SCHEDULING AND SEQUENCING OPTIMIZATION FOR HOT ROLLING MILLS

A MULTI-LEVEL ALGORITHM FOR PRODUCTION SCHEDULING AND SEQUENCING OPTIMIZATION IN HOT ROLLING STEEL MILLS

by

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A Thesis

Submitted to the School of Graduate Studies

in Partial Fulfillment of the Requirements

for the Degree

Master of Applied Science

McMaster University

MASTER OF APPLIED SCIENCE (2017) McMaster University

(CHEMICAL ENGINEERING) Hamilton, Ontario, Canada

TITLE:	A Multi-Level Algorithm for Production Scheduling and Sequencing Optimization in Hot Rolling Steel Mills
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NUMBER OF PAGES: xiv, 176

ABSTRACT

The objective of the hot rolling mill is to transform slabs of steel into thin strips which conform to specific dimensional and metallurgical customer requirements. High performance and flexibility in the operation is required due to strict customer demands, variable market conditions, and the drive for continuous improvement.

Historically human schedulers have performed the scheduling and sequencing tasks, however it is not a reasonable expectation that they consider all the complex objectives required in optimal production of a hot mill. Therefore, there are significant opportunities for improvement in this area through the application of mathematical optimization models and solution algorithms.

This work presents a set of models and a solution algorithm for optimal scheduling and sequencing of production within a hot rolling steel mill. The models and algorithms presented within this thesis are specifically developed for ArcelorMittal Dofasco's Hot Strip Mill in Hamilton, Ontario, Canada. First, a graph theoretic representation of the production block is developed along with an asymmetric travelling salesman formulation of the sequencing problem. A slab transition cost function comprised of the hot rolling process objectives is formalized. The objective of the optimization is to generate a complete block sequence which minimizes the cost of transitions between slabs thus minimizing the overall cost of production. The Concorde exact solver is leveraged for the sequencing problem. Second, the scheduling of slabs from inventory into blocks is considered in addition to sequencing. A methodology for slab clustering is defined. The novel concept of width-groups is developed and a heuristic algorithm is devised to calculate an objective for the MILP slab scheduling model. The objective of the scheduling optimization is to construct a set of blocks which minimize deviation from the calculated width-group design. A revised sequencing model, updated to reflect the relaxations enabled by the width-group design, is formulated. Industrial production and offline trials show that the proposed scheduling-sequencing framework outperforms the human scheduler in all critical performance metrics for both scheduling and sequencing. A conservative estimate of the reoccurring monetary benefits available from use of the proposed scheduling-sequencing optimization framework is greater than $1.2M CAD per year.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to my supervisor Dr. Vladimir Mahalec for his constant encouragement and guidance over the past two years. I would not be where I am today, personally or professionally, without his support.

Additionally, this thesis would not have been possible without the time and expertise of my colleagues at Dofasco. In particular, Mike Hough and Vit Vaculik who started me on this adventure as well as Andrei Ianos and everyone in Hot Mill Automation and Commercial.

I would also like to thank everyone involved in the McMaster Advanced Control Consortium for this fantastic experience.

This thesis is dedicated to my family and most especially Amanda. The last two years would not have been possible without your unwavering support and encouragement.

Kevin C Meyer

February 2017

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List of Abbreviations and Symbols

Abbreviations

ISP	Integrated Steel Plant
AMD	ArcelorMittal Dofasco
PB	Product Block
TSPTW	Travelling Salesman Problem with Time Windows
PCTSP	Prize Collecting Travelling Salesman Problem
TS	Tabu Search
VRPTW	Vehicle Routing Problem with Time Windows
PGA	Parthenogenetic Algorithm
GA	Genetic Algorithm
EO	External Optimization
PBSM	Product Block Sequencing Model
TSP	Travelling Salesman Problem
ATSP	Asymmetric Travelling Salesman Problem
ATCF	Aggregate Transition Cost Function
VBA	Visual Basic for Applications
CSV	Comma Separated Value
MDL	Model Index
HIN	Heating Index
WG	Width-Group
SSAM	Slab Scheduling and Allocation Model
MILP	Mixed Integer Linear Program

WKM	Wear Kilometers
WGA	Width Grouping Algorithm

Chapter 1

Introduction

1.1 Motivation and Research Objectives

The hot rolling mill plays a crucial role within any integrated steel plant (ISP). It is a complex and dynamic process which is tightly coupled to both the upstream steel and iron making operations as well as the downstream finishing operations. It is the single source of product flow between its upstream and downstream partners and as such every steel product sold to a customer must be processed through the hot mill. Therefore, it is of critical importance that the hot rolling operations maintain high productivity and throughput levels while continuously producing product of world-class quality.

Flexibility of the hot mill in its operation is also paramount. This is due to both internal and external factors which can result in process instability or unforeseen process downtime. Incoming raw material (steel slabs) may be highly variable in their metallurgical chemistry and starting or final product attributes. Process equipment may be damaged or unable to perform according to specification. Product may be requested by a customer that is very near the edge of the operating capabilities of the mill. Alternatively, there may be requirements to adjust the rate of production and operate at a slower pace or idle the process altogether. This could be the result of unscheduled delays at upstream or downstream operations or as a result of aggressive changes in the steel marketplace.

Changing customer requirements, a highly variable product mix, and instability in market conditions have become far more commonplace within the last decade. These items coupled with the continuous drive to reduce the cost of production and stay competitive is the new reality for integrated steel mills. As such it is imperative that the hot mill be able to operate in a highly dynamic fashion without sacrificing productivity or quality.

A key component to this dynamic operation is the ability to plan, schedule, and sequence production of the hot mill in the most optimal fashion possible. This has historically been the domain of a scheduling team who conduct planning, scheduling, and sequencing tasks for the entire integrated steel plant with dedicated staff specifically for the hot rolling mill. For the majority of firms these tasks are completed via manual processes using heuristic rules developed and evolved over decades of experimentation and knowledge building. The amount of knowledge and experience contained within these heuristics, and expertise of the schedulers, cannot be underestimated.

In order to address the problem of staying competitive in a highly dynamic marketplace mathematical optimization methods are beginning to become of great interest to ISPs in the planning, scheduling, and sequencing areas.

The research outlined in this thesis follows the investigation into the scheduling and sequencing optimization of a hot rolling mill at ArcelorMittal Dofasco (AMD) in Hamilton, Ontario, Canada. ArcelorMittal Dofasco has a long tradition of innovation and continuous improvement and as such the problems and opportunities outlined above presented excellent motivation for research in this area. There was significant support from management in the commercial, engineering, and operations departments to pursue research, develop problem formulations, and implement a solution in production for AMD's hot rolling operations. Chapter 2 presents a brief historical background of the hot rolling process and rolling mill operations at Dofasco's facility so that the reader is able to place this research in the appropriate industrial context.

The primary objective of this work was to develop a sequencing optimization model for the discrete piece-to-piece sequences of hot rolling production campaigns. As research progressed it was determined that in order to properly create intra-campaign sequences in an optimal fashion, this research needed to expand to cover scheduling of raw material for the construction of the campaigns themselves. As a result, the research outlined in this thesis covers models for both the optimization of scheduling and allocation of raw material into production campaigns as well as the internal discrete sequencing of material within those campaigns.

1.2 Main Contributions

The research conducted regarding the objectives discussed above has led to the following contributions to the research literature as well as AMD's hot rolling operations:

1. **Concept of Thickness Group Clustering.** The concept of grouping the available slab population into distinct thickness clusters for improved homogeneity and performance at the sequencing level is outlined. Multiple non-production trials are presented which demonstrate the performance gains as a result of this concept.

