investigates a utility problem that is similar to an industrial energy-intensive consumer problem (e.g. Hadera et al. 2014) which consists of load commitment and minimization of purchase and sale of electricity. For the utility, the goal of the optimization problem is to determine how much electricity to produce from own power plants and how much to buy from external electricity markets in order to satisfy a deterministic demand. Another study from a power generation perspective is done by Sarimveis et al. (2003). The study investigates a power plant that satisfies electricity and steam requirements for a pulp and paper mill. The optimization includes detailed mass and energy balances, plant shut downs as well as purchase and selling contracts for electricity.

Selected energy aspects in literature

Since energy availability and prices can be treated like any other resource in the scheduling models, many of the formulations in the literature use a discrete-time approach. Apart from the steel industry, demand-side response strategies have been investigated for other energy-intensive processes. Mitra et al. (2012a) propose a discrete-time formulation for process plants with an emphasis on switching the operating modes of the plant units. Responding to a single time-sensitive price curve of electricity the model was successfully applied to air separation and cement production processes. The same solution strategy was also applied in the context of optimal scheduling of an industrial Combined Heat and Power (CHP) plant (Mitra et al. (2013). Underutilization of the CHP plant and its response to time-sensitive electricity prices were investigated.

One interesting line of research concerning the energy aspects in scheduling is the topic of the uncertainty of the prices. Optimizing operations with regard to a single time-varying price of electricity can be found in Li et al. (2003). The air separation plant scheduling problem with partially unknown prices of energy was tackled by Ierapetritou et al (2002). Also for the air separation plant, a robust scheduling approach was proposed by Mitra et al. (2012b). The Demand-side Response has to deal with different time scales. A fast response is required in some iDSR schemes, for example in network ancillary services. Here control techniques rather than scheduling might be better suited. As investigated by Vujanic et al. (2012), robust optimization might help creating flexible schedules to support the ancillary services of cement plants.

In a study by Özdamar and Birbil (1999) a hierarchical approach is developed and tested for the tiling industry. The model aims at lot sizing and assignment of products to the kilns with the goal of energy- and inventory cost reduction. The approach consist of two stages, first, the products and the capacity are aggregated over the entire planning horizon. Next, another model is solved with detailed lot sizing and loading considerations using a heuristic.

To sum up, there is a vast literature investigating very different aspects of energy-related scheduling and production planning in process industries. However, none of the above mentioned studies dealt with pure MILP continuous-time scheduling formulation, a large batch process and an as complicated energy-cost related optimization as the problem tackled in Chapter 3.1.3. In addition, there is a very limited number of studies that deal with the integration of scheduling and energy-cost optimization with functionally separated systems as the concept developed in Chapter 4.

3 ENERGY-AWARENESS IN GENERAL PRECEDENCE CONTINUOUS-TIME SCHEDULING

This chapter is one of the two main research parts of the dissertation. It starts with stating the technical challenge behind the models, giving the contextual background of the use case. As the scope of the work deals with solving large-scale scheduling problem under energy constraints, a decomposition approach is developed since the monolithic models cannot be solved efficiently enough to tackle industrial-sized instances.

The chapter is structured as follows:

- the research motivation context of the technical challenge (Chapter 3.1.1);
- the industrial use case and the problem of optimal decision making with regard to energy such as optimal purchase, sale and deviation of actual process load from committed values (Chapter 3.1.2, 3.1.3);
- different solution strategies of extending scheduling models (Chapter 3.2.2) to answer the posed challenges in the motivation part (Chapter 3.2.3, 3.2.4, 3.4);
- monolithic and heuristic strategies for stainless-steel use case process (Chapter 3.3, 3.52.3).

The resulting models in this chapter can be employed for the functional separation of continuous-time scheduling and energy optimization, enabling an iterative scheme. The scheme is presented in Chapter 4 and also applied to the second use case of Thermo-Mechanical Pulping.

3.1 Problem description

3.1.1 Research challenge and motivation

The technical problem considered in this chapter relates to the first goal of this work which is to find an optimal production schedule of a part of a steel making process that is operated in batch mode that minimizes a weighted combination of the electricity bill and the lead times of product delivery, while satisfying complex production constraints. In the case considered here, a continuous-time based general precedence scheduling approach had already been developed for the plant (Harjunkoski and Grossmann 2001, Harjunkoski and Sand 2008, Hadera and Harjunkoski 2013) which is extended here to include awareness of the cost of electric energy. The goal is to enable an energy-intensive process plant to realize its Demand-side Response potential at the production scheduling level, finding a compromise between production delays and the cost of electricity. The main contribution of this work concerns the development of the following items:

- a generic strategy for energy-aware scheduling, accounting for time-depending cost of energy in general precedence continuous-time scheduling models;

- extension of energy-aware scheduling to generic multiple purchase contracts optimization;
- a bi-level heuristic for obtaining good solutions in reasonable times for industrial scale combined production scheduling and energy cost minimization problems.

The benefit of using a continuous-time formulation is the exact timing of the production tasks within the scheduling horizon. This is in contrast to discrete-time approaches, which discretize the time horizon into discrete time intervals. From industrial practice we consider 5-minute discretization steps as the desired level of time granularity. Such small time windows creates very large discrete-time models leading to computational limitations. Other studies showed that a 15-minute discretization (Castro et al. 2013) can still be efficient for solving 24 *h* scheduling horizon with a Resource-Task Network (RTN) based monolithic model approach. However, compared to the discrete-time formulation, continuous-time models also have some drawbacks. Due to the structure of the pricing contracts, it is much easier to account for the cost of the consumption of electricity in discrete-time scheduling models. Extending it to continuous-time formulations is not straightforward since the use of electricity has to be accounted for in fixed time intervals in which related to the resource prices are constant.

In the next chapters the purchase optimization of multiple sources of electricity, including the possibility to sell the electricity back to the grid is considered. Also, the challenge of responding to a committed load curve with penalties incurred for both under- and over-consumption is addressed. The combination of these two features has not received much attention in the process scheduling literature yet. For the given multi-stage steel plant with parallel machines at each stage, the resulting monolithic formulation of the problem is computationally intractable when the scheduling decisions (assignment and sequence binaries) are degrees of freedom for the optimization. To overcome the computational limitations a simple bi-level heuristic approach is introduced. The problem is modeled using mathematical programing with Mixed-Integer Linear Programing (MILP) and implemented in the GAMS modeling environment using the CPLEX solver.

3.1.2 Stainless-steel process

The industrial problem that is addressed in this work concerns the optimal scheduling of a part of the stainless-steel production process. The production starts with the scrap melting phase in an Electric Arc Furnace (EAF) to form a so-called heat which is the object of scheduling. The process of smelting is carried out by passing large amounts of electricity through electrodes in order to form high-temperature electric arc (up to 3500°C) that is capable of melting scrap metal. After a full heat is formed in the EAF, the heat is transported to the next stage, the Argon Oxygen Decarburization (AOD), where the carbon content of the molten steel is reduced by injecting an argon-oxygen gas mixture. In order to ensure specific parameters of the molten steel for the final stage of casting, a heat goes through the Ladle Furnace (LF) stage to adjust the chemistry and temperature to their specified values. Finally, the heat is casted in the Continuous-casting (CC) stage, where specific rules about the sequences of heats apply. The process is shown in Figure 3-1.

There are several production constraints that have to be satisfied by the scheduling model formulation. Two parallel pieces of equipment are considered with non-identical machines at each stage. For all stages, except of the CC, processing of a subsequent heat can be carried out only after an equipment specific setup has been performed. Between subsequent stages, a heat must be transported with some minimum time requirement which differs depending on the two units considered.

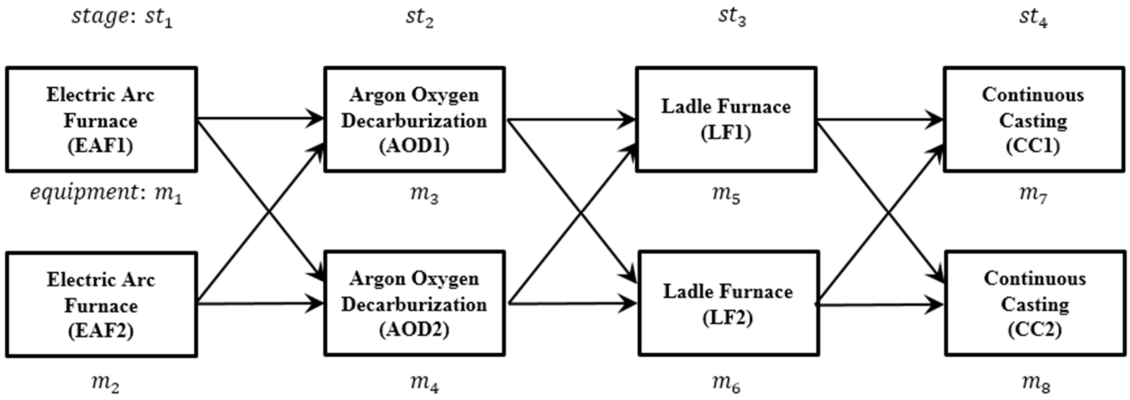


Figure 3-1 Considered Stainless-steel production process

The time spent by a heat waiting between two subsequent stages is restricted by a maximum allowed hold-up time in order to avoid a too-large drop of the temperature of the molten steel. Heats of the same heat group are casted subsequently on the CC without waiting times.

3.1.3 Energy cost

The above mentioned production process consumes large amounts of electricity, in the considered case up to 192 MW. The energy demand for this process must always be met, i.e. the plant is assumed to purchase at least the amount of electricity needed to satisfy the load curve that results from the production schedule. In this work, demand-side response strategies which preserve the total production output over some given time horizon is considered, in the computational studies they are considered over one day. The challenge addressed in this work is to determine simultaneously an optimal purchase and sales policy for electricity, with complex time- and load-sensitive purchasing options as shown in Figure 3-2, and a production schedule that defines the demand of electricity.

For the industrial case study the purchasing contracts include:

- long-term contract (base contract or base load) – constant price, constant amount of electricity delivered over time;
- short-term contract (Time-of-Use or TOU) – two price levels (on-peak and off-peak);
- spot market (day-ahead) – hourly-varying prices, known 24 hours ahead;
- onsite generation– constant price with additional start-up costs.

The long-term contract is agreed upon with a provider usually for a period of 3-12 months. Over this time, a certain fixed amount of electricity is available for the production plant at all times. The agreed amount must be purchased by the plant. Therefore, in a situation where there is no load consumption planned at some time interval, the surplus of electricity must be sold back to the grid. Establishing a long-term contract is usually considered profitable for the plant since the provider is able to offer a lower price for such a constant delivery over a long period.

The short-term contract (TOU) usually covers up to 3 months. Therefore, the price offered by the supplier is normally higher compared to the long-term contract. Here, it is assumed that the contract has two different price levels corresponding to on- and off-peak times. The off-peak price is lower than the on-peak price which applies during the daylight period.

Another contract considered in the case study is the day-ahead spot market. Here, the price follows regional fluctuations of electricity availability; therefore, it varies on an hourly basis.

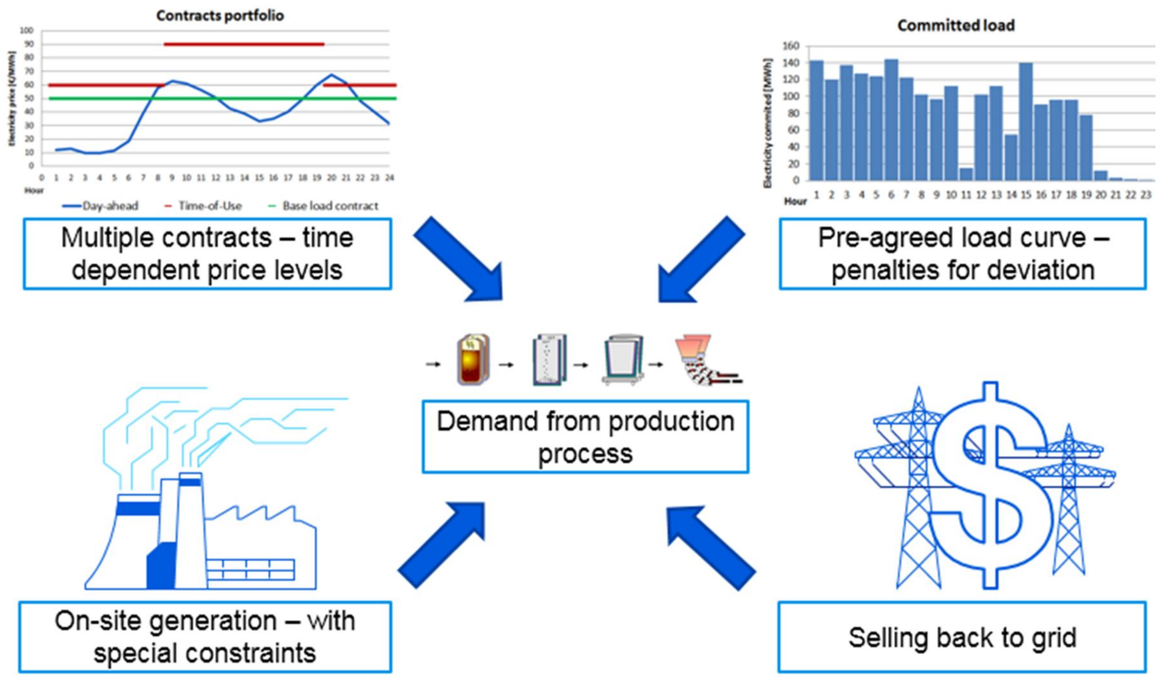


Figure 3-2 Electricity bill structure

Apart from purchase contracts, the plant may have the possibility to produce electricity internally, which is subject to additional constraints. A start-up cost needs to be accounted for in the total cost of onsite generation for each time the onsite power generation is started up. Also, minimum runtime and downtime restrictions apply to avoid frequent start-ups and shut-downs of the power plant which lead to an accelerated deterioration of the plant.

The total electricity bill can be reduced by selling electricity back to the grid. The price of selling electricity also differs on an hourly basis, depending on the regional situation in the grid. In the case of low availability of electric power, the plant can use the possibility to decrease its internal demand, to use the negotiated contracts and to use onsite generation in order to sell the electricity with a profit. This might happen especially in regions with heavy industry and at low temperatures during winter time.

The electricity bill, apart from the electricity purchase costs, accounts for the deviation penalties. It is often the case that large industrial consumers of electricity make bilateral agreements with electricity providers to follow a certain agreed load profile. Both the provider and the plant benefit from this. The provider knows in advance a very good approximation of the load levels to be balanced with supply of generation which leads to minimization of operating cost. In favor, the consumer gets a considerable reduction in the price of electricity from the provider. Therefore, often the load deviation problem is related to one single contract with pricing schemes such as for example Time-of-Use. For our case, it is assumed that the plant predicts its load consumption for a period of 24 h minimum one day before the actual load occurs. This forecast is sent to the energy supplier, committing the plant to a certain load profile. If the actual consumption differs from this plan the plant is obligated to pay penalties. For the case study, the assumption is made that both under- and over-consumption is penalized, but with a penalty-free margin.

3.2 Monolithic models development

3.2.1 Structure of the monolithic model

The proposed MILP formulation describes a power intense steel making process that produces a set of products (heats) $p \in P$ on a set of units $m \in M$, while satisfying various operational constraints. The plant is assumed to deliver a fixed number of products that are known in advance. The power consumption is both unit and product specific. The goal is to compute a one day production schedule that minimizes the total (net) cost of electricity and the weighted starting times of the tasks (i.e. a throughput related criterion). The electricity purchase includes different options and is subject to hourly price-variations. The optimization should determine the optimal amounts to be transferred from or to the electricity sources or sinks $i \in I$ at any given time interval $s \in S$. The end of the last time slot is equal to the scheduling horizon. Penalties due to the deviation from a pre-agreed load curve are incurred when a certain penalty-free buffer is exceeded and may differ for under- and over-consumption. The electricity bill can be reduced by selling the surplus of electricity. The monolithic models are described using the notation shown in Table 3-1. Additional notation introduced for the bi-level solution heuristic is given in Chapter 3.4.1.

Table 3-1 Monolithic model notation

Sets:	
P	heats (products) to be produced
HG	heat groups with defined sequence of casting
$HGP(P)$	subset of heats p mapped to corresponding heat group hg
$L(HG,P), F(HG,P)$	subset of heats p cast respectively last or first in a heat group casting sequence hg
M	equipment (machines)
EAF, AOD, LF, CC	subsets of equipment
S	time intervals
ST	production stage
$SM(ST,M)$	production stage st mapped to corresponding equipment m
$Node, I, J$	nodes in flow network denoting sources and sinks of electricity
$Pur(Node)$	purchase contracts node
$Dem(Node)$	production process electricity demand node
$Gen(Node)$	onsite generation node
$Bal(Node)$	balancing node
$Sale(Node)$	electricity sale sink node
$ARC_{i,j,s}$	defined arc between nodes i and j in time slot s
Parameters:	

$\tau_{p,m}$	processing duration of heat p on equipment m
t_m^{setup}	setup time for machine m
$t_{m,m'}^{min}$	minimum transport time from equipment m to m'
$t_{p,st}^{max}$	maximum hold-up (waiting) time after stage st
a_s	pre-agreed (committed) load curve
τ_s	electricity consumption time slot boundary
τ	time slot duration (for uniform discrete time steps of energy accounting)
$h_{p,m}$	specific power consumption of processing heat p on equipment m
$c_{s,i,j}$	electricity cost of flow from i to j in time slot s
$f_{s,i,j}^{min}, f_{s,i,j}^{max}$	minimum and maximum flow between nodes i and j
r^{min}, d^{min}	minimum run- and down-time of onsite generation
c^{start}	startup cost of onsite generation
k	coefficient of delivered power reduction due to startup of onsite generation
c	coefficient of task start time weight in the objective function
M	big M parameter (large number)

Variables:

$t_{m,p}^s, t_{m,p}^f$	positive continuous variables of starting and finishing time of heat p on equipment m
$t_{p,st}^s, t_{p,st}^f$	positive continuous variables of starting and finishing time of heat p at stage st
$w_{p,st}$	positive continuous variables of waiting time of heat p after stage st
q_s	positive continuous variables of electricity consumed in time slot s
$X_{m,p}$	binary variable, true when heat p is assigned for processing on equipment m
$V_{st,p,p'}$	binary variable, true when heat p' is processed after heat p on stage st
$Y_{p,st,s}^s, Y_{p,st,s}^f$	binary variable, true when heat p starts or finishes on stage st in the slot s
$G_{s,i,j}$	binary variable, true when generation is running in time slot s
$g_{s,i,j}^s$	pseudo-continuous positive variable denoting if onsite generation start-up occurred in time slot s
$y_{p,m,st,s}^{saux}, y_{p,m,st,s}^{faux}$	auxiliary continuous positive variable true when heat p is assigned for processing and started or finished processing on stage st in time slot s
$a_{p,m,st,s}, b_{p,m,st,s}, c_{p,m,st,s}, d_{p,m,st,s}$	positive continuous variables accounting for processing time of heat p on equipment m on stage st spent within a slot s

$o_{p,m,s}$	positive continuous variable accounting or processing time of heat p on equipment m spent within a slot s in the improved model
b_s	positive continuous variables of buffer level for allowed deviation from committed load in time slot s
b_s^o, b_s^u	positive continuous variables of upper and lower bounds for buffer in time slot s
c_s^o, c_s^u	positive continuous variables of actual over- and under-consumption in time slot s
$f_{s,i,j}$	positive continuous variables of flow from node i to j in time slot s
c_s^{gen}	positive continuous variables of cost of onsite generation in slot s
μ	continuous variable of net electricity consumption cost
δ	positive continuous variables of deviation penalties cost

For the problem described in Chapter 3.1 a monolithic model is developed. It consists of several components as shown in Figure 3-3. First, to ensure that all process specific constraints are satisfied, a scheduling model is created using the continuous-time general precedence approach (Chapter 3.2.2). The use of this approach is motivated by the required level of precision stemming from the specification by the industrial end-user. In order to optimize the purchase of electricity and to augment the schedule in order to express potential changes of load patterns, a strategy for expanding the scheduling model with energy-awareness was formulated (Chapter 3.2.3). This part of the monolithic model uses the continuous variable (used in the scheduling part) of task start time $t_{m,p}^s$ in order to find the contribution of a task to the electricity consumption within a given time interval s.

When applying this strategy for all tasks, the total electricity consumption q_s of the process in a given time interval can be computed, which is needed for the optimization of the cost of electricity (Chapter 3.2.4). This part computes optimal values in a flow network representing possible flows of electricity $f_{s,i,j}$ from sources to sinks. The optimization results in an optimal cost structure of the available purchase contracts with the exact amount of the electricity to be bought or sold under each contract. The knowledge of the process consumption during the time slots also enables to account for potential penalties δ paid due to deviations from the pre-agreed load curve, and to determine when it is profitable to under- or over-consume electricity.

The objective function of the monolithic model takes into account the weighted task start times, the net electricity consumption cost μ and the penalties δ paid for deviations. By choosing the weights in the summation, potential losses in the process (e.g. heat losses due to waiting time between the stages) or delays of the production can be traded off against the cost of electricity purchase and sales.

$$\min(\mu + \delta + c \cdot \sum_{m,p} t^s_{m,p})$$

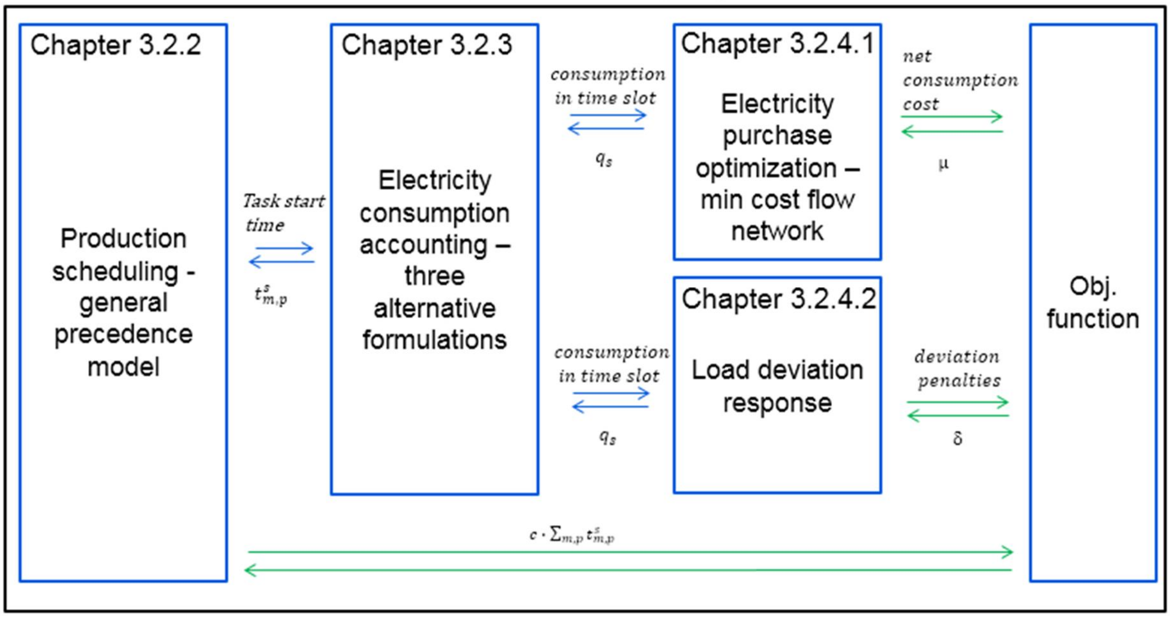


Figure 3-3 Monolithic model structure

3.2.2 Production scheduling model

The general precedence scheduling model for the stainless-steel plant used in this study is largely based on the model introduced by Harjunkoski and Grossmann (2001). This model was further extended to a more flexible formulation introducing stages and multiple machines in Harjunkoski and Sand (2008). The scheduling part of the model uses assignment and precedence binaries following equations (1-17) from Hadera and Harjunkoski (2013).

The scheduling model is based on the precedence variables and assignment variables that determine which of the parallel machines on each stage shall process a given heat. The general precedence $V_{st,p,p'}$ is true if a product p is processed before a product p' on a stage st. The assignment $X_{m,p}$ is true only when a given product p is processed on machine m. The sum Eq. (3.1) states that exactly one machine should process a heat per stage.

$$\sum_{m \in SM_{st,m}} X_{m,p} = 1 \qquad \forall p \in P, st \in ST \tag{3.1}$$

Equation (3.2) defines the finishing time $t^f_{m,p}$ as the starting time $t^s_{m,p}$ plus the selected processing length $\tau_{p,m}$.

$$t^f_{m,p} = t^s_{m,p} + X_{m,p} \cdot \tau_{p,m} \qquad \forall m \in M, p \in P \tag{3.2}$$

Since a product can be processed only once on a given machine, the unassigned machines get a zero starting time Eq. (3.3).

$$t^s_{m,p} \leq \mathrm{M} \cdot X_{m,p} \qquad \forall m \in M, p \in P \tag{3.3}$$

The stage starting and finishing times $t^s_{p,st}$,$t^f_{p,st}$ are synchronized with the corresponding machine times in Eqs. (3.4)-(3.5).

$$t^s_{p,st} = \sum_{m \in SM_{st,m}} t^s_{m,p} \qquad p \in P, st \in ST \tag{3.4}$$

$$t^{f}_{p,st} = \sum_{m \in SM_{st,m}} t^{f}_{m,p} \qquad p \in P, st \in ST \tag{3.5}$$

The scheduling model handles maximum hold-up times after processing has been completed on a given stage, equipment specific setup t_m^{setup} times and minimum transportation times. The processing on the next stage can be done only after the processing of the previous stage has finished plus some waiting time $w_{p,st}$, which serves here as a slack variable which is determined by the optimization. The production flow between subsequent stages is established in Eq. (3.6).

$$t^{s}_{p,st+1} = t^{f}_{p,st} + w_{p,st} \qquad \forall p \in P,\ st \in ST,\ st < |ST| \tag{3.6}$$

Due to process restrictions, it is necessary to enforce lower and upper bounds for the waiting times. The minimum corresponds to the physical possibility of transferring the product to the next stage, and it is equal to the minimum transportation time between machines $t^{min}_{m,m'}$ as stated in (3.7). The upper bound $t^{max}_{p,st}$ of the waiting time reflects the process constraint that a heat should not cool off below a certain level.

$$t^{min}_{m,m'}\left(X_{m,p} + X_{m',p} - 1\right) \le w_{p,st} \le t^{max}_{p,st}$$

$$\forall p \in P,\ m, m' \in M,\ st \in ST, \{st, m\} \in SM,\ \{st+1, m'\} \in SM,\quad st < |ST| \tag{3.7}$$

The precedence of the products is characterized by the fact that either p is processed after p' or p' is processed after p. Therefore, only one of the two binaries can be true. Eq. (3.8) enforces a correct sequencing.

$$V_{st,p,p'} + V_{st,p',p} = 1 \qquad \forall p, p' \in P,\ st \in ST, p < p' \tag{3.8}$$

In order to impose the common practice that the sequence of the products that are casted on a CC must propagate back to the other production stages, Eq. (3.9) is introduced.

$$V_{st,p,p'} = V_{st+1,p,p'} \qquad \forall p, p' \in P,\ st \in ST,\ p < p', st < |ST| \tag{3.9}$$

The precedence constraint in Eq. (3.10) for other stages than CC restricts that a next heat should be processed only after the previous one has finished plus a setup time.

$$t^{s}_{m,p'} \ge t^{f}_{m,p} + t^{setup}_{m} - (\mathrm{M} + t^{setup}_{m})\left(3 - V_{st,p,p'} - X_{m,p} - X_{m,p'}\right)$$

$$\forall p, p' \in P,\ m \in M,\ st \in ST, \{st, m\} \in SM,\ p \ne p', st < |ST| \tag{3.10}$$

At the CC-stage no setup time t_m^{setup} should occur to ensure continuous casting Eq. (3.11). However, a setup must be carried out between the last $L(HG, P)$ and first $F(HG, P)$, heats of different heat groups Eq. (3.12).

$$t^{s}_{m,p'} \ge t^{f}_{m,p} - \mathrm{M}\left(3 - V_{st,p,p'} - X_{m,p} - X_{m,p'}\right)$$

$$\forall p, p' \in P,\ m \in M,\ st \in ST,\ \{st, m\} \in SM,\ p \ne p',\ st = |ST| \tag{3.11}$$

$$t^{s}_{m,p'} \ge t^{f}_{m,p} + t^{setup}_{m} - (\mathrm{M} + t^{setup}_{m})\left(3 - V_{st,p,p'} - X_{m,p} - X_{m,p'}\right)$$
$$\forall p \in L(HG, P),\ p' \in F(HG, P),\ m \in M,\ st \in ST,\ \{st, m\} \in SM,\ p \ne p',\ st = |ST| \tag{3.12}$$

Constraint (3.13) ensures that heats of the same heat group are assigned to the same caster.

$$X_{m,p} = X_{m,p+1}$$
$$\forall p \in P,\ m \in M,\ hg \in HG,\ \{hg, p\} \in HGP(P), \{st, m\} \in SM, st = |ST| \tag{3.13}$$

As the heats are pre-ordered within a casting sequence, Eq. (3.14) ensures that next heat in a sequence starts immediately after the previous one has finished.

$$t^{s}_{p+1,st} = t^{f}_{p,st} \qquad \forall p \in P\backslash L(HG,P),\ st \in ST,\ st = |ST| \qquad (3.14)$$

From technical process requirements, the heat sequence within one heat group is known. The precedence of heats within one heat group is enforced and redundant values are eliminated in Eq. (3.15). Redundant sequencing variables are eliminated when comparing two identical products in Eq. (3.16).

$$V_{st,p,p'} = 1 \qquad \forall p,p' \in P, p < p',\ st \in ST, hg \in HG,\ \{hg,p\},\{hg,p'\} \in HGP(P) \qquad (3.15)$$

$$V_{st,p,p'} = 0 \qquad \forall p,p' \in P,\ st \in ST,\ p = p' \qquad (3.16)$$

Since the goal of the production plant is to meet the production targets as soon as possible, minimizing the makespan (or tasks completion time) can be specified as an objective function in the MILP model.

3.2.3 Energy-awareness extensions

In continuous-time models, it is challenging to account for resource consumption. In this work, the scheduling model described above is extended to account for the electricity consumption by each task within given time intervals of interest. The time grid with intervals in our use case corresponds to volatile electricity prices and committed load values. Therefore the length of the intervals is one hour. The scheduling model uses continuous task start time variables which are linked to the energy-aware part of the model, leading to the computation of the overall electricity consumption within a given time interval. Once the model is complemented by energy-awareness, both the electricity purchase and the load commitment can be optimized.

3.2.3.1. Six binaries model

Strategies for resource consumption accounting in continuous-time based scheduling models have been reported in the literature. Nolde and Morari (2010) presented a strategy introducing six binaries to capture six different cases (Figure 3-4) of when a task might start or end related to a considered time interval within which one is interested to know the electricity consumption from the production process. This strategy was later reformulated by Hadera and Harjunkoski (2013) to account for parallel machines at each production stage with goals of optimizing for a single price curve and load deviation problem. To reduce the model size, the starting and finishing times of tasks are replaced with corresponding stage starting and finishing times. The resulting model formulation is presented below and later used in the numerical studies to compare its performance with the event binaries strategy described in next chapters.

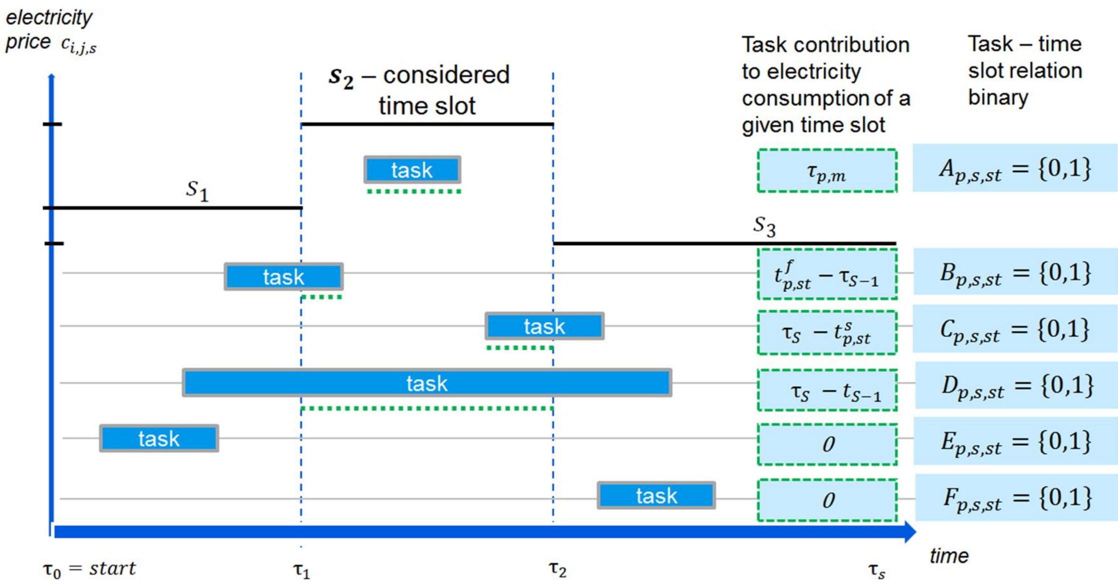


Figure 3-4 Electricity consumption for six binaries model

The literature based extension of energy-awareness for continuous-time scheduling models uses six different cases (as shown in Figure 3-4) of how a task can contribute to electricity consumption within a considered time slot:

1. A task is processed entirely within the time slot.

Processing within a time slot means that stage's finishing time $t^f_{p,st}$ occurs before the time slot's finishing time τ_s and stage's starting time $t^s_{p,st}$ occurs later than the time slot's starting time τ_{s-1}. For this case, the binary variable $A_{p,s,st}$ will be true, thus equations using Big-M formulation are written as in Eq.(3.17)- (3.18). The duration of processing within the slot will in this case be equal to the processing time of the task itself.

$$t^f_{p,st} \le \tau_s + (\mathrm{M} - \tau_s)(1 - A_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \qquad (3.17)$$

$$t^s_{p,st} \ge \tau_{s-1} - \tau_{s-1}(1 - A_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \qquad (3.18)$$

2. A task starts before and finishes within the time slot.

Second case occurs if stage's start time $t^s_{p,st}$ occurs before the lower boundary of the considered slot Eq. (3.21), however the stage's finish time $t^f_{p,st}$ is placed within the slot Eq. (3.19)- (3.20). For this case, the binary variable $B_{p,s,st}$ will be true. Processing time contribution of the task within the slot is equal to the tasks' finishing time $t^f_{p,m}$ minus the lower boundary τ_{s-1} of the considered time slot.

$$t^f_{p,st} \ge \tau_{s-1} - \tau_{s-1}(1 - B_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \qquad (3.19)$$

$$t^f_{p,st} \le \tau_s + (\mathrm{M} - \tau_s)(1 - B_{p,s,st} - A_{p,s,st}) \quad \forall p \in P, s \in S, st \in ST \qquad (3.20)$$

$$t^s_{p,st} \le \tau_{s-1} + (\mathrm{M} - \tau_{s-1})(1 - B_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \qquad (3.21)$$

3. A task starts within and finishes after the time slot.

Similarly to the second case, the task's start time $t^s_{p,st}$ occurs within the considered time interval Eq. (3.23)- (3.24) and at the same time finishing time $t^f_{p,st}$ is placed after the upper boundary of the slot Eq. (3.22). For this case, the binary variable $C_{p,s,st}$ will be true. The time a task spent within the slot will equal to the upper boundary τ_s of the slot minus the start time $t^s_{p,m}$ of the task.

$$t^f_{p,st} \geq \tau_s - \tau_s(1 - C_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.22}$$

$$t^s_{p,st} \geq \tau_{s-1} - \tau_{s-1}(1 - C_{p,s,st} - A_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.23}$$

$$t^s_{p,st} \leq \tau_s + (\mathrm{M} - \tau_s)(1 - C_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.24}$$

4. A task over-spans the time slot.

When duration of the task is longer than the time interval itself there might be a case when it over-spans the interval. This occurs only when the start time of the task $t^s_{p,st}$ is placed before the lower boundary of the time slot Eq. (3.26) and at the same time the finish time $t^f_{p,st}$ of task occurs after the upper bound of the slot Eq. (3.25). For this case the binary variable $D_{p,s,st}$ will be true. Then, the amount of time the task contributed to the time slot will be equal to the length of the time slot itself $(\tau_s - \tau_{s-1})$.

$$t^f_{p,st} \geq \tau_s - \tau_s(1 - D_{p,s,st} - C_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.25}$$

$$t^s_{p,st} \leq \tau_{s-1} + (\mathrm{M} - \tau_{s-1})(1 - D_{p,s,st} - B_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.26}$$

5. A task starts and finishes before the considered time slot.

Here both the starting time $t^s_{p,st}$ and finishing time $t^f_{p,st}$ takes place before the starting of the considered time interval τ_{s-1}. For this case, the binary variable $E_{p,s,st}$ will be true when finishing time $t^f_{p,st}$ occurs before the considered time slot, as in Eq. (3.27).

$$t^f_{p,st} \leq \tau_{s-1} + (\mathrm{M} - \tau_{s-1})(1 - E_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.27}$$

6. A task starts and finishes after the considered time slot.

Here both the starting time $t^s_{p,st}$ and finishing time $t^f_{p,st}$ takes place after the finishing of the considered time interval τ_s. For this case, the binary variable $F_{p,s,st}$ will be true when starting time $t^s_{p,st}$ occurs later than upper bound of the considered time slot, as in Eq. (3.28).

$$t^s_{p,st} \geq \tau_s - \tau_s(1 - F_{p,s,st}) \qquad \forall p \in P, s \in S, st \in ST \tag{3.28}$$

The big-M value is set to be the end of the scheduling horizon. The formulation is improved compared to Nolde and Morari (2010) by introducing second binary in the Big-M equations of similar boundary conditions as in Eq. (3.20), (3.23), (3.25), (3.26). To complete the formulation, an important constraint ensuring that there is only one of the six binaries true for a task has to be enforced, as in Eq. (3.29).

$$A_{p,s,st} + B_{p,s,st} + C_{p,s,st} + D_{p,s,st} + E_{p,s,st} + F_{p,s,st} = 1 \qquad \forall p \in P, s \in S, st \in ST \tag{3.29}$$

With the help of the binaries being true for respective cases of task-time slot relation, it is possible to capture the amount of time a given task was processed in a particular time slot. The task's consumption within the slot can be accounted for by multiplying time spent with a parameter of specific electricity consumption of the task. Therefore, with summation of all tasks the total electricity consumption in the time slot is captured with Eq.(3.30). The equation is divided by 60 to convert the unit from $MWmin$ into MWh. In the equation two problems arise. First, there are two nonlinearities from the product of binary and continuous variable. Second, the equation do not account for the fact that one of the machines in the stage does not process a task.

$$q_s = \sum_{p,st,m \in SM_{st,m}} h_{p,m}(A_{p,s,st} \cdot \tau_{p,m} + B_{p,s,st}\left(t^f_{p,st} - \tau_{s-1}\right) + \ C_{p,s,st}\left(\tau_s - t^s_{p,st}\right) + D_{p,s,st}(\tau_s - \tau_{s-1}))/60 \qquad \forall s \in S \qquad (3.30)$$

In order to deal with the latter problem, a set of auxiliary variables can be designed for which those tasks not processing a product will have the time contribution to the slot put to zero. That means, whenever a product is not assigned to a machine the binaries of respective six cases shall be put to zero. For the first case with $A_{p,s,st}$ binary, it can only be true when assignment binary $X_{m,p}$ is true, as in Eq. (3.31)-(3.32). Similarly for the $D_{p,s,st}$ binary as in Eq. (3.33)-(3.34).

$$a_{p,m,st,s} \geq A_{p,s,st} - (1 - X_{m,p}) \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.31)$$

$$a_{p,m,st,s} \leq A_{p,s,st} + 1 - X_{m,p}) \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.32)$$

$$d_{p,m,st,s} \geq A_{p,s,st} - (1 - X_{m,p}) \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.33)$$

$$d_{p,m,st,s} \leq A_{p,s,st} + 1 - X_{m,p} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.34)$$

For the other cases of $B_{p,s,st}$ and $C_{p,s,st}$ by formulating the auxiliary variable the nonlinearities can be overcome by applying an exact linearization method. The auxiliary variables have the value of the time contribution of the respective binary case only both the case binary is true and the assignment is true as well. The constraints for the two cases are shown in Eq. (3.35)-(3.42).

$$b_{p,m,st,s} \geq t^f_{p,st} - \tau_{s-1} - (\mathrm{M} - \tau_{s-1})(2 - B_{p,s,st} - X_{m,p})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.35)$$

$$b_{p,m,st,s} \leq t^f_{p,st} - \tau_{s-1} + \tau_{s-1}(2 - B_{p,s,st} - X_{m,p})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.36)$$

$$b_{p,m,st,s} \leq (\tau_s - \tau_{s-1})(1 - B_{p,s,st} + X_{p,m})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.37)$$

$$b_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) \cdot B_{p,s,st} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.38)$$

$$c_{p,m,st,s} \geq \tau_s - \ t^s_{p,st} - \tau_s(2 - C_{p,s,st} - X_{m,p})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.39)$$

$$c_{p,m,st,s} \leq \tau_s - \ t^s_{p,st} + (\mathrm{M} - \tau_s)(2 - C_{p,s,st} - X_{m,p})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.40)$$

$$c_{p,m,st,s} \leq (\tau_s - \tau_{s-1})(1 - C_{p,s,st} + X_{m,p})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.41)$$

$$c_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) \cdot C_{p,s,st} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.42)$$

With the help of the auxiliary variables the final constraint for electricity consumption accounting can be changed from Eq. (3.30) to the one shown in Eq. (3.43).

$$q_s = \sum_{p \in P, st \in ST, m \in SM_{st,m}} h_{p,m}(a_{p,m,st,s}\tau_{p,m} + b_{p,m,st,s} + \ c_{p,m,st,s} + d_{p,m,st,s}(\tau_s - \tau_{s-1}))\frac{1}{60}$$
$$\forall s \in S \qquad (3.43)$$

3.2.3.2. Event binaries model

They key idea in the approach developed here is the use of the two event binaries representing whether a given task started ($Y^{s}_{p,st,s}$) or finished ($Y^{f}_{p,st,s}$) in or before or after particular time slot s (Figure 3-5).

Since the boundaries of the time slot s are known, Big-M constraints in Eqs. (3.44)-(3.47) force the event binaries to be true in case the start or finish variable takes a value between the time slot's upper bound τ_s and lower bound τ_{s-1}.

$$t^{s}_{p,st} \geq \tau_{s-1} \cdot Y^{s}_{p,st,s} \qquad \forall p \in P, st \in ST, s \in S \qquad (3.44)$$

$$t^{s}_{p,st} \leq \tau_s + (M - \tau_s)(1 - Y^{s}_{p,st,s}) \qquad \forall p \in P, st \in ST, s \in S \qquad (3.45)$$

$$t^{f}_{p,st} \geq \tau_{s-1} \cdot Y^{f}_{p,st,s} \qquad \forall p \in P, st \in ST, s \in S \qquad (3.46)$$

$$t^{f}_{p,st} \leq \tau_s + (\mathrm{M} - \tau_s)(1 - Y^{f}_{p,st,s}) \qquad \forall p \in P, st \in ST, s \in S \qquad (3.47)$$

However, the use of the stage set st in the definition of the event binaries does not indicate which of the available equipment of this stage is actually processing. Therefore, together with the assignment variable $X_{p,m}$ two additional auxiliary pseudo-binary variables $y^{saux}_{p,m,st,s}$ and $y^{faux}_{p,m,st,s}$ can be introduced. These are true only in case the respective event binary is true and the assignment is true as well Eqs. (3.48)-(3.53).

$$y^{saux}_{p,m,st,s} \geq X_{m,p} + Y^{s}_{p,st,s} - 1 \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.48)$$

$$y^{saux}_{p,m,st,s} \leq X_{m,p} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.49)$$

$$y^{saux}_{p,m,st,s} \leq Y^{s}_{p,st,s} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.50)$$

$$y^{faux}_{p,m,st,s} \geq X_{m,p} + Y^{f}_{p,st,s} - 1 \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.51)$$

$$y^{faux}_{p,m,st,s} \leq X_{m,p} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.52)$$

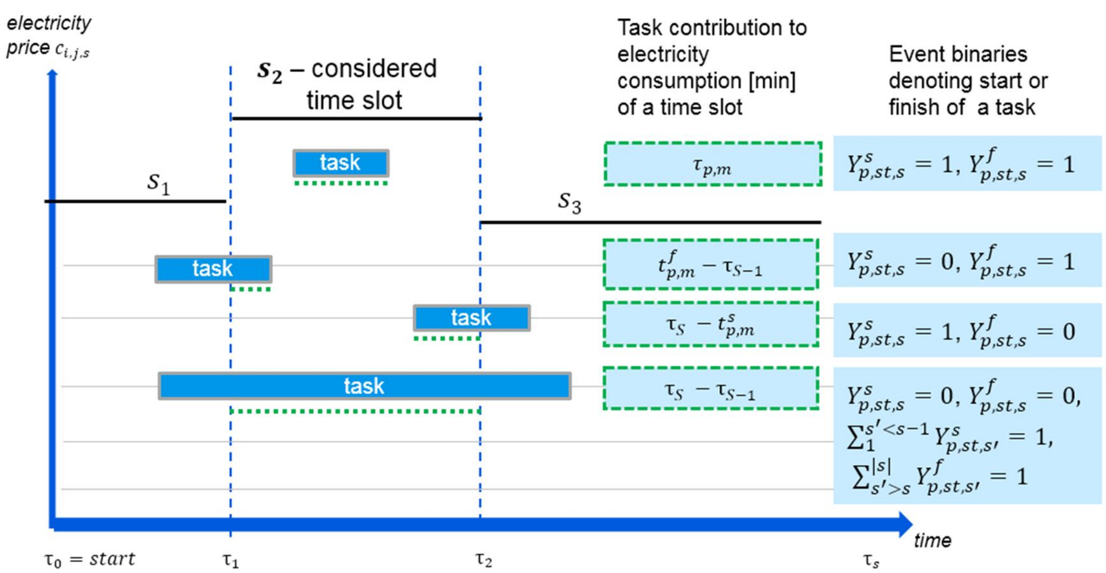


Figure 3-5 Event binaries to describe the consumption of electricity in pricing time slots

$$y_{p,m,st,s}^{faux} \leq Y_{p,st,s}^{f} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.53)$$

The two auxiliary binaries will have indices representing product p, machine m, stage st and time slot s. That enables us to introduce continuous variables that are used to capture different cases of how a particular task (here a heat processed on a unit) relates to a time slot. As shown in Figure 3-5 there are four different scenarios.

1. A task is processed entirely within the time slot

Processing within a time slot means that the start and finish time of the task must be placed within the time slot upper and lower boundary, both event binaries need to hold true. To capture this case an auxiliary variable $a_{p,m,st,s}$ is introduced as described in Equation (3.54)-(3.56).

$$a_{p,m,st,s} \geq y_{p,m,st,s}^{saux} + y_{p,m,st,s}^{faux} - 1 \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.54)$$

$$a_{p,m,st,s} \leq y_{p,m,st,s}^{saux} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.55)$$

$$a_{p,m,st,s} \leq y_{p,m,st,s}^{faux} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.56)$$

2. A task starts before and finishes within the time slot

For this case the start binary shall be zero for the considered slot. However the finish binary must hold true. That combination of the two binaries is enough to capture the time contribution $b_{p,m,st,s}$ of the task, as shown in Equation (3.57)-(3.60).

$$b_{p,m,st,s} \geq t_{p,m}^{f} - \tau_{s-1} - (\mathrm{M} - \tau_{s-1})(1 - y_{p,m,st,s}^{faux} + y_{p,m,st,s}^{saux})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.57)$$

$$b_{p,m,st,s} \leq t_{p,m}^{f} - \tau_{s-1} + \tau_{s-1}(1 - y_{p,m,st,s}^{faux})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.58)$$

$$b_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) y_{p,m,st,s}^{faux} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.59)$$

$$b_{p,m,,st,s} \leq (\tau_s - \tau_{s-1})(1 - y_{p,m,st,s}^{saux}) \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.60)$$

3. A task starts within and finishes after the time slot

In this case, the task should start between the lower and the upper bounds of the time slot and finish sometime after the upper bound. That means the start event binary is true for the slot and the finish event binary is false. The variable $c_{p,m,st,s}$ is defined by Equation (3.61)-(3.64).

$$c_{p,m,st,s} \geq \tau_s - t_{p,m}^{s} - \tau_s(1 - y_{p,m,st,s}^{saux} + y_{p,m,st,s}^{faux})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.61)$$

$$c_{p,m,st,s} \leq \tau_s - t_{p,m}^{s} + (\mathrm{M} - \tau_s)(1 - y_{p,m,st,s}^{saux})$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.62)$$

$$c_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) y_{p,m,st,s}^{saux} \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.63)$$

$$c_{p,m,st,s} \leq (\tau_s - \tau_{s-1})(1 - y_{p,m,st,s}^{faux}) \qquad \forall p \in P, m \in M, st \in ST, s \in S, \{st,m\} \in SM \qquad (3.64)$$

4. A task over-spans the full time slot

This occurs only when the start time of the task is placed before the lower bound of the time slot and at the same time the finish time of the task occurs after the upper bound of the time slot. This translates into zero values for both of the event binaries. In addition the start event binary is true in one of the earlier slots before the considered one, and similarly, the finish event binary is true in one of the later time slots. The variable $d_{p,m,st,s}$ is defined by the constraints in Equations (3.62)-(3.66). If the task either started or finished entirely before the considered slot or after the slot it does not contribute to the electricity consumption within the slot.

$$d_{p,m,st,s} \geq (\tau_s - \tau_{s-1}) \cdot \left(\sum_1^{s'<s} y_{p,m,st,s'}^{saux} + \sum_{s'>s}^{|S|} y_{p,m,st,s'}^{faux} - 1\right)$$
$$\forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.62)$$

$$d_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) \cdot \sum_1^{s'<s} y_{p,m,st,s'}^{saux} \quad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.63)$$

$$d_{p,m,st,s} \leq (\tau_s - \tau_{s-1}) \cdot \sum_{s'>s}^{|S|} y_{p,m,st,s'}^{faux} \quad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.64)$$

$$d_{p,m,st,s} \leq (\tau_s - \tau_{s-1})(1 - y_{p,m,st,s}^{saux}) \quad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.65)$$

$$d_{p,m,st,s} \leq (\tau_s - \tau_{s-1})(1 - y_{p,m,st,s'}^{faux}) \quad \forall p \in P, m \in M, st \in ST, s \in S, \{st, m\} \in SM \qquad (3.66)$$

The constraints based on the above cases yield the continuous variables $b_{p,m,st,s}$, $c_{p,m,st,s}$, $d_{p,m,st,s}$ accounting for how much time a given processing task spent within the considered time slot. Since the specific electricity consumption of the processing task is known, a proper summation of a product of the continuous variables and machine-specific electricity consumption parameter accounts for the total consumption in a given time slot Eq. (3.67). The above described approach yields fewer binaries than the one used by Nolde and Morari (2010), where six binary variables are used to describe the relation between the task and the time slot. Here only two event binaries are needed.

$$q_s = \sum_{p \in P, m \in M} h_{p,m} \left(a_{p,s,st,m} \tau_{p,m} + b_{p,s,st,m} + c_{p,s,st,m} + d_{p,s,st,m}\right)/60 \quad \forall s \in S \qquad (3.67)$$

A set of tightening constraints can help to speed up the computational performance of the model. In Eq. (3.68) and (3.69) restriction is made that for only one slot within the entire time horizon the event binary is active. Additionally, it is true only when a task exist, i.e. when a product is assigned to be processed on a machine. Eq. (3.70) accounts for total consumption of the schedule to be equal to sum of total consumption of those tasks that has been assigned.

$$\sum_{s \in S} Y_{p,st,s}^{s} = \sum_{m \in M, \{st,m\} \in SM} X_{m,p} \quad \forall p \in P, st \in ST \quad (3.68)$$

$$\sum_{s \in S} Y_{p,st,s}^{f} = \sum_{m \in M, \{st,m\} \in SM} X_{m,p} \quad \forall p \in P, st \in ST \quad (3.69)$$

$$\sum_{p \in P, m \in M} X_{m,p} \cdot h_{p,m} \cdot \pi_{p,m}/60 = \sum_{s \in S} q_s \quad (3.70)$$

3.2.3.3. Improved event binaries model

The scheduling models introduced in the previous sections was investigated in Hadera and Harjunkoski (2013) and Hadera et al. (2014) with two different energy-aware strategies for continuous-time models. In this Chapter an improvement of the original event binaries model is formulated. The event binaries allow capturing different cases of how a task can contribute to resource consumption in particular time slot of interest with a new strategy as shown in Figure 3-6.