2. **Width Grouping Algorithm.** A novel concept and solution algorithm is presented which forms the basis for the scheduling formulation and is the enabler for the performance gains at the sequencing level. Multiple non-production trials are presented which demonstrate the performance of this solution method.

3. **Formulation of the scheduling problem for the allocation of raw material to production campaigns.** A mixed integer linear programming formulation which utilizes the thickness clustering and width grouping concepts as well as a novel strategy for the scheduling of material. Multiple non-production trials are presented which demonstrate the performance of this solution method.

4. **Formulation of the sequencing problem for discrete sequences within the production campaigns.** An asymmetric travelling salesman formulation of the intra-campaign sequencing problem which is relaxed by the upper level scheduling solution. Multiple non-production as well as production trials are presented which demonstrate the performance of this solution method.

5. **Design of the solution architecture for hot rolling optimization.** The overall architecture of this optimization solution is presented. The decomposition of scheduling and sequencing into a multi-level design is described. A prototype decision support tool is introduced. Benefits and potential issues of this architecture design are discussed.

1.3 Thesis Overview

Chapter 2 – A Brief History of Hot Rolling with Industrial Context

A condensed history of hot rolling in the steel industry is given to provide some background knowledge with the industrial processes discussed in this research. Additionally, historical and current methods for the planning, scheduling, and sequencing of hot rolling operations are outlined. This background knowledge is then projected in context to ArcelorMittal Dofasco's hot rolling operation.

Chapter 3 - Literature Review

A general overview of the relevant research in production planning, scheduling, and sequencing optimization for integrated steel plants is presented. A survey of the existing literature is provided to outline solution formulations and solution methods/algorithms applied to ISP problems. Specific care is taken to identify those solutions which have been applied in practice through either production trials or simulations using plant data with feedback from the partner ISP. The current literature is also reviewed to outline architecture design for multi-level optimization solutions.

Chapter 4 – Sequencing Optimization for Hot Rolling Mill Production

This section describes the early research which investigated the discrete sequencing of slabs at the intra-campaign level only. First the problem is outlined in the context of hot rolling operations at AMD. The solution formulation and a description of improvements, discoveries, and results are presented. The final formulation of the intra-campaign sequencing optimization model is then demonstrated through performance results obtained from seven production trials at AMD.

Chapter 5 – Integrated Scheduling and Sequencing Optimization for Hot Rolling Mill Production

This section describes the second phase of research which involved expanding the research scope to include the scheduling and allocation of raw material into hot rolling campaigns and the subsequent modifications to the sequencing formulation. The problem is first described in context of hot rolling operations at AMD. The solution architecture of this multi-level formulation is then introduced along with a description of the upper and lower optimization layers. A prototype decision support tool is presented along with non-production trial results obtained using industrial data from AMD. An economic analysis is conducted and benefits are outlined in annualized cost savings as well as non-tangible advantages of the proposed solution.

Chapter 6 – Conclusions and Recommendations

Conclusions on both phases of this research are given with the results placed in context of hot rolling operations at AMD. The key results obtained from the trials are outlined and the major benefits are highlighted. Recommendations for future areas of research are proposed with a focus given to AMD's hot rolling operations.

Chapter 2

A Brief History of Hot Rolling with Industrial Context

The intent of this chapter is to provide a historical overview of hot rolling for flat products, background on the modern hot rolling process, as well as a review of the scheduling and sequencing techniques currently utilized in industry. These concepts will then be projected in context to ArcelorMittal Dofasco's hot rolling operations and the problems under investigation in this research.

2.1 Hot Rolling for Flat Steel Products

According to Roberts (1983) the earliest forms of what is considered today to be hot rolling, and the concept of a hot rolling mill originated in the latter half of the seventeenth century. Over the following centuries the hot rolling process and rolling mill design were considerably improved upon first in Europe and later North America where water power gave way to steam until finally in the early part of the twentieth century the first modern electrically powered hot rolling mills were constructed.

As documented in The Making, Shaping and Treating of Steel (United States Steel , 1985) the first modernly recognizable hot rolling steel mill was constructed in Butler, Pennsylvania in 1926. This rolling mill was the first to combine the modern principles of a four-high finishing mill stand, succesive reduction of the steel thickness through multiple finishing stands, and coiling equipment at the discharge end of the mill. This installation represents the first modern hot rolling mill as they are known today (United States Steel , 1985). From this first generation design in 1926 the hot rolling mill underwent two additional major evolutionary transitions. The second generation of hot rolling mills in the 1950's and 1960's saw the addition of increased width capability, increased drive power, tandem roughing stands, seven stand finishing mills, advanced strip cooling systems, and the addition of automatic control functions via computers (Roberts, 1983). A third generation of hot rolling mill technologies were developed in the 1970's and included improvements in instrumentation and sensors, advanced computer control of mill equipment, and innovations for throughput improvements such as the coil-box and reversing roughing mill stands (Roberts, 1983). A modern hot rolling mill consists of two or more slab reheating furances with possible provisions for a third or fourth, a scale-breaking unit, a powerful reversing roughing mill stand, a finish mill with seven stands in what is known as a four-high configuration, a long run-out table with cooling banks for metallurgical control of the steel, and one or two down-coilers (Roberts, 1983).

While the configuration of a hot rolling mill can vary depending on if the operation is newly constructed or a evolutionary site which has been upgraded over time, the basic hot rolling process is nearly indentical in any installation. Hot-rolled products are produced by reducing the thickness of an incoming slab via heating and rolling at elevanted temperatures (United States Steel , 1985). The following is an overview of the hot rolling process as outlined in the definitive text on steel-making by the United States Steel Corporation (1985). Slabs produced from the upstream steel-making operations are brought up to the required temperature inside of the reheating furances. The resultant oxide layer from reheating is removed using high pressure water sprays inside a scale-breaker unit. The slab is then processed through a roughing mill at which point the final product width is set by the edging rolls and the slab thickness reduced to a dimension acceptable by the finishing mill. This transformed slab is now refered to as a transfer bar. The transfer bar then enters the finishing mill and is successively reduced in thickness, to it's final target thickness, by each finishing mill stand. Other parameters are controlled within the finishing mill such as cross-width profile and flatness of the steel. Upon exiting the finishing mill the steel is now refered to as a strip and travels along a run-out-table where water cooling banks reduce the temperature of the strip. This controlled cooling of the strip allows for accurate control of the metallurgical properties of the steel. The strip then reaches the end of the process and is wrapped into a cylindrical coil by a down-coiler and removed to a storage yard to await further processing by downstream operations. The entire process operates in a semi-continous fashion where multiple slabs may be undergoing work in the different sub-processes of the overall hot rolling mill at any given time.

The current hot rolling mill at ArcelorMittal Dofasco was constructed in the early 1980's with operations commencing in 1983. The mill itself has undergone considerable evolution through multiple large scale improvement projects including the modernization of both rolling mill equipment as well as control and automation systems. Total tonnes produced per operating hour has increased from below 300 in 1983 to a record level of 750 in 2014.

As of 2016 AMD's hot rolling operations consist of a process layout as described below in sequential order.

1. Two Walking Beam Reheating Furances
2. One Descaling System
3. One Reversing Roughing Mill
4. One Cropshear
5. A Seven Stand Finishing Mill
6. Three Downcoilers

Continuous improvement and innovation are core AMD philosophies which have allowed the hot rolling operations to reach and maintain world class performance levels for all key operational metrics. The operation is in a constant state of evolution with engineers continuously making improvements to equipment, control systems, and process operation. In its current configuration AMD's hot mill is capable of sustaining a production rate of 5.4 million metric tonnes per year of hot rolled product. Under normal operating conditions a slab of steel is transformed into a coil every two minutes with multiple slabs at varying stages of transformation throughout the overall mill. For the age of the mill and equipment configuration these are highly impressive results, especially the throughput rate which is comparable to far more modern hot rolling mills.

Figure 2.1 illustrates the mill configuration graphically and provides a sense of the scale of the overall process and the major sub-processes.

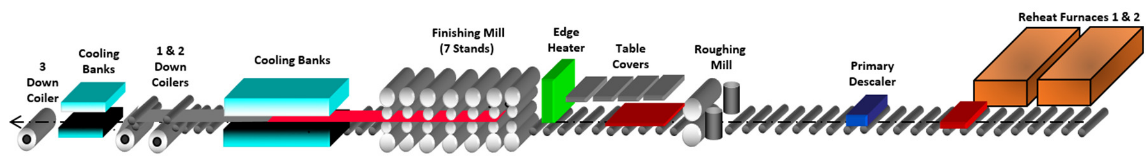

Figure 2.1 – Hot Rolling Mill Configuration at AMD

2.2 Methods for Scheduling and Sequencing of Production

The methodology for the scheduling and sequencing of hot rolling production is quite unique and contains some concepts and terminology not seen in other areas of the integrated steel plant. A production campaign, where a population of slabs is organized for hot rolling, is called a product block or line-up. These product blocks may consist of hundreds of steel stabs usually of similar metallurgical chemistry type. The individual slabs contained within a product block are sequenced into a very specific order known as a coffin-shape. Figure 2.2 illustrates the normal appearance of a coffin-shape product block. The first slabs selected are known as "break-in" material. This "break-in" section consists of slabs which present low rolling difficulty so that the mill equipment can transition from delay conditions to rolling conditions with little mechanical stress. The next section contains the "wide-out" material where the slabs gradually increase in width up to the widest slab in the product block. The final section contains the main or "body" portion of slabs for the product block where the width is gradually reduced from the widest slab to the narrowest; not necessarily in strict order of decreasing width. Product blocks are rolled through the hot mill one after another with a brief delay taken between product blocks to change the work-rolls of the finishing mill stands. The rolling of these product blocks is continuous with major delay time only occurring when unforeseen issues arise and a production stoppage is required.

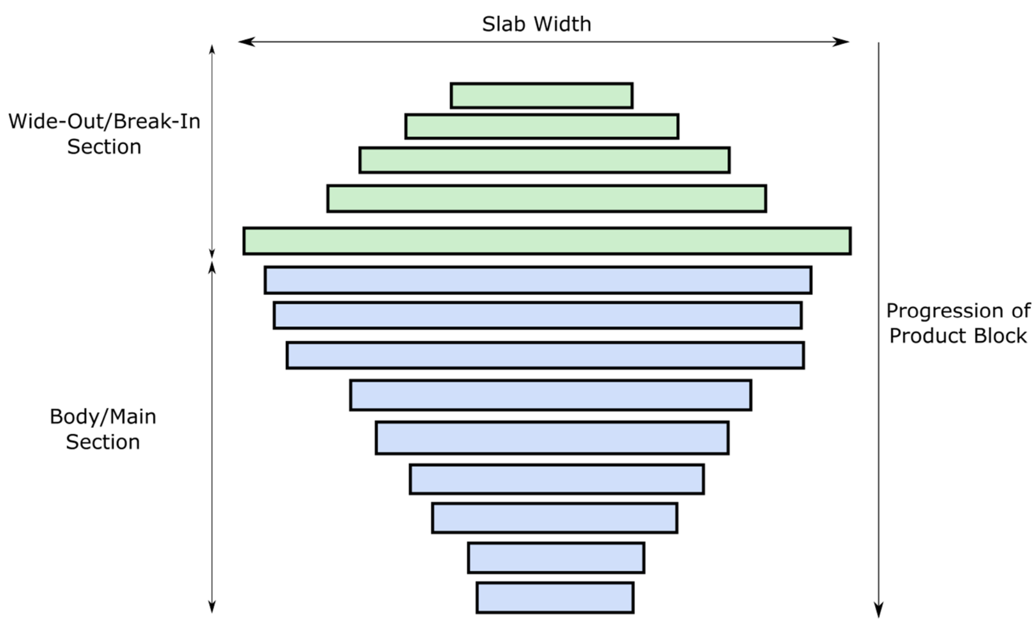

Figure 2.2 – Coffin-Type Product Block Configuration

Scheduling of hot rolling operations is performed for a multi-day horizon, typically between 4 to 7 days. However due to the highly dynamic nature of an ISP these longer horizon schedules are continuously revised, potentially on a daily basis. The term scheduling here refers specifically to the selection of slabs, creation of product blocks, and sequencing of slabs within the product blocks for the required time horizon.

As with most industrial topics which have a direct impact on a firm's profitability, production planning, scheduling, and sequencing are closely guarded concepts for all ISPs. However, in the early stages of this research an attempt was made to survey ArcelorMittal facilities around the world to better understand how similar ISP sites conduct production scheduling and sequencing. This query requested a description of the ISP's current scheduling and sequencing practices as well as questions on whether the plant is either currently leveraging or has investigated mathematical optimization in these areas. All but one ArcelorMittal ISP responded that scheduling and sequencing of their hot rolling operations is carried out by a human scheduler using heuristic rules. One ArcelorMittal ISP responded that they have investigated mathematical optimization and have implemented a decision support tool which the schedulers use to construct individual product blocks (K. Jacobs, Personal Communication, September 15 2016). This decision support tool utilizes a heuristic optimization algorithm and still requires direct involvement from the schedulers. This ArcelorMittal ISP noted good results but expressed concerns over the formulation and limited scope of their solution. No other

ArcelorMittal ISPs noted any prior or planned investigation into the application of optimization techniques to hot rolling production scheduling or sequencing.

While no ISPs outside of the ArcelorMittal group were contacted, some colleagues had knowledge of non-ArcelorMittal ISP which have investigated optimization methods for the purpose of hot rolling scheduling and sequencing. According to both F. Wang and V. Mahalec the Japanese steel industry has applied combinatorial optimization techniques to the sequencing of slabs within product blocks (Personal Communication, September 2015). Additionally, there is some evidence in the current research literature which would suggest both Japanese and Chinese firms have implemented mathematical optimization techniques to solve planning, scheduling and sequencing problems in the ISP domain. Details of this research and application are provided in Chapter 3.

While there has been tremendous innovation and improvements at ArcelorMittal Dofasco's hot rolling mill over the last three decades, the planning, scheduling, and sequencing of production continues to be a fully manual process. A team of schedulers perform planning, scheduling and sequencing tasks for all of AMD's operations over various time horizons. There exists some software-based automation at the planning level, however the scheduling and sequencing of production is performed by the scheduling team using heuristics which have been developed over decades of experimentation and learning (D. Callaghan, Personal Communication, September 8, 2015). AMD's hot rolling operations are scheduled for a 4-day time horizon where the schedulers first determine what types of material are required based on both delivery dates and finishing operations capacity requirements downstream from the hot mill. Slabs are then assigned to individual product blocks based on the metallugical type of steel and a rough sequence for the slabs is created by sorting from widest to narrowest. The scheduler then applies their personal knowledge and a set of documented rules to resequence the slabs as they feel is necessary for a production ready product block. This process is performed by the schedulers using a software application which provides some basic rule checking functionality, however the assignment of slabs to product blocks and the sequencing of those slabs in each block is a fully manual process. As a result of this work-process the resultant product blocks can be highly variable based on the personal knowledge, perferences, and experience of the scheduler.