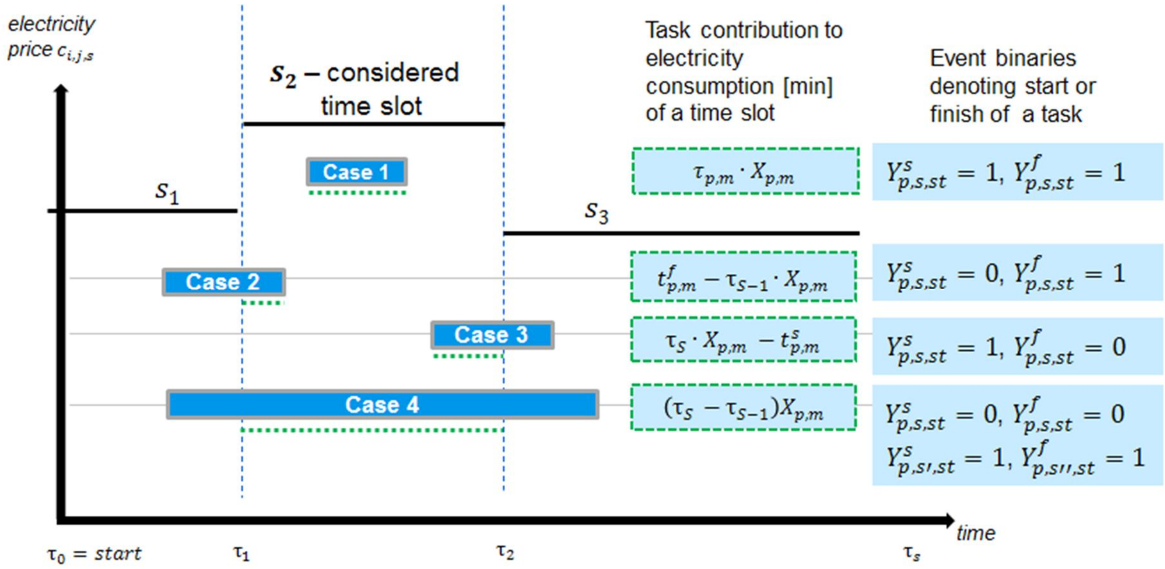


Figure 3-6 Task - time slot relations depending on the event binaries

The improvement of the energy-aware formulation is due to two modifications. Firstly, the auxiliary pseudo-binaries $y^{saux}_{p,m,st,s}$ and $y^{faux}_{p,m,st,s}$ are removed. These two were designed to take the value of the event binary, however only for those machine – product combination which was assigned to perform a give task (assignment binary $X_{p,m}$ true). The improvement of our work embeds the elimination of the not-assigned task inside of constrains for capturing the energy-awareness, as it will be explained later in explanations of the time-task slot relationship.

Secondly, the way how the model captures the amount of time a given task spent in a given energy-related time slot is changed. For a given task that is a combination of a product p and machine m a variable $o_{p,m,s}$ can be introduced. It denotes how much processing time a given task spent in a particular time slot s, see Figure 3-7 for an example.

Note that the duration of the task is $d_1 + d_2$ which corresponds to $\sum_s o_{p,m,s}$ This single continuous variable will replace the four continuous variables $a_{p,m,st,s}, b_{p,m,st,s}, c_{p,m,st,s}, d_{p,m,st,s}$ developed in Hadera et al. (2015a).

$$o_{p,m,s} = \begin{cases} d_1 \ if \ s = \tau_{s-1} \\ d_2 \ if \ s = \tau_s \\ 0 \ otherwise \end{cases}$$

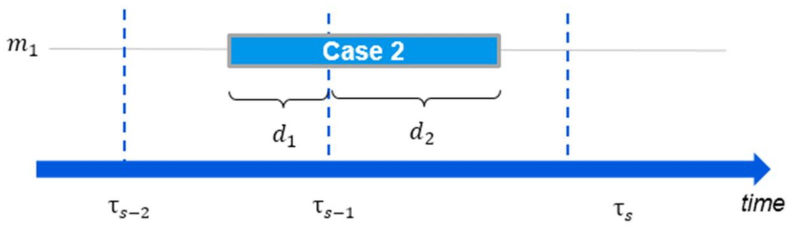


Figure 3-7 Example calculation of the time contribution variable

As we are considering uniform time intervals of 1 hour which are related to energy pricing and committed load curve, however, it should be noted that changing interval durations for each time slot ($\tau_s - \tau_{s-1}$) can be still applied in the formulation, unless otherwise stated.

First, a global constraint (valid for all cases below) is applied enforcing an upper bound for the positive variable $o_{p,m,s}$ (Eq. 71). The time contribution of a given task (p, m) to processing within a given slot cannot be longer than the length of the slot itself or the total processing time of that task. Therefore, the bound has the value of either the length of the time slot ($\tau_s - \tau_{s-1}$) or the processing time as in Eq. (3.72).

$$o_{p,m,s} \geq 0 \qquad \forall p \in P, m \in M, s \in S \tag{3.71}$$

$$o_{p,m,s} \leq \min\{\tau_{p,m}, \tau_s - \tau_{s-1}\} \cdot X_{p,m} \qquad \forall p \in P, m \in M, s \in S \tag{3.72}$$

We identify four different cases of how the task can contribute to electricity consumption.

1. A task is processed entirely within the time slot ($\mathrm{Y}^{\mathrm{s}}_{\mathrm{p,s,st}} = 1$ and $\mathrm{Y}^{\mathrm{f}}_{\mathrm{p,s,st}} = 1$)

The processing contribution $o_{p,m,s}$ to the time slot should be equal to the task processing time $\tau_{p,m}$. Moreover, the variable should be accounted only if both event binaries are true, and the task is assigned to machine m, as in Eq. (3.73). Including the assignment $X_{p,m}$ in both Equation (3.71)-(3.73) will put the variable $o_{p,m,s}$ to zero in case a task is not assigned.

$$o_{p,m,s} \geq \tau_{p,m}(Y^s_{p,s,st} + Y^f_{p,s,st} + X_{p,m} - 2) \;\; \forall p \in P, m \in M, s \in S, st \in ST, \{st, m\} \in SM \tag{3.73}$$

2. A task starts before and finishes within the time slot ($\mathrm{Y}^{\mathrm{s}}_{\mathrm{p,s,st}} = 0$ and $\mathrm{Y}^{\mathrm{f}}_{\mathrm{p,s,st}} = 1$)

In the second case the duration is the finishing time minus the time slot boundary, as in Equation (3.74)-(3.75). Since from the scheduling model it is known that unassigned tasks have starting and finishing times ($t^s_{p,m}, t^f_{p,m}$) put to zero the equations remain valid due to the assignment variable in the expression $t^f_{p,m} - \tau_{s-1} \cdot X_{p,m}$. The big M should take a value of the upper boundary of the last time slot, which is equal to the upper boundary of the scheduling horizon.

$$o_{p,m,s} \geq t^f_{p,m} - \tau_{s-1} \cdot X_{p,m} - (\mathrm{M} - \tau_{s-1})(1 - Y^f_{p,st,s} + Y^s_{p,st,s})$$
$$\forall p \in P, m \in M, s \in S, st \in ST, \{st, m\} \in SM \tag{3.74}$$

$$o_{p,m,s} \leq t^f_{p,m} - \tau_{s-1} \cdot X_{p,m} + (\mathrm{M} + \tau_{s-1})(1 - Y^f_{p,st,s} + Y^s_{p,st,s})$$
$$\forall p \in P, m \in M, s \in S, st \in ST, \{st, m\} \in SM \tag{3.75}$$

3. A task starts within and finishes after the time slot ($\mathrm{Y}^{\mathrm{s}}_{\mathrm{p,s,st}} = 1$ and $\mathrm{Y}^{\mathrm{f}}_{\mathrm{p,s,st}} = 0$)

Similarly to the previous case, the constraints (3.76)-(3.77) can be derived. The expression $\tau_s \cdot X_{p,m} - t^s_{p,m}$ captures the exact amount of processing time contribution.

$$o_{p,m,s} \geq \tau_s \cdot X_{p,m} - t^s_{p,m} - (\mathrm{M} + \tau_s)(1 - Y^s_{p,st,s} + Y^f_{p,st,s})$$
$$\forall p \in P, m \in M, s \in S, st \in ST, \{st, m\} \in SM \tag{3.76}$$

$$o_{p,m,s} \leq \tau_s \cdot X_{p,m} - t^s_{p,m} + (\mathrm{M} - \tau_s)(1 - Y^s_{p,st,s} + Y^f_{p,st,s})$$
$$\forall p \in P, m \in M, s \in S, st \in ST, \{st, m\} \in SM \tag{3.77}$$

4. A task over-spans the time slot ($\mathrm{Y}^{\mathrm{s}}_{\mathrm{p,s,st}} = 0$, $\mathrm{Y}^{\mathrm{f}}_{\mathrm{p,s,st}} = 0$ and $\mathrm{Y}^{\mathrm{s}}_{\mathrm{p,s',st}} = 1$, $\mathrm{Y}^{\mathrm{f}}_{\mathrm{p,s'',st}} = 1$)

Here, it is known that the task contribution will be equal to the time slot length for assigned tasks $(\tau_s - \tau_{s-1})X_{p,m}$. To ensure this time is captured for all the valid slots, one needs to identify the slots in between the time slots where an event starts (s') and finishes (s''), while $s' < s''$. Therefore a constraint (3.78a) can be formulated, expressing that for all of the slots with over-span $\sum_{z=s'+1}^{s''-1} o_{p,m,z}$ the processing contribution in each slot (there are $(s'' - s' - 1)$ slots) is equal to the length of the slot $(\tau_s - \tau_{s-1})X_{p,m}$, however only if both respective event binaries are true $(Y^f_{p,s'',st} + Y^s_{p,s',st} - 1)$. Since from parallel available machines at each stage only one can be chosen to process a given product, the nonlinearity in equation (11a) can be easily eliminated by summation over machines, as shown in the constraint (3.78b). Therefore, the final constraint (3.78) will ensure in linear inequalities that the processing contribution is $\tau_{s''-1} - \tau_{s'}$ in all slots strictly between s' and s''. Note that replacing the equality constraint with the inequality constraint was possible because $\tau_{s''-1} - \tau_{s'}$ is the upper bound of the summation of $o_{p,m,z}$ over z between $s' + 1$ and $s'' - 1$. In addition, if the slot duration is uniform $\tau_s - \tau_{s-1} = \tau$ it is known that the constraint should be employed for $s'' \leq s' + \lceil (\max_{m \in SM_{st,m}}\{\tau_{p,m}\})/\tau \rceil$, which basically defines a window of slots between which the task might occur.

$$\sum_{z=s'+1}^{s''-1} o_{p,m,z} = (Y^f_{p,s'',st} + Y^s_{p,s',st} - 1)(\tau_{s''-1} - \tau_{s'})X_{p,m}$$
$$\forall p \in P, m \in M, s', s'' \in S, st \in ST, \{st, m\} \in SM, s' < s'' \quad (3.78a)$$

$$\sum_{m \in SM_{st,m}} \sum_{z=s'+1}^{s''-1} o_{p,m,z} = (Y^f_{p,s'',st} + Y^s_{p,s',st} - 1)(\tau_{s''-1} - \tau_{s'})$$
$$\forall p \in P, s', s'' \in S, st \in ST, \{st, m\} \in SM, s' < s'' \quad (3.78b)$$

$$(Y^f_{p,s'',st} + Y^s_{p,s',st} - 1) \cdot (\tau_{s''-1} - \tau_{s'}) \leq \sum_{m \in SM_{st,m}} \sum_{z=s'+1}^{s''-1} o_{p,m,z} + \mathrm{M} \cdot (2 - Y^s_{p,s',st} - Y^f_{p,s'',st})$$
$$\forall p \in P, s', s'' \in S, st \in ST, s' < s'', s'' \leq s' + \lceil (\max_{m \in SM_{st,m}}\{\tau_{p,m}\})/\tau \rceil \quad (3.78)$$

The above constraint can be thought as a tightening constraint as it has no influence on the proper accounting of the variable $o_{p,m,s}$, however by creating relatively small number of equations it helps to decrease the computational time.

In all other cases a task does not contribute to the electricity consumption of the considered time slot. It means that the task either does not exist or it is processed in some other time slots. The constraint (3.79) together with Eq. (3.78) is expressing both situations.

$$\sum_{s \in S} o_{p,m,s} = \tau_{p,m} \cdot X_{p,m} \qquad \forall p \in P, m \in M \quad (3.79)$$

With the above constraints the variable $o_{p,m,s}$ will take a value of how much time a given task was processing within particular time slot s. Therefore, one can use the variable to account for electricity consumption q_s in a given time slot simply by multiplying $o_{p,m,s}$ with the task's specific electricity consumption $h_{p,m}$, as shown in equation (3.80). The expression is divided by 60 in order to convert $MWmin$ to MWh.

$$q_s = \sum_{p \in P, m \in M} h_{p,m} \cdot o_{p,m,s}/60 \qquad \forall s \in S \quad (3.80)$$

This above formulation (Eq. 3.71-3.80) and the event binaries definition (Eq. 3.44-3.47) is enough to capture the energy use. Using the problem knowledge one might think about tightening the model by adding the following set of constraints. Following the original formulation from Hadera et al. (2014) the event binaries can be related to the assignment as in Equation (3.81)-(3.82). The constraints say that the event binary can hold true only if the task exists ($X_{p,m} = 1$).

$$\sum_{s \in S} Y^s_{p,s,st} = \sum_{m \in SM_{st,m}} X_{p,m} \qquad \forall p \in P, st \in ST \quad (3.81)$$

$$\sum_{s\in S} Y^f_{p,s,st} = \sum_{m\in SM_{st,m}} X_{p,m} \qquad \forall p\in P, st\in ST \qquad (3.82)$$

Another set of constraints relates the occurrence of the event binaries with the time contribution $o_{p,m,s}$. For the time horizon, where the task has not occurred yet, the sum of event binaries start is zero as well as is the time contribution (Eq. 3.83).

$$\sum_{m\in SM_{st,m}} o_{p,m,s}/\tau_s - \tau_{s-1} \le \sum_{s'\le s} Y^s_{p,s',st} \qquad \forall p\in P, st\in ST, s\in S \qquad (3.83)$$

Similarly for the event binary finish, all of the slots after the one for which the binary holds true will put the time contribution to zero (Eq. 3.84). Applying the same thinking, constraints (3.85)-(3.86) are developed, fixing to zero some of the redundant binary values.

$$\sum_{m\in SM_{st,m}} o_{p,m,s}/\tau_s - \tau_{s-1} \le \sum_{s'\ge s} Y^f_{p,s'st} \qquad \forall p\in P, st\in ST, s\in S \qquad (3.84)$$

$$\sum_{s'>s} Y^s_{p,s',st} \le 1 - \sum_{m\in SM_{st,m}} o_{p,m,s}/\tau_s - \tau_{s-1} \qquad \forall p\in P, st\in ST, s\in S \qquad (3.85)$$

$$\sum_{s'<s} Y^f_{p,s',st} \le 1 - \sum_{m\in SM_{st,m}} o_{p,m,s}/\tau_s - \tau_{s-1} \qquad \forall p\in P, st\in ST, s\in S \qquad (3.86)$$

Another constraint linking the relation between the event binaries might be useful for handling large-scale instances. In Eq. (3.87), the fact that if the task event start has not occurred, the event finish has not occurred neither is expressed.

$$\sum_{s'=1}^{s} Y^f_{p,s',st} \le \sum_{s'=1}^{s} Y^s_{p,s',st} \qquad \forall p\in P, st\in ST, s\in S \qquad (3.87)$$

We observed that this constraint helps finding good solutions faster when solving larger instances, however for smaller easily tractable instances it slows down the computational performance. This might be related to the fact that even though the constraint reduces a bit the search space it is creating additional equations to be handled by the solver.

3.2.4 Energy cost optimization

3.2.4.1. Minimum Cost Flow Network

The tracking of the consumption of electricity over the time intervals can be used for optimizing the purchase and sales strategy. Once the scheduling model has been extended by the corresponding values of electricity consumption in the time slots, the purchase optimization can influence the schedule in such way that a mixed criteria (with e.g. task start times as used later) that include also the cost of electricity are minimized. The idea for purchase optimization is based on a Minimum-cost Flow Network (Ahuja, Magnanti and Orlin, 1993; Bertsekas, 1991) formulation with a balancing node for which the sum of all inflows is equal to the sum of all outflows (Eq. 3.88) as in Hadera et al. (2014; 2015a). The concept of using the formulation to optimize energy cost has been reported earlier by Harjunkoski et al. (2012).

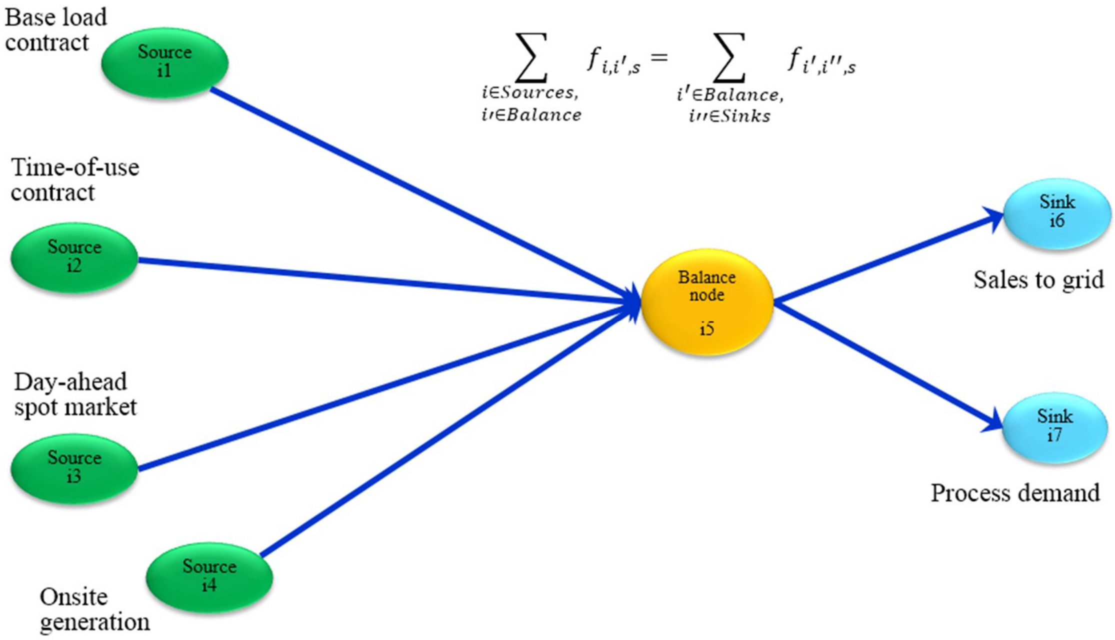


Figure 3-8 Formulation of the electricity purchase and sale optimization problem

The inflow nodes represent the possible sources of electricity. The outflow nodes are the process demand and the selling of electricity.

$$\sum_{i \in Node} f_{s,i,j'} = \sum_{j \in Node} f_{s,j',j} \qquad \forall\,(i,j'),(j',j) \in Arc, j' \in Bal, s \in S \qquad (3.88)$$

The balancing node is connected with the sink and the source nodes by arcs that are characterized by parameters and variables. An arc exists only if there is a cost defined for it. The parameters are the minimum and maximum levels of the flows between two given nodes (Eq. 3.89) and the cost function.

$$f_{s,i,j}^{min} \leq f_{s,i,j} \leq f_{s,i,j}^{max} \qquad \forall\,(i,j) \in Arc, i,j \in Node,\ s \in S \qquad (3.89)$$

The network is used to identify the most economical flows while satisfying the load from the process demand node (Eq. 3.90).

$$q_s = \sum_{i \in Node, j \in Dem} f_{s,i,j} \qquad \forall\,(i,j) \in Arc, s \in S \qquad (3.90)$$

The onsite generation is modeled using a binary variable $G_{s,i,j}$ that denotes whether the plant is in production mode (Eq. 3.91) and an auxiliary pseudo-continuous variable $g_{s,i,j}^{s}$ indicating generation start-up (Eqs. 3.92)-(3.93). Here, the Big-M value M_2 should not be less than the maximum flow on the arc between the onsite generation and the balancing node.

$$G_{s,i,j} \leq f_{s,i,j} \leq M_2 \cdot G_{s,i,j} \qquad \forall\,(i,j) \in Arc, i \in Gen, j \in Bal, s \in S \qquad (3.91)$$

$$G_{s,i,j} - G_{s-1,i,j} \leq g_{s,i,j}^{s} \leq G_{s,i,j} \qquad \forall\,(i,j) \in Arc, i \in Gen, j \in Bal, s \in S \qquad (3.92)$$

$$0 \leq g_{s,i,j}^{s} \leq 1 - G_{s-1,i,j} \qquad \forall\,(i,j) \in Arc, i \in Gen, j \in Bal, s \in S \qquad (3.93)$$

The onsite generation constraints are kept simple by considering a constant generation cost with additional start-up cost (Eq. 3.94) and a reduced production rate by a factor k for those time intervals where a start-up occurs (Eq. 3.95).

$$c_s^{gen} = \sum_{i \in Node, j \in Gen} f_{s,i,j} \cdot c_{s,i,j} + c^{start} \cdot g_{s,i,j}^{s} \qquad \forall\,(i,j) \in Arc, s \in S \qquad (3.94)$$

$$f_{s,i,j} = f_{s,i,j}^{max} \cdot G_{s,i,j} - k \cdot f_{s,i,j}^{max} \cdot g_{s,i,j}^{s} \qquad \forall\, (i,j) \in Arc, i \in Gen, j \in Bal, s \in S \qquad (3.95)$$

Moreover, a minimum runtime r^{min} and a minimum downtime d^{min} are enforced (Eqs. 3.96-3.97). The implementation of more detailed constraints that are available in literature would also be possible here, including accounting for steam flows and more detailed electricity production rates as for example in Mitra et al. (2013).

$$\sum_{s'=s}^{s+r^{min}-1} G_{s',i,j} \geq r^{min}(G_{s,i,j} - G_{s-1,i,j})$$
$$\forall\, (i,j) \in Arc, i \in Gen, j \in Bal, s \in S, s < |S| - r^{min} + 1 \qquad (3.96)$$

$$\sum_{s'=s}^{s+d^{min}-1} G_{s',i,j} \leq d^{min}(1 + G_{s,i,j} - G_{s-1,i,j})$$
$$\forall\, (i,j) \in Arc, i \in Gen, j \in Bal, s \in S, s < |S| - d^{min}+1 \qquad (3.97)$$

The final net electricity purchase cost (Eq. 3.98) is composed of the cost associated with purchase from contracts, the cost of the generation and the revenues from the electricity sold.

$$\mu = \sum_{s \in S}(\sum_{i' \in Node, j' \in Pur} f_{s,i',j'} \cdot c_{s,i,j} + c_{s}^{gen} - \sum_{i \in Node, j \in Sale} f_{s,i,j} \cdot c_{s,i,j})$$
$$\forall\, (i,j), (i',j') \in Arc \qquad (3.98)$$

3.2.4.2. Load deviation problem

Another aspect of the energy management situation of the plant is the load deviation problem. It is often the case that large industrial consumers of electricity make bilateral agreements with electricity providers to follow a certain agreed load profile. Both the provider and the plant benefit from this. The provider knows in advance a very good approximation of the load levels to be balanced with supply of generation which leads to minimization of operating cost. In return, the consumer gets a considerable reduction in the price of electricity from the provider. Therefore, often the load deviation problem is related to one single contract with pricing schemes such as for example Time-of-Use. Here, it is considered that the plant is assumed to commit to certain hourly varying levels of the total energy use. Similar to a situation if all contracts actually come from the same provider and the plant commits to some total consumption for all contracts. In case the actual consumption deviates from pre-agreed values, financial penalties are incurred. The part of the model accounting for the penalties is the set of Eq. (30-32) from Hadera and Harjunkoski (2013). For the load tracking error penalties, it is assumed that there is a penalty-free deviation (buffer) b_s that is relative to the committed consumption a_s and limited by relative upper and lower bounds b_s^o and b_s^u as stated in Eq. (3.99).

$$-a_s \cdot b_s^u \leq b_s \leq a_s \cdot b_s^o \qquad \forall s \in S \qquad (3.99)$$

The actual levels of over- and under consumption (c_s^o and c_s^u) are determined by Eq. (3.100).

$$q_s = a_s + c_s^o - c_s^u + b_s \qquad \forall s \in S \qquad (3.100)$$

The penalty term δ calculating the fines p^o, p^u for over- and under consumption is given by Eq. (3.101).

$$\delta = p^o \cdot \sum_{s \in S} c_s^o + p^u \cdot \sum_{s \in S} c_s^u \qquad (3.101)$$

The final objective function of the monolithic model in Eq. (3.102) minimizes the net electricity cost μ, the deviation penalties and the weighted sum of the task starting times $t_{p,m}^{s}$ with c being a weighting factor.

$$\min(\mu + \delta + c \cdot \sum_{p \in P, m \in M} t_{p,m}^{s}) \qquad (3.102)$$

The part of the model that concerns the deviation problem can easily be used in load commitment of one particular contract. For example, when changing the variable representing the total consumption in a time slot q_s to the amount drawn from Time-of-Use source $f_{s,i,j}$, where $i \in TOU$ and $j \in Bal$ the committed load problem of the TOU contract is obtained.

Later in Chapter 4 the load deviation cost will be considered as production-specific cost as the constraints for it are not part of the Minimum-cost Flow network formulation which handles the contracts optimization.

3.3 Industrial case study on monolithic models

3.3.1 Case study setup

The assumptions on the constraints of the steel making process include the knowledge of the sequences and assignments of products to the last stage, the Continuous-Casting (CC) stage. An assumption is made that it is known which products must be processed on one of the casters. However, the assignment of the heats to other units in other stages must be determined by the optimization. The sequence of the heats that must be processed on a particular caster is known as well. However, it is up to the optimization to determine the sequence of those products that can be processed on two different CC machines. This assumption reduces the size of the search space. It is a reasonable assumption because very often the sequence of the products to be processed is dictated by higher level planning solutions (e.g. mill-wide planning) that are directly linked with customer orders and knowledge concerning in-house inventory levels. For integrated steel plants, the further processing of the steel slabs is carried out in the Hot Rolling Mill (HRM) after the Melt Shops section (see e.g. Biondi, Saliba and Harjunkoski 2011). At the HRM section it is important to define a sequence of steel slabs to be rolled such that the cost of reheating using natural gas is minimized. This challenging optimization problem of coordination between Melt Shop and Hot Rolling Mill (Xu et al. 2012) can also determine the sequence of the products on the CC stage. Usually, the assignments and the sequences on the casters reflects the quality requirements for steel, i.e. one of the casters processes certain high quality types of steel, while the other one might not be able to deliver the same qualities. The timing of the tasks to avoid production delays and to minimize the cost of energy-related problem is subject of the optimization. For the resulting assumptions, all the relevant input data are given and described in Appendix A.

To tighten the MILP model, the calculation of lower and upper bounds for the task start variables can be carried out. For each heat group, two optimization problems are solved: minimizing and maximizing the task start time of the first product in the heat group at the CC stage. In this way it is possible to check what is the minimum value of the variable when a given heat group finishes as soon as possible on the CC. Similarly, it can be calculated what is the maximum value of the variable when a given heat group finishes as late as possible on the CC. Based on this knowledge, it is possible, using process parameters, to calculate the earliest start times and the latest start times of each task at the other stages as shown in Appendix B. The bounds obtained from the above optimization are then propagated to the monolithic model and to the heuristic optimization in order to impose upper and lower bounds for task start and finish time variables. Finding tighter bounds helps to speed up the solution of the MILP model since then many of the energy-related binaries can be set to zero.

3.3.2 Case study results and discussion

Numerical test has been performed on a 4-core Intel Xeon 2,53GHz with 16GB of RAM using GAMS/CPLEX 23.7.3. Using the same problem instances and input data (Appendix A and Table 3-2) the three strategies for energy-awareness can be tested in order to clearly asses the difference in their performance. In the next chapter event binaries models are applied within the bi-level decomposition. Note that the base load contract has a fixed amount of delivery for each hour of the day, regardless whether the electricity is needed for the production process or not. The electricity prices of both day-ahead contract cases, low price (EPEX 2013, Germany/Austria 23/09/2013) and high price (EPEX 2013, France 10/02/2012) are taken from a real spot market. The pre-agreed load curve comes from a valid production schedule which was computed not considering the energy cost in the optimization, but in our case only the lead times optimization ($c \cdot \sum_{m \in M, p \in P} t_{m,p}^{s}$, here it is assumed c=1). This follows the previous studies (Castro et al. 2013) where the schedule with optimized production-specific cost (makespan) served as a basis for the comparison with an energy-driven schedule to assess the iDSM benefits. The two first scenarios have a typical production target with the day-ahead spot market prices are high and low. In the third scenario the production target is lowered to represent underutilized capacity. The fourth scenario is similar to the latter, however the pre-agreed load curve is used as for the first two scenarios. This simulates a situation where due to for example unexpected equipment break-downs the plant cannot deliver planned number of products therefore overcommitted the load curve.

Table 3-2 Investigated problem instances

Scenario	Horizon	Products	Electricity sources and sinks
1	24 h	20	all possible, day-ahead with high prices
2	24 h	20	all possible, day-ahead with low prices
3	24 h	16	all possible, day-ahead with high prices
4	24 h	16	all possible, day-ahead with high prices, overcommitted load curve (as in Scenario 1-2 for 20 products)

Name	Model type
NM	Monolithic six binaries model (Nolde and Morari 2010, Hadera and Harjunkoski 2013)
HM	Original monolithic event binaries model (Hadera et al. 2014)
RM	Improved monolithic event binaries model (Hadera et al. 2016)
BH	Bi-level heuristic using original event binaries model (Hadera et al. 2015a)
BR	Bi-level heuristic using improved event binaries model (Hadera et al. 2016)

In Table 3-3 there are the model statistics and economic assessment of optimization runs with computation time limit of 600s. The total objective function value (MIP solution) quality is described by the value of the total weighted objective function value. As expected, it can be seen that the total number of both variables and equations is the least for the improved event binaries formulation. In all of the cases, this brings improvements in computational performance for large-scale monolithic problem, which is in general considered intractable when solving full 24 h time horizon for reasonable number of heats. For all of the considered problem instances, the improved model obtained the best solutions, better by around 1-9% compared to the original event binaries model. The difference in the solution quality between the event binaries models and the six binaries approach was the largest on the smaller problem sizes (Scenario 3-4). This statement holds true for the short computational time limit (600s) where the differences of the relative gaps between the solutions between the six binaries model and the improved event binaries model is around 10 – 18 %. For longer solution times, the improvement obtained with the event binaries model is similar. By investigating closer the economic assessment it can be noted that for most of the cases solutions of similar quality gave similar objective function cost components, for example as for HM1 and RM1. Here, in RM1 case the optimization postponed the production which resulted in higher lead times, however lower deviation penalties cost.

In Table 3-4 the same problem instances are run with the computation time limit of 3600s. Here, again it can be seen that the proposed formulation improves the upper bound faster compared than the two other models. For the two largest instances, the gap is around 9-18% better than the six binaries model, and around 2-6% better than the original event binaries model. Only in Scenario 2 the two event binaries models yield similar solutions. The corresponding economic assessment of solutions again shows quite similar cost structures for the instances with similar objective function values. One interesting exception is the difference in solutions HM2 and RM2. In the former the optimization choose to produce more electricity from the onsite generation, which could be the reason for slightly better objective function value.

In order to further assess the computational performance of the different strategies to introduce energy-awareness into the continuous-time scheduling, the models were tested with all assignment and sequencing variables fixed to the same values in all instances. In this way the complexity of the two approaches differs only in the energy-related binary decisions and the number of linear equations in the energy-awareness extension. In Table 3-5 results of optimization runs for the same scenarios are shown with stopping criterion of 2% optimality gap. From the results it can be seen that the improved formulation outperforms the alternatives in the larger scenarios. For smaller instances, the six binaries model performed better. This could be related with particular problem data which helped the solver to steer the latter approach towards better solution faster. Naturally, again the improved binaries model yielded the least number of continuous variables and equations to be solved.

Based on all the test presented earlier it can be concluded that the proposed energy-awareness strategy based on improved binaries model performs best among the three investigated strategies.

Table 3-3 Comparison of monolithic models – 600s computation limit

Scenario	Model statistics					Economic assessment						
	Binary vars	Total vars	Equations	Total cost (MIP solution)	Relative gap	Lead times [min]	Net electricity cost [€]	Electricity purchase [€]	Deviation penalties [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]
NM1	13017	29508	98095	313128	43,78%	60784	149832	161098	102512	172,55	1471,825	912
HM1	4065	29508	102335	247838	29,30%	51990	133972	151905	61876	173,49	1421,44	952
RM1	4065	10308	51375	244870	28,30%	53138	143209	151053	48522	223,065	1353,578	952
NM2	13017	29508	98095	223887	32,30%	61210	119440	98505	43236	1608,917	4	352
HM2	4065	29508	102335	200038	24,90%	53946	120989	98592	25103	1514,51	95,78	432
RM2	4065	10308	51375	193348	21,79%	53273	117602	99133	22474	1580,79	91,948	352
NM3	10181	23428	77136	174227	32,63%	42283	86071	88984	45872	1417,983	54,267	0
HM3	3229	23428	80528	155226	22,81%	33038	96508	128208	25679	82,604	1241,156	952
RM3	3229	8068	39760	147701	16,54%	32251	98162	131569	17286	100,554	1270,681	952
NM4	10181	23428	77136	234643	31,53%	43598	96266	134759	94780	77,207	1266,043	952
HM4	3229	23428	80528	204173	22,50%	36152	72846	140130	95175	142,48	1318,8	952
RM4	3229	8068	39760	183590	13,16%	37166	99105,2	133488	47319	77,735	1257,39	952

Table 3-4 Comparison of monolithic models – 3600s computation limit

Scenario	Model statistics					Economic assessment						
	Binary vars	Total vars	Equations	Total cost (MIP solution)	Relative gap	Lead times [min]	Net electricity cost [€]	Electricity purchase [€]	Deviation penalties [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]
NM1	13017	29508	98095	290708	38,97%	58763	146373	162528	85572	203,72	1466,61	952
HM1	4065	29508	102335	241136	26,80%	50796	142452	14396	47888	234,22	1349,66	952
RM1	4065	10308	51375	223028	20,95%	50908	142288	151919	29831	173,397	1425,093	952
NM2	13017	29508	98095	222167	31,20%	60282	116872	98942	45014	1649,35	16,83	312
HM2	4065	29508	102335	180023	16,10%	51598	115937	98229	12489	1635,81	56,11	352
RM2	4065	10308	51375	180236	16,12%	52433	115944	100968	11859	1661,49	74,6227	312
NM3	10181	23428	77136	156986	24,63%	39444	83531	89620	34012	1547,368	0,597	0
HM3	3229	23428	80528	146339	17,93%	32753	95840	130217	17746	83,779	1270,351	952
RM3	3229	8068	39760	146906	15,64%	31879	108889	133085	6137	119,336	1240,033	952
NM4	10181	23428	77136	221454	27,20%	42269	100104	127986	79081	110,87	1164,93	952
HM4	3229	23428	80528	180965	12,10%	35396	94723	128534	50846	46,66	1256,92	952
RM4	3229	8068	39760	175887	9,19%	36053	101195	120442	38639	19,6083	1177,27	952

Table 3-5 Comparison of models with fixed scheduling binaries – 2% gap limit

Model statistics - 2% gap					
Scenario	Binary vars	Total vars	Equations	Total cost (MIP solution)	CPUs
NM1	12861	29508	98095	195020	64,90
HM1	3593	29508	102335	194410	62,47
RM1	3593	10308	51375	194197	8,98
NM2	12861	29508	98095	166687	7,46
HM2	3593	29508	102335	166550	6,48
RM2	3593	10308	51375	166667	3,37
NM3	10069	23428	77136	129260	7,98
HM3	2865	23428	80528	135012	24,63
RM3	2865	8068	39760	135241	11,69
NM4	10069	23428	77136	174992	39,05
HM4	2865	23428	80528	174922	56,23
RM4	2865	8068	39760	174769	58,74

3.4 Bi-level heuristic

3.4.1 Decomposition strategy

When trying to solve an instance of the problem with significant flexibility in the process, i.e. when the optimization is free to assign and to sequence all products, the computational performance of the monolithic models from Chapter 3.3 is not sufficient. This is mainly due to large number of difficult to solve binary variables in the scheduling formulation and to the loose Big-M constraints, which is specific for precedence-based continuous-time models. To overcome the computational limitations, a heuristic decomposition strategy is developed.

For large-scale scheduling problems decomposition techniques have long been recognized as possible solution approaches. Starting from fundamental studies by Benders (1962) and Dantzig (1963) with row and column generation approaches, strategies have been developed for solving problems in an iterative fashion that could not be solved using a monolithic formulation. Decomposition approaches can be categorized into approaches that can be shown to converge to the true optimum (even if convergence may be slow) and approaches that discard a part of the solution space so that optimality cannot be guaranteed (decomposition heuristics). Wu and Ierapetritou (2003) presented a number of different heuristic decomposition approaches for scheduling problems. For example, one may use time decomposition where the long time horizon is divided into several smaller sub-periods with resulting sub-problems. Another important class of approaches makes use of Lagrangean decomposition to relax the original problem into a problem that is easier to solve, systematically providing a lower bound for the solution. For problems with a clear separation of planning level decisions and scheduling level decisions these can be represented in a bi-level setup where first in upper level the planning variables are determined and then fixed to solve the more detailed lower level scheduling problem. This scheme was used for example by Bassett et al. (1996).

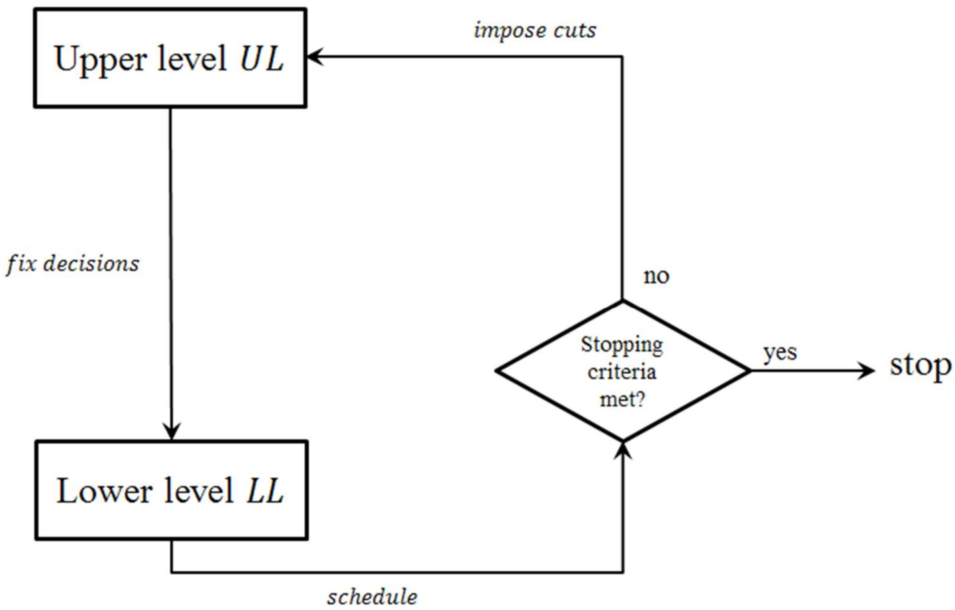


Figure 3-9 General idea of bi-level heuristic approach

Similarly in another example, Erdirik-Dogan and Grossmann (2008) use the bi-level concept for continuous multiproduct plants first solving an aggregate model to obtain an upper bound for the profit and then solving a scheduling problem to obtain a lower bound. Xu et al. (2012) developed a bi-level decomposition scheme for the coordination of a Melt Shop process with Hot Rolling section of a stainless steel plant.

Here, a bi-level scheme is utilized as well. The solution procedure consists of two problems that are solved in an iterative manner, as shown in Figure 3-9. First, an aggregate model (upper level UL) that approximates the original monolithic model is solved in order to obtain feasible values of some binary decisions. These binary decisions are passed to the full model (lower level LL) with a restriction to keep some of the variables fixed, optimizing the other continuous and binary variables, in our case the starting times and the event binaries. The full model should provide a feasible schedule and an objective function value which represents an upper bound of the optimal value. A new iteration of the algorithm starts by solving the upper problem again, with some new restrictions in the form of integer cuts that exclude previous solutions of the full model. The search space can be reduced based on the knowledge about the optimal solution provided from LL. In our particular case, since for the full problem with some of the decision variables fixed a feasible solution was obtained, at least the combination of the binaries of that solution can be removed from UL so that new values of these binaries are generated by the upper level model and the new solution is again refined by the lower level model. The algorithm iterates until stopping criterion is met, e.g. until a time limit is exceeded. For the following sections, additional notation specific for the decomposition approach is given in Table 3-6.

Table 3-6 Bi-level heuristic model notation

Sets:	
$DY_0^r, DY_1^r, DX_0^r, DX_1^r, DV_0^r, DV_1^r$	dynamic sets used in bi-level heuristic for false and true decision of the respective binaries
Variables:	
$X_{m,p}^{UL1}, X_{m,p}^{LL}, X_{m,p}^{UL2}$	binary variable in respective models UL1, LL and UL2, true when heat p is assigned for processing on equipment m
$V_{st,p,p'}^{UL1}, V_{st,p,p'}^{LL}, V_{st,p,p'}^{UL2}$	binary variable in respective models UL1, LL and UL2, true when heat p' is processed after heat p on stage st
$Y_{p,st,s}^{sUL1}, Y_{p,st,s}^{sLL}, Y_{p,st,s}^{sUL2}$	binary variable in respective models UL1, LL and UL2, true when heat p starts on stage st in the slot s
Parameters:	
$t_{m,m'}^{minUL1}, t_{m,m'}^{minLL}$	minimum transport time from equipment m to m' in respective models UL1 and LL
$t_{p,st}^{maxUL1}, t_{p,st}^{maxLL}$	maximum hold-up time after stage st in respective models UL1 and LL
RHS	sum of binary variables
α	number of neighboring slots to be evaluated
β	desired optimality gap
r	iteration number

3.4.2 Upper Level problem

The upper level problem UL consists of solving two models $UL1$ and $UL2$ as shown in Figure 3-10. $UL1$ is a simplified model of the original problem and is computed to obtain a good guess of some binary decisions, while $UL2$ is a pre-computation step for the $UL1$ starting from the second iteration as explained later. The algorithm starts with solving $UL1$, which is constructed in such way that it represents the full monolithic problem as closely as possible, while at the same time reducing the size of the MILP. In the first iteration, $UL1$ is a relaxation of the full problem. The main component of the objective function value is the electricity-related cost. It depends directly on the load pattern that results from the processing of the tasks. In the stainless-steel production process investigated in the case study, the EAF stage consumes about 88% of the total electricity needed to deliver one product. Therefore potential changes in the assignments, sequences or especially the timing of different products on that stage will have a significant impact on the final consumption pattern. Therefore, the energy-intense melting task is included in the upper level problem. A rough approximation of the lower level problem can be generated by simply scheduling the EAF stage alone, maintaining all energy-related constraints. However, the tasks on the first stage cannot be timed arbitrarily and must be sequenced according to the special continuous-casting constraints on the CC stage. For example, two subsequently casted products should be processed within a reasonable time interval in the EAF stage in order to ensure the proper delivery of the heats to continuous-casting, while at the same time satisfying all transfer and waiting time constraints between the stages.

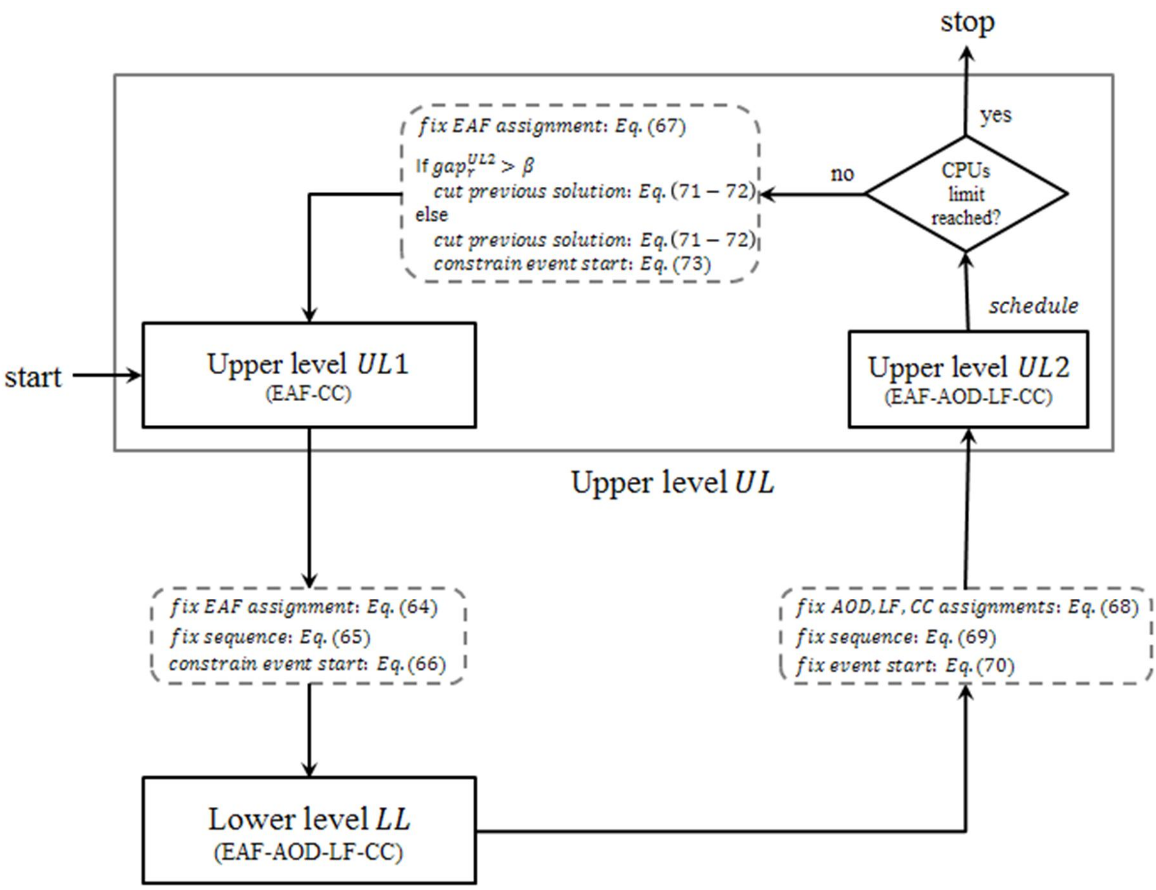


Figure 3-10 Bi-level heuristic algorithm

Since the EAF and CC stages together account for around 95% of the total Melt Shop electricity consumption, scheduling of these two stages alone should produce a good guess of the values of the variables related to the EAF and the CC of the full problem. If the last production stage is considered together with the EAF, the casting constraints are not violated and the remaining stages of AOD and LF can be scheduled on the lower level. In order to ensure feasibility of the lower model concerning decisions for these two stages, the upper level problem needs to account for the range of possible delays between processing on the EAF and on the CC stage. The equations of the $UL1$ problem are the same as in the corresponding monolithic model (and in the lower level problem), apart from removing elements and cuts, as follows:

$\min^{UL1}(Eq. 3.102)$

s.t.:

$Eq. (3.1) - (3.16)$ Scheduling model equations with new sets M and ST (Chapter 3.2.2)

$Eq. (3.44) - (3.70)$ or $Eq. (3.44) - (3.47), (3.71) - (3.80)$ Energy-awareness extension (event binaries model BH or improved event binaries model BR) with new sets M and ST (Chapter 3.2.3)

$Eq. (3.88) - (3.98)$ Electricity flow network optimization (Chapter 3.2.4.1)

$Eq. (3.99) - (3.101)$ Load deviation problem (Chapter 3.2.4.2)

$Cuts$ New constraints for other iterations than the initial one (Chapter 3.4.4)

The equipment AOD and LF are eliminated from the equipment set M. The stages $st2$ and $st3$ are eliminated from the set of production stages ST. Therefore, new values of the minimum transport times and maximum hold-up times between EAF and CC stage in the upper level problem need to be calculated based on the parameters of the full model as shown in Figure 3-11.

The new $t_{p,st}^{maxUL1}$ and $t_{m,m',CC}^{minUL1}$ replace the original $t_{p,st}^{max}$ and $t_{m,m'}^{min}$ from the monolithic model. The maximum hold-up time in the full model corresponds to the maximum time after which a heat can be processed on CC after finished on EAF as in Equation (3.103).

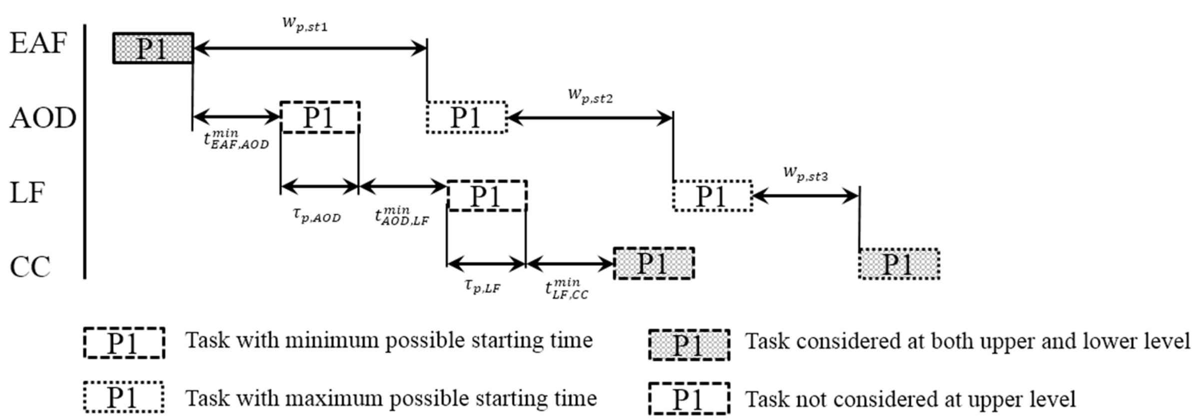


Figure 3-11 Transportation and waiting time between EAF and CC stage in UL1 problem

$$t_{p',st1}^{maxUL1} = \max_{p \in P}\{t_{p,st1}^{max}\} + \max_{p \in P}\{\tau_{p,AOD1}, \tau_{p,AOD2}\} + \max_{p \in P}\{t_{p,st2}^{max}\} + \max_{p \in P}\{\tau_{p,LF1}, \tau_{p,LF2}\} + \max_{p \in P}\{w_{p,st3}^{max}\} \qquad \forall p' \in P \qquad (3.103)$$

Similarly, the minimum transportation time between EAF and CC corresponds to the maximum possible time between these two in the full problem as in Eq. (3.104).

$$t_{EAF,CC}^{minUL1} = \min_{\substack{m \in SM(EAF,m) \\ m' \in SM(AOD,m')}} \{t_{m,m'}^{min}\} + \min_{p \in P}\{\tau_{p,AOD1}, \tau_{p,AOD2}\} + \min_{\substack{m \in SM(AOD,m) \\ m' \in SM(LF,m')}}\{t_{m,m'}^{min}\} + \min_{p \in P}\{\tau_{p,LF1}, \tau_{p,LF2}\} + \min_{\substack{m \in SM(LF,m) \\ m' \in SM(CC,m')}} \{t_{m,m'}^{min}\} \qquad (3.104)$$

In the upper level model $UL1$, the EAF stage is the first stage, followed by the CC which is the second and last production stage. Another modification of the input data of the upper level problem concerns the pre-agreed load curve. For the original full problem, the agreed curve is calculated based on a pre-defined schedule. For the same schedule, it is possible to eliminate the AOD and LF stages to obtain a load curve for the other two stages.

The second model $UL2$ of the upper level is solved after the lower level LL problem as shown in Figure 3-10. From the latter, most binary decisions are fixed and transferred to $UL2$, which essentially is the same problem as LL discussed in the next section. However, within $UL2$ the only binary decision to be determined by optimization is to find better assignments of heats to EAFs in order to pre-compute new assignment decisions on EAFs for the next iteration of $UL1$. In this way the search space of the approximate model $UL1$ is reduced and it no longer is a relaxation of original problem in the later iterations, which might prevent finding the optimal solution. However, this turned out to speed up the computational time significantly.

3.4.3 Lower Level problem

The constraints and sets of the lower level LL problem are not changed compared to the monolithic problem. However, the lower problem is solved with some fixed decisions which improve its computational performance, as discussed in details in the next Section. The model LL serves as an evaluation model for the decisions that were determined by the upper level $UL1$. After fixing some decisions, as described in the next section, LL is solved with a limitation on the solution time to avoid spending too much time in closing a small optimality gap.

3.4.4 Cuts and iterations

After Since the EAF stage is the most power intensive one, the decisions taken with regard to the assignment $X_{p,m}$ to machines of the melting stage are fixed for the LL problem as in Eq. (3.105), which helps to speed up the solving time. Further, for the same reason another variable is fixed, the sequence $V_{st,p,p'}$ on the casting stage as in Eq. (3.106). In contrast to the process assumptions where the sequence in the particular caster is known *a priori* only for particular caster, here the sequence relation of the products between the two casters (which is a degree of freedom of the monolithic problem) is fixed.

$$X_{m,p}^{LL} = X_{m,p}^{UL1} \qquad \forall p \in P, m \in EAF \qquad (3.105)$$

$$V_{st,p,p'}^{LL} = V_{st,p,p'}^{UL1} \qquad \forall p, p' \in P, p \neq p', st = |ST| \qquad (3.106)$$

Since the upper problem should provide a good approximation of the full problem, it would be beneficial to use also the energy-related information obtained from it for fixing some decisions in the lower level problem. A natural choice is the event binaries. However, since it is expected that these have a large impact on the value of the objective function, the kind of fixing needs to be carefully chosen. The fixing should still allow for giving flexibility to the model, and at the same time reduce the computational time of the full problem. After experimenting with different options, a fixing decision is developed: if the upper level problem is solved close to optimality (i.e. the gap is lower than $\beta = 2\%$) the variables of event binary start of the lower level problem $Y_{p,st,s}^{sLL}$ should be true within a neighborhood of the slots for which the binary holds true in the $UL1$ solution as shown in Eq. (3.107) where s^* denotes the time slot when the event binary starts to hold true in the $UL1$ solution.

$$\sum_{s=s^*-\alpha}^{s^*+\alpha} Y_{p,st,s}^{sLL} = 1,\ where\ s^*: Y_{p,st,s^*}^{sUL1} = 1 \qquad \forall p \in P, st \in ST \qquad (3.107)$$

If the upper level problem determined that the start of a product should occur in the $n-th$ time slot, then the start of that product in the LL solution should occur in one of the time slots within $(n-\alpha; n+\alpha)$. For the particular case, α is chosen such that it defines a neighborhood of 3 slots, which is a wide range of 7 hours in total. Since the decision of the event start binary has a direct impact on the event finish binary, there is no need for further fixing of the latter.

With the above exchange of information between models $UP1$ and LL the most important degrees of freedom in the lower level problem are the timing of EAFs (but also all the other machines) while keeping the sequence determined by the upper level.

In order to update the $UL1$ problem with new assignment decisions on EAFs (Eq. 3.108), the $UL2$ problem is solved with fixed decisions of the other binaries, as shown in Eq. (3.109)-(3.111).

$$X_{m,p}^{UL1} = X_{m,p}^{UL2} \qquad \forall p \in P, m \in EAF \qquad (3.108)$$

$$X_{m,p}^{UL2} = X_{m,p}^{LL} \qquad \forall p \in P, m \in M \backslash EAF \qquad (3.109)$$

$$V_{st,p,p'}^{UL2} = V_{st,p,p'}^{LL} \qquad \forall p, p' \in P, p \neq p', st \in ST \qquad (3.110)$$

$$Y_{p,st,s}^{sUL2} = Y_{p,st,s}^{sLL} \qquad \forall p \in P, st \in ST, s \in S \qquad (3.111)$$

The $UP2$ model has very few degrees of freedom since it can only change the binaries related to the EAF assignment. In contrast $UP1$ is the one where many important decisions can be made since this model finds the timing and sequence of products on the most important machines, especially on the EAF. The latter are then fixed at the lower level.

In the proposed approach, cuts imposed in each iteration are related to the scheduling decisions ($X_{m,p}, V_{p,p',st}$) and the energy-awareness ($Y_{p,st,s}^{s}$). Of course the latter ones are strongly related to the former since it is the timing of a task start which links both. In the case when LL is not proven to have a desired level of optimality, it can be suspected that the decisions obtained from it might not be good enough to later cut off the neighborhood of the obtained solution of event binary start variables from the solution space of $UL1$. Therefore, if for a particular iteration the desired optimality level is not obtained in the LL problem, the cut for the $UL1$ involves only removing a particular solution of LL, which means a particular combination of the binaries $X_{m,p}, V_{p,p',st}, Y_{p,st,s}^{s}$ obtained in LL as there is no need of evaluating that solution again in new iteration in the upper level problem. The cut is achieved by the constraints shown in Eq. (3.112-3.113), similar to those reported (Balas and Jeroslow 1972) and successfully used in the literature (Iyer and Grossmann 1998) for the elimination of existing binary solutions. In case where LL is solved to optimality stronger cut can be enforced by removing also the neighborhood of the event binary start as shown in Eq. (3.114), following the fixing in Equation (3.107) coming from the $UL1$.

$$RHS = \sum_{p\in P,s\in S} Y^{sUL1}_{p,st1,s} + \sum_{m\in M,p\in P} X^{UL1}_{m,p} + \sum_{p,p'\in P,p\neq p'} V^{UL1}_{st4,p,p'} \qquad (3.112)$$

$$\sum_{(p,s)\in DY^r_1} Y^{sUL1}_{p,st1,s} - \sum_{(p,s)\in DY^r_0} Y^{sUL1}_{p,st1,s} + \sum_{(m,p)\in DX^r_1} X^{UL1}_{m,p} - \sum_{(m,p)\in DX^r_0} X^{UL1}_{m,p} + \sum_{(p,p')\in DV^r_1} V^{UL1}_{st4,p,p'} - \sum_{(p,p')\in DV^r_0} V^{UL1}_{st4,p,p'} \leq RHS - 1$$

$$DY^r_0 = \{(p,s)|Y^{sUL1}_{r,p,st1,s} = 0\},\ DY^r_1 = \{(p,s)|Y^{sUL1}_{r,p,st1,s} = 1\},\ DX^r_0 = \{(m,p)|X^{UL1}_{r,m,p} = 0\},\ DX^r_1 = \{(m,p)|X^{UL1}_{r,m,p} = 1\},\ DV^r_0 = \left\{(p,p')\middle|V^{UL1}_{st4,p,p'} = 0\right\},\ DV^r_1 = \{(p,p')|V^{UL1}_{st4,p,p'} = 1\},\ p\neq p' \qquad (3.113)$$

$$\sum_{(p,s')\in DY^r_1} Y^{sUL1}_{p,st1,s'+\gamma} - \sum_{(p,s')\in DY^r_0} Y^{sUL1}_{p,st1,s'+\gamma} + \sum_{(m,p)\in DX^r_1} X^{UL1}_{m,p} - \sum_{(m,p)\in DX^r_0} X^{UL1}_{m,p} + \sum_{(p,p')\in DV^r_1} V^{UL1}_{st4,p,p'} - \sum_{(p,p')\in DV^r_0} V^{UL1}_{st4,p,p'} \leq RHS - 1$$

$$\forall\,\gamma \in (-\alpha; +\alpha), \alpha = 3,\ DY^r_0 = \{(p,s')|Y^{sUL1}_{r,p,st1,s'} = 0\},\ DY^r_1 = \{(p,s')|Y^{sUL1}_{r,p,st1,s'} = 1\},\ DX^r_0 = \{(m,p)|X^{UL1}_{r,m,p} = 0\},\ DX^r_1 = \{(m,p)|X^{UL1}_{r,m,p} = 1\},\ ,DV^r_0 = \{(p,p')|V^{UL1}_{st4,p,p'} = 0\},\ DV^r_1 = \{(p,p')|V^{UL1}_{st4,p,p'} = 1\},\ p\neq p' \qquad (3.114)$$

The algorithm performs the iterative steps as shown in Figure 3-10. The upper level problem $UL1$ is not a strict mathematical relaxation, therefore one cannot use the objective function to systematically close the gap between the lower and the upper bounds, as it was the case for example in Iyer and Grossmann (1998). In the later iterations, $UL1$ is not a relaxed problem of the monolithic model because it considers the assignment of the EAFs as fixed and as long as this fixing is not optimal the solution from the upper level problem is not a valid lower bound. The assignments coming from $UL2$ to $UL1$ are used to speed up the computation time of solving $UL1$, which most of the times is not solvable to near-optimal solutions in short times, thus giving weak solutions without the fixing. It is reasonable to use the fixing also because of its much lower importance on the objective function compared to the degrees of freedom that the $UL1$ is handling, namely timing and sequencing.

Therefore, the solution of $UL1$ does not provide an increasing lower bound. At the same time the lower level problem LL and $UL2$ provide upper bounds as a feasible solution of the monolithic problem is obtained - the latter is always at least as good as the one from LL. Since the proposed algorithm does not guarantee to converge to the optimal solution, the most reasonable stopping criterion for the iterative execution is the total time spent on computations or the desired number of iterations, which is acceptable for industrial practice as long as the algorithms yields good quality solutions in reasonable computation times.

3.5 Industrial case study on bi-level heuristic

The bi-level heuristic was tested on the same problem instances as the monolithic model. In the decomposition scheme, some modifications of the input data are needed, due to the elimination of the AOD and LF stages as explained earlier. All relevant data is given in Appendix A.

Since the heuristic approach does not guarantee to provide systematically a better upper bound with each iteration the best solution of $UL2$ among all iterations is considered to be the bi-level algorithm's solution. For the economic assessment, the best solution of $UL2$'s model among all of the iterations is reported. The results of the heuristic decomposition approaches (BH and BR) based on the event binaries model reported in Table 3-7 shows that the heuristic is always able to find better quality solutions within given time limit compared to the best monolithic strategy (RM). Especially for larger problem sizes the gain in the solution quality is more visible. Both heuristic approaches based on the event binaries models perform similarly and obtain solutions of around 9 %. For Scenarios 1 and 4, the improved binaries model performed slightly better. The similar performance is related with the way how the heuristic algorithm is designed – both models are based on the same rough approximation at the upper level, which is the key factor in general performance of the heuristic. The ultimate gap of the heuristic solutions is more than likely better than the solution from the monolithic model, however it is difficult to find a best bound or the optimal solution that would prove it. The cost structure of similar quality solutions, e.g. BH4 and BR4, are very similar as well.

Very good results of the heuristic decomposition are achieved already in the first iteration. Often after up to 3 iterations the best solution is found. In Figure 3-12 the evolution of objective function values for all models in Scenario 1 is shown. It can be observed that the $UL1$ values in each iteration of the algorithm are constant, even though due to the cuts each iteration finds different solution from all the previous ones. This is due to the fact that a slight change in the timing and assignment or sequence of products (while satisfying the cuts) is very likely to give the same objective value since there are many similar solutions in $UL1$. However, when solving the more detailed LL model the values are changing in each iteration in response to the different decisions taken in $UL1$. For the same reason, the objective function value of LL can improve in further iterations since there are AOD and LF stages added as well as the new load deviation curve. Here it can be noted that the solution quality is not expected to improve significantly in further iterations as the bi-level solution method is based on the idea that the upper level should provide a very good rough schedule already in the first iteration. The objective function value of $UL2$ always improves the solution from LL slightly by finding a better assignment on EAF units. It should be also noted that for Scenario 2 and 4 the objective function value of $UL1$ is lower than LL and $UL2$, however this is not true for Scenario 1 and 3. The reason that higher values might appear in approximated $UL1$ is larger deviation penalties paid than in detailed LL and $UL2$ due to the changed pre-agreed load curve. A general behavior of the algorithm very similar to the one shown in Figure 3-12 was observed for all of the investigated scenarios.

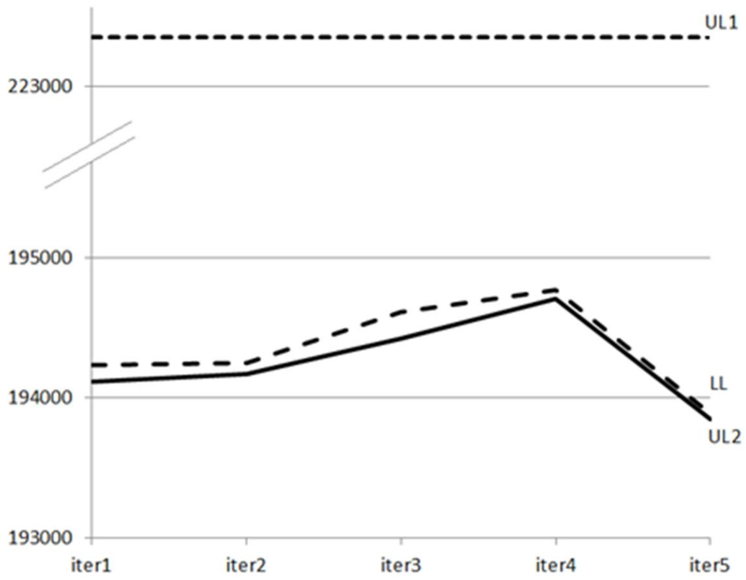


Figure 3-12 Objective function value change in each iteration for all models of BH1

One clear drawback of the proposed approach that can be noticed is that there is no clear indication of which iteration will be the best one, i.e. since there is guarantee of the systematic improvement of the objective function the best solution might be found at any iteration.

Interestingly, even though the improved binaries model (BR) is more efficient compared to the original event binaries model (BH) it does not yield noticeably better results when employed in the heuristic scheme. It can be suspected that since the improved model is faster it might allow for more total number of iterations in the algorithm, which might increase the chances of getting a better solution compared to the original event binaries model. This seems to be the case for Scenario 3 and 4 where the better performing BR model returned 5 iterations, while BH only 3 and 4 respectively.

In general, based on the investigated approaches it can be concluded that the bi-level heuristic is able to provide satisfactory solutions when solving realistic problem instances.

Table 3-7 Bi-level decomposition heuristic results - 600s computation limit

Scenario	Model statistics							Economic assessment							
	Binary vars UL2	Total vars UL2	Equations UL2	MIP solution UL2	MIP solution LL	MIP solution UL1	Relative gap	Lead times [min]	Net electricity cost [€]	Electricity purchase [€]	Deviation penalties [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	No. of iterations (best)
RM1	4065	10308	51375	244870	-	-	28,30%	53138	143209	151053	48522	223,065	1353,578	952	-
BH1	1458	29508	102335	193845	193888	227293	9,89%	46176	147087	156853	582	176,349	1456,514	952	5(5)
BR1	1458	10308	51375	193667	193832	227293	9,30%	46576	146259	157031	832	179,396	1457,204	952	5(3)
RM2	4065	10308	51375	193348	-	-	21,79%	53273	117602	99133	22474	1580,790	91,948	352	-
BH2	1458	29508	102335	165196	165285	160707	9,09%	45472	119443	101531	281	1512,868	196,161	392	5(3)
BR2	1458	10308	51375	165196	165402	160707	9,09%	45613	119338	103838	245	226,833	1521,583	352	5(4)
RM3	3229	8068	39760	147701	-	-	16,54%	32251	98162	131569	17286	100,554	1270,681	952	-
BH3	1276	23428	80528	134588	134749	169197	9,87%	30626	103057	133980	904	133,033	1243,566	952	3(1)
BR3	1276	8068	39760	134577	134592	169197	9,87%	30885	102839	134108	853	133,759	1243,567	952	5(1)
RM4	3229	8068	39760	183590	-	-	13,16%	37166	99105	133488	47319	77,735	1257,390	952	-
BH4	1276	23428	80528	176006	176244	153727	8,71%	35289	98990	123190	41727	13,130	1228,590	952	4(3)
BR4	1276	8068	39760	173873	173873	153726	8,61%	31987	99814	126177	42070	79,791	1228,357	952	5(3)

3.6 Conclusions and remarks

In this chapter a new strategy for embedding energy-awareness into a continuous-time scheduling approach has been showed. It enables optimizing production schedules of energy-intensive plants under consideration of time-sensitive prices of electricity (Chapter 3.2.4.1) and load commitment penalties (Chapter 3.2.4.2). The proposed three different approaches were compared on the same input data. The numerical experiments (Chapter 3.3) show that the use of the new event binaries is more efficient. However, both monolithic models cannot be solved within the available computation times for large-scale industrial problem instances. Therefore, a bi-level decomposition-based heuristic was developed (Chapter 3.4) to obtain good quality results in reasonable computation times.

The proposed solution scheme benefits from the exact timing of the tasks by the continuous-time scheduling representation. The model is able to capture complex price structures and to optimally determine the exact amount of electricity to be purchased and sold. The flexible part of the purchase optimization can be further extended by more complex dependencies between the contracts. The model might help assess different price levels of negotiated contracts, as well as reduce the risk associated with volatile electricity markets. An important restriction is that the plant needs to make commitments on the electricity amounts to be bought and sold on the day-ahead markets. Even more important factors are the disturbances and the technical capability to implement the optimized schedule.

To further address the limitations of the model concerning computational performance for large instances, a scheduling horizon of several days could be investigated with a rolling horizon approach. Decisions for longer time windows should be done with higher level short- and long-term planning solutions, taking into account different factors than those considered by the scheduling level. Further work could also deal with improvements of the developed algorithm towards a more rigorous scheme.

4 FUNCTIONAL DECOMPOSITION OF PROCESS SCHEDULING AND ENERGY-COST OPTIMIZATION

This chapter investigates and suggests solution approaches on how to tackle the main goal of the dissertation – integration of process scheduling and energy-cost optimization with functionally separated models of energy-aware scheduler and flow network optimizer. The chapter describes the development of a general framework and application to two different example processes. The different use cases are chosen in such a way that they differ not only in terms of the industrial process but also in generic principles of the scheduling modeling. The resulting structure of the chapter relates to the dissertation's goal and scope as follows:

- technical goal behind the functional separation is explained first as well as the motivation for the chosen use cases (Chapter 4.1);
- selected decomposition approaches are investigated (Chapter 4.2.1) to find a possible formal decomposition concept for functional separation of scheduling problems from energy cost optimization problems (Chapter 4.2.2);
- the generic framework developed as above is applied to the Thermo-Mechanical Pulping (TMP) example process (Chapter 4.3);
- in Chapter 4.4, based on recommendations from the TMP case study, the decomposition framework is applied to the stainless-steel process and the bi-level heuristic scheme investigated previously in Chapter 3.

For each use case different approach variations are investigated. Based on the industrial case study results conclusions and recommendations concerning the best performing approaches are highlighted.

4.1 Research challenge and motivation

One of the main goals of this work is to develop an approach that provides an iterative solution based upon a functional separation of process scheduling problems from energy cost optimization. The two separated problems should still serve their functions; the scheduler should provide a feasible schedule and the energy optimizer should find the best purchase and sale structure of contracts as shown in the leftmost (sequential) and rightmost (iterative) approach in Figure 4-1.

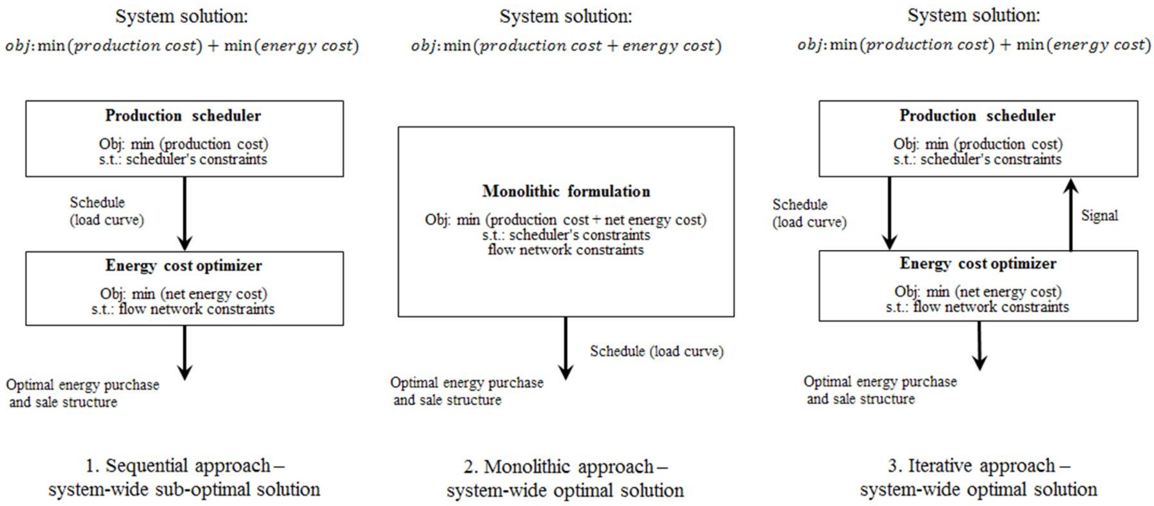


Figure 4-1 Production scheduling and energy-cost optimization integration concepts

The framework for the integration concept while keeping the models separated needs to be based on some information exchange between the two. This is in contrast to the approach reported in Chapter 3 where the steel problem has been formulated as a monolithic model (approach 2 in Figure 4-1) and solved by a MILP-based heuristic procedure. In this chapter, the goal is to find such a strategy for the separated problems that:

- converges to a system-wide optimum (approach 2 and 3 in Figure 4-1) in contrast to the one-way approach (approach 1 in Figure 4-1) of solving a scheduling problem with its production specific cost and then solving the flow network problem to find the optimal purchase and sales structure with energy specific cost;
- finds good quality solutions in reasonable times - preferably optimal, or at least as good as the corresponding monolithic formulation of the problem;
- solves the flow network problem using a fixed load curve from the scheduling problem;
- is generic enough to accommodate different scheduling approaches and industrial process types;
- if needed, involves energy-aware scheduling approaches as they have recently gained attention in literature resulting in successfully reported approaches (see Chapter 2.4).

The above directions on the behavior of the solution scheme are motivated by the benefits of keeping the two problems separated while still getting a system-wide optimal solution, which is the core research challenge. Therefore, the suggested functional separation serves as an integration strategy for the two problems. In addition, the benefits of such a functional separation are:

- keeping the models separated makes it easier for the industries to integrate production and energy management systems since
    - potentially existing solutions of both scheduling and energy purchase systems installed at the plant can be re-used;
    - both scheduling and energy purchase systems, if already existing, need not to be integrated as one monolithic solution (potentially less effort in integration);
- separation also benefits from modularity of the separated solutions, which can be provided by different system solution suppliers, in contrast to the monolithic integration which would potentially require one single supplier;
- the separated models can potentially benefit from improved computational times (easier to solve two separated problems than a single monolithic one).

In the following chapters the integration concept of functional separation is developed and tested on industrial processes. This is done for two different case studies. In addition to the stainless-steel process introduced in Chapter 3 a Thermo-Mechanical Pulping (TMP) process utilizing a discrete-time Resource-Task Network modeling approach will be investigated. The reason for this is the following:

- the two models fundamentally differ in the time representation of the scheduling models; the steel case is continuous-time while the TMP model is discrete;
- the cases also differ in scheduling modeling approaches; the steel case is based on general precedence variables, while the TMP case utilizes a Resource-Task Network (RTN) representation (see Chapter 4.3 for more details for the latter);
- the two differ in the industrial process type, the steel case is a batch process with fixed number of products that need to be processed at all stages within a given time horizon, while the TMP case is a continuous process with storage possibility and external source of final products supply;
- due to the above point the steel process has a fixed electricity consumption that has to be distributed optimally over the time horizon, while the TMP process might choose to decrease its total electricity consumption by final product supply from an external source at additional cost;
- the steel case problem is a large-scale problem for which a heuristic approach has to be used to obtain satisfactory results while the TMP model is tractable when solved with monolithic approach.

In the following chapter, the concepts of functional separation will be investigated, based on the directions drafted above.

4.2 Functional decomposition with Mean Value Cross Decomposition (MVCD)

In the following chapters, selected decomposition approaches for tackling optimization problems are described. The explanations are supported by generic examples. The solution approach identified in Chapter 4.1 was found when exploiting the special problem structure of the monolithic problem of scheduling with energy-cost optimization. The solution scheme involves two decomposition approaches, Benders' decomposition and Dantzig-Wolfe decomposition in the iterative framework of Mean Value Cross Decomposition.

4.2.1 Selected decomposition approaches

Benders' and Dantzig-Wolfe's decompositions

An important systematic decomposition scheme initially developed to tackle large-scale Linear Programming (LP) problems was proposed by Benders (1962). So-called Primal (or Benders') decomposition exploits a special block structure of a mathematical program to generate new constraints and progress towards the optimal solution. The special structure called Dual Block Angular occurs when the system consists of a number of semi-independent subsystems, linked by a set of so-called coupling (or complicating) variables. In addition, each subsystem also has its own local variables. The Benders' decomposition-based approaches usually divide a complex large problem into two levels, master and sub-problem(s), as shown in Figure 4-2.

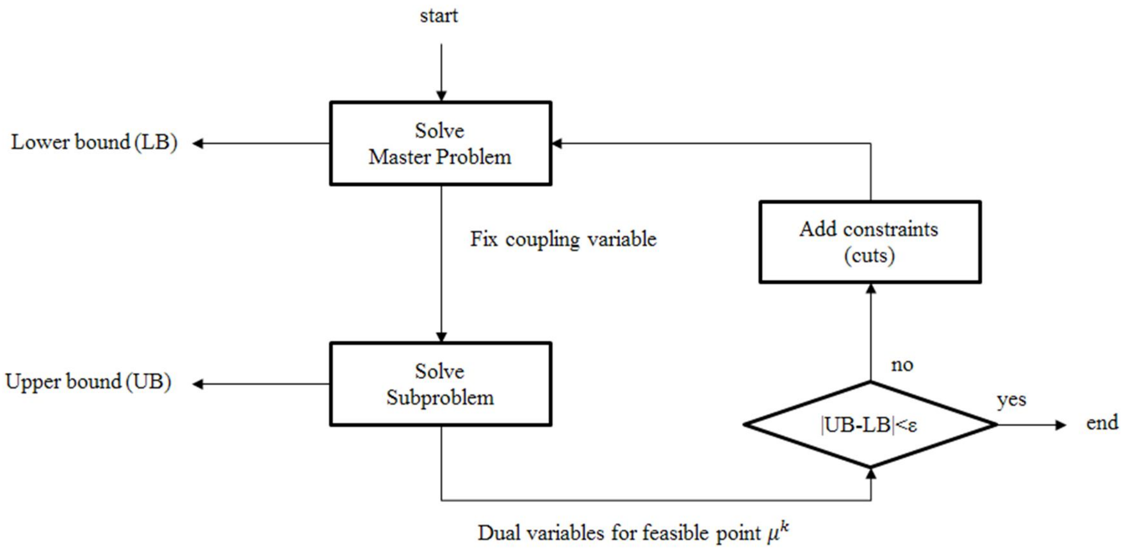


Figure 4-2 Benders' decomposition scheme

The relaxed master problem contains the complicating variables and the local variables some of which are relaxed. After solving the master problem the solution provides a lower bound (for a minimization problem) and gives the value of the complicating variable to the sub-problem(s) where it is treated as fixed. In this way, often the sub-problem is a restricted original problem, thus providing feasible solutions in every iteration. In addition, some problems are trivially separable when fixing the complicating variable – as shown later the problems considered in this dissertation are such cases of trivial separation after fixing the complicating variables. The solution of the sub-problem is an upper bound of the original problem. When iteratively solving both problems, designing efficient cuts and ensuring that from the sub-problem a feasible solution is obtained (possibly with a heuristic feasible solution finder), the method is proved to converge to optimality in a finite number of iterations (Geoffrion 1972). Benders' decomposition approaches are widely used to solve large-scale MILP scheduling problems, e.g. integrated planning and scheduling in Iyer and Grossmann (1998), Erdirik-Dogan and Grossmann (2008), Li and Ierapetritou (2009).

Apart from the Benders' variable decomposition, various other constraint decomposition techniques were developed, such as the Dantzig-Wolfe Decomposition (Dantzig and Wolfe, 1960), Column Generation (Ford and Fulkerson, 1958) and Lagrangean Decomposition (Geoffrion 1974). The Dantzig-Wolfe method (Figure 4-3) can be applied to problems with a special Primal Block Angular structure, where a number of independent (local) constraints occur with additional common coupling (complicating) constraints. Complicating constraints bind the local variables together. This structure appears in many large-scale industrial optimization problems, as pointed out in a review by Grossmann and Biegler (2004). In the variable (Primal) decomposition, fixing of the primal coupling variables separates the problem into sub-problems. In contrast, the constraint (Dual) decomposition relaxes the complicating constraints and penalizes their violation by Lagrangean multipliers (dual or price variable) in the objective function, which then decomposes the relaxed problem into sub-problems (Létocart et al. 2012).

In Lagrangean Decomposition the coupling constraints are dualized to create sub-problems, which provide (all together) a lower bound to the original problem. The restricted master problem gives the upper bound, however, often it does not return a feasible solution, therefore some techniques (e.g. Lagrangean heuristics, Geoffrion 1974) are employed to overcome this problem (e.g. Jackson and Grossmann, 2003).

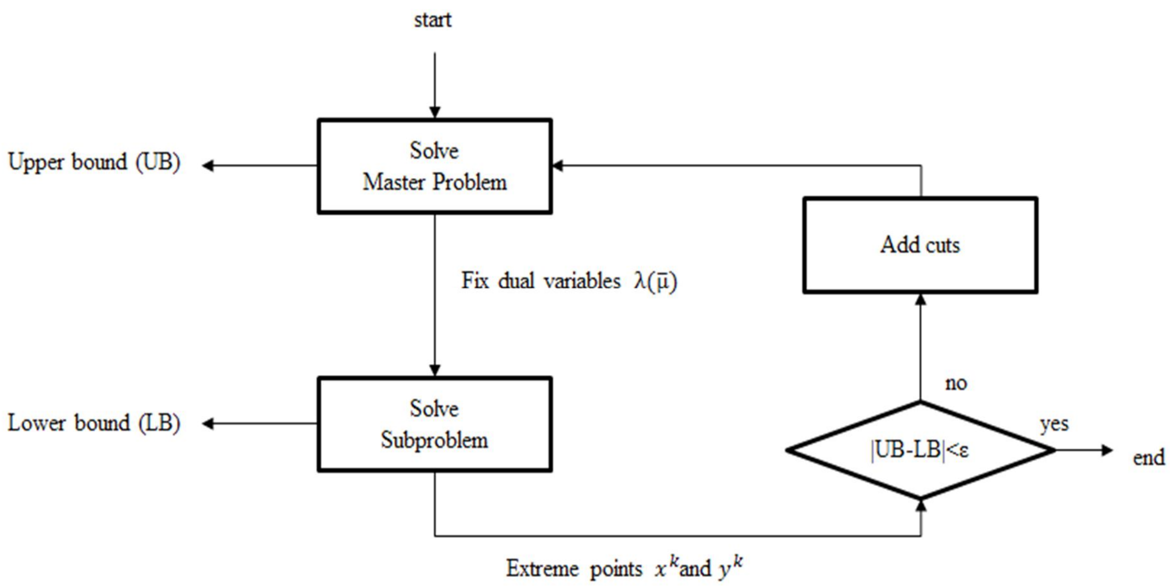


Figure 4-3 Dantzig-Wolfe decomposition scheme

The information exchange between the master and the sub-problem is the dual variable, which needs to be updated at each iteration. Some techniques have been investigated to improve the method, for example the sub-gradient method (Fisher 1981) as being effective for certain class of problems. It is reportedly less efficient for sub-problems with discrete-variables (Wu and Ierapetritou 2005).

Cross Decomposition

An approach using both of the above aforementioned strategies of Benders' and Dantzig-Wolfe decomposition was developed by Van Roy (1980, 1983) and applied to solve a capacitated location MILP-type problem (Van Roy, 1986). In the study, a Cross Decomposition is presented which iterates between sub-problems of both previously mentioned decomposition techniques. The Benders' master problem in this scheme is replaced by the Lagrangean relaxation of the original problem and the dual master problem is replaced by the Benders' sub-problem. The solution algorithm mainly iterates between the Primal and Dual sub-problems, however for every iteration a convergence test on both exchanged sets of information is required. If any of the tests fails, it is required to solve the master problem and then return to the sub-problem phase. The exchanged information are a variable $\bar{y}$ fed from the dual sub-problem to the primal sub-problem, and the dual variable $\bar{\mu}$ which is obtained from the primal and transferred to the dual sub-problem. The primal and dual sub-problems give respectively an upper and lower bound of the original problem and both also generate cuts for their respective master problems. A generic Cross Decomposition scheme is shown in Figure 4-4. One of the drawbacks of using such a decomposition scheme is the fact that every primal and dual variable needs to be stored for use in the master problem. Also solving the master problems is usually troublesome. However, once the bounds from sub-problems converge towards the same value, the original problem is solved to optimality (Holmberg, 1994a). Furthermore, under special structures, Cross Decomposition solves an MILP problem in a finite number of iterations (Holmberg, 1997). Holmberg (1990) investigates solving LP, MILP and NLP problems discussing Cross decomposition and its limitations.

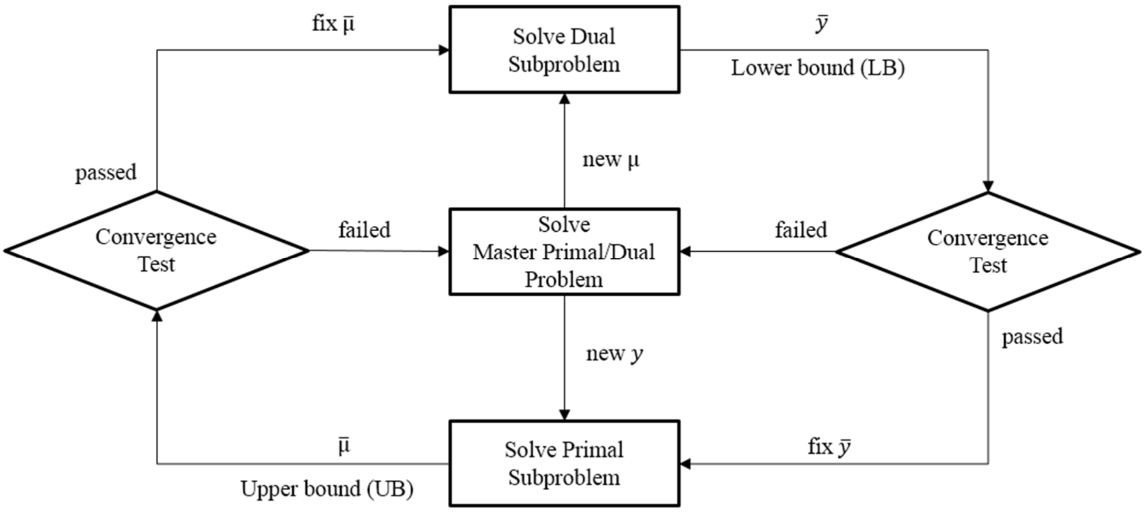


Figure 4-4 Cross Decomposition scheme

Mean Value Cross Decomposition and its variations

An interesting development from the Cross Decomposition approach is the Mean-Value Cross Decomposition (MVCD) scheme by Holmberg (1992 and 1994b). This decomposition does not involve the difficult master problems and iterates only between the sub-problems, however, using a mean value calculation of the exchanged information – referred to here as signals. It was initially developed as a decomposition scheme for tackling LP (Holmberg, 1992) and later convex nonlinear problems (Holmberg and Kiwiel, 2006). For LP problems, it was proven to converge to the optimal solution (Holmberg, 1994b). Holmberg (1997) showed that when applying MVCD to MILP problems the method yields the same bound as the Lagrangean dual. The latter can be a stronger bound than the corresponding LP relaxation. Therefore, in Holmberg (1998) the method is used in a branch-and-bound algorithm. In contrast to the Cross Decomposition, in MCVD the dual solution of the primal sub-problem is augmented by its mean values which are used as input to the dual sub-problem and similarly for the primal solution of the dual sub-problem. An effect of the mean value for MILPs is that primal feasibility may never be achieved. The MCVD has neither a primal nor dual master problem in its solution algorithm. The decomposition iterates only between the primal and dual sub-problems as shown in Figure 4-5. The mean value can be calculated using Eq. (4.1) which is shown for a signal y.

$$y^i = \frac{1}{i}\tilde{y}^{i-1} + \frac{i-1}{i}y^{i-1} \quad (4.1)$$

In the above, variable $\tilde{y}^{i-1}$is the value of $\tilde{y}$ obtained in the last iteration, while i is the number of iterations. Holmberg and Kiwiel (2006) suggest that it could be beneficial in some cases to directly use the obtained y as in Eq. (4.2). A disadvantage of the last approach (4.2) for updating the variables is that the sub-problems can no longer be solved in parallel, as in the former approach (4.1).

$$y^i = \frac{1}{i}\tilde{y}^{i} + \frac{i-1}{i}y^{i-1} \quad (4.2)$$

Holmberg (2004) mentions that the advantage of the MVCD approach is a better primal problem controllability and availability of information from the primal and dual. In Holmberg (2001) the method is shown to be less memory consuming compared to Cross Decomposition, therefore it seems to be interesting for large-scale problems where it is not essential to find the exact optimal solution. Unfortunately, there is no general proof of finite convergence to optimality for MILP problems (Holmberg, 1997) – the MILP-MVCD converges to the bound of the Lagrangean dual (to the dual gap error). If integer constraints are applied, MVDC might return infeasible values due to mean value alteration of feasible values of the exchanged variables. Holmberg (1998) overcame this using a heuristic modification which uses one of the signals directly, without calculating its mean value. This improved the practical performance and gave rise to so-called One-sided Mean-value Cross Decomposition (OSMVCD), which will also be investigated more closely in the later case studies. Another modification of the Cross Decomposition reported by Holmberg and Kiwiel (2006) is the Weighted Mean-value Cross Decomposition (WMVCD), which has been proven to converge for nonlinear convex problems. The only difference with MVDC is the updating scheme; instead of the mean value a weighted mean value is used, as in Eq. (4.3), where the mean value calculation comes from Eq. (4.1). This modification strengthens the importance of the last received signal.

$$y^i = \delta_i \tilde{y}^{i-1} + (1 - \delta_i) y^{i-1} \tag{4.3}$$

where:

$$\delta_i = \frac{\beta + \gamma}{\beta i + \gamma} \tag{4.4}$$

$$\sum_{i=0}^{\infty} \delta_i = \infty \tag{4.5}$$

The parameters for β and γ are set $a\,priori$, Holmberg and Kiwiel (2006) showed that the best values for β and γ are respectively 1 and 3 for the problems studied. In the above equations, δ_i is a weight value which moves towards zero with each iteration i.

The convergence properties for different decomposition approaches are given in Table 4-1. The one-sided versions of the MVCD (or WMVCD) decomposition cannot guarantee convergence properties. However, they provide some advantages as it will be discussed later. To summarize, for the MILP problems which are the subject of this work, in the MVCD both Benders' and Dantzig-Wolfe's sub-problems are expected to give solutions below optimum (dual gap distance from optimum). Since WMVCD has identical convergence properties as MVCD for NLP problems it can be expected that for MILP problems the WMVCD should have the same properties for MILP as MVCD, even though there is no formal proof for it.

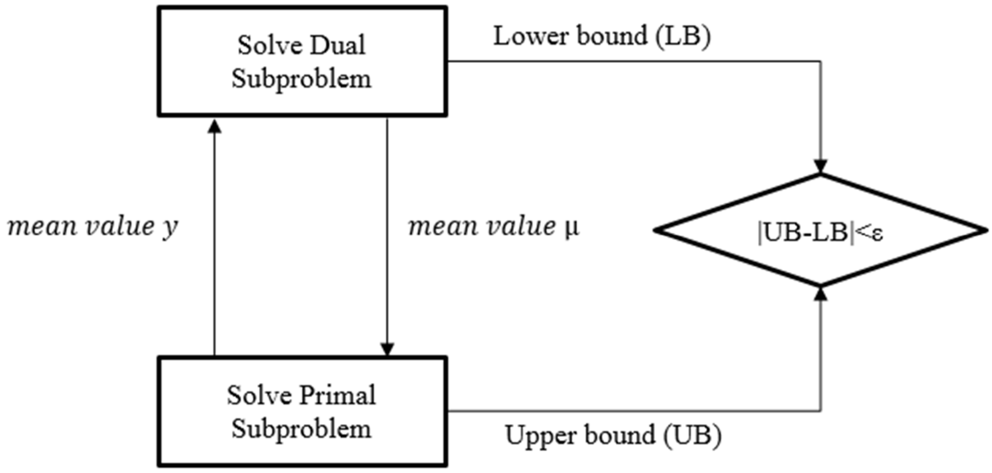


Figure 4-5 Mean Value Cross Decomposition scheme

Table 4-1 Convergence properties of different MVCD decomposition approaches

	MVCD	**WMVCD**	**OSMVCD** **OSWMVCD**
LP	Optimum (Holmberg, 1994b)	Optimum (Holmberg and Kiwiel, 2006)	No convergence proofs
NLP (with convex sets and functions)	Optimum (Holmberg and Kiwiel, 2006)		
MILP	Lagrangean dual bound (Holmberg, 1997)	No convergence proofs	

4.2.2 Functional decomposition development

As explained and motivated in Chapter 4.1 the aim is to develop a framework for functional separation of the production scheduling and energy-cost optimization. In the scheme, some information should be exchanged and certain constraints shall be kept separated from the others (flow network cost optimization separated from the scheduling problem). In case of the scheduler, the available output information is a schedule with corresponding electricity consumption pattern. For the energy optimizer, the electricity consumption is a fixed input. In the following sections it is shown that when decomposing the monolithic model, the standard sub-problems of Benders' and Dantzig-Wolfe decomposition yield respectively the desired energy-aware scheduling model and energy optimizer. Next, in treating the models in such form, Mean-Value Cross Decomposition can be applied for solving the monolithic model. The information exchanged between the models will then be the schedule, the energy purchase strategy with corresponding dual information which is available as a mathematical characteristic of the formulated problem.

4.2.2.1. Monolithic model formulation and Benders' decomposition

Let us define a simple monolithic problem of scheduling with optimization of energy cost (e.g. as described in 3.2.1 for the steel case or later in Chapter 4.3.2 for the pulping case) in the following general form:

$$min\, z(f,y) = C_1^T f + C_2^T y \tag{4.6}$$

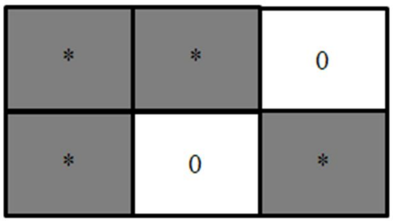
subject to

$A_1 f + D_1 x \leq b_1$ – flow network constraints (4.7)

$A_2 q + D_2 y \leq b_2$ – production scheduler constraints (4.8)

$Iq - A_3 f = 0$ – complicating constraint (4.9)

$$x \in X,\ y \in Y,\ q \in Q, f \in F, q \geq 0, f \geq 0 \tag{4.10}$$



$$\begin{pmatrix} [A_1] & [D_1] & [0 \quad 0] \\ \begin{bmatrix}0\\+A_3\\-A_3\end{bmatrix} & \begin{bmatrix}0\\0\\0\end{bmatrix} & \begin{bmatrix}D_2 & A_2\\ -I & 0\\ +I & 0\end{bmatrix}\end{pmatrix}\begin{pmatrix}f\\x\\q\\y\end{pmatrix} \le \begin{pmatrix}b_1\\b_2\\0\\0\end{pmatrix}$$

Figure 4-6 Dual-Block Angular structure of the monolithic formulation

In the above let us assume that x and y represent collectively the variables specific to the energy purchase model and energy-aware scheduler respectively. Let X and Y represent all bounds and variable types -continuous and integer requirements respectively for variables x related only to the energy problem and variables y only to the scheduling problem. I is an identity matrix. The energy purchase and sale optimization model consists of constraints representing the Minimum-cost Flow Network, while the other set of constraints is the scheduling model together with energy-awareness and committed load problem constraints. Eq. (4.9) is written separately from the others as it is a special complicating constraint of the monolithic model (so-called consensus constraint). It links the two variables f (flow of electricity amount within the minimum-cost flow network) and q (electricity amount consumed by the production process accounted in the scheduling problem) which are present in Eqs (4.7) and (4.8). $A_3 f$ represents all the electricity amounts needed to satisfy the process demand - flow from the balancing node to the process demand node. Any value change of any variable in Eq. (4.9) causes a change in the respective part of the monolithic model (Eq. 4.7 or 4.8), thus of the values of the objective function components in Eq. (4.6), either the flow network's specific cost $C_1^T f$ or production specific cost $C_2^T y$. Here it is important to note that the load deviation problem is considered to be integrated into the scheduler's problem – the load deviation cost are a part of the production specific cost therefore load deviation constraints occur in the scheduling problem. It is also possible to move the load deviation equations and deviation penalties component of the objective function value to the flow network optimization problem. However, here it is chosen to include it as the production specific cost since it is the scheduler which can directly influence the load pattern and thus the penalties cost.

When experimenting with numerical studies we discovered that the load deviation constraints actually help to speed up computation times for the scheduling problem, especially for larger instances with increased flexibility (less constrained problem with many possible feasible solutions). It could be because the load deviation constraints improve computation times by tightening the model and guiding the MILP branch and bound solver.

The constraints of the monolithic model result in a finite number of extreme points (bounded solutions) due to the bounds of the physical variables, such as storage, flow limits, capacities etc. Therefore, the decomposition schemes shown in Chapter 4.2 can be applied, as they require the assumption of bounded feasible solution regions. Since the monolithic problem has the Dual-Block Angular structure (Figure 4-6) one can apply the Benders' decomposition by fixing the variable q in the monolithic model. Then the primal sub-problem is formulated as:

$$\min_{f,x,y} h(f, y, \bar{q}) = C_1^T f + C_2^T y \tag{4.11}$$

subject to

$A_1 f + D_1 x \le b_1$ – flow network constraints (4.7)

$A_2 \bar{q} + D_2 y \le b_2$ – production scheduler constraints with fixed $\bar{q}$ (4.12)

$I\bar{q} - A_3 f = 0$ – complicating constraints with fixed $\bar{q}$ (4.13)

$x \in X,\ y \in Y, q \in Q, f \in F,\ q \geq 0, f \geq 0$

The only change in the above model is that the values of the variable $q = \bar{q} \geq 0$ are fixed. The formulation now becomes trivially decomposable into two sub-problems Eq. (4.14) and Eq. (4.17) which can be solved in parallel. The flow network optimizer thus solves:

$F_{MFN}(\bar{q}) = \min_{\mathrm{f,x}} C_1^T f$ (4.14)

subject to

$A_1 f + D_1 x \leq b_1$ – flow network constraints (4.7)

$I\bar{q} - A_3 f = 0$ – complicating constraints with fixed $\bar{q}$ (4.13)

$x \in X, q \in Q, f \in F,\ q \geq 0, f \geq 0$

The other part of the sub-problem contains the production specific constraints:

$F_{EPS}(\bar{q}) = \min_{\mathrm{y}} C_2^T y$ (4.15)

subject to

$A_2\bar{q} + D_2 y \leq b_2$ – production scheduler constraints with fixed $\bar{q}$ (4.12)

$y \in Y, q \in Q, q \geq 0$

It is important to note that the dual cost of the complicating constraint in the original sub-problem (4.11) is exactly the same as the dual cost of the complicating constraint (4.13) in the decomposed sub-problem (4.14), if $\bar{q}$ is fixed. The objective function value of the original problem (4.11) is equal to adding the decomposed sub-problems objective function values together:

$F^* = F_{MFN} + F_{EPS}$ (4.16)

The problem (4.14) is actually the flow network optimizer used in the industrial setting mentioned in the goal and scope Chapter 4.1. In contrast, the production scheduler from (4.15) is equipped with knowledge concerning electricity consumption in a given time slot, which is fixed. In practice that would mean that the model would be minimizing the production specific cost for a certain given consumption curve, which may not be feasible as discussed later.