Some time was spent working closely with the schedulers in order to understand their work-processes. After monitoring the scheduler's methods it was clear that while the product blocks they create are of good quality, they are only optimizing on two variables at most: width and thickness of the slabs. It was therefore concluded that investigating the application of mathematical optimization techniques to both the scheduling and sequencing of product blocks for hot rolling production could indeed result in high value for AMD.

It is important to note that the experience and skill present in the scheduling team cannot be underestimated. This group is the primary source of planning, scheduling, and sequencing knowledge within AMD.

Chapter 3

Literature Review

The intent of this chapter is to provide a review of the research literature which is relevant to the industrial problems investigated in this thesis. The primary topics of review are production scheduling and sequencing optimization for hot rolling mills and the solution methods and algorithms which have been applied. Solutions which have been validated using production trials or simulated using industrial data are highlighted. Publications of high importance, containing key ideas, and those which may be leveraged in an industrial setting are noted for the reader.

In this thesis scheduling is considered to be the aggregation of material into product blocks and sequencing is considered to be the discrete arrangement of the individual slabs or coils within the blocks.

3.1 Overview of the Research Literature

While production planning, scheduling, and sequencing for hot rolling operations within an integrated steel plant is not a highly active research area, there has been a moderate amount of research conducted in the general ISP domain. This introductory section summarizes the existing research literature and notes the established state of hot rolling scheduling and sequencing problems.

As noted by Jacobs et al. (1988), Zhao et al. (2009), Lopez et al. (1998) and others, hot mill scheduling and sequencing are very difficult problems with multiple competing objectives and highly complex constraints which can be difficult to model using traditional mathematical programming or classical operations research methods. The scheduling and sequencing problems themselves have been well documented as belonging to the class of NP-hard problems and as such it is very difficult if not impossible to generate truly optimal solutions in reasonable computational times. (Zhao, Wang, Liu, Wang, & Shi, 2009) (Chen, Lu, Ge, Yang, & Pan, 2012).

Research regarding hot rolling production planning, scheduling, and sequencing problems has primarily been limited to introductory reviews of functions, features, and concepts rather than detailed descriptions of optimization solution formulations and methodologies (Tang, Liu, Rong, & Yang, 2001). Research has been mainly focused in four main areas (1) Operations Research Methods, (2) Intelligent Search Methods, (3) Human-Machine Coordination, and (4) Multi-Agent Methods (Tang, Liu, Rong, & Yang, 2001). Research in the ISP domain began in the 1970's with the application of traditional operations research methods such as mathematical programming in search of true optimal solutions to scheduling problems for the individual ISP processes. Due to process technology advancements during the 1970's and 1980's, research trended towards optimization problem formulations where the hot mill was considered linked to its upstream or downstream partners. This increased both the size and complexity of the scheduling and sequencing problems and as a result combinations of the four solution methodologies noted above have comprised the core of solution design described in the literature since the 1990's. Meta-heuristics and intelligent search algorithms are the current solution methods of choice for hot rolling scheduling and sequencing problems (as well as ISP problems in general) as they provide high quality solutions in reasonable computation times. Implementation architectures where automated mathematical programming and meta-heuristic optimization algorithms are combined with human schedulers in an interactive human-machine coordination process have also been a common trend. Additionally, nearly all prior research focuses on pre-emptive or generative scheduling with no consideration given to reactive scheduling methods which are highly desirable due to the dynamic nature of ISPs (Suh, Lee, Lee, & Ko, 1998). However, one of the more recent concepts is fully automated production scheduling and sequencing using agent-based architectures where the hot rolling operations comprise a single agent in the overall ISP planning, scheduling, and sequencing system. This type of architecture enables reactive and dynamic re-scheduling and re-sequencing as a result of unforeseen production delays or process downtime.

Commonly hot mill scheduling and sequences problems are formulated as variations of the Travelling Salesman Problem (TSP) with customizations to allow for the additional objectives required by the hot rolling operation. Much of the customization to the traditional TSP formulation is as a result of integrating the scheduling and sequencing problems and thus the need to consider both slab and coil sequence transitions as well as operational requirements such as customer due dates. As these are large scale combinatorial problems intelligent search and meta-heuristic methods comprise the core of the solution methodology found in the research literature. Specific problem formulations and solution algorithms presented in the existing literature are discussed in detail in the following section.

The reader is directed to the excellent review paper by Tang et al. (2001) which provides a comprehensive overview of the current state of the research as well as references for ISP facilities which have implemented optimization solutions for production planning, scheduling, and sequencing.

The following two sections provide a detailed, chronological review of individual papers which discuss production scheduling and sequencing for hot rolling mill operations. Elaboration on the specific problem formulations and solution methodologies outlined in each paper is given. A discussion of solution architectures and design as well as operational and implementation methodologies noted in the literature is provided as a showcase of common industrial best practices.

Two important notes for the reader which apply to the following section:

1. In some cases, the problem has been formulated where the hot mill is connected to either upstream steel-making or downstream finishing operations and thus the scope may expand beyond the hot mill itself.

2. Many of the contemporary problem formulations integrate the scheduling and sequencing tasks into a single optimization problem. These formulations will be reviewed primarily in the sequencing section and will be identified for the reader.

3.2 Solution Methodologies for Hot Rolling Scheduling

Some of the earliest research conducted in the domain of hot rolling mill production scheduling is that of Redwine and Wismer (1974) who applied a mathematical programming approach to solve order scheduling in an ISP. This work considered the entire integrated steel plant and how customer orders should be scheduled over a one-week time horizon through the various internal processes. The problem formulation primarily considered basic constraints such as orders to be process, the required processing of those orders, due dates, and individual process capacities with the objective of minimizing the tardiness of final product to customers. A mixed integer programming model was developed and solved using a Bender's decomposition approach. Redwine and Wismer compared a scheduling solution generated using their method against a schedule created via computer simulation of an ISP’s heuristic rules. They found their solution to provide a schedule which was only slightly better than the heuristic rules currently used by the ISP. An important note in Redwine and Wismer's work was that they found their solution to require considerable computing time and that a natural next step would be to develop schedules using less sophisticated but faster methods (Redwine & Wismer, 1974).

As continuous casting technology became more prevalent during the later part of the 1970’s and early 1980’s the research of the time began to contemplate a link between the continuous caster and the hot rolling mill when considering production scheduling. In collaboration with Bethlehem Steel Wright et al. (1984) developed a multi-objective linear programming model to solve the hot mill scheduling problem. However, it was found to be too complex to solve with conventional computing resources at the time. Building on this first work Jacobs, Wright, and Cobbs (1988) began to consider the hot mill as a sub-process within the overall ISP and developed a goal programming approach to hot mill production scheduling; once again considering multiple objectives. Goal programming is a subset of linear programming where the sum of deviations from a weighted set of goals is minimized (Jacobs, Wright, & Cobbs, 1988). The goals considered in this work were to minimize the amount of material in inventory, to meet or exceed the projected revenue for the scheduling time horizon, and to maximize the capacity of the hot rolling process. In this work it is assumed the hot mill is being supplied by the continuous caster with what are termed as order blocks, a group of slabs which are similar in type and customer, and that these order blocks are known prior to scheduling optimization. The result of this formulation is a schedule for the timing of production of these order blocks in the hot mill which is optimized by the weighted goal objective function. Jacobs et al. compared schedules generated by their solution formulation against production schedules created by the hot strip mill scheduling group at Bethlehem Steel Corporation. Their solutions showed greater utilization of the available operational capacity in the hot rolling mill which resulted in overall higher revenue across the scheduling horizon. While the comparison results appeared promising Jacobs et al. did concede that considerable work would be required in order to implement this solution in a production environment primarily due to the highly estimated weighting factors and cost functions which were used. An interesting note made in this work is that the models used in this formulation should be small enough to be computationally efficient while providing results that are feasible, accurate, and useful enough to the management of the ISP. If solutions and schedules returned by the model can provide a strategy or information which can aid the hot mill scheduling group then the model has served its purpose (Jacobs, Wright, & Cobbs, 1988). This is an early indication of the movement towards decomposition of increasingly complex problems and the use of meta-heuristic and intelligent search optimization methods.

During the 1990's research into hot rolling production scheduling saw a shift from traditional mathematical programming and operations research methods to meta-heuristic and intelligent search solution algorithms. This was due to the difficulties in solving scheduling problems, known to be NP-hard, with mathematical programming techniques as well as advances and innovation in the field of computational optimization. Meta-heuristics developed at the time facilitated research into simultaneous scheduling and sequencing of hot rolling production as well as other areas of the ISP. As a result of this shift in problem formulation the majority of research from the mid-1990's onward considers both the scheduling of material and the sequencing of that material as an integrated (either single or multi-stage) optimization problem and not as two discrete problems. Due to this shift in formulation more recent research on hot rolling scheduling, what could be termed as second generation research, now considers topics other than simple selection and allocation of material. True scheduling problems are now typically discussed as a component of integrated scheduling-sequencing solutions.

One of the more extensively discussed topics in modern scheduling is that of fully automated or dynamic scheduling. Suh, Lee, Lee and Ko (1998) present the concept of reactive scheduling and compare a number of different strategies. Suh et al. present dynamic hot rolling scheduling as a two phase approach: (1) traditional generative scheduling where a production schedule is constructed to satisfy various constraints and (2) a reactive control phase where the generative schedule is modified as required to reconcile any differences between the original schedule and the real-time state of the hot rolling operation arising from unexpected process interruptions. The unexpected events considered in this work are delayed delivery of slabs to the hot mill, failure to meet quality control stands, and equipment breakdown. The authors propose a constraint satisfaction approach and devise ISP domain-specific strategies and heuristics for guiding the reactive re-scheduling process. These domain specific strategies are developed based on the traditional heuristics used by the human schedulers. Due to the complexity of the scheduling problem, an NP-hard problem as previously discussed, the constraints imposed may be so restrictive that the system cannot find a feasible solution. In this case it is necessary to relax some of the constraints or extend the scheduling time horizon to incorporate additional candidate slabs such that a feasible solution to the problem can be found (Suh, Lee, Lee, & Ko, 1998). Suh et al. developed a prototype application with a design following the human-machine interaction paradigm where the scheduler uses the application as a decision support tool. With this design it is the responsibility of the human scheduler to relax certain constraints if infeasible solutions are encountered; this is referred to as interactive scheduling (Suh, Lee, Lee, & Ko, 1998). Suh et al. conducted a number of simulations using their prototype however no production data comparisons or production trials were noted as having been completed and there appears to have been no collaboration with any industrial partners. This work is typical of the second generation of research into hot rolling scheduling and contains many interesting ideas, problem formulations, and designs which warrant further investigation.

A second area of research in modern steel industry scheduling is that of large-scale or global ISP scheduling. While this research area does not focus solely on the scheduling of hot rolling operations, the hot mill plays a major factor as it is commonly the bottle-neck or critical process in most ISP operations. Okano et al. (2004) present a large-scale scheduling solution for the finishing operations of an integrated steel plant in Japan. This solution considers four processes from the hot rolling mill onward: a cold mill, a continuous galvanizing line, a continuous annealing line, and an electro-galvanizing line. The Japanese ISP partner in this work had previously developed a primary-end (steelmaking and hot rolling) scheduling optimization application which is why hot rolling is not considered in this solution. However, many of the concepts and ideas presented in this research could be applied to hot rolling scheduling or in a scheduling system which integrates steel-making and hot rolling with the finishing lines. The solution developed by Okano et al. focuses on the generation of production campaigns for steel coils on the above four processes for a one-month scheduling horizon. The scheduling problem formulation involves both horizontal flows of production campaigns along timelines on each of the four noted processes and vertical flows of coils from upstream to downstream processes (Okano, et al., 2004). The solution proceeds in four main steps: (1) input coils are clustered to reduce the complexity and size of the scheduling problem, (2) campaigns are created for each process moving from downstream processes to upstream process such that the coil due dates are propagated upwards, (3) timing inconsistencies along the process flows are repair by scheduling downward, (4) coils are then sequenced within each individual campaign (Okano, et al., 2004). The overall goal of this solution is to maximize productivity and product quality through the full use of operational capacity and to minimize tardiness of final coil delivery. Okano et al. employ a graph formulation using a greedy algorithm for the clustering of similar coils, a travelling salesman with time window formulation (TSPTW) for the allocation of clusters to campaigns using nearest neighbour and 2-opt local search methods for improvement, and finally TSPTW using heuristics and local search for the internal sequencing of coils within campaigns. In order to reduce the size and complexity of the overall scheduling problem Okano et al. have decomposed the problem into smaller components which are more manageable and allow for specific optimization tasks to be completed by the different components. The distinct separation of campaign allocation and sequencing of coils is a prime example of this decomposition. This solution is capable of returning a complete schedule consisting of 20,000 to 25,000 coils for the four finishing operations for a one-month time horizon while satisfying a one-hour computational time limit. Okano et al. note that integration of this solution into the Japanese ISP's operations is nearly complete and that cost savings have yet to be determined. There are expected benefits as a result of plan lead time reduction, inventory reduction, workforce reduction, capability for quick rescheduling, and accurate due date quotation (Okano, et al., 2004). This work is again typical of the second generation of research into ISP scheduling and sequencing optimization. While considerably large and highly complex, these formulations contain many interesting concepts and ideas which can be leveraged for more compact scheduling and sequencing applications.

A second example of large-scale scheduling is the more recent investigation conducted by Xu, Sand, Harjunkoski, and Engell (2012) which considers an integrated production scheduling solution for both the steel-making and hot rolling operations of an ISP. In this work a coordination heuristic is developed which synchronizes the independent optimization solutions for steel-making scheduling (Harjunkoski & Grossmann, 2001) and hot rolling scheduling (Biondi, Saliba, & Harjunkoski, 2011) which have been developed in previous research. Through the coordination of these two existing solutions global objectives such as the maximization of hot charge ratio and the minimization of slab yard inventory may be considered (Xu, Sand, Harjunkoski, & Engell, 2012). The steel-making component of this large-scale solution, developed by Harjunkoski & Grossmann (2001), applies a decomposition approach whereby a heuristic algorithm groups similar heats of steel into blocks which are then scheduled using mathematical programming techniques in a series of sequential stages. The grouping heuristic minimizes total casting setup time through the aggregation of similar heats while the multi-stage scheduling programs minimize total makespan for the desired horizon (Harjunkoski & Grossmann, 2001). The hot rolling component of this solution, developed by Biondi, Saliba & Harjunkoski (2011), proposes a similar combination of heuristic and mathematical programming techniques to (1) construct the hot rolling product blocks and (2) schedule the product blocks for production. In the first stage a construction heuristic creates product blocks by allocating slabs such that similar material is grouped together and the required hot rolling constraints are met. These product blocks are then scheduled using a traditional mathematical programming formulation such that any violation of order due date is minimized. No discrete sequencing optimization is performed on the slabs once they have been assigned to a product block as only groups of slabs are considered. Additionally, little information is provided on the constraints employed within the heuristic however it is explicitly stated that the width profile of a product block must be strictly decreasing and that slabs of similar thickness and metallurgical grade should be grouped together (Biondi, Saliba, & Harjunkoski, 2011). Biondi et al. (2011) note that the proposed hot rolling scheduling solution has been tested using industrial data, and that it is capable of scheduling for a one-month horizon in approximately three minutes of computation time. Applying the proposed coordination heuristic to manage both steel-making and hot rolling scheduling Xu, Sand, Harjunkoski, and Engell (2012) have been able to solve industrial scheduling problems through a hybrid solution typical of the second generation of research into large-scale ISP scheduling.