The master problem of the Benders' decomposition gives a lower bound of the original problem. The problem is constructed by solving the primal sub-problem (4.11) and obtaining the extreme points μ^k (Lagrangean multipliers) from the marginal cost of the constraint (4.12):

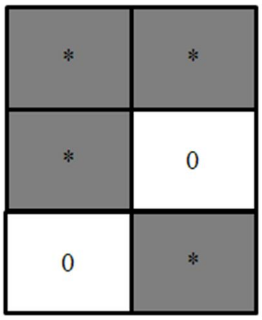
$min\, w$ (4.17)

subject to

$w \geq F_{MFN}(q) + (b_2 - A_2 q)^T \mu^{(k)} \qquad \forall k \geq 1, k \in K$ (4.18)

$q \in Q, q \geq\ 0.$ (4.19)

The master problem (4.17) consists of similar variables as the monolithic problem, with the addition of dual variables in the new constraint (4.18). In the usual Benders' scheme, for each new iteration k between the master and the sub-problem, a new constraint will be generated in (4.18). A solution of the master problem sets the value of the coupling variable $\bar{q}$ used in the sub-problem. In practice all found extreme points have to be stored while iterating, which can become a major limitation for large-scale problems.



$$\begin{pmatrix} \begin{bmatrix} +A_3 & 0 \\ -A_3 & 0 \end{bmatrix} & \begin{bmatrix} -I & 0 \\ +I & 0 \end{bmatrix} \\ [A_1 \quad D_1] & [0 \quad 0] \\ [0 \quad 0] & [D_2 \quad A_2] \end{pmatrix} \begin{pmatrix} f \\ x \\ q \\ y \end{pmatrix} \leq \begin{pmatrix} 0 \\ 0 \\ b_1 \\ b_2 \end{pmatrix}$$

Figure 4-7 Primal-Block Angular structure of the monolithic formulation

In addition, the duals present in Eq. (4.18) could be difficult to extract. The master problem is not similar to any of the initial problems related to the industrial state-of-the-art (leftmost in Figure 4-8), therefore if not needed it would be desirable not to involve the master problem in this form in the iterative scheme.

4.2.2.2. Dantzig-Wolfe decomposition

The other decomposition scheme can be applied if the original problem has Primal-Block Angular structure (Figure 4-7). The Dantzig-Wolfe decomposition (Dantzig and Wolfe, 1960), starts with applying Lagrangean relaxation on the complicating constraint (4.9) of the monolithic model with corresponding λ being a Lagrangean multiplier. The sub-problem is formulated by setting the multiplier to a fixed value $\bar{\lambda}$ as in Eq. (4.20).

$$\min\{(C_1^T - \bar{\lambda}^T A_3)f + C_2^T y + \bar{\lambda}^T q\} \tag{4.20}$$

Subject to

$A_1 f + D_1 x \leq b_1$ – flow network constraints (4.7)

$A_2 q + D_2 y \leq b_2$ – production scheduler constraints (4.8)

$x \in X,\ y \in Y,\ q \in Q, f \in F, q \geq 0, f \geq 0.$

We can notice that the above sub-problem can be further trivially decomposed in the same manner as the Benders' sub-problem. From Eq. (4.20) two partial sub-problems are obtained. First, the energy cost (flow network) optimization part (4.21):

$$\min\{(C_1^T - \bar{\lambda}^T A_3)f\} \tag{4.21}$$

subject to

$A_1 f + D_1 x \leq b_1$ – flow network constraints (4.7)

$x \in X,\ f \in F, f \geq 0.$

Second, the production cost optimization part in Eq. (4.22):

$$\min\{C_2^T y + \bar{\lambda}^T q\} \tag{4.22}$$

subject to

$A_2 q + D_2 y \leq b_2$ – production scheduler constraints (4.8)

$y \in Y,\ q \in Q, q \geq 0.$

The flow network part (Eq. 4.21) uses the dual variable of the complicating constraint and flow network constraints. The production part (Eq. 4.22) is simply a production scheduling model with energy-awareness, load commitment constraints and penalization by the dual $\bar{\lambda}$ of the consumption curve in the objective function. It can be seen as a scheduling model with response to a single energy price curve, which is widely considered in many publications (see Chapter 2.4). Fixed marginal cost values are treated here as parameters and convey the information of how much the objective function value in the energy cost optimization model would change in response to a change in consumption.

As mentioned before, the load penalties are considered to be included in the cost of the production scheduler. However, by moving the load deviation constraints into the flow network problem one could obtain the dual variable which would not only express the cost of the purchase and sale but also cost of deviation penalties. In this way, the production scheduler without load deviation included could respond to the load penalties problem by inducing the dual information in its objective function.

Further on, the master problem of the Dantzig-Wolfe decomposition, which gives an upper bound, is formed by considering the convex combination of the solutions (extreme points) from the dual sub-problems. Fixed values of $f^{(k)}$, $y^{(k)}$ and $q^{(k)}$ correspond to the solutions found by the sub-problems in iteration k. This combination is applied to the objective function and the complicating constraint in the original problem to form the dual master problem as in Eq. 4.23.

$$min\{\sum_{k\geq1}\left(C_1^T\bar{f}^{(k)} + C_2^T\bar{y}^{(k)}\right)\lambda^{(k)}\} \tag{4.23}$$

subject to

$$\sum_{k\geq1}\left(A_3\bar{f}^{(k)} - \bar{q}^{(k)}\right)\lambda^{(k)} = 0 \tag{4.24}$$

$$\sum_{k\geq1}\lambda^{(k)} = 1 \qquad \lambda^{(k)} \geq 0, \forall k \geq 1 \tag{4.25}$$

The solution idea of Dantzig-Wolfe decomposition is to solve the sub-problem and get the extreme points $f^{(k)}$, $y^{(k)}$ and $q^{(k)}$. Next, these are stored and used in the master problem, which returns the dual value (Lagrangean multiplier) $\lambda^{(k)}$ for each iteration. The latter is fixed and used as an input $\bar{\lambda}$ in the sub-problem. The master problem here again constitutes an undesired model as it includes both the flow network and production scheduling variables.

4.2.2.3. Desired iterative structure with Mean Value Cross Decomposition

As a result of both decomposition schemes, interesting sub-problems can be obtained: representing separately the flow network problem (as a partial sub-problem of the Benders' decomposition) and the energy-aware scheduling problem (as a partial sub-problem of the Dantzig-Wolfe decomposition). The latter comprises of load deviation constraints and the response to a single electricity price curve. These two decompositions can be combined in a Mean Value Cross Decomposition (MVCD; Holmberg 1992) scheme without using the master problems as shown in Figure 4-8, where the dual information of the complicating constraint is denoted by μ. The MVCD might be modified with different signal alteration schemes to form different decomposition types as discussed later. The idea of using mean values originates from the Brown-Robinson method (Brown, 1949; Robinson, 1951).

It is important to note that in order to achieve convergence of the algorithm, an upper and lower bound from the complete sub-problems (respectively Benders' and Dantzig-Wolfe) need to be compared. If for a given iteration the complete sub-problems yield the same value for the bounds (zero gap) the original monolithic problem is solved to optimality. However, in order to obtain a solution from one complete iteration (a feasible solution to the monolithic problem) it is enough to run only the partial sub-problems, as shown in Figure 4-9.

With the desired setup different iterative schemes can be constructed by changing the way how the signals are altered in each iteration (altered signals are denoted as q_t' and MC_t' in Figure 4-9). Among these the following are selected to be investigated further:

- Mean Value Cross Decomposition (MVCD) – both signals are altered by calculating their mean value (Holmberg 1992, 1994b, 1997);
- Weighted Mean Value Cross Decomposition (WMVCD) – both signals are altered by calculating their weighted mean (Holmberg and Kiwiel 2006);
- One-sided Weighted Mean Value Cross Decomposition (OSWMVCD) – only one of the signals is altered by calculating a weighted mean, the other is used directly without any changes (Holmberg 2004);
- Heuristic Cross Decomposition (HCD) – both values are used directly, without any changes.

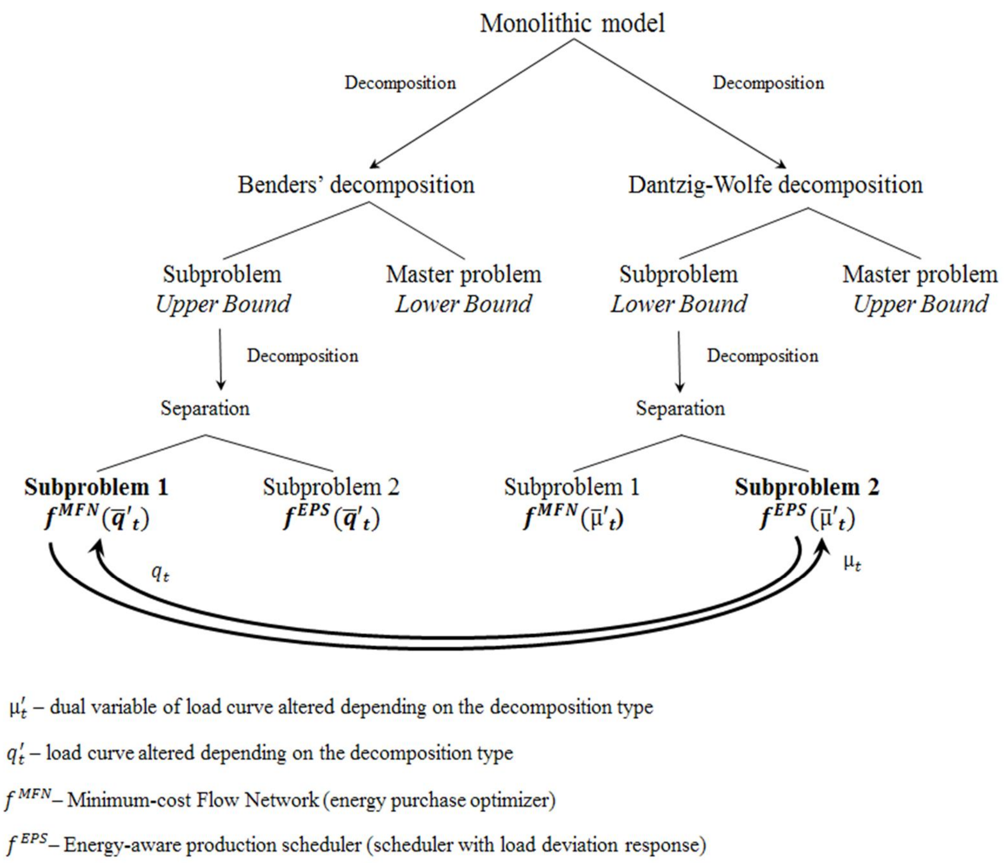


Figure 4-8 Industrial approach for the iterative framework based on decompositions

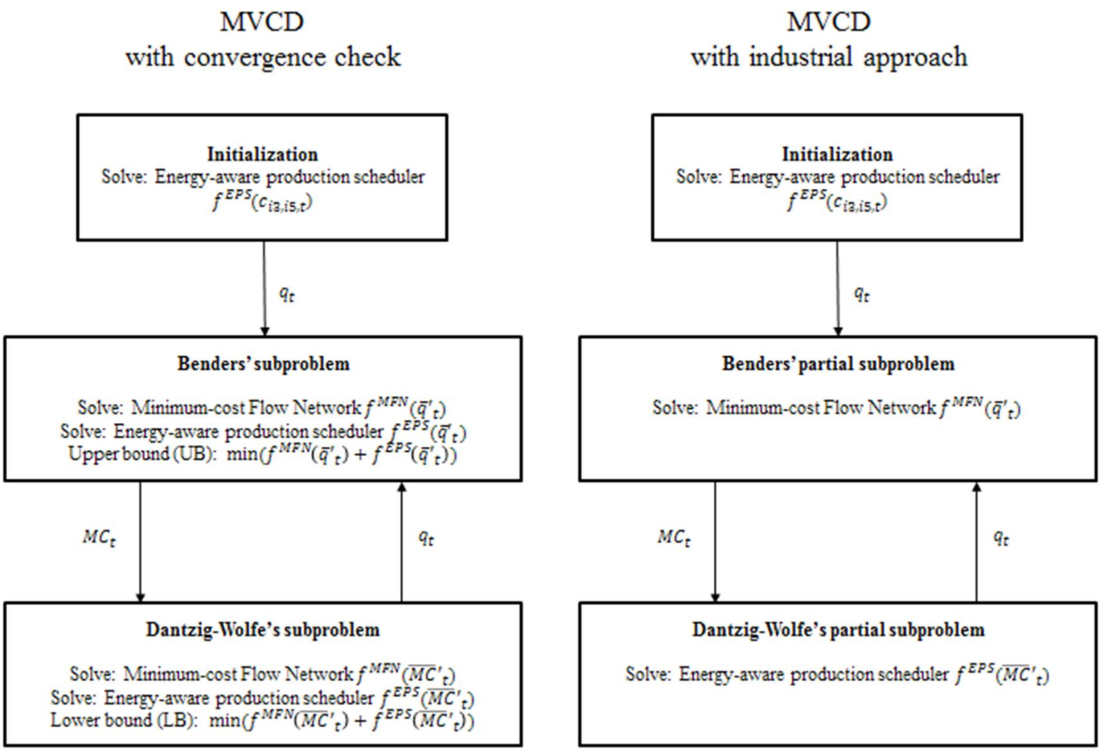


Figure 4-9 Iterative framework based on Mean Value Cross Decomposition

WMVCD has been experimentally shown to obtain better solutions faster for MILP problems (e.g. Holmberg and Kiwiel, 2006), even though it has not been proven that the method converges to optimality. Besides WMVCD, for numerical experiments, it is chosen to consider OSWMVCD for the following reasons. Firstly, the solution of complete sub-problems of the Benders' decomposition would require to solve the production part with altered mean value load variable q_t, which could potentially result in infeasibility. To overcome this, some rounding to the nearest feasible values could be introduced, however according to Holmberg (1998) this creates a duality gap and the controllability of the solution is decreasing. Secondly, the energy-aware production scheduling model returns the time-sensitive load curve which is always feasible for the flow network, therefore it would not be desired to alter it before sending to the flow network problem, as the latter would return the dual variables for potentially infeasible load pattern. Therefore, it makes sense to use OSWMVCD which alters by the weighted mean value only the signal coming from the energy purchase optimization. This is also an approach suggested by Holmberg (1998) as a promising way to overcome the signal infeasibility. In this way, the load pattern of the production model will response to a slow change (since the signal alteration considers previous values) in the energy cost. In order to see if it would be profitable to use both signals directly a heuristic approach is investigated, hereafter called Heuristic Cross Decomposition. In all of the above approaches it is important to note that in order to observe convergence the objective function values of the complete sub-problems (complete Benders' and complete Dantzig-Wolfe) have to be taken into account. However, to obtain the solution, it is sufficient to iterate only between partial sub-problems. Hereafter, such setting is called an industrial approach (as in Figure 4-8). This strategy would be very desirable since it does not require a lot of changes compared to the traditional industrial state-of-the-art models, except of extending the production model with energy-awareness, such as in Chapter 3.2.3 for the steel case.

Interpretation of Mean Value Cross Decomposition

Benders' and Dantzig-Wolfe decomposition techniques can be regarded as price and resource directive driven methods. The Mean Value Cross Decomposition methods is a mixed decomposition that applies both price and resource directives simultaneously (other mixed decomposition methods are discussed in literature e.g. early works of Aoki 1971, Heal 1971, Obel 1978). In Cross Decomposition (Van Roy, 1983) a subproblem receives both prices of some resources and allocation levels of some other resources. However, the two directives are used in an alternating fashion, not at once such as in MVCD. In addition, it is difficult to formulate a master problem that would update both prices and allocation in an advantageous way while still being computationally tractable.

MVCD, in the separable case, has been shown by Holmberg (1992) to correspond to a two-person, zero-sum, finite matrix game. In the game the players find the best counter strategy based on the mean values of all previously used strategies of the other player. In the demand-side management scheme it is also visible that the problem of coordinating the scheduling with energy-cost optimization can be seen as a game where two players compete on resource (how much electricity to use in different time periods) and its price (marginal cost of electricity).

4.3 Application to the discrete-time RTN model of the Thermo-Mechanical Pulping case

Due to the reasons stated previously in Chapters 2.3 and 4.1 it is chosen to investigate the developed functional separation scheme on a Thermo-Mechanical Pulping process example. The process has a certain flexibility and contains a production stage with a large electrical load. A Resource-Task Network (RTN) discrete-time approach was chosen to formulate the MILP model. The RTN framework can utilize both the discrete- and continuous-time approaches (see for example Castro, Barbosa-Póvoa and Matos, 2003), however here the first one is chosen to differentiate from the strategy used to solve the steel case. The RTN approach has been recognized as a promising method for solving some of the industrial scheduling problems under energy constraints (Merkert et al., 2015) due to its flexibility in handling utilities and its compact, tight formulation. Moreover, there are cases of successful implementation of RTN based scheduling for solving industrial, large-scale problems such the one at the Dow Chemical Company where the RTN approach was used to tackle optimization of several multipurpose production facilities (Wassick and Ferrio, 2011). The discrete-time representation is used because it is enough for the pulping case to approximate the production with uniform one-hour time intervals. What is also important, the discrete-time approach will differentiate from the continuous-time approach presented for the steel case, providing more thorough assessment of the iterative scheme, since it represents a completely different nature of the modeling strategy. According to Harjunkoski et al. (2014) there are two major modeling approaches usually used for scheduling problems. In the first one (used for the steel case) model variables and constraints are matched to real problem entities in a sequencing production environment, with a set of stages and units at each stage. The second approach converts real life settings into variables and constraints by representing them in a more generic network model based on materials, tasks, units and utilities. The most common representations of the second approach are State-task Network (STN) and Resource-task Network (RTN). The latter has been chosen here as it emerged as one of the most important scheduling modeling approaches in last decades.

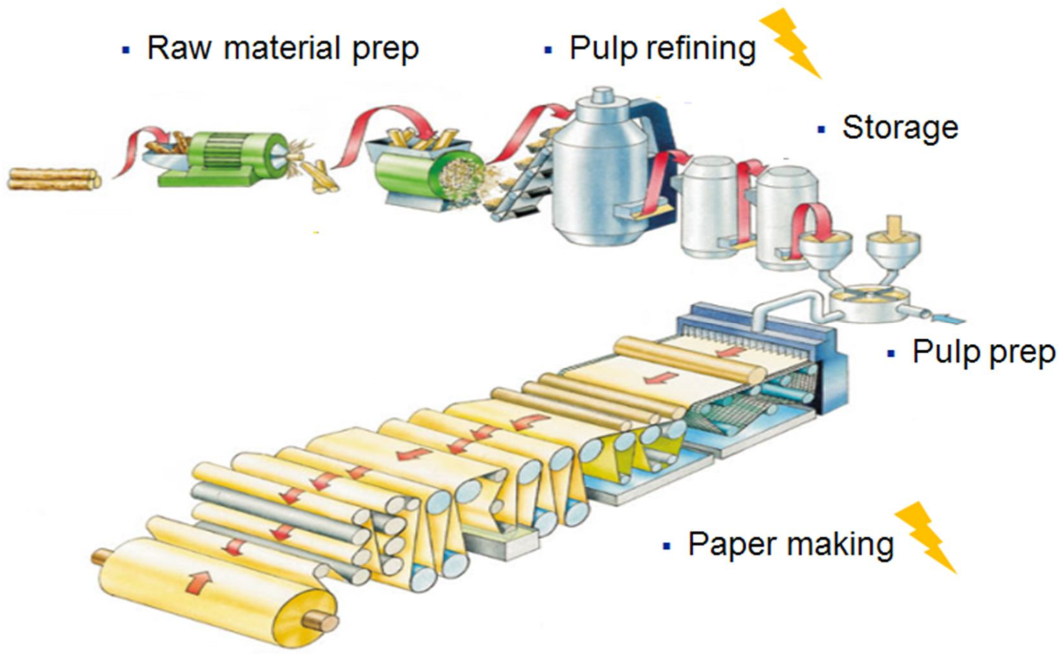


Figure 4-10 Typical integrated mill production stages

4.3.1 Thermo-Mechanical Pulping process

The second industrial process that is investigated in order to apply and test the strategies developed within the goals of the dissertation is Thermo-Mechanical Pulping (TMP).

The process lies at the heart of the paper production supply chain, which starts when the raw materials for the process are extracted in the forest where trees are cut into logs and chopped at chip mills to form wood chips. Next, sometimes together with re-usable byproducts such as sawdust, pulp waste or agricultural residues, wood chips are fed to the pulping mills that produce different types of pulp. The pulp is usually put into storage tanks from where it can be either sold as a product or fed to the paper machines to produce paper rolls of various sizes (Malik and Qiu, 2008). The type of paper produced does not change the basic process. A typical integrated pulp and paper production mill process is shown in Figure 4-10, where energy-intensive stages are indicated.

The most important stage of the pulp making can be done by the two different processes of thermo-mechanical or chemical process. The type of production varies and depends on the characteristics of the wood used, for example which type of trees is used and the geographical location where the tree was growing. In the chemical pulping process, the lignin in the wood is removed from the cellulosic fibers via chemicals. In the mechanical process the lignin is not removed but is derived from the cellulosic fibers in refiners. Mechanical pulping is about 50 % cheaper, however, the chemical pulping provides higher strength properties and due to energy production of by-products (black liquor production), it can generate more energy than it needs for producing pulp (Bajpai 2012). At the mechanical pulping stage the fibers are separated by applying mechanical energy on the wood, which breaks the bounds between fibers to create single fibers and fiber fragments. The lignin is not removed but is maintained to achieve high yield and better strength properties. Among the existing techniques for mechanical pulping there is the Thermo-Mechanical Pulping. It is used to produce such end products like newsprint, printing paper and tissue paper. The most used raw material for TMP is softwood. Apart from the wood, a large amount of energy is used in the form of steam and electricity, therefore the latter is an essential factor of the total production cost

(Pulkkinen and Ritala, 2008). For the TMP process, the pulp is not always bleached, especially if the final product is newsprint (Bajpai 2012).

Before the final stage of paper making a stock preparation stage is needed. This stage consists of mixing different pulp, dilution and adding of chemicals, which results in that the raw stock is converted into a slurry form, called finished stock (furnish). This slurry is then pumped into the paper machine that forms the paper by removing the water from the furnish (Bajpai 2012). The paper making stage is also a very energy intensive process which by itself is an interesting subject of research, including the optimal cutting of paper to meet customer demand at minimum trim loss (Harjunkoski et al., 1996).

For the purpose of the industrial case study it is chosen to investigate a stand-alone TMP mill with several pulp refiners and one storage tank, following studies of Pulkkinen and Ritala (2008) and Karagiannoloulos et al. (2014). Since it is not an integrated mill, the paper machine is excluded. However, that stage could be thought as expressed in a form of certain demand for pulp, as in Figure 4-11. The scheduling problem to answer in the TMP case is to determine how many of the refiners should run in which of the time slots. Note that it is not considered which refiners should run as there is only one pulp type to be produced and here it is assumed that the considered refiners are all identical and running in parallel.

Therefore, the amount processed by one refiner in each time slot is the same for all, as well as electricity consumption, start-up and shut-down costs. After the pulp is produced, it goes to a storage tank, with minimum and maximum capacity constraints, from where it can be drawn in order to satisfy the deterministic demand. The plant is assumed to have the option of buying the pulp from external sources at an in advance known price, which is also a realistic assumption, thus allows the mill to have additional degree of process flexibility that could be exploited by the industrial Demand-side Management strategy. This is an interesting differentiator from work reported on the steel case by for example Sun et al. (2013) and Hadera et al. (2015a) where the process is assumed to have to deliver fixed amount of products with deterministic total electricity consumption.

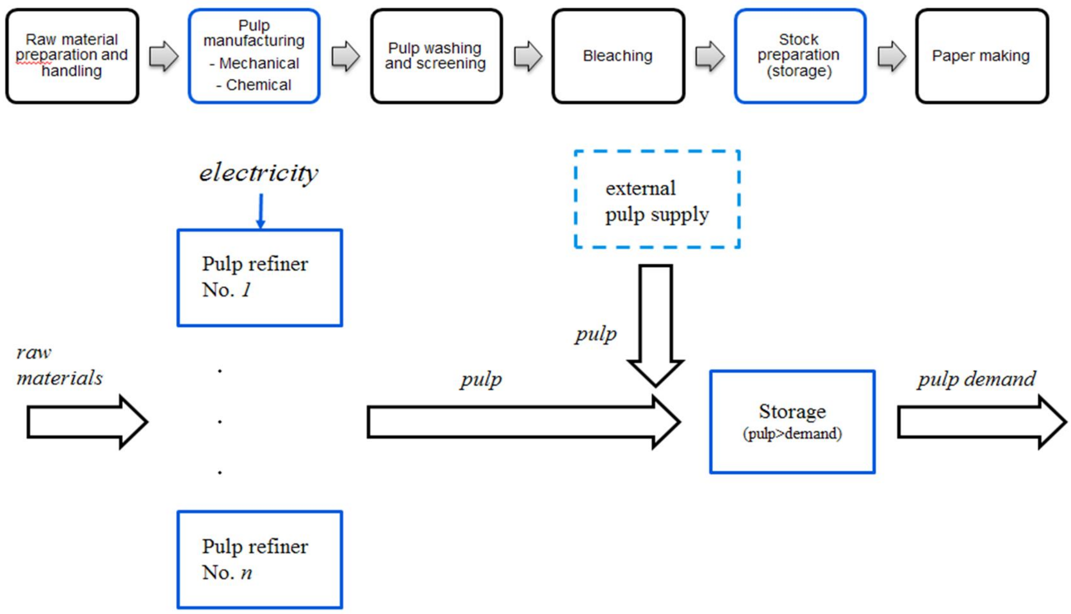


Figure 4-11 Pulp and paper production process with considered stages

The optimization goal is to determine how to distribute the consumption over time while satisfying production constraints and minimizing energy cost. For the considered TMP case, buying pulp from an external source, the optimization strategy should enable the model to lower the amount of produced pulp when the electricity prices become high and instead buy more from the external source.

4.3.2 Monolithic model

The purpose of the monolithic model development is to serve as a basis for the development of the models involved in the Cross Decomposition scheme and also to provide optimal solutions for quality assessment of the solutions obtained from the decomposition scheme.

The RTN approach used here is based on the STN developed by Kondili et al. (1993) which shapes the mathematical scheduling formulation by consideration of states for products between tasks. The STN was extended by Pantelides (1994) to develop RTN by considering the entities in a problem as limited resources that are being consumed or produced by tasks. The main idea behind the RTN approach is to have a uniform description of all resources. The resources are not only limited to raw materials, but are any materials and equipment used in production by processing tasks. The tasks transform the input resources into another (new) resources (Pantelides, 1994).

As the RTN modeling approach views entire processes as bipartite graphs with resources and tasks as nodes, identification of both is the first step in the modeling. Secondly, one needs to properly capture the relation of resources to tasks (consumption and production). Once this is done the superstructure of the problem can be drawn, which enables to derive so-called structural parameters helping to model interactions of resources during task execution. The structural parameters are then used in a general balance equation which captures if there is an excess of a resource $R_{i,t}$ available or not. The excess resource can be consumed or produced in batch (denoted on superstructure drawing with dashed arrows), continuous (solid arrows) or instantaneous manner (dashed arrows).

An RTN model characterizes tasks by two sets of variables, $N_{i,t}(\overline{N}_{i,t,t'})$ denoting start of task i at event point t (ending at t') and $\xi_{i,t}(\bar{\xi}_{i,t,t'})$ denoting the amount handled by the task. In addition there are five sets of structural parameters to give total resource consumption/production in proportion to amount handled by the task as explained in Table 4-2. Typically these parameters take a value of -1 or 1. The interaction with system surroundings can occur discretely with inputs, represented by $\prod^{in}$, and outputs, represented with $\prod^{out}$.

Table 4-2 Structural parameters of RTN-based modeling

$\mu_{r,i}$	discrete interaction of resource *r* linked to variable $N_{i,t}$ for the start of the task *i*
$\overline{\mu}_{r,i}$	discrete interaction of resource *r* linked to variable $N_{i,t}$ for the end of the task *i*
$v_{r,i}$	discrete interaction of resource *r* linked to variable $\xi_{i,t}$ for the start of the task *i*
$\overline{v}_{r,i}$	discrete interaction of resource *r* linked to variable $\xi_{i,t}$ for the end of the task *i*
$\lambda_{r,i}$	continuous interaction of resource *r* during task i, linked to $\xi_{i,t}$

For the RTN modeling, an one hour discretization step is used as it corresponds to the energy-related pricing information and at the same time satisfies the process requirements for exactness, for example the refiners should not be switched on and off more than once in an hour. The optimization should select how many refiners should run at each time interval. Due to quality and cost reasons, the refiners are assumed to produce at fixed full rate or not at all (Pulkkinen and Ritala 2008). To keep the model simple, it is assumed that the plant processes one type of pulp which is realistic and follows for example Karagiannoloulos et al. (2014). The objective function of the model minimizes the operating cost consisting of production cost (start-up and shut-down of refiners) and electricity cost. Following Karagiannoloulos et al. (2014), however, it is possible to include other factors such as e.g. operator availability cost.

In Figure 4-12 the resulting superstructure of the considered case is shown. The tasks are represented by rectangles while resources are represented by circles. Continuously produced or consumed resources are the raw material RM and $pulp^{int}$, whereas the resource of bought pulp ($pulp^{ext}$) is consumed discretely. The last material resource (fp) is the final product resource, i.e. the pulp ready to satisfy the demand. Each pulping task uses an equipment resource m, a refiner. The storage tank s and dummy equipment b for the buying task complete the list of the equipment resources. An important utility resource is the electricity Ut, modeled following Castro et al. (2009) and Sun et al. (2013). All the resources have connection to a task. The continuous pulping tasks consume RM to produce $pulp^{int}$. The batch task of pulp buying consumes discrete resource $pulp^{ext}$ to produce discrete resource $pulp^{int}$. The latter is fed to the hybrid task of storage, i.e. the task continuously consumes $pulp^{int}$ to produce final pulp fp and sends it back to storage discretely, to satisfy demands in batches. This strategy for treating the storage tank was introduced by Castro et al. (2009). The hybrid task uses the variable $\xi^{*}_{i,t}$ to capture the processed amount that is continuously sent to storage. For keeping track of the amount kept in the tank, available immediately before the end of a time slot, the excess resource variable $R^{end}_{r,t}$ is introduced, which is also used for determining the initial amount available in the storage (Castro et al. 2009). Further, the input from the system surrounding is the maximum amount of electricity that can be consumed in a time slot and the output is the demand of products for each time slot. Initially available resources ($R^{0}_{r,t}$) are given except of rm and $pulp^{ext}$ which are considered as variables for the optimization. The equipment $EQ1, EQ2$ and $EQ3$ are available at the beginning of the time horizon.

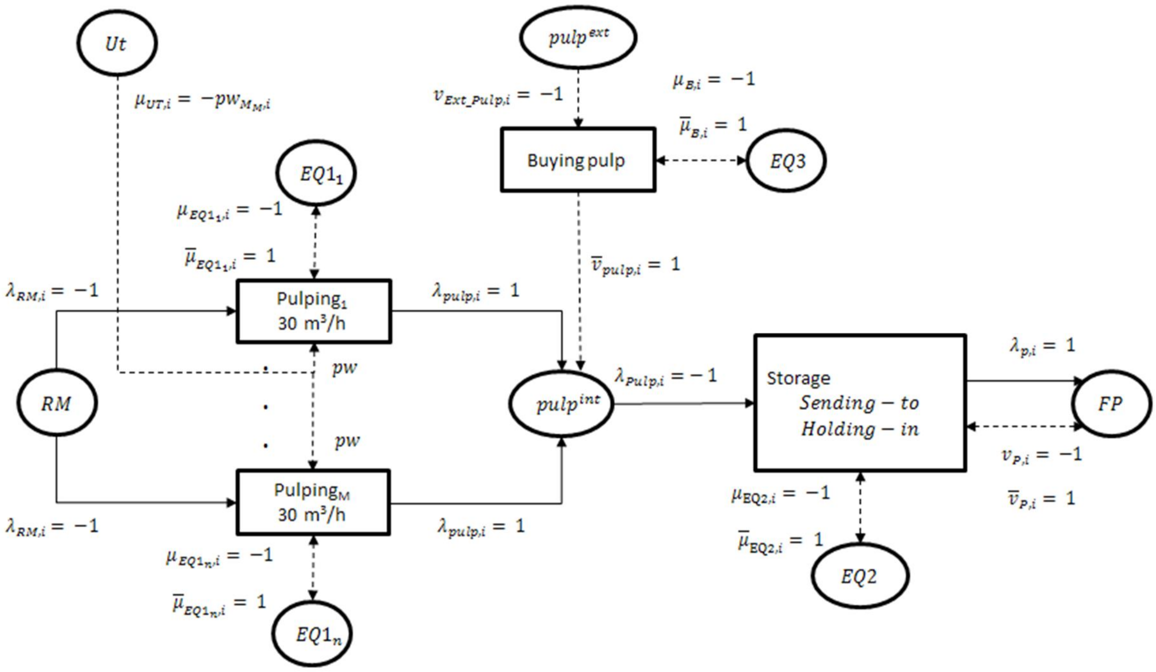


Figure 4-12 Pulping case RTN superstructure

The formulation notation is shown in the Table 4-3. The model constraints follow.

Table 4-3 RTN monolithic model notation

Sets:	
R	set of resources
I	set of production tasks
T	time intervals
$EQ1_m \subseteq R$	equipment resources: refiners m
$EQ2_s \subseteq R$	equipment resources: storage tank s
$EQ3_b \subseteq R$	equipment resources: buying resource b
$RM \subseteq R$	raw material resources
$pulp^{ext} \subseteq R$	externally bought pulp
$pulp^{int} \subseteq R$	pulp resources
$UT \subseteq R$	utility resources (electricity)
$CT \subseteq R$	continuous resources (pulp, external pulp, raw material)
$FP \subseteq R$	final product resources
$I^C \subseteq I$	continuous tasks (pulping)
$I^B \subseteq I$	buying task
$I^S \subseteq I$	storage (stock preparation) task
Parameters:	
l^{max}	maximum capacity volume of storage tank [m^3]
l^{min}	minimum required volume of pulp in storage tank [m^3]
l^{init}	initial volume in the stock preparation tank [m^3]
u	production rate of one refiner in one time slot [m^3]
u^{max}	maximum production output of all refiners in one time slot [m^3]
b^{max}	maximum allowed amount of pulp that can be bought externally in any time slot [m^3]
c^{start}	start-up cost of refiners[€]
c^{end}	shut-down cost of refiners [€]
$\Pi_{r,t}^{in}$	resource input to the system (electricity) in time slot t [MW]
$\Pi_{r,t}^{out}$	resource output from the system (pulp) in time slot t – pulp demand[m^3]
c_t^{pulp}	market price for pulp in time slot t [€/m^3]
p^{el}	power consumption of one refiner in one time slot [MW]

Variables:

$N_{i,t}$	binary, execution of task i in time t
$\xi_{i,t}$	continuous, non-negative variable, amount handled (processed) by task i in time t
$\xi_{i,t}^{*}$	continuous, non-negative variable, amount continuously sent to storage by task i during time slot t
$R_{r,t}$	continuous, non-negative variable, amount of resource r available at time t
$R_{r,t}^{end}$	continuous, non-negative variable, amount of resources r available immediate before the end of time interval t
$R_{r,t}^{0}$	continuous, non-negative variable, amount of initial resources available at the beginning of the time horizon
n_t^{ref}	integer, non-negative variable, number of refiners producing pulp during time slot t
$pulp_t^{ext}$	continuous, non-negative variable, amount of pulp bought externally and delivered to the storage in time slot t
$pulp_t^{int}$	continuous, non-negative variable, amount of pulp made internally and delivered to storage during time period t
q_t	consumed electricity in time period t [MWh]
n_t^{start}	continuous, non-negative variable, number of refiners starting their operation during time slot t
n_t^{end}	continuous, non-negative variable, number of refiners stopping their operation during the time slot t
c^{ref}	cost of start-up and shut-down of refiners
$c^{extpulp}$	cost of buying pulp from external source
δ	load deviation penalties cost
μ	net electricity cost of selling and buying electricity

The objective function of the problem is to minimize the cost of: net electricity cost (similarly as the variable μ in the steel case described in Chapter 3.2.4), penalties for load deviation δ (as variable δ in the case of steel described in Chapter 3.2.4), cost of pulp bought, startup and shut-down cost of refiners, as shown in Equation (4.26).

$$min(c^{el} + \delta + c^{extpulp} + c^{ref}) \tag{4.26}$$

The core of the RTN formulation is the excess resource balance equation, shown in Equation (4.27).

$$R_{r,t} = R_{r,t}^{0}|_{t=1} + R_{r,t-1}^{end}|_{r\in R^{RM}\cup R^{pulp}\cup R^{FP}} + R_{r,t-1}|_{r\in R^{EQ1}\cup R^{EQ2}\cup R^{EQ3}\cup R^{Ext_{pulp}}} + \sum_{i\in I}(\mu_{r,i}N_{i,t} + v_{r,i}\xi_{i,t} + \overline{\mu}_{r,i}N_{i,t-1}) + \sum_{i\in I^{s}}(\overline{\mu}_{r,i}N_{i,t\,|t=1}) + \Pi_{r,t}^{in}\,|_{r\in R^{UT}} - \Pi_{r,t}^{out}\,|_{r\in R^{FP}}$$
$$\forall r \in R, t \in T \tag{4.27}$$

The structural parameters help to add (production) or take away (consumption) the resource amount for given times interval. For the first time slot, the initial amount value $R^{0}_{r,t}|_{t=1}$ is taken into consideration, however not for the remaining time slots since the value of the previous time slots is available. To note, this is not applied for the resource of electricity, since otherwise the resource availability would propagate from one time to another (Castro et al., 2009). Instead, the utility is supplied by the variable $\Pi^{in}_{r,t}\,|_{r\in R^{UT}}$ denoting external input to the system. For handling the continuous resources, Equation (4.28) is completing the previous balance equation by considering the amount of resource available and processed in a given time.

$$R^{end}_{r,t} = R_{r,t} + \sum_{i\in I^{C}} \lambda_{r,i}\xi_{i,t} + \sum_{i\in I^{S}} \left(\overline{v}_{r,i}\xi_{i,t} + \lambda_{r,i}\xi^{*}_{i,t}\right) + \sum_{i\in I^{B}} \left(\overline{v}_{r,i}\xi_{i,t}\right)$$
$$\forall\, r \in R^{RM} \cup R^{pulp^{int}} \cup R^{FP}, t \in T \qquad (4.28)$$

It can be noted that from this equation the volume of the tank is captured by $R_{r,t}$ for resource of the final product, as it consists of the amount available in the previous time slot ($R^{end}_{r,t-1}$ or $R^{0}_{r,t}|_{t=1}$ in case of the first time slot), the amount taken to satisfy the final product demand ($\Pi^{out}_{r,t}$), the amount being produced ($\sum_{i\in I^{S}}(\lambda_{r,i}\xi^{*}_{i,t})$) and bought ($\sum_{i\in I^{B}}(\overline{v}_{r,i}\xi_{i,t})$). To enforce a proper balance of the $pulp^{int}$ resource in the last time period constraint (4.29) is added.

$$R^{end}_{r,t} = 0 \qquad \forall r \in pulp^{int}, t = |T| \qquad (4.29)$$

Using the variable of resource excess, the upper bound of all equipment resources is enforced, to represent the equipment individually.

$$R^{max}_{r,t} = 1 \qquad \forall r \in R^{EQ1} \cup R^{EQ2} \cup R^{EQ3}, \forall t \in T \qquad (4.30)$$

To achieve no intermediate storage of $pulp^{int}$ between the refiners and the tank and to send the final product directly to storage, no excess resource is enforced with Eq. (4.31).

$$R^{max}_{r,t} = 0 \qquad \forall r \in R^{pulp^{int}} \cup R^{FP}, t \in T \qquad (4.31)$$

Another constraint ensures that there is enough final pulp in the storage tank to satisfy the demand for it (Equation 4.32). Even though the resource balance equations enforce the fact that the demand is always satisfied by the pulp available in the storage tank an additional constraint is formulated (4.32) that in a way serves as a safety buffer level.

$$R^{end}_{r,t} \geq \Pi^{out}_{r,t} \qquad \forall r \in R^{FP}, t \in T \qquad (4.32)$$

Since the storage tank is subject to a capacity limitation, Eq. (4.33) defines an upper limit on the amount kept in the tank (l^{max}). In addition, the minimum desired tank level can be set here as well by enforcing the lower bound with the desired parameter (l^{min})

$$l^{min} \leq R^{end}_{r,t} \leq l^{max} \qquad \forall r \in R^{FP}, t \in T \qquad (4.33)$$

Another constraint in Eq. (4.34) restricts the amount handled by the hybrid task such that it does not exceed the sum of the initial volume, amount produced and maximum amount of pulp bought.

$$\xi_{i,t} + \xi^{*}_{i,t} \leq \left(l^{init} + b^{max} + u^{max}\right) \cdot N_{i,t} \qquad \forall i \in I^{S},\ \forall t \in T \qquad (4.34)$$

Equation (4.35) enforces proper amounts handled by the continuous tasks of refiners, being either equal to the production rate or zero otherwise.

$$\xi_{i,t} = u \cdot N_{i,t} \qquad \forall i \in I^{c}, t \in T \qquad (4.35)$$

For the task of buying pulp from the external source, it should be limited by the desired level b^{max}, as in Equation (4.36).

$$\xi_{i,t} \leq b^{max} \cdot N_{i,t} \qquad \forall i \in I^B, t \in T \tag{4.36}$$

A few redundant but helpful variables which can track resource amounts are introduced next. These will not have any noticeable influence on the solution quality or performance, but will return variables that can be compared easily with the ones from Karagiannoloulos et al. (2014). To capture the number of refiners running at a given time interval the variable n_t^{ref} is given by the sum of all executed continuous tasks as in Eq. (4.37). To capture the pulp produced from the refiners and pulp bought variables in Eqs (4.38-4.39) are introduced.

$$n_t^{ref} = \sum_{i \in I^C} N_{i,t} \qquad \forall t \in T \tag{4.37}$$

$$pulp_t^{int} = \sum_{i \in I^C} \xi_{i,t} \qquad \forall t \in T \tag{4.38}$$

$$pulp_t^{ext} = \sum_{i \in I^B} \xi_{i,t} \qquad \forall t \in T \tag{4.39}$$

The important equation for obtaining the amount of electricity that is consumed by the system at a given time interval Eq. (4.40) is performed for each time slot.

$$q_t = p^{el} \cdot \sum_{i \in I^C} N_{i,t} \qquad \forall t \in T \tag{4.40}$$

Following the model from Karagiannoloulos et al. (2014), to capture the number of refiners starting up or shutting down, the constraint (4.41) is used. It accounts for the number of the refiners running in the previous time interval, number of the refiners starting up in the current time slot, and number of refiners shutting down in the slot. It is assumed that there is no running refiners at the beginning of the scheduling horizon and the optimization is free to choose which ones should run at the end of the horizon.

$$n_t^{ref} = n_{t-1}^{ref} + n_t^{start} - n_t^{end} \qquad \forall t \in T \tag{4.41}$$

Lastly, all production costs given in the objective function can be accounted. The cost of the pulp bought from external sources is given in Equation (4.42) by considering its price c_t^{pulp}.

$$c^{extpulp} = \sum_{t=1}^{T} c_t^{pulp} \cdot pulp_t^{ext} \tag{4.42}$$

The cost for startup and shut downs of refiners is simply accounted by Equation (4.43).

$$c^{ref} = \sum_{t=1}^{T} \left(c^{start} \cdot n_t^{start} + c^{end} \cdot n_t^{end} \right) \tag{4.43}$$

We assume that for the considered production process the energy cost optimization problem has the same structure as for the previously described steel case. The plant has the option to choose from multiple contracts and onsite generation, and has the possibility to sell electricity back to the grid. In addition, the load deviation problem is considered. Therefore, one can apply the same equations as for the steel case, Eqs (3.88) - (3.98) from Chapter 3.2.4, in order to optimize the energy-related cost (purchase/sale cost and load deviation penalties). Note that the TMP scheduling model also has the variable accounting for the electricity consumption in a time slot (q_t), which is the only requirement for the minimum-cost flow network in order to find the optimal purchase/sale structure and the only variable needed for the load deviation response extension. Adding the energy-optimization network distinguishes the problem to be handled from the problem in Karagiannoloulos et al. (2014), who consider one single price curve of electricity cost.

4.3.3 Framework structure and case study setup

In Chapter 4.2 it was shown that for a monolithic production scheduling problem with energy cost optimization based on the Minimum-cost Flow Network it is possible to use a special problem structure in order to arrive at a decomposition approach consisting of two functionally separated problems. Application of the decomposition strategy to the Thermo-Mechanical Pulping case (Chapter 4.3.2) results in the following two problems. First, production scheduler with production specific costs, load deviation response and optimization of single energy price curve – scheduler of Dantzig-Wolfe sub-problem as in Eq. (4.44).

$$min(\delta + c^{extpulp} + c^{ref} + q_t \cdot \overline{MC_t}) \tag{4.44}$$

subject to

$Eq. (4.27 - 4.43)$ – production scheduling constraints (Chapter 4.3.2)

$Eq. (3.99 - 3.101)$ – load deviation problem (Chapter 3.2.4.2)

Secondly, the energy model to optimize the purchase and net sale cost, under the assumption of a given load distribution – flow network Benders' sub-problem as in Eq. (4.45).

$$min(\mu) \tag{4.45}$$

subject to

$$f_{i5,j7,t} = \bar{q}_t \qquad \forall t \in T \tag{4.46}$$

$Eq. (3.88 - 3.89),\ (3.91 - 3.98)$ – flow network constraints (Chapter 3.2.4.1)

The above mentioned two models are partial sub-problems of Cross Decomposition. To test the convergence behavior, the objective function values of the complete sub-problems are needed (Figure 4-9). The remaining parts are formulated following the two decomposition approaches. First, production scheduler with regular production specific costs, load deviation response and fixed load curve – scheduler of Benders' sub-problem as in Eq. (4.47).

$$min(\delta + c^{extpulp} + c^{ref}) \tag{4.47}$$

subject to

$Eq. (4.27 - 4.43)$ – production scheduling constraints (Chapter 4.3.2)

$Eq. (3.99 - 3.101)$ – load deviation problem (Chapter 3.2.4.2)

where $q_t = \bar{q}_t \qquad \forall t \in T$

Secondly, the energy model to optimize the purchase and net sale cost, under the assumption of a given load distribution – flow network Benders' sub-problem as in Eq. (4.48).

$$min(\mu - f_{i5,j7,t} \cdot \overline{MC_t}) \tag{4.48}$$

subject to

$Eq. (3.88 - 3.89),\ (3.91 - 3.98)$ – flow network constraints (Chapter 3.2.4.1)

As previously stated, the information signals exchanged between sub-problems (either partial or complete) are:

- the schedule's load curve (q_t) created by the production model and sent to the flow network model;

- flow network's marginal cost curve (MC_t) from constraint (4.49) that is sent to the production model.

These signals can be used directly or they can be augmented according to the different decomposition approaches, as explained in Chapter 4.2.

The iterative algorithm needs to be initialized, for this purpose the production scheduling model is solved first. It can be solved using no energy-awareness while optimizing only production-specific cost. Another option is to use the energy-aware model with response to an arbitrary price curve, for example a historical marginal cost profile or a price of the contract that is expected to have the highest influence on the purchasing structure (i.e. expected to be exploited the most). As noted by Holmberg (1997), it is important to come up with first signal such that it has a reasonable magnitude, otherwise the Mean Value Cross Decomposition scheme might not be effective. Based on experience, the initial scheduler's problem is solved using the day-ahead spot market price ($c_{i3,j5,t}$) in place of the MC curve which is used in the next iterations (Eq. 4.49).

$$min(\delta + c^{extpulp} + c^{ref} + q_t \cdot c_{i3,i5,t}) \tag{4.49}$$

subject to

$Eq.(4.27 - 4.43)$ – production scheduling constraints (Chapter 4.3.2)

$Eq.(3.99 - 3.101)$ – load deviation problem (Chapter 3.2.4.2)

The production model solved with the marginal cost curve in each iteration will augment its load curve (schedule) such that it will move the load towards less expensive time intervals (assuming that there is no significant disadvantageous influence on the production specific cost). The flow network model in each iteration will find the best purchasing and selling strategy for a given load (schedule). The solution consists of two parts, the schedule and the corresponding optimal purchasing and selling structure. However, in contrast to the simple industrial approach (leftmost in Figure 4-1), where a schedule is generated without any energy-awareness and then sent to the flow network model, in the Mean Value Cross Decomposition approach the schedule is generated using the knowledge on the direction to move the load in time such that it is beneficial to the welfare of the overall system which consist of both, energy cost and production costs.

As mentioned earlier, when applying the iterative decomposition framework, two approaches can be taken (Figure 4-9): considering the complete sub-problems to prove convergence or considering partial sub-problems which is enough to find a feasible solution to the monolithic problem. For the TMP process (Chapter 4.3.4), it is chosen to show the convergence on only one variation of the Mean Value Cross Decomposition: One-sided Weighted Mean Value Cross Decomposition. The reasoning behind this choice is that within the complete Benders' sub-problem the production scheduler needs to be solved with augmented mean values of the load curve. This is likely to result in infeasibility (production scheduling model is solved assuming a fixed load curve which might be infeasible). Therefore, the load curve should be sent directly without its mean value calculation. Weighted mean value (instead of regular mean) is chosen as it has been noted as faster converging by Holmberg and Kiwiel (2006). In contrast to the convergence test model, when considering the industrial approach where only parts of the complete Benders' and Dantzig-Wolfe sub-problems are considered, it is possible to alter both signals.

Since the original monolithic model could be solved in reasonable computation times it is possible to obtain the optimal solution. This can be compared to the industrial approach using the iterative framework. The latter does not produce upper and lower bounds but only a feasible solution, which can be compared to the optimal one from the monolithic model. This is also one of the motivation points for the TMP case study, which in contrast to the steel case is considered to be solvable within reasonable computation times for the problem instances.

The case study is designed such that for different solution approaches (monolithic model, convergence test and industrial approach) five problem instances are tested as shown in Figure 4-13. Different prices of day-ahead spot market (EPEX 2013) are considered in the scenarios, similarly to the steel problem in Chapter 3.5. For the industrial approach, the four variations of the Mean Value Cross Decomposition identified earlier are tested.

The overview of the test instances is given in Table 4-4. Scenario 1 serves as a base case with a time horizon of five days and full electricity contracts portfolio similar to the one used in the steel case, but with modifications on the flow capacities. Detailed input data and modifications compared to the steel case input data made specifically for the TMP problem instances are described in Appendix C. In Scenario 2 higher day-ahead market prices are considered, which should result in high amounts of electricity to be sold back to the market (exploitation of negotiated contracts, i.e. base load and TOU). To consider a case with very high capacity utilization and very low process flexibility the number of refiners to be used is set to 3 in Scenario 3. Scenario 4 takes no penalties for load deviation and no revenues from electricity sale and in addition it considers the base load contract to be flexible – the lower bound of the flow from its node in the flow network is set to zero therefore there is no strict condition to draw electricity from this contract at a fixed rate in all time slots. Scenario 5 is similar to the base case and a two week time horizon is considered here.