3.3 Solution Methodologies for Hot Rolling Sequencing

Sequencing of hot rolling production is the logical next step in the optimization of rolling mill operations after completing the allocation and scheduling of raw materials. As with all sequencing tasks the arrangement of incoming slabs for rolling in the hot mill is a computationally difficult problem made even more complex by the unique and challenging constraints required by the hot rolling process. Truly optimal solutions are typically impossible to obtain as the problem is known to be NP-hard. Due to the inherent complexity of the sequencing problem the research literature available on production sequencing in hot rolling operations is more recent than that of production scheduling and begins mainly with the arrival of meta-heuristic and intelligent search methods.

An early article published on the topic of sequencing optimization for hot rolling in the steel industry is that presented by Petersen, Sorensen, and R.V.V. Vidal (1992). Here the authors describe a strategy for sequencing slabs through a hot rolling mill although the operation in question is not explicitly stated as a coil producing hot mill and may possibly be a hot rolling mill for steel plate. Nevertheless, parallels can still be drawn between the sequencing method described here and that required by a strip producing hot rolling mill. Petersen et al. outline a solution in which the primary goal is to synchronize the reheating furnace and the rolling mill. The authors note that due to sequencing of dissimilar slabs consecutively into the furnace the mill sees uneven production flow. Frequently the mill is waiting for the furnace to adequately heat a slab to the required temperature or conversely the furnace is ready to discharge the next slab but the mill is still processing a current slab. Additionally, optimizing the sequence of slabs charged into the furnace will result in more efficient use of the reheating energy. Sequencing of the slabs is combinatorial in nature and the number of feasible solutions grows exponentially with the number of slabs to be scheduled. A problem of this complexity cannot be solved using traditional or exact optimization methods due to the effects of combinatorial explosion and therefore heuristic methods are utilized (Petersen, Sorensen, & Vidal, 1992). Petersen et al. apply a construction heuristic to solve the combinatorial problem of slab sequencing using a method belonging to the family of greedy algorithms. In addition to discrete slab sequences the authors also consider multiple stages each containing a sequence of slabs. The ordering of these stages is formulated as a tree-like graph structure and solved using a shortest-path algorithm. This problem formulation was selected due to the ease of implementation on a computer, the ability to implement the required constraints within the heuristic solver, and the reasonable computation times expected (Petersen, Sorensen, & Vidal, 1992). Petersen et al. compared the results from their solution to the sequences created by a Danish steel company specifically targeting three key metrics: (1) maximize synchronized production, (2) minimize wasted heating area in the furnace, and (3) minimize delivery time lag. The comparison results showed that the heuristic approach resulted in sequences with much higher performance metrics than the sequences developed by the steel mill. Overall utilization of the reheating furnace had increased by 20% and the operational capacities of the reheating furnace and the rolling mill were much closer to one another while the delivery time on average had been reduced by one week. In conclusion Petersen et al. make an important note in that management at the steel mill was very happy about the possibility of having a tool which the schedulers could use to simulate different strategies by altering the weightings of the objectives. In practice it is impossible to fix the weightings of the different objectives as production requirements are constantly changing. It was noted that the collaborating steel mill in this research had decided to implement this solution in production and that first trials were being conducted with promising results.

In the late 1990's Lopez, Carter, and Gendreau (1998) conducted research into a combined scheduling and sequencing optimization formulation for hot rolling production. Interestingly this work was conducted in collaboration with Dofasco in Hamilton, Ontario, Canada, the same ISP whose hot rolling operation is investigated in this thesis.

Lopez et al. focus on the selection and allocation of slabs from inventory into multiple product blocks (PBs) and then the sequencing of the slabs within these PBs. The authors note the multiple conflicting objectives of obtaining smooth sequences of slabs with similar characteristics (width, hardness, gauge, and heating efficiency), maximizing product quality, maximizing operational capacity, minimizing wasted energy, and avoiding delays in delivering final product. The authors also consider the complex constraints required in hot rolling at Dofasco especially the coffin-shape of width in the product blocks as well as the wide-out and come-down or body portion of the PB. In the wide-out portion of the PB the slab sequence is constrained from narrow to wide and in the come-down portion wide to narrow as to avoid wearing the mill rolls and incurring quality issues. Lopez et al. explicitly state that slabs should be scheduled in non-increasing order of width in the come-down portion of the product block (Lopez, Carter, & Gendreau, 1998). Another more complex constraint is the placement of critical products within the PB as some coils have high quality surface requirements and must be processed early in the product block. In this work the scheduling and sequencing problem is formulated with four objectives which consider all constraints required by the hot rolling operation: (1) maximize product quality, (2) maximize productivity, (3) maximize on-time delivery, and (4) minimize wasted energy. Lopez et al. recognize the two distinct components of scheduling and sequencing in this problem and apply two unique formulations to model the problem. The scheduling component is represented as a knapsack problem while the sequencing component is represented as an asymmetric travelling salesman problem (ATSP). However, the two separate tasks are considered simultaneously and solved using a prize collecting travelling salesman problem formulation (PCTSP). The PCTSP is a variation of the traditional TSP that includes a knapsack-type constraint which allows for both the scheduling of slabs into PBs and sequence of those slabs. The formulation is analogous to a salesman who travels between cities at a cost (the sequence penalty) but also receives a prize for each city visited (scheduling profit) or a penalty for each city not visited (scheduling loss). The salesman wishes to minimize his travel cost (complete PB sequence cost) while visiting enough cities to obtain a predetermined prize (minimum required slabs to be scheduled). In order to solve this problem Lopez et al. implemented a tabu search (TS) method using an iterative local search meta-heuristic. Tabu search maintains a list of previously visited neighbour solutions which may drive the algorithm into possibly worse solution space but also helps it avoid becoming stuck at a local optimum while in search of the global optimum (Lopez, Carter, & Gendreau, 1998). Generating a number of product blocks using this solution method results in a set of scheduled slabs and a set of unscheduled slabs. Further improvements are then carried out by iteratively exchanging scheduled and unscheduled slabs between the PBs until a stopping criterion is reached. Lopez et al. implemented their solution in a prototype application and tested the heuristic method against 18 production product blocks created by the Dofasco schedulers. The results obtained by the heuristic showed an average of 14% improvement in operational capacity, an improvement in smoothing of PB sequence by 39%, and an improvement in inclusion of priority orders by 38%. Lopez et al. note that in roughly 15 minutes this solution method can generate a very good product block schedule and sequence. While this work does appear quite comprehensive and considers many of the complex sequencing constraints required by AMD's hot rolling operation it was never put into production. Nothing is known about this work internally at AMD even though the authors note that Dofasco was excited about the results and planned to conduct production trials in the following months. This lack of follow-through, even though the authors had conducted thorough research work and developed a robust problem formulation and solution algorithm, speaks to the difficultly and complexity of implementing optimization solutions in industrial environments.