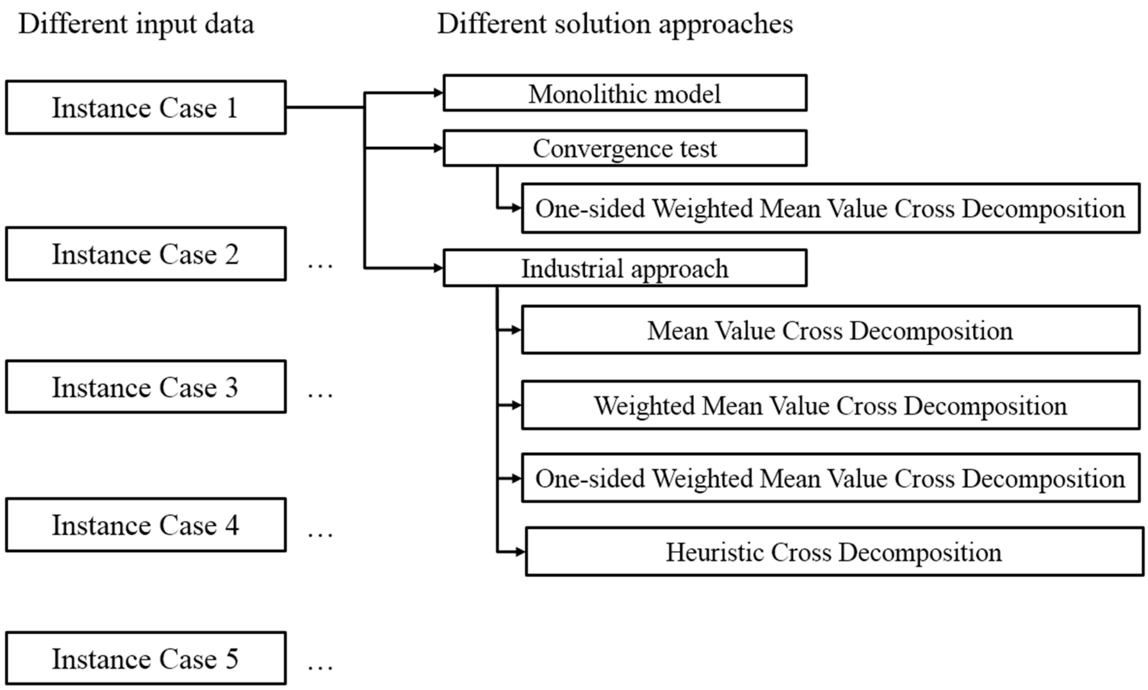


Figure 4-13 Structure of the TMP case study experiments with Cross Decompositions

Table 4-4 Description of the TMP test cases

Scenario	Time horizon	No. of refiners	Electricity sources and sinks
1	120 h	5	all possible, day-ahead with Germany 2013 prices
2	120 h	5	all possible, day-ahead with France 2012 prices
3	120 h	3	all possible, day-ahead with Germany 2013 prices
4	120 h	5	all possible, no deviation penalties, no revenues for selling
5	336 h	5	all possible, day-ahead with Germany 2013 prices
Name	Model type		
RTN	Monolithic RTN model		
CRTN	Convergence test model based on One-Sided Weighted Mean Value Cross Decomposition		
IMV	Industrial approach with Mean Value Cross Decomposition		
IWMV	Industrial approach with Weighted Mean Value Cross Decomposition		
IOWMV	Industrial approach with One-sided Weighted Mean Value Cross Decomposition		
IHCD	Industrial approach with heuristic Cross Decomposition (direct signals)		

With the above explained numerical experiment setup the problem instances are solved and discussed in the next section.

4.3.4 Case study results and discussion

All the test instances have been solved using GAMS/CPLEX 24.1.2 with default solver settings on a Personal Computer with Intel® Core™ i5-2400 CPU @ 3.10 GHz and 4 GB RAM. The input data is described in Appendix C. It is important to note that the shut-down and start-up cost representing the production-specific cost are scaled down. This is done to balance the production and energy costs, similarly to the idea of the cost weight coefficient (c) reported for the steel case problem in Eq. (3.102) in Chapter 3.2. Detailed results obtained from the investigation of the approaches presented in the next pages are shown in Appendix D, unless otherwise stated.

4.3.4.1. Monolithic model results

First the monolithic model is investigated (Chapter 4.3.2) that provides the optimal solution of the problem instances. The knowledge of the optimal MIP value will be useful particularly for the industrial approach model types since for this approach there is no convergence check nor clear termination criteria for the algorithm. The model statistics are shown in Table 4-5, while the solution structure is reported in Table 4-6.

Table 4-5 RTN: Model statistics for the monolithic RTN models

Scenario	Binary variables	Total variables	Equations	Optimal MIP	CPUs	Nodes	Iterations
RTN1	960	6374	5402	219637,2	1,141	205	1608
RTN2	960	6374	5402	-623600	1,096	326	2218
RTN3	720	5652	4922	320072,83	0,798	0	678
RTN4	960	5773	5041	122869,17	340,926	867023	2204369
RTN5	2688	17822	15122	615072,76	8817,443*	8229912	68916891

*terminated at 0,02% gap (due to memory limitations)

Table 4-6 RTN: Model results for the monolithic RTN models

Scenario	Economic assessment flow network								Total consumption [MWh]	Economic assessment scheduler				
	Costs				Quantities					Costs			Quantities	
	Net electricity cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]
RTN1	167909	179837	46287	34360	1875	302	560	720	3817	250	38578	12900	10410	5
RTN2	-676568	702010	1670930	292352	0	8044	4792	10830	3806	250	39118	13600	10380	5
RTN3	155541	168420	47238	34360	1604	335	560	735	3564	34750	126890	2890	9720	695
RTN4	114559	114559	0	0	3630	0	0	0	3795	250	0	8060	10350	5
RTN5	471146	504543	129604	96208	5250	861	1568	2016	10703	0	108276	35650	29190	0

It can be observed that for scenarios 1-3 the solution is found in less than 1 CPUs, however for Scenario 4 and 5, optimal solution is reached after 6 and 146 minutes, respectively. Here it is important to note that for both cases a very good solution (proved to be less than 0,5% from optimality) is obtained already in few seconds. However, further proving optimality is time consuming for these scenarios. For Scenario 4, where the problem is less constrained due to no deviation penalties, there could be several similar solutions existing in the search space and thus the solver explores a high number of nodes before finally reaching optimality. In Scenario 5, the large computational effort is due to the much larger problem size (time horizon of 14 days instead of 5 or less in the other scenarios). For all test instances involved in the Mean Value Cross Decomposition approaches, the computation time was limited to 180 *s*, unless otherwise stated, in order to avoid large computational time in scenarios 4 and 5. Increasing the time limit would not change noticeably the solution since the solutions obtained within these limits are close to the optimal solution as it will be shown later.

4.3.4.2. Convergence test with complete sub-problems

For the convergence test using the One-sided Weighted Mean Value Cross Decomposition (unless otherwise stated) the signal of the dual from EFN model can be altered using two variants of the mean value calculation as previously shown in Equation (4.1) and (4.2) for the mean value calculations in Chapter 4.2.1, respectively called later option 1 and option 2. Further, as suggested by Holmberg and Kiwiel (2006) the parameters for weighted mean calculation are $\beta=1$ and $\gamma=3$. For all problem instances, the initialization of the production part model (initialization in Figure 4-9) is done using day-ahead market prices instead of Marginal Cost curve. The production part could also be solved alone i.e. without any response to energy price, however for the considered problem nature is it beneficial to distribute the load according to a good guess of a possible Marginal Cost in the first iteration. For all convergence cases, the Dantzig-Wolfe' sub-problem provides a valid lower bound following the Lagrangean theory. The Benders' sub-problem provides a valid upper bound since the solution is always feasible due to no alteration of the valid load curve coming from the Dantzig-Wolfe's sub-problem.

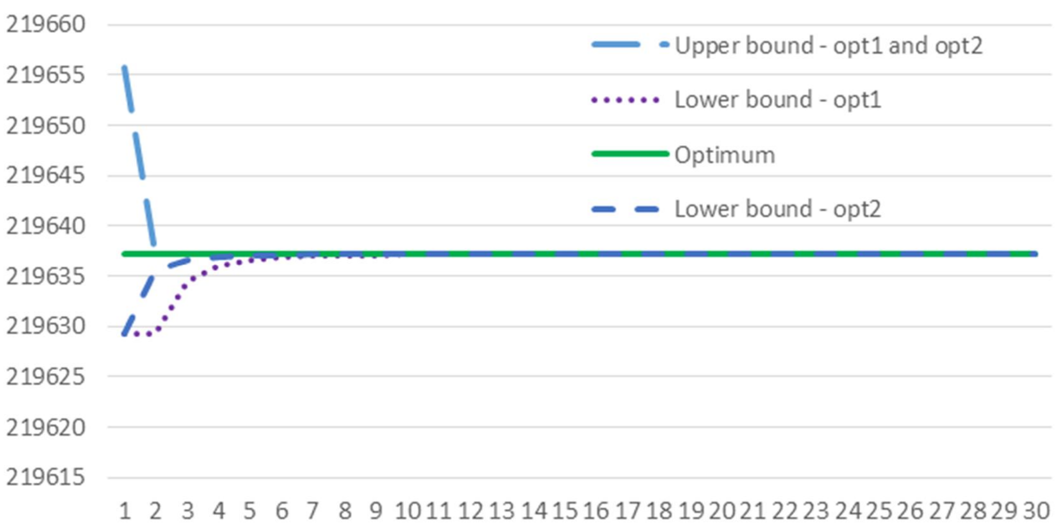


Figure 4-14 CRTN: Iteration results of Scenario 1

In Figure 4-14 results of convergence test for Scenario 1 are shown. It can be observed that the upper and lower bound close the gap at the optimal solution value. For both options of the mean value calculations, the upper bound yields the same results. It can also be noted that option 2 performs slightly better due to stronger move towards optimality of the lower bound. With option 2 the optimality is very close after 3 iterations (takes 13 iterations in total to reach exact optimality), while with option 1 it takes 5 iterations to almost close the gap (20 iterations in total).

Detailed results of the optimization runs are reported in Table 4-7-Table 4-8 and also Table D-1 - Table D-2. For both options, it can be noted that the optimal value of the upper bound is found faster than the lower one. This behavior might be related to the fact that the models solved at the lower bound are larger and have more flexibility, since the production scheduling model there is solved with regards to the Marginal Cost curve. In contrast to the upper bound problems where the production scheduling model is given a load distribution, therefore is much easier to solve. It can be also noted that although each single model of the iterative framework is solved faster than the monolithic model the total time needed to solve all the sub-problems until optimum is longer. The size of all four models involved in the decomposition scheme is shown in Table 4-9 together with comparison of all other decomposition variations discussed later. Naturally, all of the models within the decomposition scheme are smaller than the monolithic model. The scheduling problems are always larger than the flow network's problems. In Table 4-8, where the structure of the optimal solution is shown it can be observed that the decomposition found a solution with the same objective function value as the monolithic model, however the structure of the solution is slightly different. Since the objective function has different components, the level of one component here is leveraged by a change in the level of another components. In this case, the decomposition chose to more from the day-ahead market, buy less from TOU contract and sell more back to the grid compared to the solution of the monolithic model. However, in both solutions the net electricity cost is the same as well as the production specific costs.

Table 4-7 CRTN-opt1: Iteration results for Scenario 1

Iteration	MIP				CPUs				Gap			
	Bender' sub-problem		Dantzig-Wolfe sub-problem		Bender' sub-problem		Dantzig-Wolfe sub-problem		Bender' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	51858	167797,69	198330,59	21877,85	0,614	0,581	1,314	0,567	0%	0%	0%	0%
2	51728	167909,2	197751,35	21877,85	0,644	0,478	1,566	0,782	0%	0%	0%	0%
3	51728	167909,2	197751,35	21897,85	0,683	0,560	1,238	0,574	0%	0%	0%	0%
4	51728	167909,2	197736,68	21903,56	0,639	0,464	1,189	0,548	0%	0%	0%	0%
5	51728	167909,2	197732,49	21905,71	0,631	0,569	1,161	0,481	0%	0%	0%	0%
6	51728	167909,2	197730,92	21906,66	0,682	0,581	1,187	0,518	0%	0%	0%	0%
7	51728	167909,2	197730,22	21907,14	0,642	0,473	1,291	0,597	0%	0%	0%	0%
8	51728	167909,2	197729,87	21907,40	0,611	0,715	1,291	0,552	0%	0%	0%	0%
9	51728	167909,2	197729,68	21907,55	0,623	0,609	1,188	0,502	0%	0%	0%	0%
10	51728	167909,2	197729,57	21907,64	0,639	0,468	1,308	1,293	0%	0%	0%	0%
11	51728	167909,2	197729,50	21907,70	0,709	0,585	1,171	0,577	0%	0%	0%	0%
12	51728	167909,2	197729,46	21907,74	0,633	0,572	1,315	0,565	0%	0%	0%	0%
13	51728	167909,2	197729,43	21907,77	0,871	0,565	1,152	0,572	0%	0%	0%	0%
14	51728	167909,2	197729,41	21907,79	2,136	0,574	1,361	0,576	0%	0%	0%	0%
15	51728	167909,2	197729,40	21907,80	0,682	0,575	1,297	0,545	0%	0%	0%	0%
16	51728	167909,2	197729,39	21907,81	0,658	0,645	1,180	0,586	0%	0%	0%	0%
17	51728	167909,2	197729,38	21907,82	0,619	0,474	1,212	0,570	0%	0%	0%	0%
18	51728	167909,2	197729,37	21907,82	0,648	0,679	1,352	0,587	0%	0%	0%	0%
19	51728	167909,2	197729,37	21907,83	0,651	0,558	1,247	0,493	0%	0%	0%	0%
20..30	51728	167909,2	197729,37	21907,83	0,629	0,578	1,328	0,575	0%	0%	0%	0%

Table 4-8 CRTN-opt1: Model results for Scenario 1

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP				
	Costs				Quantities					Costs			Quantities	
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]
1	167798	280611	50886	34360	5100	225	560	796	3817	250	38578	13030	10410	5
2..30	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5

	Upper bound	Lower bound
1	219655,69	219629,20
2	219637,20	219629,20
3	219637,20	219634,53
4	219637,20	219636,06
5	219637,20	219636,63
6	219637,20	219636,88
7	219637,20	219637,01
8	219637,20	219637,08
9	219637,20	219637,12
10	219637,20	219637,14
11	219637,20	219637,16
12	219637,20	219637,17
13	219637,20	219637,18
14	219637,20	219637,18
15	219637,20	219637,19
16	219637,20	219637,19
17	219637,20	219637,19
18	219637,20	219637,19
19	219637,20	219637,19
20..30	219637,20	219637,20

Table 4-9 Model sizes for all decomposition scenarios

Model	Scenario	Total variables				Equations				Binary variables			
		Bender's sub-problem		Dantzig-Wolfe sub-problem		Bender's sub-problem		Dantzig-Wolfe sub-problem		Bender's sub-problem		Dantzig-Wolfe sub-problem	
		scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
CRTN		4817	1441	4938	1321	3725	1561	3726	1441	840	120	840	120
IMV		-	1441	4938	-	-	1561	3726	-		120	840	
IWMV	1	-	1441	4938	-	-	1561	3726	-		120	840	
IOWMV		-	1441	4938	-	-	1561	3726	-		120	840	
IHCD		-	1441	4938	-	-	1561	3726	-		120	840	
CRTN		4817	1441	4938	1321	3725	1561	3726	1441	840	120	840	120
IMV		-	1441	4938	-	-	1561	3726	-	-	120	840	-
IWMV	2	-	1441	4938	-	-	1561	3726	-	-	120	840	-
IOWMV		-	1441	4938	-	-	1561	3726	-	-	120	840	-
IHCD		-	1441	4938	-	-	1561	3726	-	-	120	840	-
CRTN		4215	1441	4216	1321	3245	1561	3246	1441	600	120	600	120
IMV		-	1441	4216	-	-	1561	3246	-	-	120	600	-
IWMV	3	-	1441	4216	-	-	1561	3246	-	-	120	600	-
IOWMV		-	1441	4216	-	-	1561	3246	-	-	120	600	-
IHCD		-	1441	4216	-	-	1561	3246	-	-	120	600	-
CRTN		4456	1201	4457	1081	3484	1441	3485	1321	840	120	840	120
IMV		-	1201	4457	-	-	1441	3485	-	-	120	840	-
IWMV	4	-	1201	4457	-	-	1441	3485	-	-	120	840	-
IOWMV		-	1201	4457	-	-	1441	3485	-	-	120	840	-
IHCD		-	1201	4457	-	-	1441	3485	-	-	120	840	-
CRTN		13793	4033	13794	3697	10421	4369	10422	4033	2352	336	2352	336
IMV		-	4033	13794	-	-	4369	10422	-	-	336	2352	-
IWMV	5	-	4033	13794	-	-	4369	10422	-	-	336	2352	-
IOWMV		-	4033	13794	-	-	4369	10422	-	-	336	2352	-
IHCD		-	4033	13794	-	-	4369	10422	-	-	336	2352	-

Table 4-10 CRTN: Iteration results for Scenario 2

Model type	Iteration	MIP				CPUs				Gap			
		Benders' sub-problem		Dantzig-Wolfe's sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
		scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
CRTN-op1	1	51858	-673378	198330,59	-962128	0,633	0,742	1,269	0,437	0%	0%	0%	0%
	2..30	52968	-676568	338528	-962128	0,634	0,442	1,125	0,467	0%	0%	0%	0%
CRTN-op2	1	51858	-673378	198330,59	-962128	0,634	0,455	1,416	0,457	0%	0%	0%	0%
	2..30	52968	-676568	338528	-962128	0,648	0,469	1,414	0,469	0%	0%	0%	0%

Table 4-11 CRTN: Model results for Scenario 2

Model type	Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
		Costs				Quantities					Costs			Quantities			
		Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
CRTN-op1 & opt2	1	-673378	451870	1675550	292352	0	4733	4792	10885	3817	250	38578	13030	10410	5	-621520	-623600
	2..30	-676568	451870	1675550	292352	0	4733	4792	10885	3806	250	39118	13600	10380	5	-623600	-623600

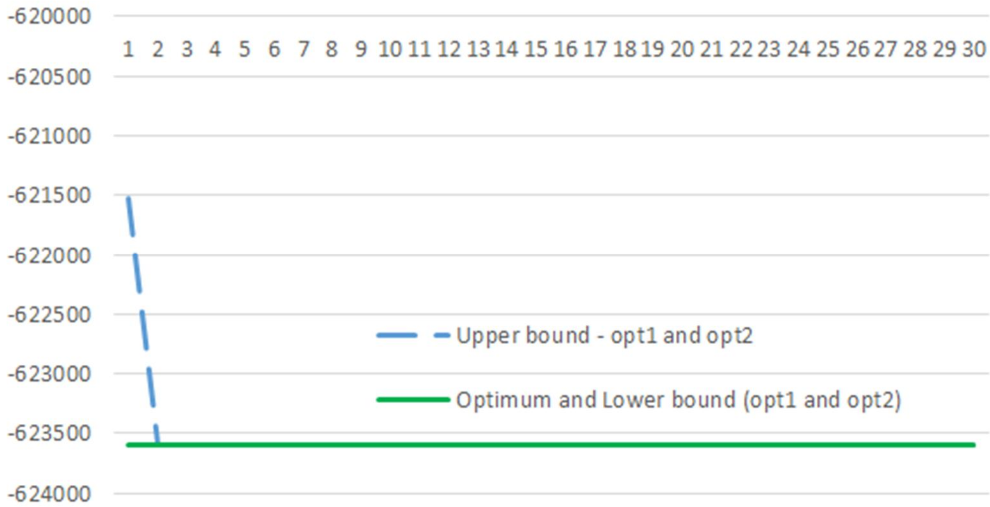


Figure 4-15 CRTN: Iteration results of Scenario 2

In Figure 4-15, results for Scenario 2 are shown. Both options for calculating the mean value yield the same results. The lower bound finds optimal value at the first iteration, while the upper bound closes the gap at the second one. This behavior is probably related to the input data, i.e. for this particular scenario it happened that the Marginal Cost signal from EFN model gave very good indication, which allowed to use the negotiated contracts to buy electricity and sell it with very high profit compared to the production specific cost. The computation time of the models involved in the two iterations leading to optimality showed very similar values as for Scenario 1. Note that the optimal lower bound was found with the first iteration. This is probably why the upper bound converged in the next iteration.

When solving Scenario 3, which is the smallest instance of the monolithic model, the upper and lower bounds hit directly the optimal solution at the first iteration (Figure 4-16) with computation time of any model being under 2s. The lower bound obtained in the first iteration directly hits the optimum. This is related to the fact that the process flexibility does not really allow for much load changes since only 3 refiners are available for delivery of the same pulp amount as in the all other cases which consider 5 refiners. Detailed results of Scenario 3 for all of the investigated model types are shown in Table 4-12 (model statistics) and Table 4-13 (solution structure).

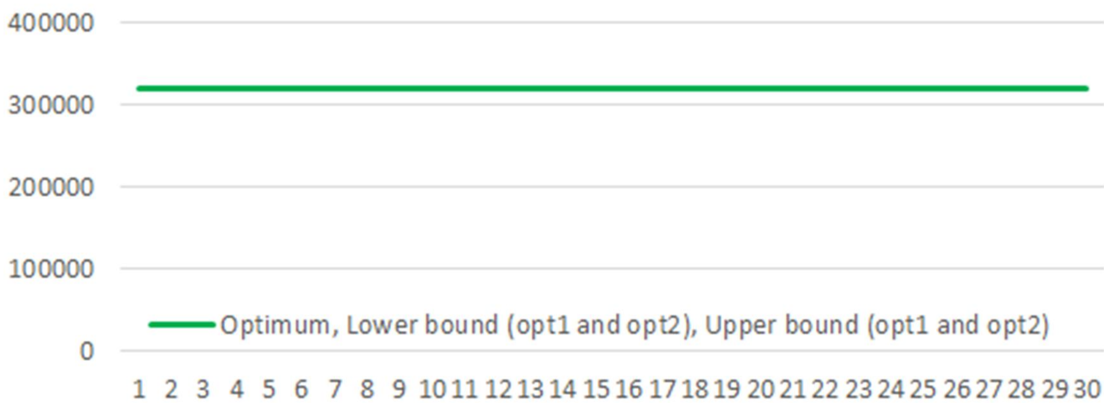


Figure 4-16 CRTN: Iteration results of Scenario 3

Table 4-12 Iteration results for Scenario 3 of all model types

Model type	Iteration	MIP				CPUs				Gap			
		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
		scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
CRTN-op1	1	164530	155541,83	298313,98	21757,85	0,460	0,417	0,495	0,592	0%	0%	0%	0%
	2..30	164530	155541,83	298313,98	21757,85	0,605	0,562	0,736	0,526	0%	0%	0%	0%
CRTN-op2	1	164530	155541,83	298858,48	21757,85	0,492	0,474	0,614	0,728	0%	0%	0%	0%
	2..30	164530	155541,83	298313,98	21757,85	0,594	0,466	0,625	0,496	0%	0%	0%	0%
IMV	1	-	155541,83	298858,48	-	-	0,422	0,662	-	-	0%	0%	-
	2..30	-	155541,83	298313,98	-	-	0,482	0,639	-	-	0%	0%	-
IWMV	1	-	155541,83	298858,48	-	-	0,582	0,688	-	-	0%	0%	-
	2..30	-	155541,83	298313,98	-	-	0,476	0,676	-	-	0%	0%	-
IOWMV	1	-	155541,83	298858,48	-	-	0,513	0,771	-	-	0%	0%	-
	2..30	-	155541,83	298313,98	-	-	0,524	0,811	-	-	0%	0%	-
IHCD	1	-	155541,83	298858,48	-	-	0,393	0,471	-	-	0%	0%	-
	2..30	-	155541,83	298313,98	-	-	0,371	0,536	-	-	0%	0%	-

Table 4-13 Model results for Scenario 3 of all model types

Model type	Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
		Costs				Quantities					Costs			Quantities			
		Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
CRTN-op1	1	155542	311000	48182	34360	5600	225	560	751	3564	34750	126890	2890	9720	695	320071,83	320071,83
	2..30	155542	311000	48182	34360	5600	225	560	751	3564	34750	126890	2890	9720	695	320071,83	320071,83
CRTN-op2	1	155541,83	311000	48181,74	34360	5600	225	560	751	3564	34750	126890	2890	9720	695	320071,83	320071,83
	2..30	155541,83	311000	48181,74	34360	5600	225	560	751	3564	34750	126890	2890	9720	695	320071,83	320071,83
IMV	1	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
	2	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
IWMV	1	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
	2..30	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
IOWMV	1	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
	2..30	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
IHCD	1	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-
	2..30	155541,83	168420,53	47238,7	34360	1604	335	560	735	3564	34750	126890	2890	9720	695	320071,83	-

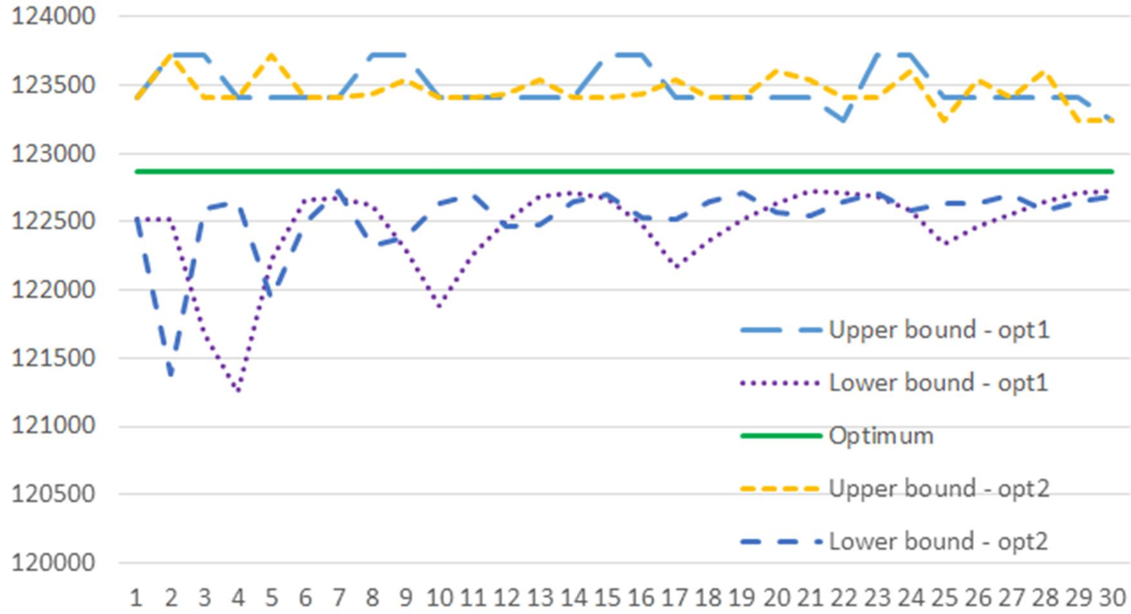


Figure 4-17 CRTN: Iteration results of Scenario 4

Scenario 4 is an instance which is not as easy to solve using the monolithic model as Scenarios 1-3. Results are shown in Figure 4-17, which indicate no convergence for this problem instance. Both the lower and the upper bound do not reach the optimal value, although the best upper bound value is only 0,3% from the optimal value, while the lower bound is even closer. The structure of the algorithm's best solution such as the flow network contracts is also very similar to the optimal monolithic solution.

The lack of optimality might be related to three main reasons. First, there is a computational limit set to 180s for which the production scheduling models at the lower bound fail to solve the problem to optimality in some iterations. However, the solutions usually have an optimality gap of 0,08% (or less), which is practically a negligible error. After tests with selected examples solved to optimality the behavior is the same. Therefore, the optimality gap is not the reason for non-convergence. Secondly and more importantly, this particular problem may not reach the optimum due to the duality gap of the lower bound problem due to Lagrangean relaxation. When exchanging the dual information in Mean Value Cross Decomposition in MILPs there is always a potential error of the duality gap since the Dantzig-Wolfe's sub-problem is used with the relaxed constraint in the objective function (Holmberg, 1997). Especially by investigating closer the convergence process for a larger number of iterations (Figure 4-18) it can be observed that the lower bound seems to reach a constant value – probably the dual gap, while the upper bound is less stable. Thirdly, the upper bound does not converge nor stabilize itself also due to no mean value calculation of the previous solution on the load signal. Although, for practical applications One-sided MVCD shows very good results, there is no guarantee of upper bound or lower bound convergence (to optimality or to the dual gap error) when using One-sided Weighted Mean Value Cross Decomposition.

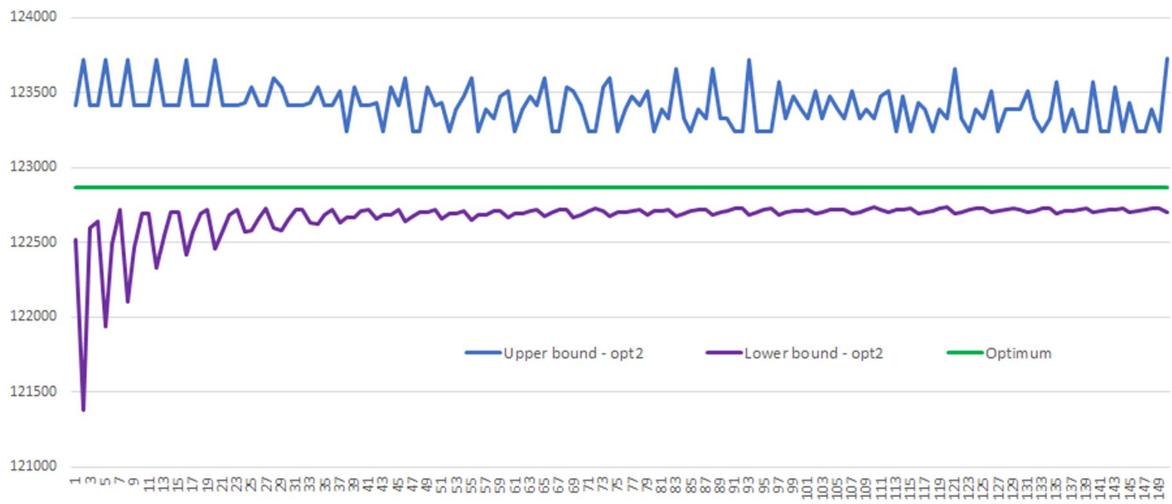


Figure 4-18 CRTN-opt2: Iteration results of Scenario 4 for 150 iterations

To investigate further the behavior of the decomposition scheme for this particular scenario two strategies can be employed, as suggested in studies by Holmberg (1997) for MILP problems and Holmberg and Kiwiel (2006) for NLP problems:

- feasibility repair heuristic – use the mean values on load variable (q_t) and then round the variable to the closest feasible values;
- relaxation of integer variables – relax some of the integer variables to overcome the infeasibility problem of the mean value calculation on load variable.

The first approach is more suitable for practical purposes as it can produce a feasible schedule for which an optimal flow network structure can be obtained. However, since here the focus is to check the convergence properties, the additional problem of the flow network is not solved. The second approach would not produce a feasible schedule, but the convergence to the dual gap should be observed since both the upper and lower bound are still mathematically valid.

The feasibility repair is applied to the scheduler of Benders' sub-problem. A simple Eq. (4.50) replaces Eq. (4.40). It forces the number of running refiners to express as closely as possible the augmented load (q_t') in a feasible manner. This is done by rounding the quotient of the weighted mean load value (option 2) and the electrical consumption of one refiner (all refiners are identical) to the nearest integer value.

$$\sum_{i \in I^c} N_{i,t} = round\left(q_t'/p^{el}\right) \qquad \forall t \in T \tag{4.50}$$

In Figure 4-19 it can be observed that the Benders' sub-problem returns cyclically higher and lower values than the optimal solutions or the lower bound. This is due to the infeasible weighted mean value of the load curve in the flow network model of the complete sub-problem. It can be noted that the behavior of the algorithm is not stable and does not seem to be stabilizing even after 150 iterations. The figure reports the upper bound as a summation of production costs from the Dantzig-Wolfe's scheduler (pulp buying cost and start-up/shut-down cost) and electricity cost that comes from a flow network solved with fixed load resulting from the Dantzig-Wolfe's sub-problem. In this way for each iteration a feasible upper bound is constructed (upper bound – iteration). Additionally, for better clarity, the best upper bound found among all previous iterations is drawn as a staircase line. The best objective function value found in iteration 43 is 123054,5 which is only 0,15% from optimality (see Table D-11 in Appendix D for more details).

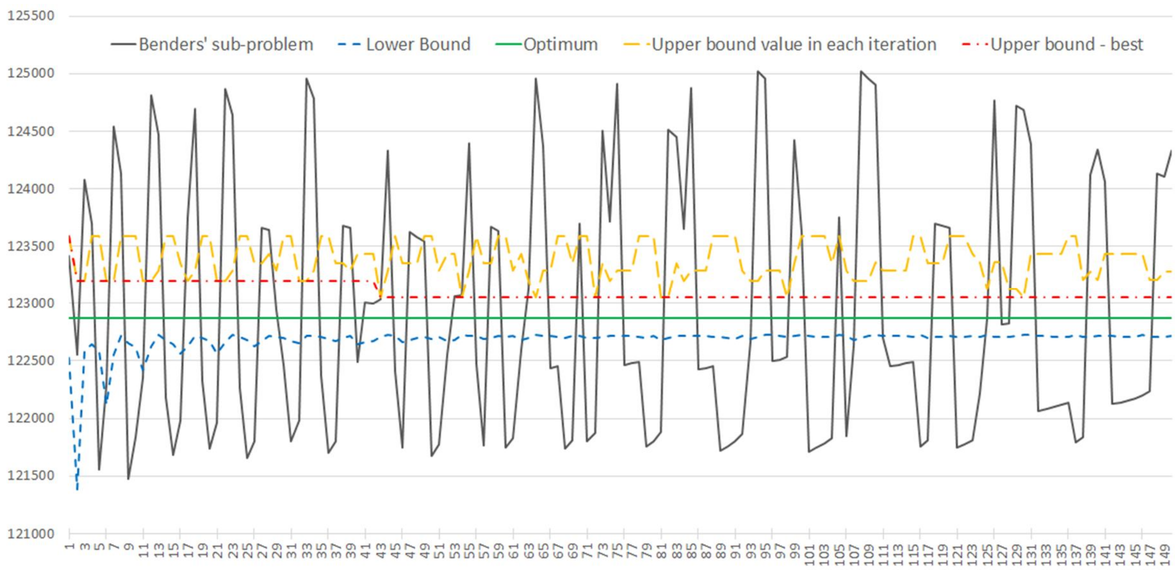


Figure 4-19 CRTN-opt2: OWMVCD with feasibility repair heuristic - results of Scenario 4

A drawback of the feasibility repair heuristic strategy is that in practice it would be difficult to know when to stop the algorithm since it does not converge.

In the second approach, some of the integer variables linked to the load curve should be relaxed to allow infeasible augmented values. In general, finding the right values to relax in a complex MILP model can be a major challenge. For the considered problem, the variable representing the execution of the pulping task in refiners has direct influence on the load, therefore it can be relaxed as follows (4.51):

$$N_{i,t} \in R, 0 \leq N_{i,t} \leq 1 \qquad \forall t \in T, i \in I^c \tag{4.51}$$

The Benders' sub-problem becomes feasible for any mean value resulting from the Dantzig-Wolfe's sub-problem. For Scenario 4, the relaxation gives the behavior as shown in Figure 4-20.

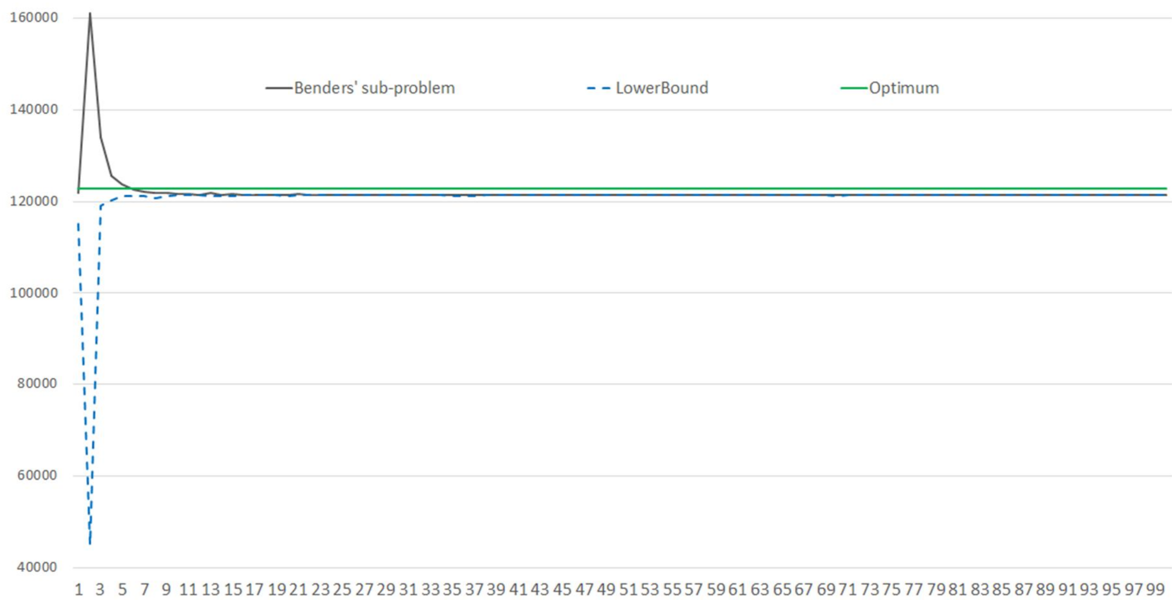


Figure 4-20 CRTN-opt2: OWMVCD with relaxed integers - results of Scenario 4

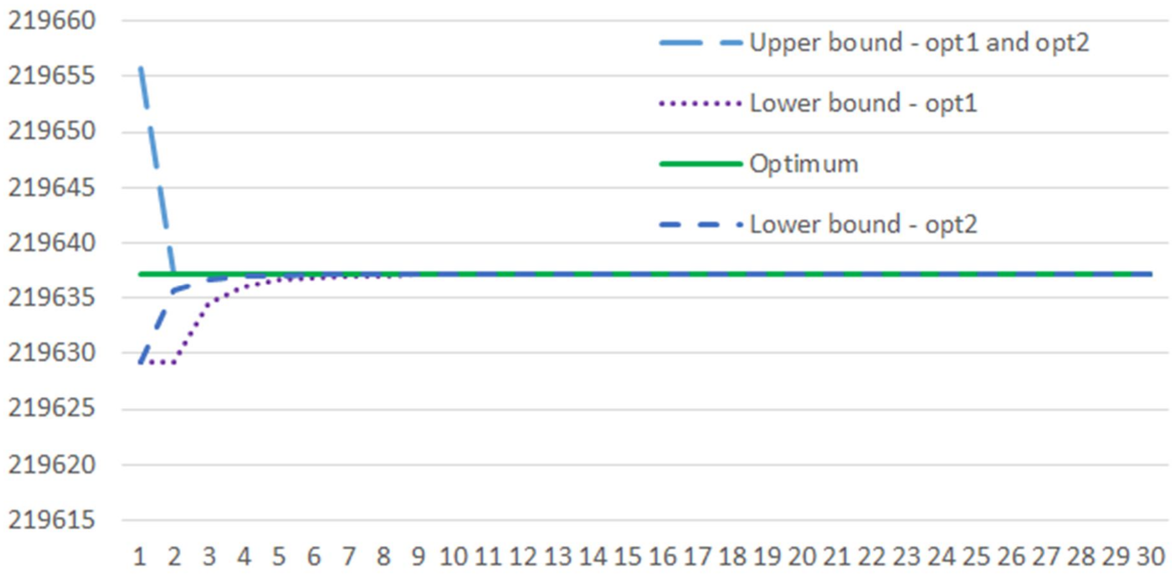


Figure 4-21 CRTN: Iteration results of Scenario 5

The corresponding results in Table D-12 show a relatively fast convergence of both sub-problems to a stabilized range of values around 121440 for the upper bound and 121370 for the lower bound. After the 15^{th} iteration the difference between the bounds oscillates in a range of around 20-200. Lack of precise convergence of both bounds to one single value could be explained by the fact that not all of the integer variables are relaxed as in the proved case (Holmberg 1997). The value of the dual gap seems to be around 1% below the optimal solution. The objective function values in the second iteration can be explained by the algorithm's response to the initialization step.

As shown by Holmberg (1997) the mean value strategy applied on both sub-problems can be expected to achieve very good results. The final solution is infeasible, however a heuristic strategy could be further applied to find a feasible schedule which would reduce the duality gap. More general conclusions with regard to the behavior and convergence properties of the decomposition scheme are discussed later in Chapter 4.3.4.7.

In the last instance of Scenario 5 both bounds reach the optimal solution within few iterations. This is similar to Scenario 1 and could be related to the fact that both instances have the same input data, however just the size (scheduling horizon) differs. The iteration results are shown in Figure 4-21.

The above test instances show the convergence behavior of the developed decomposition scheme. However, to get a feasible solution only the partial problems of the two decomposition schemes can be solved as shown later for the "industrial approach". In any of the following approaches, whenever a mean value is calculated the option 2 is used as it showed slightly better performance in the convergence tests.

4.3.4.3. Industrial approach with MVCD

The industrial approach solves only the two interesting parts of the sub-problems as explained earlier (Chapter 4.3.3). On both signals (load curve and Marginal Cost curve), the mean value is calculated before solving the partial sub-problems. Detailed results of all problem instances (except Scenario 3 which has been reported earlier) solved using MVCD with a limitation to 30 iterations limitation is shown in Table D-15-Table D-22. The algorithm's solution for Scenario 1 is shown in Figure 4-22. The solution of each iteration (called later as decomposition solution) consists of the summation of both objective function values of partial sub-problems as explained earlier. Based on the scheduler's problem, which provides a load curve, an additional solution of the corresponding flow network can be computed. Summation of both objective functions provides a valid upper bound. It can be observed that for Scenario 1 the optimal upper bound calculated based on the decomposition solution is found already in iteration 2.

Decomposition solution value of the iterations other than initial happen to yield lower than optimal values due to infeasible mean values of the load curve that can be used in solving the flow network problem and its cost. It can be observed that with each iteration the decomposition slows down in the move towards the optimal solution and does not reach it in 30 iterations. However, it should be noted that for all of the following cases with such behavior it looks that the optimality could be reached when performing a sufficiently large number of iterations, since the objective function always improves with new iteration. This is related to the nature of the mean value calculation and relatively slow influence of the current signal. Similar convergence behavior is seen for Scenario 2 in Figure 4-23. An optimal upper bound is found already in the second iteration of the algorithm.

For Scenario 3 again the decomposition yields the optimal solution with the first iteration as in the previous decomposition variations.

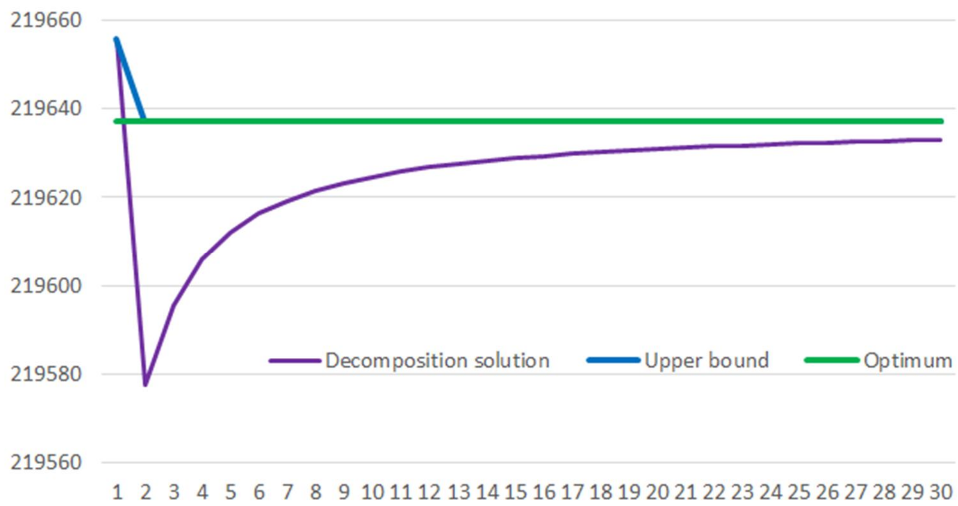


Figure 4-22 IMV: Iteration results for Scenario 1

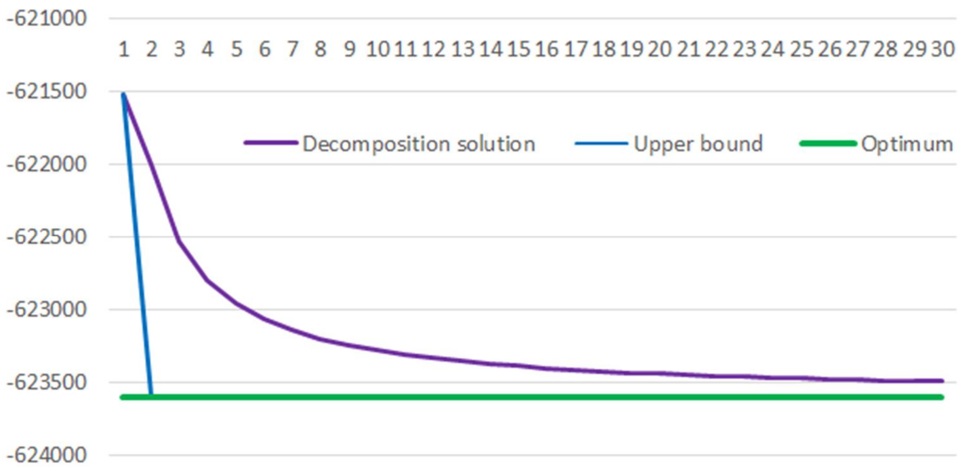


Figure 4-23 IMV: Iteration results for Scenario 2

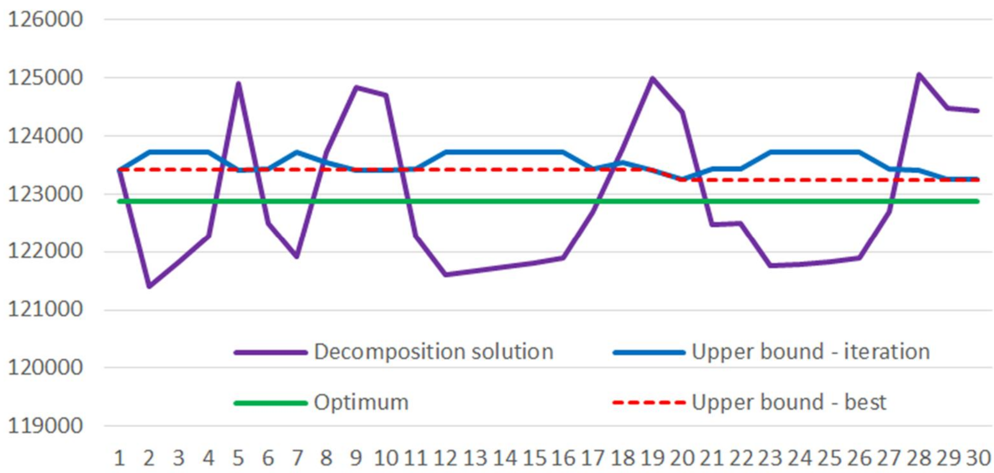


Figure 4-24 IMV: Iteration results for Scenario 4

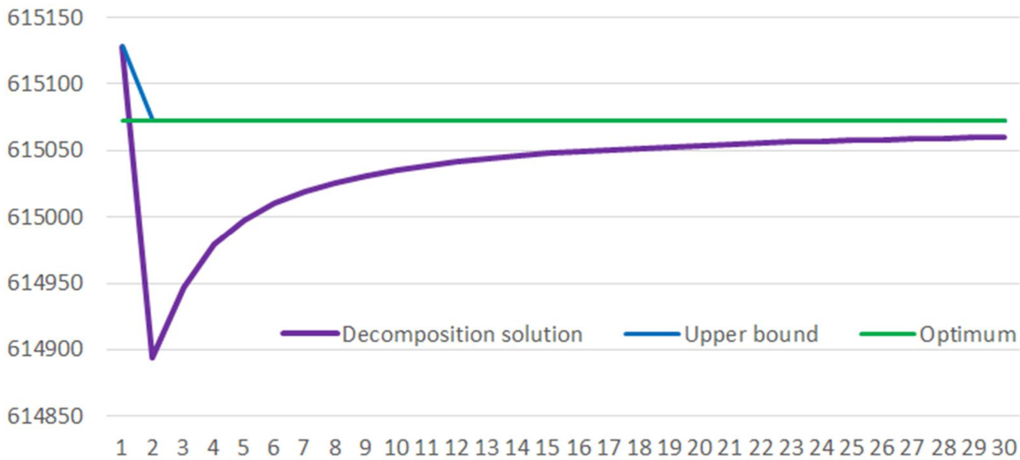


Figure 4-25 IMV: Iteration results for Scenario 5

Next, the case of Scenario 4 (Figure 4-24), which does not yield optimum in the convergence test, does not reach the optimal solution in the industrial approach. The solutions better than the optimal solution (below the optimality line) are clearly those for which one of the partial models – flow network – received an altered signal (altered load curve), which in general not achievable by the real process (not feasible), thus the objective function value may became better than the monolithic optimal. The iterations oscillate due to cyclically similar relative signal values. Again for this case there are some partial model instances which are not solved to optimality within the 180s limitation as can be seen in the detailed results in Table D-19 - Table D-20, however this is not the reason for the decomposition's lack of optimality in this scenario as the obtained solution were almost exactly the same as the optimal solution. In this particular setting the infeasibility of the load curve given to the flow network problem could also contribute to slow convergence behavior. However, it can be expected that the duality gap plays the biggest role in that. It should be noted that still the solution closest to optimality which is found in iteration 20 is only 0,13% far from optimality, but the solution is infeasible. The last instance of Scenario 5 presented in Figure 4-25 shows similar behavior to Scenario 1 and also does not reach the optimum in 30 iterations.

4.3.4.4. Industrial approach with Weighted MVCD

Iteration results for the Weighted Mean Value Cross Decomposition (WMCD) approach using the partial sub-problems of Benders' and Dantzig-Wolfe's decomposition are shown in Figure 4-26 - Figure 4-28. As expected, the decomposition solution performs better than the Mean Value Cross Decomposition. In general, the behavior of both are similar, however the decomposition solution in WMCD approach yields the optimal solution much faster due to a stronger response to the previous solution (signal). Identically to IMV, the upper bound is found already in the second iteration for all of scenarios except Scenario 4.The solving times of each partial sub-problem are very similar to the MVCD. More detailed results of this approach are reported in Table D-23 - Table D-30. Again, Scenario 3 is solved in the first iteration. In Scenario 4 there is no optimality reached and the quality of the obtained solutions is identical to the one obtained from MVCD. Here, again better (lower) than optimal infeasible solutions are found due to altered (with weighted mean) load curve signal.