Building upon the research into reactive rather than generative optimization in the scheduling domain, Cowling, Ouelhadj, and Petrovic (2003) developed a similar method which integrates the scheduling and sequencing problems into a single formulation contained within a multi-agent dynamic architecture. Cowling et al. note that in recent years global competitiveness and changing customer requirements have underlined the importance of not only effective production optimization but also the need to handle the modern, highly dynamic nature of an ISP's operations. Traditional centralized systems are not well suited for the real-world needs of an ISP and multi-agent systems have proven successful in solving dynamic planning, scheduling, and sequencing problems (Cowling, Ouelhadj, & Petrovic, 2003). These dynamic multi-agent scheduling systems are more robust than traditional generative systems and are adaptable and flexible enough to handle the disturbances found in the real-time operations of an ISP. The concept of a multi-agent solution in the ISP domain is that each manufacturing resource of the plant is represented as an agent which is responsible for completing its own local scheduling and/or sequencing tasks. Information is then transmitted between various agents so that real-time updates of new schedules, sequences, or even physical process disturbances can be communicated to all agents within the system. Cowling et al. consider only the hot rolling mill and continuous caster in their work and provide some details on the architecture of their multi-agent system design. Cowling et al. describe the hot rolling mill agent in a similar fashion to Lopez et al. (1998) with similar constraints on the width profile of the coffin-shape PBs, desired smooth jumps between coil thickness, hardness, and width, as well as limits on rolling lengths of the PBs. Again, the width profile of a PB is constrained to be strictly decreasing in width within the body section. The problem is formulated once again as a prize collecting travelling salesman problem where the coils are represented as a digraph with weightings on the nodes representing scheduling costs (priority of coil to be scheduled) and weightings on the arcs representing sequencing costs (transition cost calculated as a combination of width, thickness, and hardness) (Cowling, Ouelhadj, & Petrovic, 2003). A tabu search solution methodology is employed to solve the problem with an initial solution constructed using a greedy algorithm. Improvements to the initial solution are made by applying coil swaps, coil insertions, and coil sequence reversals where coils are selected from either the set of scheduled slabs or the set of unscheduled slabs. The problem formulation, solution algorithms and general solution methodology described by Cowling et al. are nearly identical to those described by Lopez et al (1998). One of the biggest differences between the two pieces of work is that Cowling et al. introduce the concept of rescheduling strategies which is facilitated by the multi-agent architecture. The hot mill agent can attempt to resolve scheduling and sequencing issues dynamically based on real-time information delivered from other agents in the system. For example, if a generated schedule becomes infeasible due to unavailable slabs or other process disturbances the hot mill agent can be informed and attempt an automatic re-scheduling and re-sequencing based on this new information. A number of strategies are presented for this situation which range from ignoring the real-time updates to complete re-scheduling and re-sequence of the product blocks as well as many other options in between. Cowling et al. created a prototype application and compared results generated by this system to those constructed by an industrial ISP partner. These results showed that the reactive scheduling strategies performed quite well. However, in most cases a full re-scheduling and re-sequencing of the product blocks was required for best performance after a large number of real-time events had occurred.

Although the work of Cowling et al. (2003) did not involve any production trials with the ISP partner, Cowling continued research in this area and evolved the original prototype application into a commercial decision support system for steel hot rolling mill scheduling and sequencing optimization (Cowling, 2003). Much of the original research was maintained included the PCTSP formulation and the use of the tabu search meta-heuristic as the solution algorithm. In this commercial system Cowling has developed further ISP-specific scheduling and sequencing heuristics which are then guided by the tabu search approach. An example of this is the idea of parallel construction of product blocks where each product block is seeded with a skeleton of the coffin-shape width profile and then filled in using a custom heuristic. Rather than diving deeply into the technical aspect of the commercial system which has been developed, Cowling provides a comprehensive description of the system architecture as well as the issues and considerations which must be accounted for when implementing scheduling and sequencing optimization solutions in an industrial environment. The reader is highly encouraged to review this paper if implementing a production system themselves. While no references to specific firms are given, this commercial system is widely used at various ISP sites around the world and provides results which are consistently better than a manual planning system (Cowling, 2003).

Two of the most recent research papers which investigate hot rolling mill production optimization are those of Zhao, Wang, Liu, Wang, and Shi (2009) and Chen, Lu, Ge, Yang, and Pan (2012). Both of these research groups consider scheduling and sequencing of hot rolling as an integrated problem and apply intelligent search and meta-heuristic solution algorithms to solve the problem.

Zhao et al. (2009) provide what is currently the most comprehensive model of hot rolling scheduling and sequencing optimization in the contemporary research literature. This research was conducted in collaboration with Shanghai Baosteel Ltd. in China and it is clear the researchers were interested in building a production capable system. The work builds on much of the previous research; however the author's formulation of the problem includes a tremendous amount of industrially relevant considerations and nearly the entire set of complex constraints required in the industrial hot rolling of steel. Zhao et al. consider the maximization of hot rolling operational capacity as the primary objective with maximizing the hot-charge ratio as a secondary objective. Different charging schemes including direct-charge, hot-charge, cold-charge, and direct-rolling are considered as a main component of Zhao et al.'s work. They consider all the detailed constraints of previous research such as the coffin-shape of the PB, limited rolling length at the same width, the placement of surface critical material, and smooth sequence transitions in width, gauge, and hardness. Also considered are smooth transitions in furnace discharge, finishing, and coiling temperatures. Strictly increase or decreasing width is once again considered as a constraint in the sequencing of the slabs within a product block (Zhao, Wang, Liu, Wang, & Shi, 2009). Zhao et al. propose a vehicle routing problem with time window formulation (VRPTM) for the slab scheduling problem. This formulation allows consideration of the time requirements by each of the different charging schemes which are a focus of this work. Unlike previous research, sequencing optimization in this formulation is completed as part of the VRPTM however additional sequencing is performed at a secondary level where slabs with similar characteristics are swapped to improve the hot-charge ratio of the individual product blocks. This specific sequencing layer is decoupled from the core scheduling-sequencing VRPTM task. Once again, as the VRPTM is an NP-complete problem exact solutions are nearly impossible to derive in acceptable computational time and therefore intelligence search and meta-heuristic methods are leveraged (Zhao, Wang, Liu, Wang, & Shi, 2009).

Zhao et al. propose the use of a modified parthenogenetic algorithm (PGA) with custom heuristic rules to solve the scheduling problem. Sequencing for the improvement of hot-charge ratio is performed using a tabu search based local search meta-heuristic. This problem formulation and solution methodology has been implemented by Baosteel China with 2 years in the hot rolling production environment (Zhao, Wang, Liu, Wang, & Shi, 2009). Zhao et al. note that this system has been very helpful for plant logistics and has improved operational capacity utilization, energy savings due to higher hot-charge ratio and reduced equipment setup times. An interesting note is that the average rolling length of the product blocks constructed by this solution are 62.33 km which are considerably shorter than those rolled by AMD at 100 km on average. This indicates the scheduling and sequencing problem at AMD is even more complex than at Baosteel Ltd.

The work by Chen et al. (2012) presents a recent investigation into hot rolling scheduling and sequencing and provides a very similar description of the problem and constraints as that of the contemporary research works. A description of the problem identical to that provided by Zhao et al. (2009), Lopez et al. (1998), and Cowling et al. (2003) is given with nearly the same detailed set of constraints. Once again the sequence of width within the body section of the product block is specifically constrained to be in descending order. Chen et al. investigate additional details of industrially required constraints in the scheduling and sequencing problems such as selecting specific slabs for the break-in section of the PB, special placement of slabs with high quality requirements within the body of the PB, and a more detailed sequencing transition cost calculation. The concept of simultaneously solving the two sub-tasks of scheduling and sequencing is considered rather than the sequential solution method previous works have implemented. Chen et al. describe the scheduling and sequencing problem as a PCTSP in a formulation identical to the one described by Lopez et al. (1998). A mixture of genetic algorithm (GA) and external optimization (EO) are employed to simultaneously solve the two tasks with a custom heuristic to construct the break-in and wide-out portion of each PB. A prototype application was developed and sets of production data collected from a collaborating ISP were used to generate simulation results. Multiple PBs must be scheduled one by one in this system and require 320 seconds per product block. Chen et al. note overall improvements in transition costs of the product block sequences returned by this solution versus those generated by the collaborating ISP.