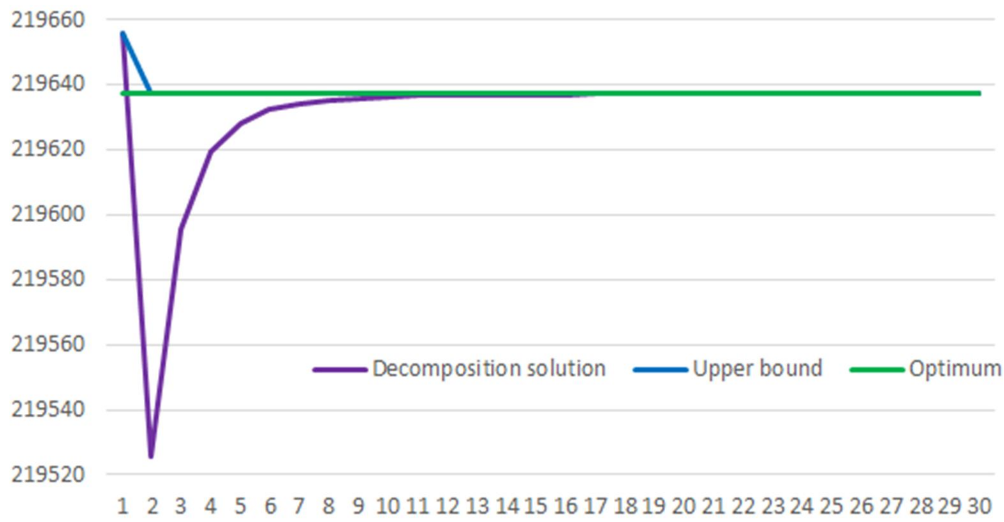


Figure 4-26 IWMV: Iteration results for Scenario 1

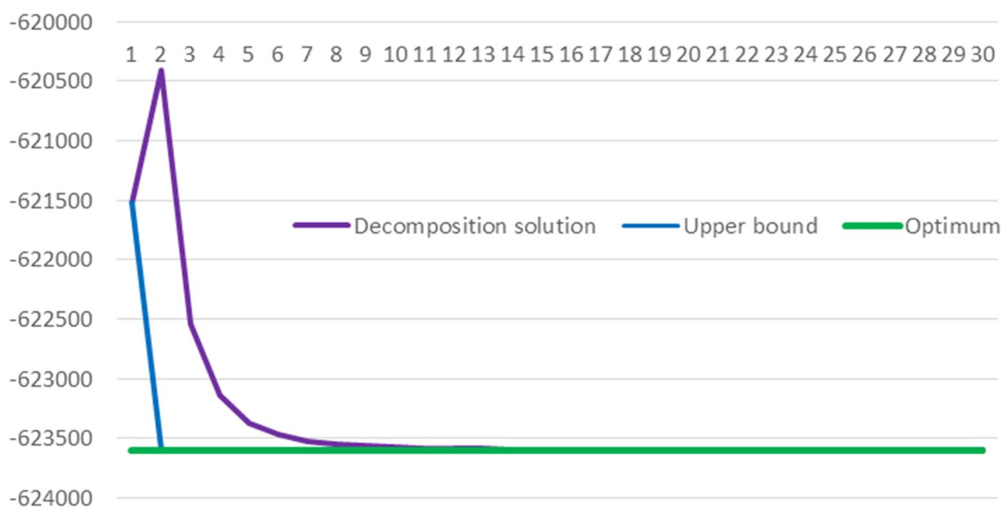


Figure 4-27 IWMV: Iteration results for Scenario 2

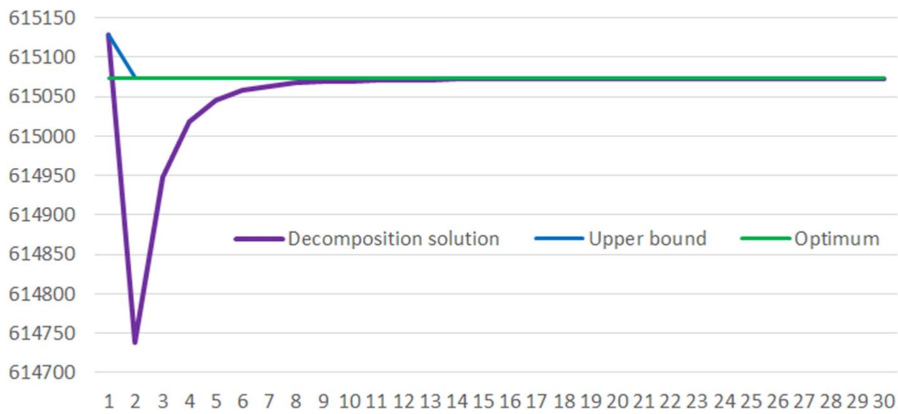


Figure 4-28 IWMV: Iteration results for Scenario 5

4.3.4.5. Industrial approach with One-sided Weighted MVCD

Another variation of the Cross Decomposition is to use one of the signals directly without any alteration. In our problem setup it could make sense to apply the direct signal to the flow network problem to avoid getting a purchase structure (flow network solution) for an infeasible load curve (since it was altered to take mean value). If a direct load curve is used in the flow network the entire iteration should never yield solutions better than the optimal, since both solutions from the partial problems are feasible in the original monolithic problem.

Detailed results including objective function values of iterations are reported in Table D-31 - Table D-38. In can be concluded that the behavior of the OWMVD algorithm is very similar to the previous approaches, however optimal solutions are obtained with a slightly less number of iterations. For example, in Scenario 1, 2 and 5 optimality is reached in 2 iterations. Again, Scenario 3 is solved directly. Scenario 4 does not reach optimality, but the best objective value (123246,34 - identical with the one found by IMV and IWMV) is found faster (already in iteration 15 not 20). It can be concluded that for the considered case study, OWMVD seems to give the best performance above all of the investigated approaches – it requires the least number of iterations to obtain the optimal solutions and only 2 models are solved in one iteration in contrast to 4 models solved for the convergence tests. It is worth mentioning that also experiments with OWMVD using option 1, to calculate the mean value were performed, however did not give a better behavior than option 2.

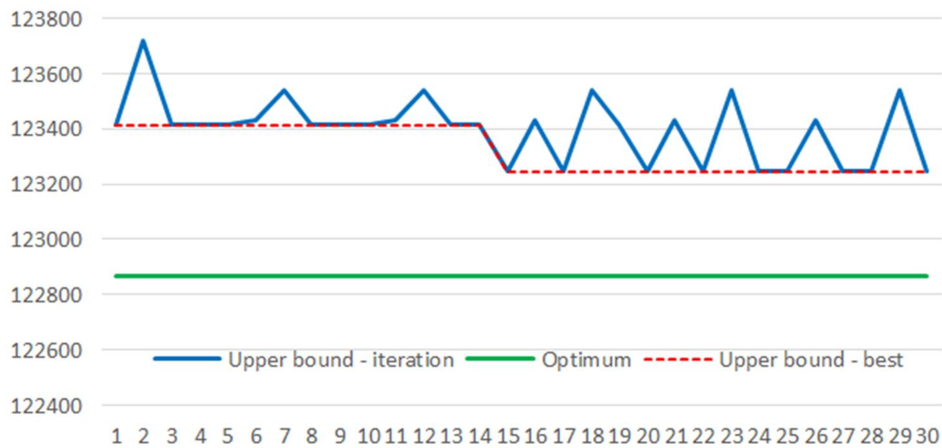


Figure 4-29 IOWMV: Iteration results for Scenario 4

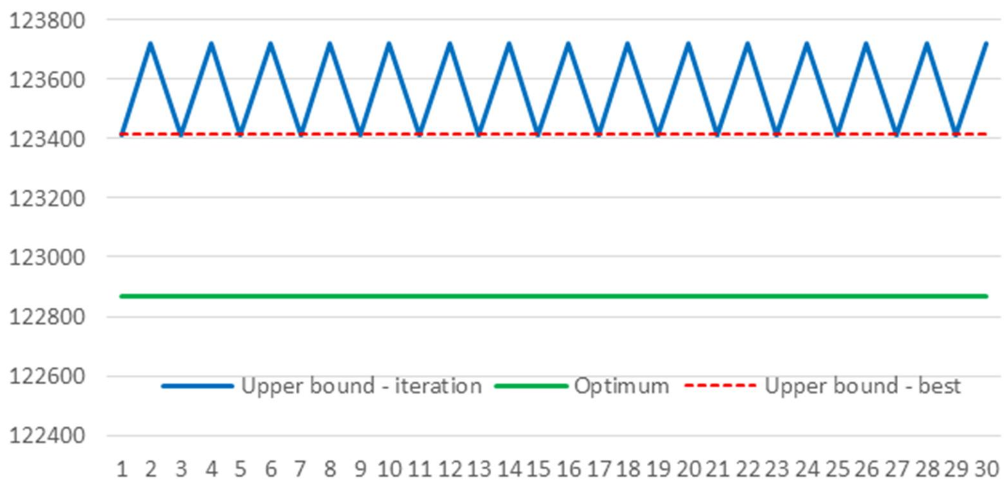


Figure 4-30 IHCD: Iteration results for Scenario 4

4.3.4.6. Industrial approach with heuristic Cross Decomposition

In this approach, both signals are not altered at all and are sent directly to the other partial sub-problems during the iterative algorithm. This allows avoiding the infeasibility problems, however it is not proven to yield convergence. The iteration behavior of the IHCD approach turned out to be exactly the same as in the case of IOWMV, except of Scenario 4. In addition, all solution times were also very similar to all other approaches. The detailed results of Scenario 4 are given in Appendix D. From Figure 4-30, which shows the iteration results of Scenario 4, it can be observed that the algorithm oscillates between two solutions. The exchanged signals are cyclically identical with the best one being worse than the best ones found by the other approaches. Since there is no alteration on the signals, the algorithm seems to get stuck having no incentive to change its behavior. In this sense, it is expected that the IOWMV is the best choice of the Cross Decomposition variation among all the investigated approaches. In addition, the best solution of the IHCD approach is by 0,1% worse than the best one from IOWMV. However, on the other hand this solution scheme is easy to handle since the feasible signals always provide feasible solutions. Moreover, the cyclic solutions can be easily detected and the algorithm can be stopped. Therefore, for practical implementation this method provides advantages.

4.3.4.7. Discussion on performance and limitations

In Chapters 4.3.4.1-4.3.4.6 different approaches that utilize the idea of Mean Value Cross Decomposition are presented. The iterative framework solves Benders' sub-problem with a flow network model and the Dantzig-Wolfe sub-problem with production schedule. Proving the convergence of the algorithm can be shown in two ways. First, solving complete sub-problems of Benders' and Dantzig-Wolfe decomposition to compare the upper and the lower bound. Second, the decomposition result can be compared with the optimal solution of the original monolithic problem. In all of the investigated approaches solutions very close to optimal, if not optimal, have been found in reasonable times.

Computational performance

From the detailed results for different instances, it can be noted that it usually takes longer for the decomposition approach to return the optimal solutions when compared to the monolithic model. In order to further asses the computational time performance, it was chosen to investigate the

IOWMV and HCD approach and compare it to the monolithic model solution times. The results are shown in Table 4-14. It can be seen clearly that for Scenarios 1-3, the monolithic model is faster. However, under certain stopping criteria for the problematic Scenario 4-5, the decomposition approaches perform quite similar to the monolithic. Moreover, the IHCD approach computes slightly faster for easy-to-solve instances (Scenarios 1-3), while IOWMV is slightly better when solving the problematic Scenarios 4-5. In general, it should be noted that the TMP process case forms relatively small problem instances for which the monolithic as well as all of the decomposition approaches find industrially acceptable solutions very fast.

Table 4-14 Computational time comparison

Scenario	RTN			IOWMV		IHCD	
	MIP	CPUs	Gap	CPUs	Gap	CPUs	Gap
1	219637,2	0,74	0%	1,82*	0%	1,60*	0%
2	-623600	0,53	0%	2,03*	0%	1,78*	0%
3	320072,8	0,47	0%	0,35*	0%	0,35*	0%
4	122869	10,54***	<0,01%	10,10***[1]	0,47%**	10,18***[3]	0,54%**
5	615072	10,47***	<0,01%	10,13***[2]	0%**	10,72***[2]	0%**

* time to obtaining first optimal solution

** best iteration with stopping limitation of relative gap 1 %

*** stopping limitation set to 10 s

[1]total of 15 iterations; [2]total of 13 iterations; [3]total of 14 iterations;

Solution quality performance and limitations

One limitation of the approach to use the dual information is that in practice it might sometimes be difficult to obtain the dual cost from an LP solution of a MILP problem. Also, it should be noted that it is difficult to assess what the necessary conditions are, apart from the special structure that allows formulating Benders' and Dantzig-Wolfe sub-problems, for the framework to obtain acceptable solutions. One possible weak point of the framework is the quality of the Marginal Cost signal obtained from the flow network when no mean values on both signals are used. Even though complicated network structures were investigated and similarly good solutions were obtained, it is not certain that the dual information from an LP solution of a MILP problem is correct. To be more precise, the Marginal Cost applies to certain load parameter bounds where the LP solution of the flow network is optimal for the given load bounds. Therefore, if the scheduler stays within the load bounds, it will provide the system-wide optimal solution. However, if the load exceeded the bounds, the Marginal Cost information is no longer "correct" and the flow network's solution for which the dual was obtained is not optimal anymore (actually regardless of whether the original problem was LP or MILP). Because of this, the dual information gives a correct indication, but only, for limited load bounds which are likely to be exceeds. Another interpretation of the quality of the MC signal is that it is proven (Holmberg 1997) to be a valid signal, but only over the convex hull (convexified set of the original problem) of Benders' sub-problem. Therefore if no mean values on the other signal are used then the scheme is not proven to stay within the convex hull. Nevertheless, for practical example problems, the Marginal Cost curve turns out to provide a very good guess of where the scheduler should move the load to in different time intervals. It can be suspected that this is due to the fact that:

- when load changes by a small amount the electricity contracts structure does not have significant price changes per MWh of electricity consumed, therefore also corresponding Marginal Cost curve does not have significant pattern changes with different load levels;
- industrial loads result from the production process which is always constrained (e.g. due to final product demand requirements) thus the load values do not have full flexibility but usually small ranges within which they can be changed.

When discussing Scenario 4, there is a very useful and important characteristic of the Mean Value Decomposition structure with mean value calculated on both signals. It is the fact that the lower bound produced by the Dantzig-Wolfe sub-problem, if enough iterations are admitted, eventually should converge as close to the optimal solution level as the dual gap allows.

This is shown in Figure 4-31 where the shaded area represents the convex hull of the monolithic problem with the complicating constraint or Benders' sub-problem region without the complicating constraint). In other words, the lower bound can be as good as the Lagrangean dual of the original monolithic problem, possibly performing even better than the LP relaxation of the monolithic problem (see optimal solution of LP relaxation in Figure 4-31). This was also shown in Holmberg (1997) where the convergence properties of such decomposition for MILP problems were investigated thoroughly. As for the Benders' sub-problem (the upper bound), if the mean values on both signals and all integer variables (if needed) are used (integer requirements are relaxed), the lowest solution it can reach for a minimization problem is exactly the lower bound's highest value, i.e. the solution value of the Benders' sub-problem (in our case using a fixed variable q_t) might be lower than the true optimum however, will never be lower than the best (highest) lower bound. If there is no dual gap then the lower bound can only go up until the true optimum of course, and also the upper bound will reach it.

In this case, to overcome the infeasibility problem of the variable q, the signal can be used directly without its mean value augmentation (One-sided Mean Value) such that it corresponds to a feasible schedule. For the investigated instances, the lower bound eventually finds very good solutions that approach the Lagrangean dual as in Scenario 4 (Dantzig-Wolfe sub-problem solution). When the corresponding q information is used in the flow network model in the Benders' sub-problem, the upper bound will produce very good quality solutions as well, especially when the dual gap is relatively small. If there is no dual gap, the One-sided Mean Value yields optimal solutions due to the fact that the lower bound finds the optimal objective function value of the monolithic model. The practical interpretation of this situation is the following. As seen in the investigated cases when iterating between the sub-problems, the schedule might eventually stabilize itself such that even when the MC signal from the flow network changes with each iteration, the schedule will not change due to process restrictions and especially due to integer decisions. From the industrial point of view, this is very appealing since the production schedule is the dominant cost-factor which is the most important in the integration of energy and production management.

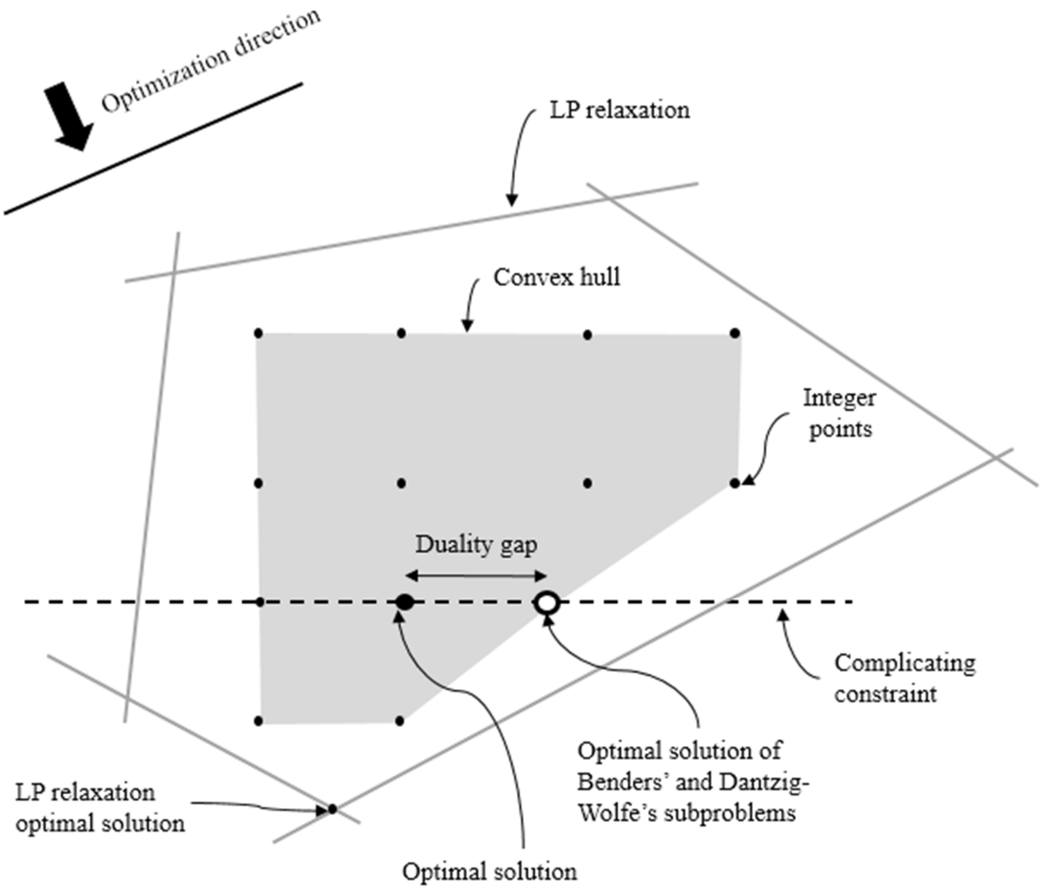


Figure 4-31 Simplified geometrical representation of MVCD scheme limitations

With the above arguments concerning the Mean Value convergence properties and theoretical lack of performance proofs of the One-sided Mean Value, one could investigate how to augment the Mean Value scheme such that it provides practically useful solution. An interesting approach to overcome the infeasibility problem would be to try to solve two different models at the upper bound level – one for finding q values from a feasible schedule and the other one could provide q's from a relaxed version of the scheduler which then could be used for solving the Benders' sub-problem. In this way, it could be still possible to obtain feasible solutions (from the former model), but at the same time the Benders' sub-problem could use a mean value signal (from the latter model). In this way, the Benders' sub-problem could result in better solutions than in the case of the one-sided version. Another way of dealing with the infeasibility problem which would hopefully allow for closing the upper bound is to construct a specialized heuristic that could smartly round up the infeasible q values to feasible integer levels, as suggested also by Holmberg (1997). As it was shown in the convergence tests with Scenario 4 this approach might however still not close the gap between the sub-problems. For practical implementations, it might be difficult to assess when to stop the algorithm since there is no stabilization of the algorithm's solution. Another way has been suggested by Holmberg (2004): to use One-sided Mean Value for certain number of iterations and interrupt it with Mean Value calculation occasionally. For some problems, it should help to steer the convergence better than using OSWMVCD alone, however it is difficult (if possible at all without numerical experiments) to establish the number of iterations when to switch between the two.

In general, if a successful way of overcoming the infeasibility problem when using Mean Value calculation on both sides is found the scheme is expected to yield better solution results than the methods based on subgradient optimization. This is because the Lagrangean based methods are exploiting the "corners" of the convexified set and then use a heuristic to project then into a feasible solution satisfying the complicating constraint as well.

Summary of conclusions

From the cases investigated, the following conclusions can be drawn concerning different Cross Decomposition approaches:

- Best approach: One-sided Weighted Mean Value Cross Decomposition (OSWMVCD) with signal alteration using stronger influence of the last received signal (Equation 21) performed better than the other approaches with mean value calculation, i.e. Mean Value and Weighted Mean Value Cross Decomposition. The former approach moved considerably slower towards optimality then the other approaches. Moreover, using direct signals in IHCD seems to work as good as OSWMVCD for the considered instances, but is expected show worse behavior in problematic instances with duality gap;
- Stopping criteria: when using only partial solutions it might not be clear when to stop the algorithm in case of problematic instances, because the convergence tests cannot be done due to the lack of the lower bound. However, for the scenarios investigated the algorithm should terminate as soon as there is no improvement of the solution with new iterations. For practical purposes, in an industrial setting, the stopping criterion could simply be the total time limit combined with termination when there is no significant solution improvement with new iteration;
- Optimality: there is no guarantee, when using OSWMVCD, that the algorithm will converge to optimality. In addition, probably due to the MILP duality gap, none of the investigated approaches can solve problematic instances to optimality, for example in Scenario 4 where the dual gap is present. In summary, the following might contribute to the lack of optimality in certain problem instances:
    - duality gap of MILP models in Benders' sub-problem – as noted by Holmberg (1997), Holmberg and Kiwiel (2006) and discussed earlier;
    - one-sided instead of regular mean value calculation on both signals automatically does not guarantee convergence of the solution to the dual gap (if present) of the Benders' sub-problem (Holmberg 1997);
    - unbalanced sub-problems – Holmberg (1997) posed a suspicion that when using MVCD both sub-problems shall be of a similar size. When for example two unbalanced problems are solved, one very large and second small, the optimality might not be reached. For our case, the flow network problem is a smaller problem then the scheduler;
    - relative gap – not solving the sub-problems to optimality might also of course contribute to the overall lack of optimality of the algorithm, however in the investigated instances this is not seen to be an issue;
- Controllability: MVCD takes many iterations to solve to optimality due to the weak influence of the last received solution from one of the sub-problems. The heuristic approach IHCD gave similar results to the OSWMVCD, however on the problematic instance (Scenario 4) showed oscillation around two identical solutions. This is because the signals are not altered, therefore might cycle back between identical values.
- Computation time: for the example here the decomposition increases the computational time compared to the monolithic approach. However, for the TMP case the results were still obtained in reasonable times.

Even though the investigated decomposition scheme cannot be proven to converge, it shows very good results for the instances investigated, which is potentially relevant for industrial use as it allows for functional separation of the models as well.

4.4 Application to continuous-time bi-level heuristic of the stainless-steel case

In Chapter 4.2 it was shown that for a monolithic production scheduling problem with energy cost optimization based on the Minimum-cost Flow Network it is possible to use the special problem structure in order to arrive at the decomposition approach consisting of two functionally separated problems. To solve the monolithic stainless steel case investigated in Chapter 3.2 using the Mean Value Cross Decomposition idea, one could apply it directly in a similar manner as for the TMP case in the previous chapter using partial sub-problems. However, due to the large-scale nature of the scheduling problem, the MVCD scheme cannot be applied directly since it would result in an intractable scheduling problem. Therefore, here the bi-level heuristic from Chapter 3.4 is employed. It allows to investigate different integration variations. In the following chapter first the Mean Value Cross Decomposition is applied to a monolithic problem to create Benders' and Dantzig-Wolfe partial sub-problems - the latter being not tractable. Therefore, in the next chapters two different options of bi-level heuristic integration with One-sided Weighted MVCD and heuristic Cross Decomposition are investigated in order to solve the problem in reasonable times.

4.4.1 Heuristic framework structure

If the Mean Value Cross Decomposition approach solving only partial sub-problems is applied to the monolithic steel scheduling problem using the improved event binaries model from Chapter 3 two optimization problems are obtained. First, the production scheduler with regular production specific costs (summation of task start times with a weighting factor), load deviation response (deviation penalties δ) and optimization of single energy price curve (dual information from the flow network) – scheduler of Dantzig-Wolfe sub-problem as in Eq. (4.52).

$$min(\delta + c \cdot \textstyle\sum_{p\in P,m\in M} t_{p,m}^{s} + q_s \cdot \overline{MC_s}) \qquad (4.52)$$

subject to

$Eq.(3.1 - 3.16)$ – production scheduling constraints (Chapter 3.2.2)

$Eq.(3.44 - 3.47, 3.71 - 3.80)$ – energy-awareness constraints of improved event binaries model (Chapter 3.2.3.3)

$Eq.(3.99 - 3.102)$ – load deviation problem (Chapter 3.2.4.2)

The above formulation applies to all three monolithic model variations assessed in Chapter 3.3 if the energy-awareness constraints are chosen according to the variation option. However, since the improved event binaries (Chapter 3.2.3.3) were concluded to be the most efficient, from this point this variation of the energy-awareness is referred as the monolithic steel plant scheduling model.

Secondly, the energy model with optimization of purchase and sales net cost (net electricity cost), under the assumption of a given load distribution – flow network Benders' sub-problem.

$$min(\mu) \qquad (4.53)$$

subject to

$$f_{i5,j7,s} = \bar{q}_s \qquad \forall s \in S \tag{4.54}$$

$Eq. (3.88 - 3.89),\ (3.91 - 3.98)$ – flow network constraints (Chapter 3.2.4.1)

As previously stated, the signals exchanged between the sub-problems (either partial or complete) are the load curve (q_s) from the schedule and the flow network's marginal cost curve (MC_s). These signals can be used directly or can be augmented according to different decomposition approaches, as explained in Chapter 4.2.

From the closer investigation of the general problem in Chapter 4.2.2.3 it can be concluded that it is sufficient to solve the above mentioned two partial sub-problems to get a solution to the original monolithic problem. Moreover, in the investigation of the Mean Value Cross Decomposition concepts applied to the TMP case (Chapter 4.3), it has been concluded, similarly as in the available literature studies (e.g. Holmberg and Kiwiel 2006), that the One-sided Weighted Mean Value Cross Decomposition is faster in finding optimality than the regular One-sided Mean Value. For our cases, also the Heuristic Cross Decomposition using direct signals gave good results event tough cycling between two identical solutions can occur. Therefore, for the application of the decomposition concepts to the steel case, these two approaches – OSWMVCD and HCD with solving only the partial problems – are investigated.

Compared to the TMP case there are important differences which need to be taken into account when solving the steel problem:

- the targeted instances of the TMP monolithic model are solvable to optimality, while the steel instances of the monolithic model are not (Chapter 3.3.2);
- the partial sub-problems of the TMP models are solvable to optimality (or very close to optimality) in reasonable times, while the steel partial sub-problem of Dantzig-Wolfe's decomposition is not tractable since after extraction of the flow network problem from the monolithic formulation the model is still very large for the targeted instances (see the size of the problems in Table 4-16).

The first point has the implication that for the example case study it will not be possible to compare the results of the decomposition concept to the monolithic model (for targeted large-scale instances) to exactly asses its performance. However, it will be possible to compare it with the bi-level heuristic results reported earlier in Chapter 3.5. That in turn implies the use of the same problem instances (input data). For the second point, the bi-level heuristic structure (Chapter 3.4) must be applied in a way that allows obtaining satisfactory solutions in reasonable times. Two different integration approaches are proposed as explained in the next chapters.

4.4.1.1. Bi-level heuristic as Dantzig-Wolfe sub-problem

Since the scheduler in the Mean Value Cross Decomposition scheme is the non-tractable bottleneck, the first approach is to simply use the bi-level heuristic to solve it in reasonable times as shown in Figure 4-32. In the following text s is used to denote time intervals, following the notation from Chapter 3.

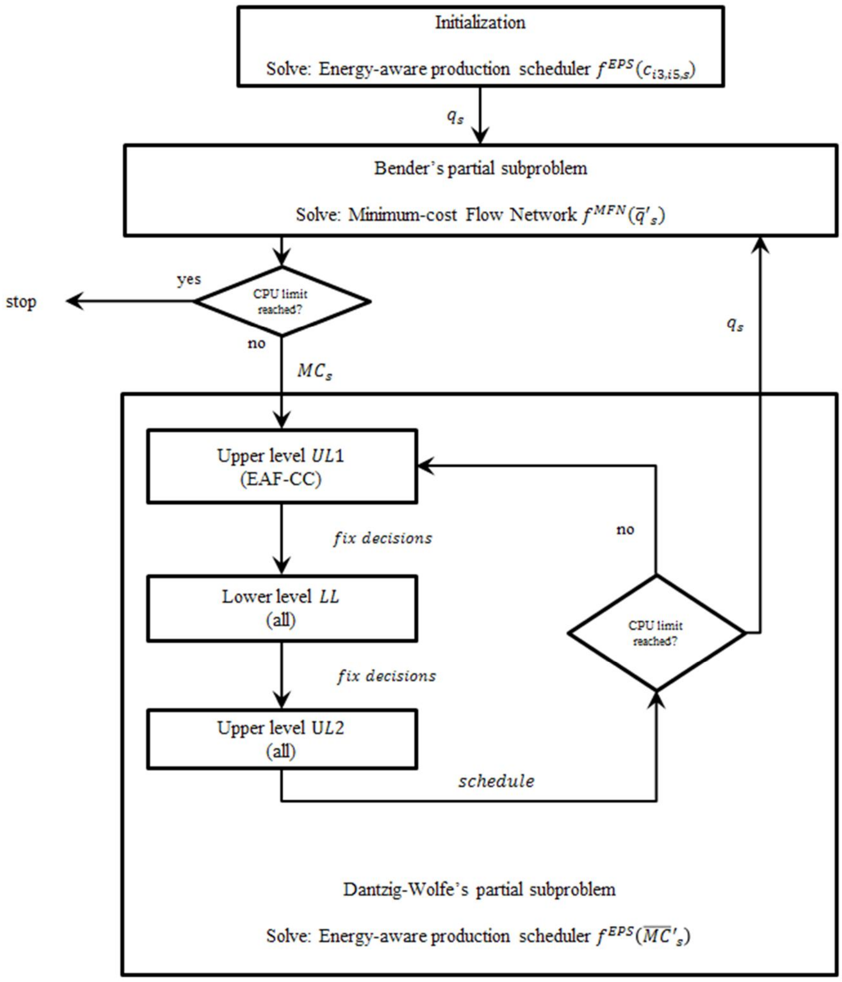


Figure 4-32 Bi-level heuristic as Dantzig-Wolfe partial sub-problem

In the proposed approach, the initialization step and the solution of the flow network problem is performed similarly as for the TMP case. The production scheduling model is chosen as the one to be solved first. Again, the model is solved using the day-ahead spot market price ($c_{i3,i5,s}$) instead of the Marginal Cost curve as a parameter in the objective function. Since the full space scheduler is not tractable, the approximated model $UL1$ is used in the initialization step. The model formulation is as follows.

$$min_{init-EPS(c_{i3,i5,s})}(\delta + c \cdot \sum_{p\in P,m\in M} t^s_{p,m} + \sum_{s\in S} q_s \cdot c_{i3,i5,s}) \quad (4.55)$$

subject to:

$Eq.(3.1 - 3.16)$ – scheduling model equations with new sets M and ST (Chapter 3.2.2)

$Eq.(3.44 - 3.47),\ (3.71 - 3.80)$ – energy-awareness extension with improved event binaries model (Chapter 3.2.3.3) with new sets M and ST

$Eq.(3.99 - 3.102)$ – load deviation problem (Chapter 3.2.4.2)

After the first Marginal Cost signal is received, the upper level problem $UL1$ can be computed using the formulation presented in Chapter (3.4.2), however with a modified objective function and without the flow network constraints as in problem (4.56).

$$min_{UL1-EPS(\overline{MC_s})}(\delta + c \cdot \sum_{p\in P,m\in M} t^s_{p,m} + \sum_{s\in S} q_s \cdot \overline{MC_s}) \quad (4.56)$$

subject to:

$Eq.(3.1-3.16)$ – scheduling model equations with new sets M and ST (Chapter 3.2.2)

$Eq.(3.44-3.47),\ (3.71-3.80)$ – energy-awareness extension with improved event binaries model (Chapter 3.2.3.3) with new sets M and ST

$Eq.(3.99-3.102)$ – load deviation problem (Chapter 3.2.4.2)

$Cuts$ – new constraints for other internal bi-level heuristic iteration than initial (Chapter 3.4.4)

Similarly as for the monolithic bi-level heuristic the above models (4.55) and (4.56) have no stages $st2, st3$ (AOD and LF process steps) included. The parameters of maximum hold-up time and minimum transportation time are augmented as previously described in Chapter 3.4.2. The upper level problem for the case study in Chapter 3.5 was solved using a computational time limitation of 120s, therefore in the MVCD scheme the same strategy is followed in an attempt to fairly compare the models. Similar as before, the results of the approximated $UL1$ model are used to fix some binary variables in the full space problem LL to obtain a feasible schedule. This is done exactly in the same way as before (assignment, sequence and event start), as described in Chapter 3.4. The model (LL) is formulated following the Dantzig-Wolfe partial sub-problem as well, with modified objective function and eliminated flow network constraints:

$$\min_{LL-EPS(\overline{MC_s})}(\delta + c \cdot \sum_{p\in P, m\in M} t^s_{p,m} + \sum_{s\in S} q_s \cdot \overline{MC_s}) \tag{4.57}$$

subject to:

$Eq.(3.1-3.16)$ – scheduling model equations (Chapter 3.2.2)

$Eq.(3.44-3.47),\ (3.71-3.80)$ – energy-awareness extension with improved event binaries model (Chapter 3.2.3.3)

$Eq.(3.99-3.102)$ – load deviation problem (Chapter 3.2.4.2)

The results of the above formulated problem LL are used as an input to the problem $UL2$ which aims at finding a better assignment on EAF stage, while keeping all the sequences and event start binary variables fixed to the values obtained from LL, exactly as described previously in Chapter 3.4.3 - 3.4.4 with the dual information in the objective function similarly as in (4.57).

The internal loop of the bi-level heuristic iterates between the models $UL1$, LL and $UL2$ until the time limitation of 180s is reached, since in this case there is no indication of optimality as a stopping criterion - similarly as for the case of the bi-level heuristic use for the monolithic model. The internal loop time limitation should allow for making few iterations of the bi-level heuristic within the global stopping criterion of the total global computational time limit of the entire algorithm. After the computation limit for the internal loop has been reached, the best iteration (minimal objective function value of $UL2$) is chosen to get the schedule's solution and its corresponding load curve which is next fed to the flow network problem (4.53) to start a new iteration of the outer loop. In order to fairly compare the entire algorithm with the monolithic bi-level approach, the total computational time limit is set to 600s. Since the flow network problem is solvable in seconds, the total time limitation allows for performing around 2 - 4 outer iterations between the MVCD's partial sub-problems.

4.4.1.2. Bi-level heuristic with dual information at the upper level

The second approach differs in the way the internal loop iterates. When investigating more closely the nature of the bi-level heuristic, it can be noted that the upper level problem $UL1$ serves basically as an indicator of the direction of where it is worth looking for the optimal solutions of the monolithic problem. The remaining problems at lower level LL and upper level $UP2$ are only evaluating and refining the proposed guesses provided by $UP1$. Following this idea, another structure of the bi-level heuristic integration with Mean Value Cross Decomposition concept can be formulated as shown in Figure 4-33. The algorithm starts with solving the initialization step similarly as in the previous integration approach (4.55). The resulting load curve is used in Benders' partial sub-problem (4.53) which gives the first Marginal Cost curve needed in the Dantzig-Wolfe's partial sub-problem.

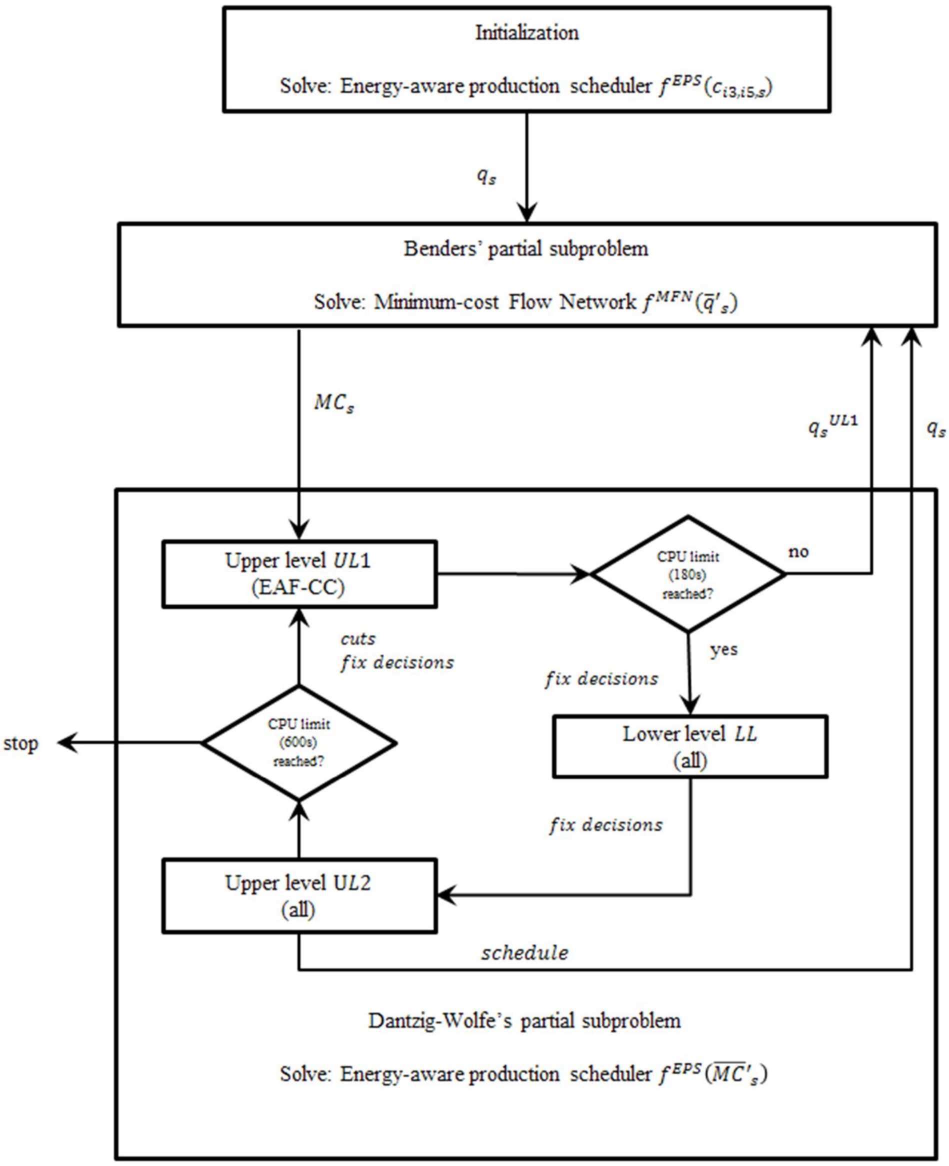


Figure 4-33 Bi-level heuristic with dual information at the upper level with rough scheduler

In this approach, the upper level model $UL1$ is formulated exactly in the same way as in the previous integration (4.56). The difference is in the iteration scheme of the inner loop. Here, the

$UL1$ problem iterates with the flow network problem and exchanges the signals. Again, a time limitation of 120s is enforced for the $UL1$ model and 180s for the total time spent on iterating between the $UL1$ and the flow network model. This allows for performing a few iterations and the best result (minimum objective function value of $UL1$) is taken into consideration when fixing the decisions for the subsequently solved LL problem. Here, the LL model formulation differs from the other integration case and follows the original bi-level heuristic – does not include the Marginal Cost curve in the objective function:

$$\min_{LL-EPS}(\delta + c \cdot \sum_{p\in P, m\in M} t_{p,m}^{s}) \qquad (4.58)$$

subject to:

$Eq. (3.1 - 3.16)$ – scheduling model equations (Chapter 3.2.2)

$Eq. (3.44 - 3.47),\ (3.71 - 3.80)$ – energy-awareness extension with improved event binaries model (Chapter 3.2.3.3)

$Eq. (3.99 - 3.102)$ – load deviation problem (Chapter 3.2.4.2)

The decisions to be fixed in LL are the same as in the other integration case and the same as in the monolithic bi-level heuristic in Chapter 3.4.3 (assignment, sequence, event binary start). Next, again the $UL2$ model is solved with all binaries fixed except of the EAF assignment in order to get the final schedule with a load curve. The latter is then used as an input to solve the flow network problem and the new iteration of the outer loop starts. The outer loop is allowed to iterate for the total time of 600s, for comparison reasons, similarly as in the other integration case and original monolithic bi-level heuristic study.

It is important to note that, compared to the previous approach, here the flow network problem (4.53) is solved using two different load curves, one rough load curve coming from the $UP1$ problem (internal iteration) and the other one coming from a full schedule solution of $UP2$ problem (outer iteration). In this way, potentially two different load curves are evaluated by the flow network to give the dual information signal which is later used in the $UP1$ problem.

4.4.2 Industrial case study setup

The case study is designed such that for each different integration approach there are four problem instances tested which are the same instances and input data as in the original bi-level heuristic formulated on the corresponding monolithic model in Chapter 3.3. Furthermore, as shown for the TMP case, different signal updating schemes can be used in the two integration cases. For the case study, the two best performing updating schemes from the TMP case are taken, namely One-sided Weighted Mean Value and Heuristic (direct signals) Cross Decomposition. For the Weighted Mean calculations, the option found to be better performing for the TMP case (option 2 – Eq. 4.2) is chosen. The experiments are summarized in Figure 4-34.

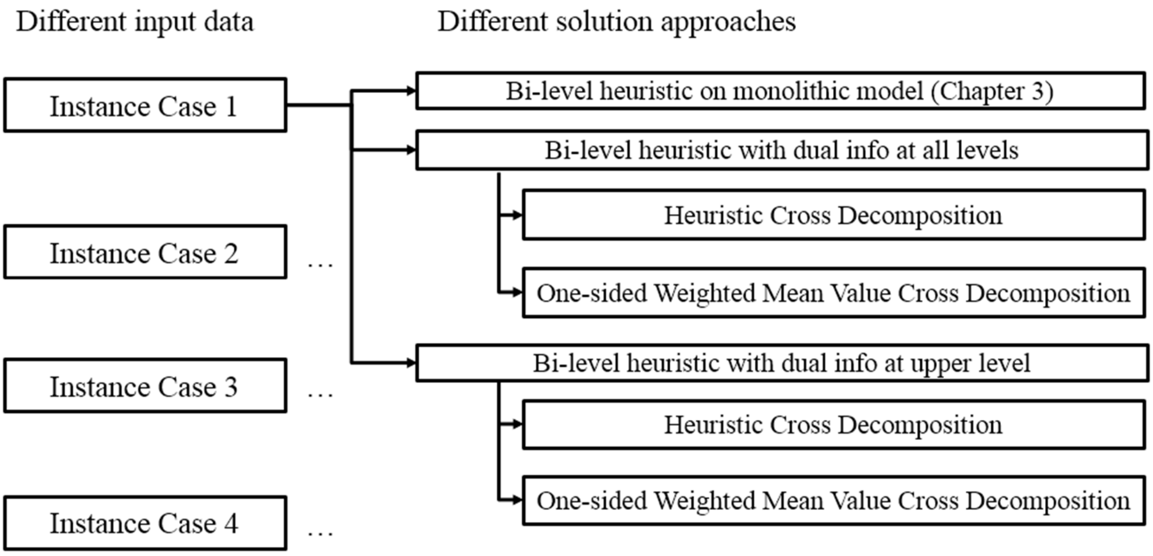


Figure 4-34 Structure of the steel case study experiments with Cross Decompositions

The overview of the basic information regarding the problem instances is given in Table 4-15. For comparison reasons, the results of the model BR are reported again. The detailed information with regard to the input data and differences between the instances is given in Appendix A and Chapter 3.5.

Table 4-15 Investigated problem instances for Cross Decomposition on the steel case

Scenario	Horizon	Products	Electricity sources and sinks
1	24 h	20	all possible, day-ahead with high prices (France 2012)
2	24 h	20	all possible, day-ahead with low prices (Germany/Austria 2013)
3	24 h	16	all possible, day-ahead with high prices (France 2012)
4	24 h	16	all possible, day-ahead with high prices (France 2012), overcommitted pre-agreed load curve (as for 20 products)

Name	Model type
BR	Bi-level heuristic using improved event binaries model (Hadera et al. 2016)
DH	Bi-level heuristic with Marginal Cost curve at all levels and Heuristic Cross Decomposition (direct signals)
DO	Bi-level heuristic with Marginal Cost curve at all levels and One-sided Weighted Mean Value Cross Decomposition
WH	Bi-level heuristic with Marginal Cost curve only in $UL1$ and Heuristic Cross Decomposition (direct signals)
WO	Bi-level heuristic with Marginal Cost curve only in $UL1$ and One-sided Weighted Mean Value Cross Decomposition

4.4.3 Case study results and discussion

The two investigated integration options were tested with the same problem instances as the original bi-level heuristic for the monolithic problem. Also the total computational time is limited to 600s. All the test problems have been solved using GAMS/CPLEX 24.0.2 and a Personal Computer with Intel® Core™ i5-2450M CPU @ 2.50 GHz and 4 GB RAM.

In Table 4-16 the model statistics are reported on all investigated models. The Marginal Cost component indicates the objective function value of the additional component due to the dual information – load q_s multiplied by the dual variable MC'_s. To complete the results the corresponding best iteration results with economic assessment are shown in Table 4-17. Here the decomposition approaches are also compared with the best performing bi-level heuristic applied on the monolithic model (models BR1-4) as reported earlier in Chapter 3.5.

When comparing the relative gap of the solutions provided by the heuristic approach with direct signals (DH or WH) against One-sided Weighted Mean approach (DO or WO) it can be seen that both provide almost identical solutions. Only in scenario DH4 the solution without changing the signals performed slightly better than DO4. Nearly for all of the cases not only the gap, but also the solution structure such as the economic assessment values is very similar. The reason behind it is that the difference between the two approaches in signal augmentation in the MC signal is not significant enough to result in two very different schedules, especially since the scheduling problem is strongly constrained and the flexibility in the process itself does not permit very different load curves (schedules).

For both signal exchange schemes DH-DO (or WH-WO) the total number of iterations within 600s was similar and the best solution was found usually in 1-4 iterations of the algorithm. It is also important to note that the approach using the MC only at the upper level (WH and WO) usually performs more iterations with Benders' sub-problem. When comparing the relative gap of both approaches to the results obtained from applying the bi-level heuristic (BR) directly to the monolithic model (results reported in Chapter 3.5) it can be noted that the Mean Value Cross Decomposition approaches yield similar results. The impact on the quality of the solutions is not only due to efficiency of the MVCD itself, but also depends very much on how well the upper level problem approximates the full space problem. Therefore, even assuming that the MC signal is perfect and is able to provide very good direction on how to change the schedule such that it converges to the optimal solution some error can still be present (solution gap) due to the heuristic nature of the bi-level algorithm.

It cannot be clearly stated that one of the approaches is best, however as previously investigated the One-Sided Mean Value Cross Decomposition (DO and WO) should be a better choice than the heuristic variations of Cross Decomposition using direct signals. This due to the risk of the oscillation between two similar solutions between Benders' sub-problem and the bi-level heuristic. The option with dual information at the upper level only is probably a more interesting choice than the other scheme since it enables a more intensive information exchange with Bender's sub-problem, which in principle should be advantageous, especially since the nature of the Mean Value Cross Decomposition concepts for convex problems are such that they require a large number of iterations to converge to optimality (Holmberg and Kiwiel 2006).

Table 4-16 Model statistics of bi-level heuristic with MVCD integration

Scenario	Model statistics																	
	Scheduler												MC component			Flow network		
	Binary vars			Total vars			Equations			Total objective (MIP solution)						Binary vars	Total vars	Equations
	UL1	LL	UL2	UL1	LL	UL2	UL1	LL	UL2	UL1	LL	UL2	UL1	LL	UL2			
DH1 DO1	1689	2668	1434	5084	10044	10044	34881	70451	70431	256255	193639	193600	404230	430529	430471	24	265	305
WH1 WO1	1669	3334	1434	5104	10044	10044	34902	70451	70431	514613	46000	46000	404230	-	-	24	265	305
DH2 DO2	1669	3334	1434	5104	10044	10044	34895	70451	70431	170612	165426	165426	93648	92249	92249	24	265	305
WH2 WO2	1669	3334	1434	5104	10044	10044	34923	70451	70431	144616	45773	45773	93648	-	-	24	265	305
DH3	1445	2344	1252	3964	7804	7804	27272	54960	54944	174692	178641	178236	352655	364498	364852	24	265	305
DO3	1445	2344	1252	3964	7804	7804	27272	54960	54944	174546	178704	178288	352655	364293	364657	24	265	305
WH3 WO3	1445	2344	1252	3964	7804	7804	27272	54960	54944	435290	72970	72702	352655	-	-	24	265	305
DH4 DO4	765	1558	706	2302	4510	4510	14137	28495	28483	208602	200277	200274	-203627	-213417	-213425	18	199	227
WH4 WO4	765	1558	706	2314	4510	4510	14151	28495	28483	-114823	107340	107275	-228444	-	-	18	199	227

Table 4-17 Results assessment of bi-level heuristic with MVCD integration

Scenario	Iteration results				Economic assessment							
	Total cost - best solution	Relative gap	No. of iterations	Best Iteration	Lead times [min]	Net cost [€]	Electricity purchase [€]	Deviation penalties [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sale [MWh]
BR1	193667	9,30%	5	3	46470	146315	157131	1047	180,030	1457,367	952,000	677,730
DH1 DO1	193915	9,31%	3	1	46919	145890	157329	1106	184,117	1455,375	952,000	679,525
WH1 WO1	197338	9,47%	10	4	45658	151338	156032	342	166,767	1457,033	952,000	663,833
BR2	165196	7,23%	5	4	45641	119489	99114	273	1508,583	159,833	432,000	188,750
DH2 DO2	165428	7,24%	3	1	45460	119646	104196	323	1516,107	233,700	352,000	189,840
WH2 WO2	165238	7,23%	10	7	45474	119465	103998	299	1520,113	229,217	352,000	189,363
BR3	134578	9,87%	5	1	30893	102888	134133	811	133,900	1243,567	952,000	944,133
DH3	134699	9,88%	3	1	30975	102888	134221	836	134,300	1243,767	952,000	944,133
DO3	134664	9,88%	3	1	30973	102849	134179	841	134,059	1243,767	952,000	943,892
WH3 WO3	136855	10,04%	5	1	30369	106486	133969	0	132,867	1243,767	952,000	942,700
BR4	173873	8,61%	5	3	31988	99814	126178	42071	79,792	1228,357	952,000	874,815
DH4	174908	8,66%	3	1	32034	98636	128302	44238	83,437	1251,665	952,000	901,269
DO4	175648	8,69%	3	1	31509	98191	129327	45948	90,192	1250,081	952,000	906,340
WH4 WO4	176148	8,72%	3	1	36116	105167	129283	34865	15,984	1271,913	952,000	854,164

To sum up, the following conclusions can be drawn concerning different Mean Value Cross Decomposition variations and the bi-level heuristic integration options:

- Best approach: both One-sided Weighted Mean Value Cross Decomposition (OWMVCD) and Heuristic Cross Decomposition gave very similar results. Also, the two different options of integration do not differ much in the solution quality for the investigated instances. The option with dual information at the upper level only allows for performing a higher number of iterations;
- Stopping criteria: for all of the investigated approaches there are no clear stopping criteria for the algorithm since there is no convergence test that could be performed. Therefore, the stopping criteria should follow the same criteria as for solving the original bi-level heuristic on the monolithic problem – computational time limit;
- Optimality: when solving MILP models using any of the investigated approaches there is no guarantee that the algorithm will converge. When applying the MVCD decomposition concept to the bi-level strategy, the algorithm can yield as good solutions as good the upper level problem is in approximating the original full space problem. This is similar to the bi-level approach applied on the monolithic problem (Chapter 3.5);
- Controllability: for all of the investigated approaches there is no guarantee to improve the solution with each iteration of the algorithm;
- Computation time: all of the investigated variations obtained satisfactory results within the computational time, giving the best solution in similar time ranges.

The most important conclusion is that the investigated instances show that the decomposition scheme is useful for obtaining satisfactory quality solutions while solving functionally separated problems of the process scheduling and energy-cost optimization.

5 CONCLUSIONS

The goal of this work was to develop and to test two approaches: a monolithic formulation and a concept for functional decomposition of process scheduling and energy cost optimization. The work specifically aimed to tackle the continuous-time precedence-based steel scheduling problem with energy-cost optimization. Another industrial process considered was Thermo-Mechanical Pulping for which the resulting scheduling problem was modeled using RTN approach. This served as a test case for showing convergence behavior and different functional decomposition variations based on Mean Value Cross Decomposition. The integration of production scheduling and energy cost optimization using both strategies – monolithic and functionally decomposed – leads to the following conclusions:

- an energy-intensive industry may exploit energy-aware scheduling models to reduce the operating cost and achieve system-wide optimality of combined energy- and production-specific cost;
- continuous-time general precedence scheduling problems, which benefit from exactness, can be extended to account for use of energy resources which allows for further optimization of energy-related cost;
- since the optimization of multiple energy contracts is done using a generic and theoretically well-defined Minimum-Cost Flow Network concept it has the potential to accommodate various real-life purchase-and sales structures, while still keeping the functional decomposition concept valid;
- the load deviation problem and the optimization of multiple energy contracts can be included in both continuous- and discrete-time scheduling approaches in order to support the assessment of different price levels of the negotiated contracts, as well as to reduce the risk associated with volatile electricity markets;
- the developed bi-level heuristic provides satisfactory solutions within reasonable solution times when solving large-scale problems; the quality of the solutions from the bi-level heuristic depends on how closely the simplified model at the upper level approximates the original monolithic problem;
- the generic flow network for handling the optimization of energy purchase and sales can provide useful information of the marginal cost, which can be used for functional separation of the process scheduling from the energy cost optimization and it is easy to interpret;
- the Thermo-Mechanical Pulping process may benefit from the functional separation by Mean Value Cross Decomposition to achieve system-wide optimal (or close to optimal) solutions while keeping the scheduling solution separated from the flow network problem which brings specific advantages from the industrial point of view;

- the bi-level heuristic can be exploited in order to solve the energy-aware scheduling problem applying the Mean Value Cross Decomposition, while keeping the scheduling separated from the flow network problem, and achieve solutions of comparable quality than the bi-level heuristic applied on the monolithic problem.

The functional decomposition concept has great potential within the energy-intensive industries since it allows to exploit potentially existing scheduling and energy-cost optimization solutions without integrating them into one monolithic problem. Such an approach increases the modularity of the installed solutions and they may be provided by different technology vendors.

5.1 Limitations of the developed concepts

It is important to note that there are many uncertainties in the potential integration of the production scheduling and energy-cost optimization. The work presented here is a research investigation, thus some assumptions were necessary to simplify the complexity of the real-world problem. Some of the important limitations of this study include:

- deterministic nature of the data and problem formulation
    - the plant needs to make commitments on the amounts of electricity to be bought and sold on the day-ahead markets, therefore the simplification is made throughout the dissertation that the price of electricity on the day-ahead market is known – this might have an impact on the final schedule usefulness in practice;
    - important factors are disturbances and the technical capability to realize the optimized schedule exactly, this might have a significant impact on the schedule's potential benefits of iDSR;
- computational performance limitations
    - the bi-level heuristic cannot yet solve very large problem instances in realistic computation times, such as for example a one week horizon;
    - the functional decomposition requires a number of iterations between the scheduler and the energy cost flow network optimizer, which might increase the total time spent on computation compared to monolithic approaches;
- controllability of the solution algorithms
    - the bi-level heuristic does not provide a systematic improvement of the solution in each iteration due to not using a relaxation at the upper level;
    - when the one-sided version of the Mean Value Cross Decomposition is used there are no proven convergence properties, therefore no guarantee of optimal or close to optimal solutions can be provided;
    - if the Mean Value Cross Decomposition scheme is used, the solution might not obtain the optimal values due to the duality gap present in the Lagrangean relaxation;
    - when the bi-level heuristic is applied to the functional decomposition scheme, it can be expected that both methods, which do not provide optimality by themselves, could amplify the error thus resulting in unsatisfactory solutions;
- applicability and generic nature of the solutions
    - the bi-level heuristic is a tailor-made method to solve a particular scheduling problem and even though the resource energy could be replaced by a number of other types of resources, the generic nature of this solution method is questionable;

- the functional decomposition scheme is dependent on the problem nature and the identified special structure: the scheduler responds to one single energy-price curve and energy-cost optimizer provides the dual information based on the assumption of the consensus constraint (that the process load is equal to the demand in the flow network). Although the resource directive of the decomposition methods seems to be very generic, it is difficult to predict how the heuristic method would behave for very different scheduling problems.

In consequence, not taking into account many of the above mentioned unknowns and circumstances could have an impact on the potential advantages of the developed concepts. Therefore, further investigation of the main limitations as discussed in the next chapter could strengthen the main conclusions drawn from this work.

5.2 Recommendations for future work

The research and findings drawn from this work lay out a potential base for the future industrial implementation of the main concepts studied here. In general, it would be interesting to expand the frames of the functional decomposition as well as to improve the bi-level heuristic approach. Therefore, further investigations could be related to the following:

- bi-level heuristic and the steel case
  - to improve the quality of the heuristic solutions, a better approximation at the upper level problem could be found, ideally such that it would provide systematically a valid lower bound which would improve with each iteration of the algorithm;
  - to address further the computational limitations of the steel problem for larger instances. A scheduling horizon of several days could be investigated with a rolling horizon approach, here decisions for longer time windows should be done with higher level short- and long-term planning solutions taking into account different factors than those considered by the scheduling level;
- generic energy-awareness and cost optimization
  - the flow network can be extended to other energy resources as for example gas or steam which would open up the possibility to coordinate production processes involving both the use and production of steam (or other resources) as a subject of optimization;
  - to address the computational performance of the energy-awareness extensions for general precedence continuous-time models, potentially even tighter energy-awareness strategies could be developed, which use less equations and less variables in order to lower the computational burden especially related to the event binaries;
- functional decomposition concept
  - an efficient feasibility constructor for the One-sided Mean Value Cross Decomposition could be investigated based on a Mean Value Cross Decomposition that exploits proven MVCD convergence properties and at the same time obtaining feasible solutions with OSWMVCD;
  - exploit further theoretical convergence conditions for the investigated One-sided Weighted Mean Value Cross Decomposition to see under what conditions it could converge similarly to the MVCD;

    - a deeper sensitivity information study for the particular formulation of the flow network problem of energy purchase and sales optimization could explain how useful the dual information of the complicating constraint is;
- uncertainty and disturbances
    - address uncertainty of the energy prices as well as potential effect of the process disturbances by introducing robust optimization approaches, especially at the upper level problem of the bi-level heuristic;
- industrial implementation
    - the improved energy-awareness formulation could be used to expand already installed general precedence based continuous-time scheduling solutions, eg in the case that already has been reported for the stainless-steel manufacturer ThyssenKrupp-AST (Gajic et al. 2014; Harjunkoski et al. 2015);
    - a possible extension of the functional decomposition would be to apply the suggested framework in a multiple mill production planning environment, where energy purchase takes place in a centralized center. The center would act as a price coordinator using the internal electricity price i.e. marginal costs, and the mill side would return their load demands back to the centralized center for global purchasing (price/resource competition).

Another line of further research concerns the developed decomposition concept and the flexibility of the resource driven directive. The electricity resource used in the scheduling model and the electricity-cost optimization in the other model can be easily exchanged with other types of resources. It could be related for example to equipment wear-off and maintenance issues or raw material consumption (e.g. chemical compounds, water, steam etc.). It might also be possible to include several different resources in one optimization model which would penalize the corresponding marginal cost in the objective function of the scheduling problem in order to approach system-wide optimal solution.

More detailed and problem-specific studies will lead to a faster market introduction of the promising concepts that were developed in this work.

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APPENDIX A

Input data for continuous-time monolithic models case study

Following the Demand Response strategy the plant has the goal of delivering a fixed number of heats (products) within a scheduling horizon of 24 h. Due to the continuous casting requirement, products are divided within heat groups as defined in Table A-1.

Table A-1 Heat group definition

Group	Heat (product)
HG1	P1-P3
HG2	P4-P7
HG3	P8-P12
HG4	P13-P16
HG5	P17-P20

For the test cases with fewer products the last heats were excluded respectively to the total number of heats in a given problem instance. Processing times and specific electricity consumption of the tasks are given in Table A-2, while setup times are reported in Table A-3. Minimum transportation times and maximum waiting (hold-up) times after processing on a given stage are shown in Table A-4 and Table A-5 respectively.

Table A-2 Processing times and electricity consumption

	EAF1, EAF2	AOD1, AOD2	LF1, LF2	CC1, CC2
P1-P20	85 [min]	8 [min]	45 [min]	60 [min]
	85 [MW]	2 [MW]	2 [MW]	7 [MW]

Table A-3 Setup times [min]

Machine	Setup time	Machine	Setup time
EAF1, EAF2	9	LF2	5
AOD1, AOD2	5	CC1	50
LF1	15	CC2	70

Table A-4 Transportation times [min]

	AOD1	AOD2	LF1	LF2	CC1	CC2
EAF1	10	25				
EAF2	25	10				
AOD1			4	20		
AOD2			20	4		
LF1					20	45
LF2					45	20

Table A-5 Hold-up time between stages [min]

	ST1	ST2	ST3
P1-P20	60	90	60

The input data concerning the electricity purchase limits is shown in Figure A-1. Note that the capacity of the onsite generation node denotes the power plant capacity.

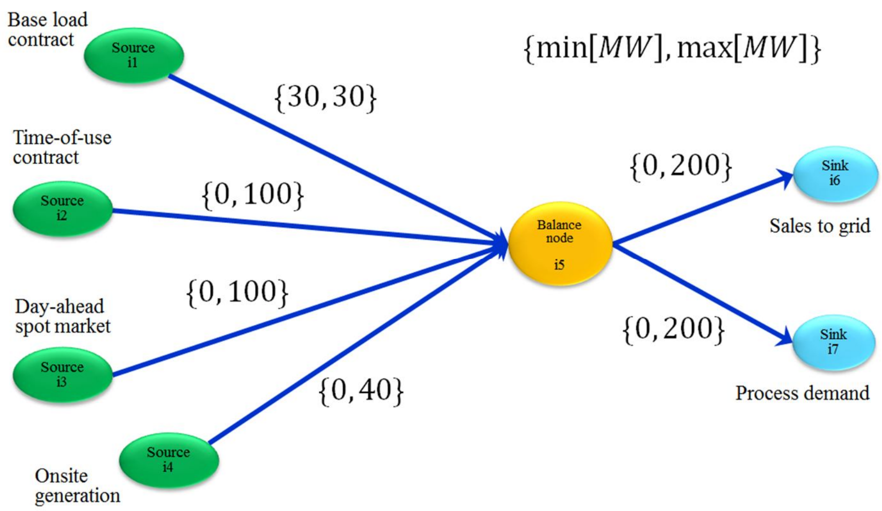

Figure A-1 Bounds for flows in the purchase flow network

Note that the base load contract has a fixed amount of delivery for each hour of the day, regardless whether the electricity is needed for the production process or not. The prices of electricity and committed load curve are shown in Table A-6 and Table A-7. The electricity prices of both day-ahead contract cases, low price (EPEX 2013, Germany/Austria 23/09/2013) and high price (EPEX 2013, France 10/02/2012) are taken from a real spot market. The pre-agreed load curve comes from a valid production schedule which considers no energy cost in the optimization, but in our case only the lead times optimization ($c \cdot \sum_{m \in M, p \in P} t^{s}_{m,p}$). This follows the previous studies (Castro et al. 2013) where the schedule with optimized production-specific cost (makespan) served as a basis for the comparison with energy-driven schedule to assess the iDSM benefits.

Table A-6 Electricity prices for case studies

Time interval	Base load prices [€]	Day-ahead high prices [€]	Day-ahead low prices [€]	TOU [€]
s1	52	95	12,0	65
s2	52	113	13,1	65
s3	52	90	9,8	65
s4	52	75	9,8	65
s5	52	61	11,5	65
s6	52	85	18,8	65
s7	52	140	39,1	65
s8	52	186	57,9	65
s9	52	176	62,7	65
s10	52	605	61,0	65
s11	52	431	56,1	65
s12	52	177	50,7	65
s13	52	146	42,6	90
s14	52	100	38,8	90
s15	52	100	33,0	90
s16	52	83	35,1	90
s17	52	73	40,5	90
s18	52	110	49,5	90
s19	52	162	59,9	90
s20	52	143	67,5	90
s21	52	117	61,4	90
s22	52	84	48,5	90
s23	52	94	39,9	90
s24	52	87	31,5	90

We assume that the income from selling back electricity to the grid are also time sensitive and are equal to 75% of the cost of a day-ahead market in the same time slot. The cost of onsite generation and other related parameters are shown Table A-8. The allowed buffer for over- and under-consumption can be found in Table A-9, together with other load-deviation problem related parameters.

Table A-7 Pre-agreed load curve for the steel process

Time interval	Load curve Scenario 1, 2, 4 [MWh]	Load curve Scenario 3 [MWh]
s1	170	170
s2	146,17	144,5
s3	170,87	167,16
s4	153,57	147,33
s5	156,03	151,03
s6	182,2	177
s7	162,77	154,18
s8	155,77	151,967
s9	183,37	177
s10	157,7	156,167
s11	157,9	155,817
s12	182,33	177
s13	156,47	72,16
s14	174,33	7,81
s15	169,12	9,33
s16	99,9	7
s17	18,15	7
s18	15,73	6,18
s19	10,32	0
s20	7	0
s21	1,98	0
s22	0	0
s23	0	0
s24	0	0

Table A-8 Onsite generation parameters

Cost of onsite generation [€/MWh]	61
Minimum run of onsite [h]	3
Minimum down time [h]	3
Start-up cost [€]	1000
Reduced production rate due to start-up	20%

Table A-9 Load deviation problem parameters

Over-consumption penalty [€/MWh]	100
Under-consumption penalty [€/MWh]	80
Buffer for over-consumption	3%
Buffer for under-consumption	4%

Input data for bi-level decomposition case study

The new maximum waiting times and minimum transportation times of the upper level $UL1$ that were calculated using Equations (62-63) are shown in Table A-10 and Table A-11.

Table A-10 Upper level $UL1$ problem maximum waiting times

	ST1	ST2
P1-P20	161	90

Table A-11 Upper level $UL1$ problem minimum transportation times

	CC1	CC2
EAF1	155	161
EAF2	161	155

The committed load curve for the upper level problem $UL1$ modified by considering the lower consumption due to omitting the AOD and LF stages is shown in Table A-12.

Table A-12 Pre-agreed load curve for the upper level $UL1$ problem

Time interval	Load curve UL1 Scenario 1, 2, 4 [MWh]	Load curve UL1 Scenario 3 [MWh]
s1	170	170
s2	144,5	144,5
s3	167,17	167,167
s4	147,33	147,33
s5	151,03	151,03
s6	177	177
s7	157,1	154,183
s8	151,97	151,96
s9	177	177
s10	153,37	156,167
s11	152,9	155,817
s12	177	177
s13	151,5	72,167
s14	168,5	7,817
s15	163,15	9,333
s16	94,83	7
s17	12,02	7
s18	14	6,183
s19	8,98	0
s20	7,00	0
s21	1,98	0
s22	0	0
s23	0	0
s24	0	0

APPENDIX B

Algorithm for finding start time variable bounds

Table B-1 Algorithm details

The lower and upper bound of $t_{p,st}^{s}$

initialize $t_{p,st}^{s,min} = t_{p,st}^{s,max} = 0$

for $st = st_4, hg \in HG, p \in F(HG, P)$ do

set $t_{p,st}^{s,min} = \begin{cases} \min(t_{p,st}^{s}) \\ s.t. \\ Scheduler\ constraints \end{cases}$

set $t_{p,st}^{s,max} = \begin{cases} \max(t_{p,st}^{s}) \\ s.t. \\ Scheduler\ constraints \end{cases}$

end for

Find the bounds of the other products at the last stage

for $st = st_4, hg \in HG, p \in P/F(HG, P)$ do

for $p \in F(HG, P) + 1, \ldots, p \in L(HG, P)$ do

$t_{p,st}^{s,min} = t_{p-1,st}^{s,min} + \min_{m \in SM(st,m)} \tau_{p-1,m}$

$t_{p,st}^{s,max} = t_{p-1,st}^{s,max} + \max_{m \in SM(st,m)} \tau_{p-1,m}$

end for

end for

Set the upper bound in the other stages as equal to the upper bound at the last stage

$t_{p,st}^{s,max} = t_{p,st4}^{s,min} \; \forall p \in P, st \in ST$

Find the upper bound in stages other than last stage

for $st \in st_4, \ldots, st_2, P \in P$ do

for $st' = st - 1$ do

$t_{p,st'}^{s,max} = t_{p,st}^{s,max} - \min_{m \in SM(st',m)} \tau_{p,m} - \min_{m \in SM(st,m), m' \in SM(st',m')} \; t_{m,m'}^{min},$

end for

end for

Find the lower bound in stages 1-3

for $st \in st_1, \ldots, st_3, P \in P$ do

for $st' = st + 1$ do

$t^{s,min}_{p,st'} = t^{s,min}_{p,st} + \min_{m \in SM(st',m)} \tau_{p,m} + \min_{m \in SM(st,m), m' \in SM(st',m')} t^{min}_{m,m'}$,

end for

end for

APPENDIX C

Input data for Thermo-Mechanical Pulping case study

The main sources for the input data for the TMP scheduling are the two studies, Karagiannopoulos et al. (2014), Pulkkinen and Ritala (2008) and also results from discussions with industrial experts. Since the purchase network assumed for the case study is the same as for the steel case the prices also remain the same, i.e. as in Appendix A, unless otherwise stated. The flow cost of selling electricity back to the grid is set here to be equal to the day-ahead prices. The only exception is Scenario 4 where there is no revenue for selling accounted ($c_{i5,j6,t} = 0, \forall t \in T$), the base load contract is not anymore a constant delivery of electricity (lower bound of the flow is zero: $f_{i1,j5,t}^{LO} = 0$) and there are no deviation penalties. The demand curve for final pulp product is deterministic, one day curve shown in Table C-1 is copied through the entire scheduling horizon as many times as required problem instance horizon.

Table C-1 Demand curve for final pulp product

Time slot	Demand [m^3/h]	Demand high [m^3/h]
t1	50	100
t2	90	180
t3	80	160
t4	165	330
t5	40	80
t6	80	160
t7	60	120
t8	40	80
t9	40	80
t10	165	330
t11	50	100
t12	40	80
t13	90	180
t14	160	320
t15	40	80
t16	50	100
t17	160	320
t18	150	300
t19	55	110
t20	40	80
t21	110	220
t22	50	100
t23	230	360
t24	50	100

The pre-agreed load curve as an input for the load deviation optimization is shown in Table C-2.

Table C-2 Pre-agreed load curve for the TMP process

Time slot	Pre-agreed load curve [MWh]
t1	20
t2	35
t3	31
t4	65
t5	16
t6	31
t7	24
t8	16
t9	16
t10	65
t11	20
t12	16
t13	35
t14	63
t15	16
t16	20
t17	63
t18	59
t19	22
t20	16
t21	43
t22	20
t23	90
t24	20

The parameters for the other energy-related cost and contracts which are changed compared to the input parameters reported for the steel case are shown in Table C-3.

Table C-3 Energy-cost related parameters changed

Upper limit of the base-load contract [MWh]	15
Lower limit of the base-load contract [MWh] for Scenario 4	0
Upper limit of sale [MWh]	100
Onsite generation start-up cost [€]	40
Buffer for over-consumption	0,05
Buffer for under-consumption	0,05

The input parameters of the scheduling problem are presented in Table C-4.

Table C-4 TMP scheduling model parameters

External pulp price [€/m^3]	50
External pulp price low [€/m^3]	5
Maximum amount of pulp that can be bought in one time slot [m^3]	200
Start-up cost of one refiner [€]	80
Shut-down cost of one refiner [€]	50
Volume of preparation tank at start of time horizon [m^3]	250
Production rate of one refiner [m^3/h]	30
Power consumption of one refiner [MW]	11
Maximum volume of the storage tank [m^3]	500
Minimum volume of the storage tank [m^3]	50

APPENDIX D

TMP case study results of Cross Decomposition

Table D-1 CRTN-opt2: Iteration results for Scenario 1

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	51858	167797,69	198330,59	21877,85	0,602	0,529	1,342	0,509	0%	0%	0%	0%
2	51728	167909,20	197751,35	21901,85	0,625	0,577	1,132	0,620	0%	0%	0%	0%
3	51728	167909,20	197733,75	21905,85	0,554	0,557	1,209	0,529	0%	0%	0%	0%
4	51728	167909,20	197730,82	21906,99	0,635	0,600	1,316	0,655	0%	0%	0%	0%
5	51728	167909,20	197729,98	21907,42	0,720	0,601	1,192	0,922	0%	0%	0%	0%
6	51728	167909,20	197729,66	21907,61	0,637	0,634	1,126	0,558	0%	0%	0%	0%
7	51728	167909,20	197729,52	21907,71	0,637	0,576	1,142	0,628	0%	0%	0%	0%
8	51728	167909,20	197729,45	21907,76	0,637	0,574	1,397	0,624	0%	0%	0%	0%
9	51728	167909,20	197729,42	21907,79	0,638	0,681	1,199	0,598	0%	0%	0%	0%
10	51728	167909,20	197729,39	21907,81	0,826	0,558	1,318	0,562	0%	0%	0%	0%
11	51728	167909,20	197729,38	21907,82	0,653	0,564	1,282	0,624	0%	0%	0%	0%
12	51728	167909,20	197729,37	21907,83	0,654	0,588	1,293	0,661	0%	0%	0%	0%
13..30	51728	167909,20	197729,37	21907,83	0,646	0,668	1,239	0,630	0%	0%	0%	0%

Table D-2 CRTN-opt2: Model results for Scenario 1

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	167798	280611	50886	34360	5100	225	560	796	3817	250	38578	13030	10410	5	219655,69	219629,20
2	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219635,60
3	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219636,67
4	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219636,97
5	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,09
6	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,14
7	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,16
8	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,18
9	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,18
10	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
11	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
12	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
13..30	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,20

Table D-3 CRTN-opt1: Iteration results for Scenario 4

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	10000	113414,95	123201,99	0	0,493	0,412	1,265	0,461	0%	0%	0%	0%
2	6750	116971,90	122524,34	0	0,474	0,460	46,433	0,365	0%	0%	0%	0%
3	6750	116971,90	122524,34	-1518,00	0,478	0,345	47,553	0,361	0%	0%	0%	0%
4	10000	113414,95	123201,99	-1951,71	0,562	0,459	1,419	0,376	0%	0%	0%	0%
5	10000	113414,95	123201,99	-975,86	0,571	0,455	1,506	0,454	0%	0%	0%	0%
6	10000	113414,95	123201,99	-542,14	0,491	0,456	1,952	0,422	0%	0%	0%	0%
7	10000	113414,95	123201,99	-325,29	0,531	0,474	12,350	0,537	0%	0%	0%	0%
8	6750	116971,90	123001,43	-207,00	0,515	0,507	50,796	0,438	0%	0%	0%	0%
9	6750	116971,90	122827,94	-897,00	0,521	0,358	48,832	0,411	0%	0%	0%	0%
10	10000	113414,95	123201,99	-1321,62	0,495	0,470	2,022	0,508	0%	0%	0%	0%
11	10000	113414,95	123201,99	-944,01	0,564	0,427	1,529	0,397	0%	0%	0%	0%
12	10000	113414,95	123201,99	-692,27	0,494	0,497	2,092	0,438	0%	0%	0%	0%
13	10000	113414,95	123201,99	-519,21	0,494	0,450	2,706	0,483	0%	0%	0%	0%
14	10000	113414,95	123201,99	-397,04	0,504	0,357	9,006	0,472	0%	0%	0%	0%
15	6750	116971,90	123106,67	-308,81	0,627	0,483	180,651	0,488	0%	0%	0,081%	0%
16	6750	116971,90	122977,26	-723,16	0,529	0,465	35,224	0,469	0%	0%	0%	0%
17	10000	113414,95	123201,99	-1033,93	0,625	0,461	2,897	0,478	0%	0%	0%	0%
18	10000	113414,95	123201,99	-836,99	0,632	0,458	1,971	0,569	0%	0%	0%	0%
19	10000	113414,95	123201,99	-684,81	0,622	0,452	2,283	0,461	0%	0%	0%	0%
20	10000	113414,95	123201,99	-565,71	0,631	0,448	2,697	0,471	0%	0%	0%	0%
21	10000	113414,95	123201,99	-471,43	0,632	0,554	4,040	0,529	0%	0%	0%	0%
22	9480	113766,34	123192,74	-396,00	0,635	0,445	4,199	0,670	0%	0%	0%	0%
23	6750	116971,90	123105,14	-335,08	0,812	0,633	180,550	0,491	0%	0%	0,012%	0%
24	6750	116971,90	123015,79	-622,77	0,624	0,447	85,185	0,462	0%	0%	0%	0%
25	10000	113414,95	123201,99	-859,09	0,589	0,475	3,329	0,550	0%	0%	0%	0%
26	10000	113414,95	123201,99	-740,59	0,600	0,469	2,347	0,464	0%	0%	0%	0%
27	10000	113414,95	123201,99	-641,85	0,635	0,547	2,723	0,467	0%	0%	0%	0%
28	10000	113414,95	123201,99	-559,03	0,636	0,453	3,100	0,520	0%	0%	0%	0%
29	10000	113414,95	123201,99	-489,15	0,632	0,554	5,061	0,496	0%	0%	0%	0%
30	9480	113766,34	123197,93	-429,86	0,628	0,447	116,633	0,513	0%	0%	0%	0%

Table D-4 CRTN-opt1: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122524,34
2	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122524,34
3	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	121683,99
4	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	121250,28
5	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122226,13
6	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122659,85
7	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122676,14
8	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122620,94
9	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122304,99
10	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	121880,37
11	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122257,98
12	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122509,72
13	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122682,78
14	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122709,63
15	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122668,45
16	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122478,83
17	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122168,06
18	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122365,00
19	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122517,18
20	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122636,28
21	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122721,31
22	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34	122709,14
23	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122680,71
24	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	122579,22
25	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122342,90
26	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122461,40
27	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122560,14
28	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122642,96
29	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122708,78
30	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34	122722,37

Table D-5 CRTN-opt1: Iteration results for Scenario 5

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	144316	470812,23	555446,50	61251,98	1,054	0,936	181,334	0,996	0%	0%	0,043%	0%
2	143926	471146,76	553796,78	61251,98	1,055	0,901	181,018	0,860	0%	0%	0,045%	0%
3	143926	471146,76	553796,78	61311,98	1,275	0,782	180,976	0,973	0%	0%	0,045%	0%
4	143926	471146,76	553752,78	61329,12	1,067	0,898	181,001	0,981	0%	0%	0,045%	0%
5	143926	471146,76	553740,21	61335,55	1,056	0,923	181,083	0,981	0%	0%	0,045%	0%
6	143926	471146,76	553735,49	61338,41	1,090	1,100	181,036	0,976	0%	0%	0,045%	0%
7	143926	471146,76	553733,40	61339,84	1,107	0,989	181,014	0,854	0%	0%	0,045%	0%
8	143926	471146,76	553732,35	61340,62	0,987	0,890	180,998	0,903	0%	0%	0,045%	0%
9	143926	471146,76	553731,78	61341,07	1,037	0,882	180,952	0,997	0%	0%	0,045%	0%
10	143926	471146,76	553731,45	61341,35	0,866	0,820	181,017	0,945	0%	0%	0,045%	0%
11	143926	471146,76	553731,24	61341,53	1,109	0,921	180,904	1,090	0%	0%	0,045%	0%
12	143926	471146,76	553731,11	61341,65	1,205	0,967	181,086	0,994	0%	0%	0,045%	0%
13	143926	471146,76	553731,02	61341,73	1,057	0,955	181,089	1,022	0%	0%	0,045%	0%
14	143926	471146,76	553730,96	61341,79	1,047	0,863	180,984	0,956	0%	0%	0,045%	0%
15	143926	471146,76	553730,92	61341,83	1,129	0,987	181,097	0,977	0%	0%	0,045%	0%
16	143926	471146,76	553730,89	61341,86	1,003	0,931	181,070	0,969	0%	0%	0,045%	0%
17	143926	471146,76	553730,87	61341,89	1,112	0,898	181,062	1,086	0%	0%	0,045%	0%
18	143926	471146,76	553730,85	61341,90	1,163	0,976	181,019	0,992	0%	0%	0,045%	0%
19	143926	471146,76	553730,84	61341,92	1,065	0,891	180,992	1,280	0%	0%	0,045%	0%
20	143926	471146,76	553730,83	61341,93	1,083	0,892	181,030	0,896	0%	0%	0,045%	0%
21	143926	471146,76	553730,82	61341,94	1,052	0,920	180,963	1,512	0%	0%	0,045%	0%
22	143926	471146,76	553730,81	61341,94	1,084	1,000	181,114	1,042	0%	0%	0,045%	0%
23	143926	471146,76	553730,81	61341,95	1,078	0,886	181,056	1,072	0%	0%	0,045%	0%
24	143926	471146,76	553730,80	61341,95	1,045	0,984	181,038	0,952	0%	0%	0,045%	0%
25	143926	471146,76	553730,80	61341,96	1,005	0,834	181,005	1,066	0%	0%	0,045%	0%
26	143926	471146,76	553730,80	61341,96	1,042	0,964	181,029	1,018	0%	0%	0,045%	0%
27..30	143926	471146,76	553730,79	61341,96	1,065	1,005	181,040	1,117	0%	0%	0,045%	0%

Table D-6 CRTN-opt1: Model results for Scenario 5

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	470812	629785	141109	96208	9200	630	1568	2209	10703	0	108276	36040	29190	0	615128,23	615048,76
2	471147	629785	141109	96208	9200	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615048,76
3	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615064,76
4	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615069,33
5	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615071,05
6	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615071,81
7	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,19
8	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,40
9	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,52
10	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,59
11	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,64
12	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,67
13	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,69
14	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,71
15	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,72
16	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,73
17	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,74
18	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,74
19	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,74
20	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
21	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
22	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
23	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
24	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
25	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
26	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
27..30	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,76

Table D-7 CRTN-opt2: Iteration results for Scenario 1

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	51858	167797,69	198330,59	21877,85	0,602	0,529	1,342	0,509	0%	0%	0%	0%
2	51728	167909,20	197751,35	21901,85	0,625	0,577	1,132	0,620	0%	0%	0%	0%
3	51728	167909,20	197733,75	21905,85	0,554	0,557	1,209	0,529	0%	0%	0%	0%
4	51728	167909,20	197730,82	21906,99	0,635	0,600	1,316	0,655	0%	0%	0%	0%
5	51728	167909,20	197729,98	21907,42	0,720	0,601	1,192	0,922	0%	0%	0%	0%
6	51728	167909,20	197729,66	21907,61	0,637	0,634	1,126	0,558	0%	0%	0%	0%
7	51728	167909,20	197729,52	21907,71	0,637	0,576	1,142	0,628	0%	0%	0%	0%
8	51728	167909,20	197729,45	21907,76	0,637	0,574	1,397	0,624	0%	0%	0%	0%
9	51728	167909,20	197729,42	21907,79	0,638	0,681	1,199	0,598	0%	0%	0%	0%
10	51728	167909,20	197729,39	21907,81	0,826	0,558	1,318	0,562	0%	0%	0%	0%
11	51728	167909,20	197729,38	21907,82	0,653	0,564	1,282	0,624	0%	0%	0%	0%
12	51728	167909,20	197729,37	21907,83	0,654	0,588	1,293	0,661	0%	0%	0%	0%
13..30	51728	167909,20	197729,37	21907,83	0,646	0,668	1,239	0,630	0%	0%	0%	0%

Table D-8 CRTN-opt2: Model results for Scenario 1

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	167798	280611	50886	34360	5100	225	560	796	3817	250	38578	13030	10410	5	219655,69	219629,20
2	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219635,60
3	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219636,67
4	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219636,97
5	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,09
6	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,14
7	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,16
8	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,18
9	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,18
10	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
11	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
12	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,19
13..30	167909	280611	50886	34360	5100	225	560	796	3817	250	38578	12900	10410	5	219637,20	219637,20

Table D-9 CRTN-opt2: Iteration results for Scenario 4

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	10000	113414,95	123201,99	0,00	0,513	0,398	1,361	0,467	0%	0%	0%	0%
2	6750	116971,90	122524,34	-1821,60	0,524	0,441	45,925	0,498	0%	0%	0%	0%
3	10000	113414,95	123201,99	-607,20	0,624	0,453	1,591	0,458	0%	0%	0%	0%
4	10000	113414,95	123201,99	-260,23	0,514	0,463	3,321	0,529	0%	0%	0%	0%
5	6750	116971,90	122906,01	-1268,61	0,611	0,604	56,367	0,466	0%	0%	0%	0%
6	10000	113414,95	123201,99	-704,79	1,160	0,447	1,746	0,504	0%	0%	0%	0%
7	10000	113414,95	123201,99	-422,87	0,623	0,448	3,102	0,521	0%	0%	0%	0%
8	7530	115900,51	123144,03	-765,90	0,608	0,469	116,144	0,510	0%	0%	0%	0%
9	8700	114837,73	123088,80	-814,20	0,625	0,440	4,871	0,486	0%	0%	0%	0%
10	10000	113414,95	123201,99	-563,68	0,624	0,458	2,778	0,474	0%	0%	0%	0%
11	10000	113414,95	123201,99	-402,63	0,610	0,466	10,852	0,433	0%	0%	0%	0%
12	7530	115900,51	123102,26	-659,58	0,633	0,456	8,068	0,432	0%	0%	0%	0%
13	8700	114837,73	123130,57	-722,38	0,635	0,423	5,812	0,472	0%	0%	0%	0%
14	10000	113414,95	123201,99	-552,41	0,614	0,459	3,019	0,481	0%	0%	0%	0%
15	10000	113414,95	123201,99	-429,65	0,617	0,452	17,311	0,466	0%	0%	0%	0%
16	7530	115900,51	123134,18	-626,82	0,623	0,453	180,802	0,497	0%	0%	0,079%	0%
17	8700	114837,73	123158,05	-683,62	0,520	0,454	9,044	0,551	0%	0%	0%	0%
18	10000	113414,95	123201,99	-553,40	0,622	0,451	3,159	0,507	0%	0%	0%	0%
19	10000	113414,95	123201,99	-452,79	0,616	0,459	8,099	0,562	0%	0%	0%	0%
20	8050	115549,12	123162,19	-611,64	0,644	0,450	65,494	0,462	0%	0%	0%	0%
21	8700	114837,73	123176,53	-661,50	0,615	0,455	7,511	0,495	0%	0%	0%	0%
22	10000	113414,95	123201,99	-555,66	0,621	0,455	3,611	0,482	0%	0%	0%	0%
23	10000	113414,95	123201,99	-470,17	0,671	0,451	9,566	0,551	0%	0%	0%	0%
24	8050	115549,12	123181,27	-602,92	0,631	0,448	80,208	0,499	0%	0%	0%	0%
25	9480	113766,34	123183,81	-516,79	0,630	0,460	8,658	0,489	0%	0%	0%	0%
26	8700	114837,73	123152,69	-571,13	0,630	0,439	21,256	0,494	0%	0%	0%	0%
27	10000	113414,95	123201,99	-494,98	0,643	0,554	27,491	0,500	0%	0%	0%	0%
28	8050	115549,12	123196,01	-607,40	0,636	0,544	13,134	0,566	0%	0%	0%	0%
29	9480	113766,34	123196,14	-531,47	0,629	0,446	3,328	0,547	0%	0%	0%	0%
30	9480	113766,34	123178,43	-467,05	0,631	0,572	5,471	0,484	0%	0%	0%	0%

Table D-10 CRTN-opt2: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122524,34
2	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	121380,39
3	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122594,79
4	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122645,78
5	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90	121933,38
6	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122497,20
7	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122721,16
8	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51	122322,90
9	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73	122387,79
10	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122638,31
11	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122699,63
12	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51	122470,99
13	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73	122479,61
14	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122649,58
15	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122704,52
16	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51	122531,23
17	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73	122518,37
18	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122648,59
19	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122709,40
20	115549	115549	0	0	3639,8	21	0	0	3798,4	250	0	7800	10350	5	123599,12	122564,89
21	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73	122540,49
22	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122646,33
23	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122711,10
24	115549	115549	0	0	3639,8	21	0	0	3798,4	250	0	7800	10350	5	123599,12	122580,89
25	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34	122635,90
26	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73	122630,86
27	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95	122701,02
28	115549	115549	0	0	3639,8	21	0	0	3798,4	250	0	7800	10350	5	123599,12	122588,75
29	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34	122646,96
30	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34	122681,78

Table D-11 CRTN-opt2: WMVCD with feasibility repair heuristic

Iteration	Benders' subproblem	Lower bound	Upper bound-iteration	Upper bound	Iteration	Benders' subproblem	Lower bound	Upper bound-iteration	Upper bound	Iteration	Benders' subproblem	Lower bound	Upper bound-iteration	Upper bound
1	123414,9	122524,3	123586,9	123586,9	51	121775,9	122709,3	123285,4	123054,5	101	121711,2	122719,1	123586,9	123054,5
2	122558,1	121380,4	123202	123202	52	122555,4	122671,1	123433	123054,5	102	121747,3	122711,7	123586,9	123054,5
3	124080,1	122594,8	123202	123202	53	123060,4	122680	123433	123054,5	103	121781,7	122704,6	123586,9	123054,5
4	123700	122645,8	123586,9	123202	54	123067,7	122724,6	123054,5	123054,5	104	121826,6	122706,5	123356	123054,5
5	121554,7	122585,1	123586,9	123202	55	124398,2	122721,1	123285,4	123054,5	105	123754	122730,1	123586,9	123054,5
6	122290,3	122117,7	123202	123202	56	122471,6	122715,1	123586,9	123054,5	106	121851	122721,3	123285,4	123054,5
7	124543,3	122551,4	123202	123202	57	121769	122687	123356	123054,5	107	122637,9	122677,7	123202	123054,5
8	124133	122717,5	123586,9	123202	58	123667,2	122703	123356	123054,5	108	125019,2	122696,6	123202	123054,5
9	121475,1	122653,1	123586,9	123202	59	123631,4	122717,2	123586,9	123054,5	109	124961,9	122714,6	123202	123054,5
10	121839,5	122613,5	123586,9	123202	60	121743,5	122704,9	123586,9	123054,5	110	124907,2	122726,4	123359,2	123054,5
11	122355,9	122414,9	123202	123202	61	121825,5	122714,2	123285,4	123054,5	111	122703,5	122721,5	123285,4	123054,5
12	124814,7	122624,8	123202	123202	62	122602	122680,1	123433	123054,5	112	122455,6	122718,9	123285,4	123054,5
13	124464,8	122722,9	123285,4	123202	63	123125,1	122696,5	123202	123054,5	113	122467,3	122716,5	123285,4	123054,5
14	122182,6	122678,8	123586,9	123202	64	124956,7	122722,8	123054,4	123054,5	114	122478,4	122714,1	123285,4	123054,5
15	121681,8	122644,5	123586,9	123202	65	124366,6	122721,4	123285,4	123054,5	115	122489,1	122708,4	123586,9	123054,5
16	121982,8	122559,3	123356	123202	66	122438,5	122717,1	123285,4	123054,5	116	121755	122723,7	123586,9	123054,5
17	123751,2	122627,1	123202	123202	67	122458,7	122709,7	123586,9	123054,5	117	121806,4	122696,8	123356	123054,5
18	124692,1	122718,3	123285,4	123202	68	121734	122699,3	123586,9	123054,5	118	123701,5	122704,5	123356	123054,5
19	122325,9	122702	123586,9	123202	69	121809,1	122715	123356	123054,5	119	123682,2	122712	123356	123054,5
20	121739,5	122671,1	123586,9	123202	70	123701,2	122714	123586,9	123054,5	120	123663,7	122717,9	123586,9	123054,5
21	121968,3	122560,4	123202	123202	71	121800,3	122703,8	123586,9	123054,5	121	121744,2	122711,7	123586,9	123054,5
22	124866,4	122663	123202	123202	72	121878,7	122695,3	123054,5	123054,5	122	121776,8	122712,5	123586,9	123054,5
23	124643,1	122722,8	123285,4	123202	73	124506,2	122710,2	123356	123054,5	123	121813,7	122714,8	123436,2	123054,5
24	122264,9	122705,6	123586,9	123202	74	123715,4	122718,7	123202	123054,5	124	122223,1	122708,4	123359,2	123054,5
25	121652,7	122679,7	123586,9	123202	75	124913,3	122721,4	123285,4	123054,5	125	122875,6	122723,9	123128,2	123054,5
26	121800,3	122629	123356	123202	76	122461	122717,6	123285,4	123054,5	126	124764	122710	123359,2	123054,5
27	123657,7	122669,3	123356	123202	77	122477,6	122714,1	123285,4	123054,5	127	122815,1	122710,4	123359,2	123054,5
28	123641,6	122714,4	123433	123202	78	122493,2	122707,8	123586,9	123054,5	128	122826,8	122704,4	123128,2	123054,5
29	122940,4	122709,7	123285,4	123202	79	121759,3	122698,8	123586,9	123054,5	129	124723,5	122717,3	123128,2	123054,5
30	122465,5	122695,3	123586,9	123202	80	121802,9	122721,2	123586,9	123054,5	130	124681,6	122728,2	123054,4	123054,5
31	121800,1	122675,2	123586,9	123202	81	121883,2	122680	123054,5	123054,5	131	124386,5	122724,7	123436,2	123054,5
32	121981,6	122655,4	123202	123202	82	124511	122697,6	123054,5	123054,5	132	122066,7	122720,6	123436,2	123054,5
33	124955,7	122716,2	123202	123202	83	124452,2	122714	123356	123054,5	133	122086,1	122716,7	123436,2	123054,5

34	124789,1	122717,3	123285,4	123202	84	123652,8	122718	123202	123054,5	134	122104,7	122712,8	123436,2	123054,5
35	122369	122705,3	123586,9	123202	85	124876,9	122721,9	123285,4	123054,5	135	122122,8	122709,2	123436,2	123054,5
36	121698,8	122686,7	123586,9	123202	86	122424,2	122718,6	123285,4	123054,5	136	122140,1	122704,4	123586,9	123054,5
37	121801,9	122673,1	123356	123202	87	122440,6	122715,4	123285,4	123054,5	137	121791,6	122723,5	123586,9	123054,5
38	123683,2	122698,3	123356	123202	88	122456,1	122712,5	123586,9	123054,5	138	121840,3	122708,7	123205,2	123054,5
39	123657,7	122717,7	123285,4	123202	89	121718,8	122704,3	123586,9	123054,5	139	124120,3	122711,4	123279	123054,5
40	122493,5	122645,3	123433	123202	90	121759,3	122696,5	123586,9	123054,5	140	124343	122721,1	123205,2	123054,5
41	123005,5	122658,9	123433	123202	91	121797,6	122689,2	123586,9	123054,5	141	124057,9	122720,2	123436,2	123054,5
42	123001,6	122671,1	123433	123202	92	121867,9	122718,7	123285,4	123054,5	142	122125	122716,5	123436,2	123054,5
43	123031,5	122704,6	123054,5	123054,5	93	122670,4	122690,9	123202	123054,5	143	122141,4	122712,9	123436,2	123054,5
44	124327,5	122726,8	123285,4	123054,5	94	125022,2	122712	123202	123054,5	144	122157,3	122709,5	123436,2	123054,5
45	122412,2	122717,8	123586,9	123054,5	95	124956,6	122725,4	123285,4	123054,5	145	122172,7	122706,1	123436,2	123054,5
46	121745,4	122661,1	123356	123054,5	96	122499	122722,3	123285,4	123054,5	146	122200,9	122725,7	123436,2	123054,5
47	123621,7	122682,7	123356	123054,5	97	122510,7	122719,3	123285,4	123054,5	147	122237,6	122706,3	123205,2	123054,5
48	123581,8	122702,2	123356	123054,5	98	122534,2	122709,9	123054,5	123054,5	148	124132,5	122710,7	123205,2	123054,5
49	123545,7	122704,1	123586,9	123054,5	99	124423,9	122720,4	123356	123054,5	149	124104,3	122712,5	123279	123054,5
50	121676	122690,5	123586,9	123054,5	100	123623,2	122726,9	123586,9	123054,5	150	124332,6	122721,7	123279	123054,5

Table D-12 CRTN-opt2: Iteration results of WMVCD with relaxed integers for Scenario 4

Iteration	Upper bound	Lower bound	Iteration	Upper bound	Lower bound	Iteration	Upper bound	Lower bound	Iteration	Upper bound	Lower bound
1	121953,57	115036,67	26	121487,23	121347,27	51	121460,15	121386,99	76	121442,07	121382,1
2	161024,42	44885,721	27	121472,98	121356,77	52	121451,61	121383,72	77	121437,1	121380,11
3	133947,09	119069,61	28	121456,18	121385,47	53	121443,84	121380,74	78	121432,45	121378,25
4	125594,28	120219,04	29	121442	121379,96	54	121436,75	121378,03	79	121428,07	121376,5
5	123722,65	121164,59	30	121429,98	121375,32	55	121430,27	121375,56	80	121423,96	121374,85
6	122664,94	121316,66	31	121419,72	121371,38	56	121424,34	121373,3	81	121420,1	121373,31
7	122200,96	121291,22	32	121410,93	121368,01	57	121418,9	121371,23	82	121416,46	121371,85
8	122005,56	120825,82	33	121509,57	121355,45	58	121413,91	121369,33	83	121413,03	121370,49
9	121954,05	121198,62	34	121516,16	121387,95	59	121409,32	121367,59	84	121409,8	121369,2
10	121765,97	121377,73	35	121435,26	121201,47	60	121433,4	121359,73	85	121406,76	121367,98
11	121645,06	121366,98	36	121477,91	121269,85	61	121441,97	121378,98	86	121399,14	121364,16
12	121536,31	121344,88	37	121515,22	121329,45	62	121422,99	121369,39	87	121436,03	121358,46
13	121882,42	121314,53	38	121547,98	121381,61	63	121418,13	121387,98	88	121441,94	121374,86
14	121543,28	121163,49	39	121528,44	121385,11	64	121413,63	121385,24	89	121447,53	121383,46
15	121611,67	121325,26	40	121511,17	121381,08	65	121409,46	121382,71	90	121407,67	121363,04
16	121555,06	121382,3	41	121495,86	121377,52	66	121405,6	121380,36	91	121426,53	121384,03
17	121512,61	121373,98	42	121482,26	121374,36	67	121402,01	121378,18	92	121423,01	121387,5
18	121480,26	121367,74	43	121470,13	121371,56	68	121400,84	121376,16	93	121419,66	121385,62
19	121467,58	121346,6	44	121459,29	121369,05	69	121410,26	121387,11	94	121416,49	121383,83
20	121508,24	121265,96	45	121440,79	121364,14	70	121420,52	121305,92	95	121413,49	121382,14
21	121565,37	121367,71	46	121424,17	121353,57	71	121443,8	121335,79	96	121410,63	121380,54
22	121529,76	121382,67	47	121445,4	121344,07	72	121465,51	121363,64	97	121407,92	121379,01
23	121501	121376,29	48	121455,21	121379,62	73	121459,06	121388,93	98	121405,34	121377,56
24	121477,56	121371,13	49	121438,39	121332,9	74	121453,02	121386,5	99	121402,88	121376,19
25	121443,23	121365,61	50	121469,53	121372,75	75	121447,36	121384,23	100	121400,55	121374,88

Table D-13 CRTN-opt2: Iteration results for Scenario 5

Iteration	MIP				CPUs				Gap			
	Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem		Benders' sub-problem		Dantzig-Wolfe sub-problem	
	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network	scheduler	flow network
1	144316	470812,23	555446,50	61251,98	1,079	0,996	181,325	0,996	0%	0%	0,043%	0%
2	143926	471146,76	553796,78	61323,98	1,091	0,990	181,086	1,004	0%	0%	0,045%	0%
3	143926	471146,76	553743,98	61335,98	0,922	1,101	181,062	1,047	0%	0%	0,045%	0%
4	143926	471146,76	553735,18	61339,41	1,101	0,935	181,051	0,977	0%	0%	0,045%	0%
5	143926	471146,76	553732,67	61340,69	1,029	0,906	181,023	0,905	0%	0%	0,045%	0%
6	143926	471146,76	553731,72	61341,27	0,948	0,898	180,970	0,945	0%	0%	0,045%	0%
7	143926	471146,76	553731,30	61341,55	1,004	0,884	180,971	0,932	0%	0%	0,045%	0%
8	143926	471146,76	553731,09	61341,71	0,959	0,841	181,052	1,022	0%	0%	0,045%	0%
9	143926	471146,76	553730,98	61341,80	1,013	0,857	180,979	5,947	0%	0%	0,045%	0%
10	143926	471146,76	553730,91	61341,85	0,955	0,929	182,321	0,872	0%	0%	0,045%	0%
11	143926	471146,76	553730,87	61341,89	0,985	0,795	181,218	0,970	0%	0%	0,045%	0%
12	143926	471146,76	553730,85	61341,91	0,947	0,873	181,063	0,973	0%	0%	0,045%	0%
13	143926	471146,76	553730,83	61341,93	1,008	0,957	181,005	0,986	0%	0%	0,045%	0%
14	143926	471146,76	553730,82	61341,94	1,088	0,886	181,039	1,016	0%	0%	0,045%	0%
15	143926	471146,76	553730,81	61341,95	1,042	0,894	181,086	0,971	0%	0%	0,045%	0%
16	143926	471146,76	553730,80	61341,96	1,108	0,923	181,040	1,045	0%	0%	0,045%	0%
17..30	143926	471146,76	553730,80	61341,96	1,103	0,917	181,065	1,046	0%	0%	0,045%	0%

Table D-14 CRTN-opt2: Model results for Scenario 5

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound	Lower bound
	Costs				Quantities					Costs			Quantities			
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]		
1	470812	629785	141109	96208	9200	630	1568	2209	10703	0	108276	36040	29190	0	615128,23	615048,76
2	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615067,96
3	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615071,16
4	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,07
5	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,42
6	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,57
7	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,65
8	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,69
9	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,71
10	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,73
11	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,74
12	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,74
13	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
14	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
15	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
16	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,75
17..30	471147	623514	141109	96208	9100	630	1568	2209	10703	0	108276	35650	29190	0	615072,76	615072,76

Table D-15 IMV: Iterations results and model statistics for Scenario 1

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	167797,69	198330,59	0,570	1,300	0%	0%
2	167849,45	197751,35	0,546	1,453	0%	0%
3	167867,36	197751,35	0,598	1,088	0%	0%
4	167877,82	197744,02	0,622	1,272	0%	0%
5	167884,10	197740,35	0,498	1,185	0%	0%
6	167888,28	197738,15	0,462	1,095	0%	0%
7	167891,27	197736,68	0,625	1,379	0%	0%
8	167893,51	197735,64	0,579	1,113	0%	0%
9	167895,25	197734,85	0,543	1,147	0%	0%
10	167896,65	197734,24	0,459	1,193	0%	0%
11	167897,79	197733,75	0,595	1,262	0%	0%
12	167898,74	197733,35	0,563	1,139	0%	0%
13	167899,55	197733,02	0,473	1,213	0%	0%
14	167900,24	197732,73	0,504	1,281	0%	0%
15	167900,83	197732,49	0,582	1,281	0%	0%
16	167901,36	197732,28	0,598	1,202	0%	0%
17	167901,82	197732,10	0,638	1,278	0%	0%
18	167902,23	197731,94	0,536	1,223	0%	0%
19	167902,59	197731,79	0,575	1,310	0%	0%
20	167902,92	197731,67	0,770	2,953	0%	0%
21	167903,22	197731,55	0,540	1,528	0%	0%
22	167903,50	197731,45	0,576	2,576	0%	0%
23	167903,74	197731,35	0,605	1,343	0%	0%
24	167903,97	197731,26	0,674	2,872	0%	0%
25	167904,18	197731,18	0,659	1,227	0%	0%
26	167904,37	197731,11	0,570	1,708	0%	0%
27	167904,55	197731,04	0,649	5,728	0%	0%
28	167904,72	197730,98	0,615	1,232	0%	0%
29	167904,87	197730,92	0,510	1,346	0%	0%
30	167905,02	197730,87	0,562	1,286	0%	0%

Table D-16 IMV: Model results for Scenario 1

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	167798	179251	45813	34360	1889	280,000	560	712,000	3817	250	38578	13030	10410	5	219655,69
2	167849	179302	45813	34360	1878	291,000	560	712,000	3817	250	38578	12900	10410	5	219577,45
3	167867	179360	45853	34360	1875	294,667	560	712,667	3817	250	38578	12900	10410	5	219595,36
4	167878	179479	45961	34360	1875	296,500	560	714,500	3817	250	38578	12900	10410	5	219605,82
5	167884	179551	46027	34360	1875	297,600	560	715,600	3817	250	38578	12900	10410	5	219612,10
6	167888	179598	46070	34360	1875	298,333	560	716,333	3817	250	38578	12900	10410	5	219616,28
7	167891	179632	46101	34360	1875	298,857	560	716,857	3817	250	38578	12900	10410	5	219619,27
8	167894	179658	46124	34360	1875	299,250	560	717,250	3817	250	38578	12900	10410	5	219621,51
9	167895	179678	46142	34360	1875	299,556	560	717,556	3817	250	38578	12900	10410	5	219623,25
10	167897	179694	46157	34360	1875	299,800	560	717,800	3817	250	38578	12900	10410	5	219624,65
11	167898	179707	46169	34360	1875	300,000	560	718,000	3817	250	38578	12900	10410	5	219625,79
12	167899	179717	46179	34360	1875	300,167	560	718,167	3817	250	38578	12900	10410	5	219626,74
13	167900	179727	46187	34360	1875	300,308	560	718,308	3817	250	38578	12900	10410	5	219627,55
14	167900	179734	46194	34360	1875	300,429	560	718,429	3817	250	38578	12900	10410	5	219628,24
15	167901	179741	46200	34360	1875	300,533	560	718,533	3817	250	38578	12900	10410	5	219628,83
16	167901	179747	46206	34360	1875	300,625	560	718,625	3817	250	38578	12900	10410	5	219629,36
17	167902	179752	46211	34360	1875	300,706	560	718,706	3817	250	38578	12900	10410	5	219629,82
18	167902	179757	46215	34360	1875	300,778	560	718,778	3817	250	38578	12900	10410	5	219630,23
19	167903	179761	46219	34360	1875	300,842	560	718,842	3817	250	38578	12900	10410	5	219630,59
20	167903	179765	46222	34360	1875	300,900	560	718,900	3817	250	38578	12900	10410	5	219630,92
21	167903	179769	46225	34360	1875	300,952	560	718,952	3817	250	38578	12900	10410	5	219631,22
22	167903	179772	46228	34360	1875	301,000	560	719,000	3817	250	38578	12900	10410	5	219631,50
23	167904	179774	46231	34360	1875	301,043	560	719,043	3817	250	38578	12900	10410	5	219631,74
24	167904	179777	46233	34360	1875	301,083	560	719,083	3817	250	38578	12900	10410	5	219631,97
25	167904	179779	46235	34360	1875	301,120	560	719,120	3817	250	38578	12900	10410	5	219632,18
26	167904	179782	46237	34360	1875	301,154	560	719,154	3817	250	38578	12900	10410	5	219632,37
27	167905	179784	46239	34360	1875	301,185	560	719,185	3817	250	38578	12900	10410	5	219632,55
28	167905	179786	46241	34360	1875	301,214	560	719,214	3817	250	38578	12900	10410	5	219632,72
29	167905	179787	46242	34360	1875	301,241	560	719,241	3817	250	38578	12900	10410	5	219632,87
30	167905	179789	46244	34360	1875	301,267	560	719,267	3817	250	38578	12900	10410	5	219633,02

Table D-17 IMV: Iterations results and model statistics for Scenario 2

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	-673378,00	198330,59	0,468	1,199	0%	0%
2	-674973,00	338528	1,157	1,164	0%	0%
3	-675504,67	338528	0,509	1,149	0%	0%
4	-675770,50	338528	0,506	1,239	0%	0%
5	-675930,00	338528	0,482	1,257	0%	0%
6	-676036,33	338528	0,510	1,258	0%	0%
7	-676112,29	338528	0,510	1,166	0%	0%
8	-676169,25	338528	0,459	1,298	0%	0%
9	-676213,56	338528	0,499	1,298	0%	0%
10	-676249,00	338528	0,527	1,158	0%	0%
11	-676278,00	338528	0,442	1,220	0%	0%
12	-676302,17	338528	0,502	1,291	0%	0%
13	-676322,62	338528	0,495	1,277	0%	0%
14	-676340,14	338528	0,438	1,220	0%	0%
15	-676355,33	338528	0,508	1,169	0%	0%
16	-676368,63	338528	0,499	1,260	0%	0%
17	-676380,35	338528	0,479	1,081	0%	0%
18	-676390,78	338528	0,506	1,256	0%	0%
19	-676400,11	338528	0,464	1,107	0%	0%
20	-676408,50	338528	0,496	1,272	0%	0%
21	-676416,10	338528	0,479	1,286	0%	0%
22	-676423,00	338528	0,559	1,194	0%	0%
23	-676429,30	338528	0,493	1,263	0%	0%
24	-676435,08	338528	0,504	1,259	0%	0%
25	-676440,40	338528	0,555	1,200	0%	0%
26	-676445,31	338528	0,493	1,258	0%	0%
27	-676449,85	338528	0,480	1,195	0%	0%
28	-676454,07	338528	0,502	1,253	0%	0%
29	-676458,00	338528	0,476	1,262	0%	0%
30	-676461,6667	338528	0,548	1,314	0%	0%

Table D-18 IMV: Model results for Scenario 2

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	-673378	705200	1670930	292352	0	8055,00	4792	10830	3817	250	38578	13030	10410	5	-621520,00
2	-674973	703605	1670930	292352	0	8049,50	4792	10830	3806	250	39118	13600	10380	5	-622005,00
3	-675505	703073	1670930	292352	0	8047,67	4792	10830	3806	250	39118	13600	10380	5	-622536,67
4	-675771	702808	1670930	292352	0	8046,75	4792	10830	3806	250	39118	13600	10380	5	-622802,50
5	-675930	702648	1670930	292352	0	8046,20	4792	10830	3806	250	39118	13600	10380	5	-622962,00
6	-676036	702542	1670930	292352	0	8045,83	4792	10830	3806	250	39118	13600	10380	5	-623068,33
7	-676112	702466	1670930	292352	0	8045,57	4792	10830	3806	250	39118	13600	10380	5	-623144,29
8	-676169	702409	1670930	292352	0	8045,38	4792	10830	3806	250	39118	13600	10380	5	-623201,25
9	-676214	702364	1670930	292352	0	8045,22	4792	10830	3806	250	39118	13600	10380	5	-623245,56
10	-676249	702329	1670930	292352	0	8045,10	4792	10830	3806	250	39118	13600	10380	5	-623281,00
11	-676278	702300	1670930	292352	0	8045,00	4792	10830	3806	250	39118	13600	10380	5	-623310,00
12	-676302	702276	1670930	292352	0	8044,92	4792	10830	3806	250	39118	13600	10380	5	-623334,17
13	-676323	702255	1670930	292352	0	8044,85	4792	10830	3806	250	39118	13600	10380	5	-623354,62
14	-676340	702238	1670930	292352	0	8044,79	4792	10830	3806	250	39118	13600	10380	5	-623372,14
15	-676355	702223	1670930	292352	0	8044,73	4792	10830	3806	250	39118	13600	10380	5	-623387,33
16	-676369	702209	1670930	292352	0	8044,69	4792	10830	3806	250	39118	13600	10380	5	-623400,63
17	-676380	702198	1670930	292352	0	8044,65	4792	10830	3806	250	39118	13600	10380	5	-623412,35
18	-676391	702187	1670930	292352	0	8044,61	4792	10830	3806	250	39118	13600	10380	5	-623422,78
19	-676400	702178	1670930	292352	0	8044,58	4792	10830	3806	250	39118	13600	10380	5	-623432,11
20	-676409	702170	1670930	292352	0	8044,55	4792	10830	3806	250	39118	13600	10380	5	-623440,50
21	-676416	702162	1670930	292352	0	8044,52	4792	10830	3806	250	39118	13600	10380	5	-623448,10
22	-676423	702155	1670930	292352	0	8044,50	4792	10830	3806	250	39118	13600	10380	5	-623455,00
23	-676429	702149	1670930	292352	0	8044,48	4792	10830	3806	250	39118	13600	10380	5	-623461,30
24	-676435	702143	1670930	292352	0	8044,46	4792	10830	3806	250	39118	13600	10380	5	-623467,08
25	-676440	702138	1670930	292352	0	8044,44	4792	10830	3806	250	39118	13600	10380	5	-623472,40
26	-676445	702133	1670930	292352	0	8044,42	4792	10830	3806	250	39118	13600	10380	5	-623477,31
27	-676450	702128	1670930	292352	0	8044,41	4792	10830	3806	250	39118	13600	10380	5	-623481,85
28	-676454	702124	1670930	292352	0	8044,39	4792	10830	3806	250	39118	13600	10380	5	-623486,07
29	-676458	702120	1670930	292352	0	8044,38	4792	10830	3806	250	39118	13600	10380	5	-623490,00
30	-676462	702116	1670930	292352	0	8044,37	4792	10830	3806	250	39118	13600	10380	5	-623493,67

Table D-19 IMV: Iterations results and model statistics for Scenario 4

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	113414,95	123201,99	0,499	1,379	0%	0%
2	114662,12	122524,34	0,591	48,322	0%	0%
3	115077,85	122524,34	0,598	47,436	0%	0%
4	115517,21	122524,34	0,571	39,559	0%	0%
5	114911,56	123201,99	0,564	15,289	0%	0%
6	114970,12	123182,20	0,587	114,989	0%	0%
7	115171,95	123080,94	0,521	180,735	0%	0,074%
8	115026,95	123121,76	0,540	12,734	0%	0%
9	114839,74	123201,99	0,498	3,498	0%	0%
10	114697,26	123201,99	0,487	10,390	0%	0%
11	114748,69	123182,20	0,557	30,272	0%	0%
12	114845,41	123131,54	0,467	108,202	0%	0%
13	114927,24	123080,94	0,577	180,660	0%	0,071%
14	114997,39	123038,12	0,598	180,516	0%	0,007%
15	115058,18	123001,43	0,528	38,787	0%	0%
16	115134,72	122969,62	0,522	39,057	0%	0%
17	115171,19	123148,80	0,434	55,147	0%	0%
18	115099,20	123166,67	0,512	68,264	0%	0%
19	114993,30	123201,99	0,490	9,563	0%	0%
20	114931,95	123195,06	0,517	8,487	0%	0%
21	114947,71	123182,20	0,503	180,577	0%	0,056%
22	114962,04	123156,75	0,509	17,233	0%	0%
23	115003,23	123131,54	0,497	76,255	0%	0%
24	115040,98	123105,14	0,544	61,653	0%	0%
25	115075,71	123080,94	0,495	180,706	0%	0,073%
26	115146,77	123058,68	0,521	180,595	0%	0,063%
27	115165,69	123161,64	0,493	49,378	0%	0%
28	115052,86	123201,99	0,478	11,994	0%	0%
29	115008,49	123197,58	0,527	16,283	0%	0%
30	114967,09	123192,64	0,391	4,653	0%	0%

Table D-20 IMV: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	113415	113415	0	0	3795,800	0	0	0	3799,3	250	0	9750	10350	5	123414,95
2	114662	114662	0	0	3630,800	0	0	0	3797,8	250	0	6500	10350	5	121412,12
3	115078	115078	0	0	3575,800	0	0	0	3797,8	250	0	6500	10350	5	121827,85
4	115517	115517	0	0	3563,550	7,625	0	0	3797,8	250	0	6500	10350	5	122267,21
5	114912	114912	0	0	3597,800	0	0	0	3799,3	250	0	9750	10350	5	124911,56
6	114970	114970	0	0	3586,833	0	0	0	3798	250	0	7280	10350	5	122500,12
7	115172	115172	0	0	3574,000	2,229	0	0	3797,8	250	0	6500	10350	5	121921,95
8	115027	115027	0	0	3581,925	0,3	0	0	3798,7	250	0	8450	10350	5	123726,95
9	114840	114840	0	0	3605,156	0	0	0	3799,3	250	0	9750	10350	5	124839,74
10	114697	114697	0	0	3624,220	0	0	0	3799,3	250	0	9750	10350	5	124697,26
11	114749	114749	0	0	3615,836	0	0	0	3798	250	0	7280	10350	5	122278,69
12	114845	114845	0	0	3603,333	0	0	0	3797,8	250	0	6500	10350	5	121595,41
13	114927	114927	0	0	3592,754	0	0	0	3797,8	250	0	6500	10350	5	121677,24
14	114997	114997	0	0	3583,686	0	0	0	3797,8	250	0	6500	10350	5	121747,39
15	115058	115058	0	0	3575,827	0	0	0	3797,8	250	0	6500	10350	5	121808,18
16	115135	115135	0	0	3570,488	0,769	0	0	3797,8	250	0	6500	10350	5	121884,72
17	115171	115171	0	0	3570,129	1,676	0	0	3798	250	0	7280	10350	5	122701,19
18	115099	115099	0	0	3573,367	0,6	0	0	3798,7	250	0	8450	10350	5	123799,20
19	114993	114993	0	0	3583,937	0	0	0	3799,3	250	0	9750	10350	5	124993,30
20	114932	114932	0	0	3591,240	0	0	0	3798,9	250	0	9230	10350	5	124411,95
21	114948	114948	0	0	3588,419	0	0	0	3798	250	0	7280	10350	5	122477,71
22	114962	114962	0	0	3585,855	0	0	0	3798	250	0	7280	10350	5	122492,04
23	115003	115003	0	0	3580,635	0	0	0	3797,8	250	0	6500	10350	5	121753,23
24	115041	115041	0	0	3575,850	0	0	0	3797,8	250	0	6500	10350	5	121790,98
25	115076	115076	0	0	3571,448	0	0	0	3797,8	250	0	6500	10350	5	121825,71
26	115147	115147	0	0	3569,954	1,285	0	0	3797,8	250	0	6500	10350	5	121896,77
27	115166	115166	0	0	3569,511	1,719	0	0	3798	250	0	7280	10350	5	122695,69
28	115053	115053	0	0	3574,279	0	0	0	3799,3	250	0	9750	10350	5	125052,86
29	115008	115008	0	0	3579,648	0	0	0	3798,9	250	0	9230	10350	5	124488,49
30	114967	114967	0	0	3584,660	0	0	0	3798,9	250	0	9230	10350	5	124447,09

Table D-21 IMV: Iterations results and model statistics for Scenario 5

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	470812,23	555446,50	0,965	180,900	0%	0,043%
2	470967,50	553796,78	0,868	180,913	0%	0,045%
3	471021,25	553796,78	0,894	180,888	0%	0,045%
4	471052,63	553774,78	0,904	180,990	0%	0,045%
5	471071,45	553763,78	0,872	180,990	0%	0,045%
6	471084,01	553757,18	0,883	181,011	0%	0,045%
7	471092,97	553752,78	1,050	181,281	0%	0,045%
8	471099,69	553749,64	0,957	181,375	0%	0,045%
9	471104,92	553747,28	1,485	181,276	0%	0,045%
10	471109,11	553745,45	1,839	182,321	0%	0,045%
11	471112,53	553743,98	1,192	181,205	0%	0,045%
12	471115,38	553742,78	1,125	181,701	0%	0,045%
13	471117,80	553741,78	0,980	181,055	0%	0,045%
14	471119,87	553740,93	0,900	181,081	0%	0,045%
15	471121,66	553740,21	1,636	181,724	0%	0,045%
16	471123,23	553739,58	1,884	181,856	0%	0,045%
17	471124,61	553739,03	1,582	181,850	0%	0,045%
18	471125,84	553738,54	1,799	181,901	0%	0,045%
19	471126,94	553738,11	1,859	181,940	0%	0,045%
20	471127,93	553737,73	1,872	182,428	0%	0,045%
21	471128,83	553737,38	1,636	182,387	0%	0,045%
22	471129,65	553737,07	1,759	182,312	0%	0,045%
23	471130,39	553736,78	1,521	182,309	0%	0,045%
24	471131,07	553736,52	1,997	181,827	0%	0,045%
25	471131,70	553736,28	1,380	181,531	0%	0,045%
26	471132,28	553736,06	1,509	182,618	0%	0,045%
27	471132,81	553735,86	1,666	181,725	0%	0,045%
28	471133,31	553735,67	1,635	182,011	0%	0,045%
29	471133,78	553735,49	1,729	181,778	0%	0,045%
30	471134,21	553735,33	1,484	181,652	0%	0,045%

Table D-22 IMV: Model results for Scenario 5

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	470812	502786	128182	96208	5292	795	1568	1992	10703	0	108276	36040	29190	0	615128,23
2	470967	502941	128182	96208	5259	828	1568	1992	10703	0	108276	35650	29190	0	614893,50
3	471021	503113	128300	96208	5250	839	1568	1994	10703	0	108276	35650	29190	0	614947,25
4	471053	503471	128626	96208	5250	844,5	1568	1999,500	10703	0	108276	35650	29190	0	614978,63
5	471071	503685	128822	96208	5250	847,8	1568	2002,8	10703	0	108276	35650	29190	0	614997,45
6	471084	503828	128952	96208	5250	850	1568	2005	10703	0	108276	35650	29190	0	615010,01
7	471093	503931	129046	96208	5250	851,57	1568	2006,571	10703	0	108276	35650	29190	0	615018,97
8	471100	504007	129116	96208	5250	852,75	1568	2007,750	10703	0	108276	35650	29190	0	615025,69
9	471105	504067	129170	96208	5250	853,67	1568	2008,667	10703	0	108276	35650	29190	0	615030,92
10	471109	504114	129213	96208	5250	854,4	1568	2009,4	10703	0	108276	35650	29190	0	615035,11
11	471113	504153	129249	96208	5250	855	1568	2010	10703	0	108276	35650	29190	0	615038,53
12	471115	504186	129279	96208	5250	855,5	1568	2010,5	10703	0	108276	35650	29190	0	615041,38
13	471118	504213	129304	96208	5250	855,92	1568	2010,923	10703	0	108276	35650	29190	0	615043,80
14	471120	504237	129325	96208	5250	856,29	1568	2011,286	10703	0	108276	35650	29190	0	615045,87
15	471122	504257	129344	96208	5250	856,6	1568	2011,6	10703	0	108276	35650	29190	0	615047,66
16	471123	504275	129360	96208	5250	856,875	1568	2011,875	10703	0	108276	35650	29190	0	615049,23
17	471125	504291	129375	96208	5250	857,12	1568	2012,118	10703	0	108276	35650	29190	0	615050,61
18	471126	504305	129387	96208	5250	857,33	1568	2012,333	10703	0	108276	35650	29190	0	615051,84
19	471127	504318	129399	96208	5250	857,53	1568	2012,526	10703	0	108276	35650	29190	0	615052,94
20	471128	504329	129409	96208	5250	857,7	1568	2012,7	10703	0	108276	35650	29190	0	615053,93
21	471129	504339	129418	96208	5250	857,86	1568	2012,857	10703	0	108276	35650	29190	0	615054,83
22	471130	504348	129427	96208	5250	858	1568	2013	10703	0	108276	35650	29190	0	615055,65
23	471130	504357	129435	96208	5250	858,13	1568	2013,13	10703	0	108276	35650	29190	0	615056,39
24	471131	504365	129442	96208	5250	858,25	1568	2013,25	10703	0	108276	35650	29190	0	615057,07
25	471132	504372	129448	96208	5250	858,36	1568	2013,36	10703	0	108276	35650	29190	0	615057,70
26	471132	504378	129454	96208	5250	858,46	1568	2013,462	10703	0	108276	35650	29190	0	615058,28
27	471133	504385	129460	96208	5250	858,56	1568	2013,556	10703	0	108276	35650,00001	29190	0	615058,81
28	471133	504390	129465	96208	5250	858,64	1568	2013,643	10703	0	108276	35650,00001	29190	0	615059,31
29	471134	504396	129470	96208	5250	858,72	1568	2013,724	10703	0	108276	35650	29190	0	615059,78
30	471134	504400	129474	96208	5250	858,80	1568	2013,8	10703	0	108276	35650	29190	0	615060,21

Table D-23 IWMV: Iterations results and model statistics for Scenario 1

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	167797,69	198330,59	0,526	1,344	0%	0%
2	167797,69	197751,35	0,635	2,844	0%	0%
3	167867,36	197751,35	0,478	1,158	0%	0%
4	167891,27	197736,68	0,569	1,136	0%	0%
5	167900,24	197732,49	0,531	1,183	0%	0%
6	167904,22	197730,92	0,470	1,203	0%	0%
7	167906,21	197730,22	0,651	1,150	0%	0%
8	167907,30	197729,87	0,459	1,116	0%	0%
9	167907,93	197729,68	0,492	1,341	0%	0%
10	167908,32	197729,57	0,499	1,280	0%	0%
11	167908,57	197729,50	0,560	1,130	0%	0%
12	167908,74	197729,46	0,557	1,281	0%	0%
13	167908,86	197729,43	0,561	1,245	0%	0%
14	167908,94	197729,41	0,610	1,273	0%	0%
15	167908,99	197729,40	0,560	1,133	0%	0%
16	167909,04	197729,39	0,533	1,272	0%	0%
17	167909,07	197729,38	0,578	1,211	0%	0%
18	167909,10	197729,37	0,587	1,277	0%	0%
19	167909,11	197729,37	0,659	1,274	0%	0%
20	167909,13	197729,37	0,515	1,313	0%	0%
21	167909,14	197729,36	0,626	1,250	0%	0%
22	167909,15	197729,36	0,520	1,245	0%	0%
23	167909,16	197729,36	0,521	1,406	0%	0%
24	167909,16	197729,36	0,553	1,223	0%	0%
25	167909,17	197729,36	0,566	1,346	0%	0%
26	167909,17	197729,36	0,479	1,326	0%	0%
27	167909,18	197729,35	0,580	1,215	0%	0%
28	167909,18	197729,35	0,612	1,238	0%	0%
29	167909,18	197729,35	0,642	1,150	0%	0%
30	167909,18	197729,35	0,626	1,341	0%	0%

Table D-24 IWMV: Model results for Scenario 1

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	167798	179251	45813	34360	1889	280	560	712	3817	250	38578	13030	10410	5	219655,69
2	167798	179251	45813	34360	1889	280	560	712	3817	250	38578	12900	10410	5	219525,69
3	167867	179360	45853	34360	1875	294,67	560	712,67	3817	250	38578	12900	10410	5	219595,36
4	167891	179632	46101	34360	1875	298,86	560	716,86	3817	250	38578	12900	10410	5	219619,27
5	167900	179734	46194	34360	1875	300,43	560	718,43	3817	250	38578	12900	10410	5	219628,24
6	167904	179780	46236	34360	1875	301,13	560	719,13	3817	250	38578	12900	10410	5	219632,22
7	167906	179803	46256	34360	1875	301,48	560	719,48	3817	250	38578	12900	10410	5	219634,21
8	167907	179815	46268	34360	1875	301,67	560	719,67	3817	250	38578	12900	10410	5	219635,30
9	167908	179822	46274	34360	1875	301,78	560	719,78	3817	250	38578	12900	10410	5	219635,93
10	167908	179827	46278	34360	1875	301,85	560	719,85	3817	250	38578	12900	10410	5	219636,32
11	167909	179829	46281	34360	1875	301,89	560	719,89	3817	250	38578	12900	10410	5	219636,57
12	167909	179831	46283	34360	1875	301,92	560	719,92	3817	250	38578	12900	10410	5	219636,74
13	167909	179833	46284	34360	1875	301,94	560	719,94	3817	250	38578	12900	10410	5	219636,86
14	167909	179834	46285	34360	1875	301,95	560	719,95	3817	250	38578	12900	10410	5	219636,94
15	167909	179834	46285	34360	1875	301,96	560	719,96	3817	250	38578	12900	10410	5	219636,99
16	167909	179835	46286	34360	1875	301,97	560	719,97	3817	250	38578	12900	10410	5	219637,04
17	167909	179835	46286	34360	1875	301,98	560	719,98	3817	250	38578	12900	10410	5	219637,07
18	167909	179835	46286	34360	1875	301,98	560	719,98	3817	250	38578	12900	10410	5	219637,10
19	167909	179836	46287	34360	1875	301,98	560	719,98	3817	250	38578	12900	10410	5	219637,11
20	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,13
21	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,14
22	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,15
23	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,16
24	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,16
25	167909	179836	46287	34360	1875	301,99	560	719,99	3817	250	38578	12900	10410	5	219637,17
26	167909	179836	46287	34360	1875	302,00	560	720,00	3817	250	38578	12900	10410	5	219637,17
27	167909	179836	46287	34360	1875	302,00	560	720,00	3817	250	38578	12900	10410	5	219637,18
28	167909	179836	46287	34360	1875	302,00	560	720,00	3817	250	38578	12900	10410	5	219637,18
29	167909	179836	46287	34360	1875	302,00	560	720,00	3817	250	38578	12900	10410	5	219637,18
30	167909	179836	46287	34360	1875	302,00	560	720,00	3817	250	38578	12900	10410	5	219637,18

Table D-25 IWMV: Iterations results and model statistics for Scenario 2

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	-673378	198330,59	0,452	1,213	0%	0%
2	-673378	338528	0,424	1,135	0%	0%
3	-675504,67	338528	0,511	1,204	0%	0%
4	-676112,29	338528	0,499	1,162	0%	0%
5	-676340,14	338528	0,503	1,274	0%	0%
6	-676441,41	338528	0,479	1,287	0%	0%
7	-676492,05	338528	0,472	1,197	0%	0%
8	-676519,67	338528	0,440	1,243	0%	0%
9	-676535,78	338528	0,489	1,098	0%	0%
10	-676545,69	338528	0,472	1,268	0%	0%
11	-676552,07	338528	0,511	1,269	0%	0%
12	-676556,32	338528	0,502	1,157	0%	0%
13	-676559,24	338528	0,489	1,278	0%	0%
14	-676561,30	338528	0,454	1,118	0%	0%
15	-676562,79	338528	0,469	1,299	0%	0%
16	-676563,88	338528	0,511	1,073	0%	0%
17	-676564,71	338528	0,484	1,193	0%	0%
18	-676565,34	338528	0,515	1,149	0%	0%
19	-676565,82	338528	0,471	1,175	0%	0%
20	-676566,20	338528	0,459	1,183	0%	0%
21	-676566,50	338528	0,452	1,210	0%	0%
22	-676566,74	338528	0,479	1,294	0%	0%
23	-676566,93	338528	0,527	1,251	0%	0%
24	-676567,09	338528	0,494	1,196	0%	0%
25	-676567,22	338528	0,487	1,261	0%	0%
26	-676567,33	338528	0,464	1,184	0%	0%
27	-676567,42	338528	0,490	1,275	0%	0%
28	-676567,49	338528	0,441	1,310	0%	0%
29	-676567,56	338528	0,498	1,260	0%	0%
30	-676567,61	338528	0,524	1,251	0%	0%

Table D-26 IWMV: Model results for Scenario 2

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	-673378	705200	1670930	292352	0	8055	4792	10830	3817	250	38578	13030	10410	5	-621520,00
2	-673378	705200	1670930	292352	0	8055	4792	10830	3806	250	39118	13600	10380	5	-620410,00
3	-675505	703073	1670930	292352	0	8047,67	4792	10830	3806	250	39118	13600	10380	5	-622536,67
4	-676112	702466	1670930	292352	0	8045,57	4792	10830	3806	250	39118	13600	10380	5	-623144,29
5	-676340	702238	1670930	292352	0	8044,79	4792	10830	3806	250	39118	13600	10380	5	-623372,14
6	-676441	702137	1670930	292352	0	8044,44	4792	10830	3806	250	39118	13600	10380	5	-623473,41
7	-676492	702086	1670930	292352	0	8044,26	4792	10830	3806	250	39118	13600	10380	5	-623524,05
8	-676520	702058	1670930	292352	0	8044,17	4792	10830	3806	250	39118	13600	10380	5	-623551,67
9	-676536	702042	1670930	292352	0	8044,11	4792	10830	3806	250	39118	13600	10380	5	-623567,78
10	-676546	702032	1670930	292352	0	8044,08	4792	10830	3806	250	39118	13600	10380	5	-623577,69
11	-676552	702026	1670930	292352	0	8044,05	4792	10830	3806	250	39118	13600	10380	5	-623584,07
12	-676556	702022	1670930	292352	0	8044,04	4792	10830	3806	250	39118	13600	10380	5	-623588,32
13	-676559	702019	1670930	292352	0	8044,03	4792	10830	3806	250	39118	13600	10380	5	-623591,24
14	-676561	702017	1670930	292352	0	8044,02	4792	10830	3806	250	39118	13600	10380	5	-623593,30
15	-676563	702015	1670930	292352	0	8044,02	4792	10830	3806	250	39118	13600	10380	5	-623594,79
16	-676564	702014	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623595,88
17	-676565	702013	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623596,71
18	-676565	702013	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623597,34
19	-676566	702012	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623597,82
20	-676566	702012	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623598,20
21	-676566	702012	1670930	292352	0	8044,01	4792	10830	3806	250	39118	13600	10380	5	-623598,50
22	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623598,74
23	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623598,93
24	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,09
25	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,22
26	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,33
27	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,42
28	-676567	702011	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,49
29	-676568	702010	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,56
30	-676568	702010	1670930	292352	0	8044,00	4792	10830	3806	250	39118	13600	10380	5	-623599,61

Table D-27 IWMV: Iterations results and model statistics for Scenario 4

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	113414,95	123201,99	0,468	1,420	0%	0%
2	114662,12	122524,34	0,452	51,496	0%	0%
3	115077,85	122524,34	0,455	48,599	0%	0%
4	115517,21	122524,34	0,495	38,041	0%	0%
5	114911,56	123201,99	0,432	14,491	0%	0%
6	114970,12	123182,20	0,448	111,376	0%	0%
7	115171,95	123080,94	0,521	180,697	0%	0,073%
8	115026,95	123121,76	0,541	12,414	0%	0%
9	114839,74	123201,99	0,517	3,788	0%	0%
10	114697,26	123201,99	0,478	9,772	0%	0%
11	114748,69	123182,20	0,519	29,651	0%	0%
12	114845,41	123131,54	0,536	99,097	0%	0%
13	114927,24	123080,94	0,551	180,660	0%	0,070%
14	114997,39	123038,12	0,454	172,478	0%	0%
15	115058,18	123001,43	0,441	36,269	0%	0%
16	115134,72	122969,62	0,531	36,108	0%	0%
17	115171,19	123148,80	0,459	53,053	0%	0%
18	115099,20	123166,67	0,528	64,874	0%	0%
19	114993,30	123201,99	0,481	9,149	0%	0%
20	114931,95	123195,06	0,515	8,044	0%	0%
21	114947,71	123182,20	0,482	180,579	0%	0,055%
22	114962,04	123156,75	0,480	17,059	0%	0%
23	115003,23	123131,54	0,418	71,697	0%	0%
24	115040,98	123105,14	0,498	60,012	0%	0%
25	115075,71	123080,94	0,524	180,685	0%	0,072%
26	115146,77	123058,68	0,475	180,630	0%	0,062%
27	115165,69	123161,64	0,552	45,894	0%	0%
28	115052,86	123201,99	0,479	11,424	0%	0%
29	115008,49	123197,58	0,561	15,131	0%	0%
30	114967,09	123192,64	0,450	4,578	0%	0%

Table D-28 IWMV: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	113415	113415	0	0	3795,80	0	0	0	3799,3	250	0	9750	10350	5	123414,95
2	114662	114662	0	0	3630,80	0	0	0	3797,8	250	0	6500	10350	5	121412,12
3	115078	115078	0	0	3575,80	0	0	0	3797,8	250	0	6500	10350	5	121827,85
4	115517	115517	0	0	3563,55	7,625	0	0	3797,8	250	0	6500	10350	5	122267,21
5	114912	114912	0	0	3597,80	0	0	0	3799,3	250	0	9750	10350	5	124911,56
6	114970	114970	0	0	3586,83	0	0	0	3798	250	0	7280	10350	5	122500,12
7	115172	115172	0	0	3574,00	2,229	0	0	3797,8	250	0	6500	10350	5	121921,95
8	115027	115027	0	0	3581,93	0,3	0	0	3798,7	250	0	8450	10350	5	123726,95
9	114840	114840	0	0	3605,16	0	0	0	3799,3	250	0	9750	10350	5	124839,74
10	114697	114697	0	0	3624,22	0	0	0	3799,3	250	0	9750	10350	5	124697,26
11	114749	114749	0	0	3615,84	0	0	0	3798	250	0	7280	10350	5	122278,69
12	114845	114845	0	0	3603,33	0	0	0	3797,8	250	0	6500	10350	5	121595,41
13	114927	114927	0	0	3592,75	0	0	0	3797,8	250	0	6500	10350	5	121677,24
14	114997	114997	0	0	3583,69	0	0	0	3797,8	250	0	6500	10350	5	121747,39
15	115058	115058	0	0	3575,83	0	0	0	3797,8	250	0	6500	10350	5	121808,18
16	115135	115135	0	0	3570,49	0,769	0	0	3797,8	250	0	6500	10350	5	121884,72
17	115171	115171	0	0	3570,13	1,676	0	0	3798	250	0	7280	10350	5	122701,19
18	115099	115099	0	0	3573,37	0,6	0	0	3798,7	250	0	8450	10350	5	123799,20
19	114993	114993	0	0	3583,94	0	0	0	3799,3	250	0	9750	10350	5	124993,30
20	114932	114932	0	0	3591,24	0	0	0	3798,9	250	0	9230	10350	5	124411,95
21	114948	114948	0	0	3588,42	0	0	0	3798	250	0	7280	10350	5	122477,71
22	114962	114962	0	0	3585,85	0	0	0	3798	250	0	7280	10350	5	122492,04
23	115003	115003	0	0	3580,63	0	0	0	3797,8	250	0	6500	10350	5	121753,23
24	115041	115041	0	0	3575,85	0	0	0	3797,8	250	0	6500	10350	5	121790,98
25	115076	115076	0	0	3571,45	0	0	0	3797,8	250	0	6500	10350	5	121825,71
26	115147	115147	0	0	3569,95	1,285	0	0	3797,8	250	0	6500	10350	5	121896,77
27	115166	115166	0	0	3569,51	1,719	0	0	3798	250	0	7280	10350	5	122695,69
28	115053	115053	0	0	3574,28	0	0	0	3799,3	250	0	9750	10350	5	125052,86
29	115008	115008	0	0	3579,65	0	0	0	3798,9	250	0	9230	10350	5	124488,49
30	114967	114967	0	0	3584,66	0	0	0	3798,9	250	0	9230	10350	5	124447,09

Table D-29 IWMV: Iterations results and model statistics for Scenario 5

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	470812,23	555446,50	0,924	180,972	0%	0,043%
2	470812,23	553796,78	0,894	181,016	0%	0,045%
3	471021,25	553796,78	0,896	180,990	0%	0,045%
4	471092,97	553752,78	0,945	181,023	0%	0,045%
5	471119,87	553740,21	0,960	181,080	0%	0,045%
6	471131,82	553735,49	0,878	181,003	0%	0,045%
7	471137,80	553733,40	0,997	181,036	0%	0,045%
8	471141,06	553732,35	0,975	181,081	0%	0,045%
9	471142,96	553731,78	0,853	181,004	0%	0,045%
10	471144,13	553731,45	0,981	180,973	0%	0,045%
11	471144,88	553731,24	0,911	181,038	0%	0,045%
12	471145,38	553731,11	0,997	181,056	0%	0,045%
13	471145,73	553731,02	1,636	181,433	0%	0,045%
14	471145,97	553730,96	1,747	181,380	0%	0,045%
15	471146,14	553730,92	1,100	183,212	0%	0,045%
16	471146,27	553730,89	0,909	181,246	0%	0,045%
17	471146,37	553730,87	1,280	181,232	0%	0,045%
18	471146,45	553730,85	1,028	181,169	0%	0,045%
19	471146,50	553730,84	1,242	181,393	0%	0,045%
20	471146,55	553730,83	1,914	181,639	0%	0,045%
21	471146,58	553730,82	0,954	181,246	0%	0,045%
22	471146,61	553730,81	1,016	181,118	0%	0,045%
23	471146,63	553730,81	1,021	181,108	0%	0,045%
24	471146,65	553730,80	0,905	181,209	0%	0,045%
25	471146,67	553730,80	0,929	181,146	0%	0,045%
26	471146,68	553730,80	1,128	181,188	0%	0,045%
27	471146,69	553730,79	1,991	181,646	0%	0,045%
28	471146,70	553730,79	1,671	182,231	0%	0,045%
29	471146,71	553730,79	1,655	181,837	0%	0,045%
30	471146,71	553730,79	1,329	182,409	0%	0,045%

Table D-30 IWMV: Model results for Scenario 5

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Decomposition solution
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	470812	502786	128182	96208	5292	795	1568	1992	10703	0	108276	36040	29190	0	615128,23
2	470812	502786	128182	96208	5292	795	1568	1992,000	10703	0	108276	35650	29190	0	614738,23
3	471021	503113	128300	96208	5250	839	1568	1994,000	10703	0	108276	35650	29190	0	614947,25
4	471093	503931	129046	96208	5250	851,57	1568	2006,571	10703	0	108276	35650	29190	0	615018,97
5	471120	504237	129325	96208	5250	856,29	1568	2011,286	10703	0	108276	35650	29190	0	615045,87
6	471132	504373	129449	96208	5250	858,38	1568	2013,381	10703	0	108276	35650	29190	0	615057,82
7	471138	504441	129512	96208	5250	859,43	1568	2014,429	10703	0	108276	35650	29190	0	615063,80
8	471141	504478	129545	96208	5250	860	1568	2015,000	10703	0	108276	35650	29190	0	615067,06
9	471143	504500	129565	96208	5250	860,33	1568	2015,333	10703	0	108276	35650	29190	0	615068,96
10	471144	504513	129577	96208	5250	860,54	1568	2015,538	10703	0	108276	35650	29190	0	615070,13
11	471145	504522	129585	96208	5250	860,67	1568	2015,670	10703	0	108276	35650	29190	0	615070,88
12	471145	504528	129590	96208	5250	860,76	1568	2015,758	10703	0	108276	35650	29190	0	615071,38
13	471146	504532	129594	96208	5250	860,82	1568	2015,819	10703	0	108276	35650	29190	0	615071,73
14	471146	504534	129596	96208	5250	860,86	1568	2015,861	10703	0	108276	35650	29190	0	615071,97
15	471146	504536	129598	96208	5250	860,89	1568	2015,892	10703	0	108276	35650	29190	0	615072,14
16	471146	504538	129600	96208	5250	860,91	1568	2015,915	10703	0	108276	35650	29190	0	615072,27
17	471146	504539	129601	96208	5250	860,93	1568	2015,932	10703	0	108276	35650	29190	0	615072,37
18	471146	504540	129601	96208	5250	860,94	1568	2015,945	10703	0	108276	35650	29190	0	615072,45
19	471147	504541	129602	96208	5250	860,95	1568	2015,955	10703	0	108276	35650	29190	0	615072,50
20	471147	504541	129603	96208	5250	860,96	1568	2015,963	10703	0	108276	35650	29190	0	615072,55
21	471147	504541	129603	96208	5250	860,97	1568	2015,969	10703	0	108276	35650	29190	0	615072,58
22	471147	504542	129603	96208	5250	860,97	1568	2015,974	10703	0	108276	35650	29190	0	615072,61
23	471147	504542	129603	96208	5250	860,98	1568	2015,978	10703	0	108276	35650	29190	0	615072,63
24	471147	504542	129604	96208	5250	860,98	1568	2015,981	10703	0	108276	35650	29190	0	615072,65
25	471147	504542	129604	96208	5250	860,98	1568	2015,984	10703	0	108276	35650	29190	0	615072,67
26	471147	504543	129604	96208	5250	860,99	1568	2015,986	10703	0	108276	35650	29190	0	615072,68
27	471147	504543	129604	96208	5250	860,99	1568	2015,988	10703	0	108276	35650	29190	0	615072,69
28	471147	504543	129604	96208	5250	860,99	1568	2015,990	10703	0	108276	35650	29190	0	615072,70
29	471147	504543	129604	96208	5250	860,99	1568	2015,991	10703	0	108276	35650	29190	0	615072,71
30	471147	504543	129604	96208	5250	860,99	1568	2015,992	10703	0	108276	35650	29190	0	615072,71

Table D-31 IOWMV and IHCD: Iterations results and model statistics for Scenario 1

Model type	Iteration	MIP		CPU		Gap	
		Benders' sub-problem flow network	Dantzig-Wolfe sub-problem scheduler	Benders' sub-problem flow network	Dantzig-Wolfe sub-problem scheduler	Benders' sub-problem flow network	Dantzig-Wolfe sub-problem scheduler
IOWMV	1	167797,69	198330,59	0,480	1,150	0%	0%
	2..30	167909,20	197751,35	0,518	1,052	0%	0%
IHCD	1	167797,69	198330,59	0,540	1,242	0%	0%
	2..30	167909,2	197751,35	0,487	1,283	0%	0%

Table D-32 IOWMV and IHCD: Model results for Scenario 1

Model type	Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound
		Costs				Quantities					Costs			Quantities		
		Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
IOWMV & IHCD	1	167798	179251	45813	34360	1889	280	560	712	3817	250	38578	13030	10410	5	219655,69
	2..30	167909	179837	46287	34360	1875	302	560	720	3817	250	38578	12900	10410	5	219637,20

Table D-33 IOWMV and IHCD: Iterations results and model statistics for Scenario 2

Model type	Iteration	MIP		CPU		Gap	
		Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
		flow network	scheduler	flow network	scheduler	flow network	scheduler
IOWMV	1	-673378	198330,59	0,458	1,361	0%	0%
	2..30	-676568	338528	0,446	1,294	0%	0%
IHCD	1	-673378	198330,59	0,429	1,445	0%	0%
	2..30	-676568	338528	0,480	1,125	0%	0%

Table D-34 IOWMV: Model results for Scenario 2

Model type	Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound
		Costs				Quantities					Costs			Quantities		
		Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
IOWMV & IHCD	1	-673378	705200	1670930	292352	0	8055	4792	10830	3817	250	38578	13030	10410	5	-621520
	2..30	-676568	702010	1670930	292352	0	8044	4792	10830	3806	250	39118	13600	10380	5	-623600

Table D-35 IOWMV: Iterations results and model statistics for Scenario 4

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	113414,95	123201,99	0,439	1,319	0%	0%
2	116971,90	122524,34	0,536	44,153	0%	0%
3	113414,95	123201,99	0,431	1,891	0%	0%
4	113414,95	123201,99	0,527	2,837	0%	0%
5	113414,95	123201,99	0,508	14,687	0%	0%
6	115900,51	123182,20	0,542	109,809	0%	0%
7	114837,73	123153,57	0,463	12,202	0%	0%
8	113414,95	123201,99	0,510	3,187	0%	0%
9	113414,95	123201,99	0,515	3,830	0%	0%
10	113414,95	123201,99	0,434	10,498	0%	0%
11	115900,51	123182,20	0,467	29,543	0%	0%
12	114837,73	123173,81	0,532	11,117	0%	0%
13	113414,95	123201,99	0,468	3,728	0%	0%
14	113414,95	123201,99	0,437	12,769	0%	0%
15	113766,34	123197,58	0,529	16,762	0%	0%
16	115900,51	123182,20	0,522	39,495	0%	0%
17	113766,34	123179,69	0,507	7,076	0%	0%
18	114837,73	123166,67	0,501	66,710	0%	0%
19	113414,95	123201,99	0,456	9,880	0%	0%
20	113766,34	123195,06	0,472	8,129	0%	0%
21	115900,51	123182,20	0,564	180,663	0%	0,081%
22	113766,34	123181,67	0,548	37,367	0%	0%
23	114837,73	123173,81	0,513	42,423	0%	0%
24	113766,34	123199,65	0,485	4,753	0%	0%
25	113766,34	123193,60	0,470	4,602	0%	0%
26	115900,51	123182,20	0,517	180,498	0%	0%
27	113766,34	123182,90	0,454	36,788	0%	0%
28	113766,34	123178,14	0,474	22,192	0%	0%
29	114837,73	123169,47	0,483	51,747	0%	0%
30	113766,34	123192,64	0,487	4,561	0%	0%

Table D-36 IOWMV: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
2	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90
3	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
4	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
5	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
6	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51
7	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73
8	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
9	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
10	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
11	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51
12	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73
13	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
14	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
15	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
16	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51
17	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
18	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73
19	113415	113415	0	0	3795,8	0	0	0	3799,3	250	0	9750	10350	5	123414,95
20	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
21	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51
22	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
23	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73
24	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
25	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
26	115901	115901	0	0	3574	21	0	0	3798	250	0	7280	10350	5	123430,51
27	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
28	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34
29	114838	114838	0	0	3691,8	14	0	0	3798,7	250	0	8450	10350	5	123537,73
30	113766	113766	0	0	3730	0	0	0	3798,9	250	0	9230	10350	5	123246,34

Table D-37 IOWMV and IHCD: Iterations results and model statistics for Scenario 5

Model type	Iteration	MIP		CPU		Gap	
		Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
		flow network	scheduler	flow network	scheduler	flow network	scheduler
IOWMV	1	470812,23	555446,50	0,989	180,974	0%	0,043%
	2..30	471146,76	553796,78	0,993	181,103	0%	0,045%
IHCD	1	470812,23	555446,50	0,810	180,859	0%	0,043%
	2..30	471146,76	553796,78	0,963	180,933	0%	0,045%

Table D-38 IOWMV and IHCD: Model results for Scenario 5

Model type	Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound
		Costs				Quantities					Costs			Quantities		
		Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
IOWMV & IHCD	1	470812	502786	128182	96208	5292	795	1568	1992	10703	0	108276	36040	29190	0	615128,23
	2..30	471147	504543	129605	96208	5250	861	1568	2016	10703	0	108276	35650	29190	0	615072,76

Table D-39 IHCD: Iterations results and model statistics for Scenario 4

Iteration	MIP		CPU		Gap	
	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem	Benders' sub-problem	Dantzig-Wolfe sub-problem
	flow network	scheduler	flow network	scheduler	flow network	scheduler
1	113414,95	123201,99	0,472	1,400	0%	0%
2	116971,90	122524,34	0,538	44,352	0%	0%
3	113414,95	123201,99	0,466	1,530	0%	0%
4	116971,90	122524,34	0,538	49,369	0%	0%
5	113414,95	123201,99	0,506	1,663	0%	0%
6	116971,90	122524,34	0,528	47,483	0%	0%
7	113414,95	123201,99	0,509	1,781	0%	0%
8	116971,90	122524,34	0,532	44,707	0%	0%
9	113414,95	123201,99	0,445	1,533	0%	0%
10	116971,90	122524,34	0,400	44,625	0%	0%
11	113414,95	123201,99	0,328	1,447	0%	0%
12	116971,90	122524,34	0,486	45,314	0%	0%
13	113414,95	123201,99	0,451	1,604	0%	0%
14	116971,90	122524,34	0,528	44,237	0%	0%
15	113414,95	123201,99	0,456	1,524	0%	0%
16	116971,90	122524,34	0,449	45,241	0%	0%
17	113414,95	123201,99	0,465	1,572	0%	0%
18	116971,90	122524,34	0,497	44,717	0%	0%
19	113414,95	123201,99	0,431	1,654	0%	0%
20	116971,90	122524,34	0,440	47,963	0%	0%
21	113414,95	123201,99	0,422	1,755	0%	0%
22	116971,90	122524,34	0,439	50,778	0%	0%
23	113414,95	123201,99	0,436	1,554	0%	0%
24	116971,90	122524,34	0,547	44,224	0%	0%
25	113414,95	123201,99	0,434	1,643	0%	0%
26	116971,90	122524,34	0,506	43,941	0%	0%
27	113414,95	123201,99	0,448	1,628	0%	0%
28	116971,90	122524,34	0,552	44,945	0%	0%
29	113414,95	123201,99	0,482	1,617	0%	0%
30	116971,90	122524,34	0,547	46,076	0%	0%

Table D-40 IHCD: Model results for Scenario 4

Iteration	Economic assessments EFN								Total slot consumption [MWh]	Economic assessments PP					Upper bound
	Costs				Quantities					Costs			Quantities		
	Net cost [€]	Electricity purchase [€]	Sales Revenue [€]	Generation Cost [€]	Day-ahead market [MWh]	TOU [MWh]	Onsite generation [MWh]	Sold Electricity [MWh]		External Pulp Cost [€]	Deviation penalties [€]	Start-End Cost [€]	Pulp Produced [m3]	Pulp Bought [m3]	
1	113415	113415	0	0	3795,8		0	0	3799,3	250	0	9750	10350	5	123414,95
2	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90
3	113415	113415	0	0	3795,8		0	0	3799,3	250	0	9750	10350	5	123414,95
4	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
29	113415	113415	0	0	3795,8		0	0	3799,3	250	0	9750	10350	5	123414,95
30	116972	116972	0	0	3535,8	35	0	0	3797,8	250	0	6500	10350	5	123721,90

Curriculum Vitae

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