3.4 Architecture Design for ISP Optimization Solutions

In the contemporary research literature there exist a number of common solution architectures as well as best practices in terms of implementation. It is useful to review these topics for those readers who are practitioners and may be deploying these types of solutions in an industrial production environment.

One of the most commonly discussed solution architectures is that of human-machine interaction. Human-machine interaction is the concept of cooperation between the human scheduler and the scheduling/sequencing software application such that the scheduler can leverage the software as a decision support tool while applying their expert knowledge of the hot rolling process. With this type of design, the optimization software is not run in a purely automatic fashion but rather as an integrated part of the scheduler's tasks. Much of the research in both scheduling and sequencing optimization of hot rolling production follows this design pattern. In the work by Suh et al. (1998) the authors utilize human-machine interaction where the user may relax certain constraints if infeasibilities are found or if the scheduler wishes to run "what-if" type analysis. Chen et al. (2012) also developed their prototype following the human-machine design pattern with the optimization component operating in a semi-automatic fashion. In this implementation the scheduler sets the scheduling time horizon, constraints, and parameters with the system providing assistance based on the data provided. This human-machine interaction paradigm enhances the speed at which schedulers can make modifications to the schedule while also enhancing their decision making capabilities. Zhao et al. (2009) also leverage the human-machine design pattern in their production application used at Baosteel Ltd. In a practical manufacturing setting this design architecture provides more flexibility than traditional scheduling and sequencing methods as the scheduler can adjust objective priorities, technical rules, and maintain overall consistency with the hot rolling production environment (Zhao, Wang, Liu, Wang, & Shi, 2009). The commercial hot rolling scheduling system developed by Cowling (2003) is also a decision support tool developed using the human-machine interaction paradigm. Cowling specifically notes that human-machine interaction allows for the flexibility, computational power, and iterative speed required by the human scheduler. Cowling also reiterates the fact that the human-machine paradigm enables fast modification with minimal system reconfiguration which supports an ISP's frequently changing technical and commercial constraints.

Due to the highly complex and computationally difficult nature of the hot rolling scheduling and sequencing problems decomposition is another common design pattern found in the research literature. This concept was more prevalent in earlier research work while more recent works propose integrated scheduling and sequencing. However, as contemporary research is now focusing on more complex formulations and integrating ISP sub-processes the idea of problem decomposition has once again become popular. Decomposition plays an important role in implementation of these solution methods as in practical applications the optimization formulations must be small enough to be computationally efficient and produce results which are feasible, accurate, and useful to the operations. While global solutions are ideal, if a model's results can provide scheduling or sequencing strategies or information which can aid the scheduling team in developing production schedules and PB sequences for the hot rolling operation then the formulation has served its purpose (Jacobs, Wright, & Cobbs, 1988). An excellent example of the decomposition design pattern is in the work of Okano et al. (2004) where the authors indicate that while the entire multi-process finishing line scheduling problem could be formulated and solved as a single optimization problem, handling such a large problem is not practical in regards to development and maintenance of the models. It is far more beneficial to decompose the overall problem into smaller components for which specific and customized heuristic solution methods can be developed (Okano, et al., 2004). Okano et al. reduce the problem complexity via decomposition by clustering of similar material prior to scheduling and by executing different optimization engines for each of the finishing processes. The work of Chen and Wang (1997) focuses primarily on a planning kernel for ISP production optimization however their formulation does include reference to the fact that the planning, scheduling, and sequencing problems are decomposed from one another. The generated optimal plans constructed at the global planning stage are passed to lower layers of the system where local scheduling and sequencing optimization may be conducted (Chen & Wang, 1997). In the more recent work of Chen et al. (2012) the authors decompose their detailed and complex formulation of the scheduling and sequencing problems into a scheduling layer and a sequencing layer. This decoupling of the scheduling task from the sequencing task allows for bespoke heuristics to be applied to each problem where the product blocks constructed at the scheduling level are further improved at the sequencing level.

The final common design pattern found in the hot rolling production research literature is that of reactive optimization and multi-agent architectures. These are relatively more contemporary concepts which build on the previous research to allow for more comprehensive planning, scheduling, and sequencing systems. The works by Suh et al. (1998), Cowling et al. (2003), and Cowling (2003) all outline formulations for dynamic and reactive optimization where initial product blocks are scheduled and/or sequenced and then updated based on real-time information delivered by either human-machine interaction or a multi-agent network. Suh et al. (1998) present reactive optimization as a function of their scheduling application whereby the human scheduler indicates to the system that operational conditions have changed in the hot mill and that new product blocks must be scheduled and sequenced. Cowling et al. (2003) present a similar concept regarding reactive scheduling however in this formulation the hot rolling operation is a single agent within a multi-agent system and can be informed directly by other agents that new hot mill product blocks must be constructed. In the multi-agent architecture each ISP sub-process is assigned to an agent who independently constructs schedules and sequences specific to its local operation. This reactive scheduling and sequencing can occur without any human involvement. Cowling's (2003) later work built upon these concepts and resulted in the development of a commercial solution employing multi-agent architectures for dynamic scheduling in steel hot rolling mills.

Chapter 4

Sequencing Optimization for Hot Rolling Mill Production

This chapter presents the first phase of research into production scheduling and sequencing optimization in collaboration with ArcelorMittal Dofasco's hot rolling operations. The main objective of this section is to outline the problem in context of AMD's operations and present the formulations and solution methodologies applied. Performance results are illustrated in the form of industrial production trials conducted at AMD's hot mill. Finally, issues and findings gained from this initial work are reviewed as a preface to the second phase of research.

4.1 An Overview of the Problem in Context

As is common practice with most integrated steel plants worldwide ArcelorMittal Dofasco utilizes a team of schedulers to conduct planning, scheduling, and sequencing tasks using manual heuristic methods developed over decades of learning and innovation. While the problems of production scheduling and sequencing in hot rolling are well known to be difficult and few industrial ISPs have applied mathematical optimization techniques to solve them, management at AMD was interested in pursuing this research for two reasons. The first is a recognized need for improvement in the area of scheduling and sequencing in order to stay competitive in the marketplace and secondly as a safeguard against knowledge loss through attrition due to an aging workforce. In initial discussions AMD management outlined that they were interested in a solution for optimizing the slab sequences of product blocks which had been previously constructed by the scheduling team. For management this would deliver both a solution for rigorous and reliable product block sequencing optimization and effectively collect, consolidate, and document the product block sequencing knowledge in a model or software application.

The scheduling team at AMD consists of many individuals with dedicated staff for the hot rolling operations. The hot mill schedulers construct product blocks for a four-day time horizon which is frequently updated on a daily or potentially hourly basis depending on conditions in the production environment. The schedulers use a proprietary software tool to construct product blocks for release to hot mill operational management who confirm final approval of the PB sequences. Product blocks are normally constructed one at a time by the schedulers where a typical work-flow is followed:

1. Determine the types and number of required product blocks for construction over the appropriate time horizon.
    - These parameters are determined based on customer due dates and downstream process operational capacity requirements.

   - These calculations are completed in a manual fashion by the scheduler.
2. Allocate slabs into a product block from the available inventory.
   - Priority is normally given to slabs with the nearest downstream delivery due date.
   - This generates the body portion of the PB.
3. Sort the current slab sequence from wide to narrow.
   - A simple sorting function is available in the software tool.
4. Check if any sequencing rule violations exist and swap or delete slabs to remove the violations.
   - The software tool provides automatic identification of rule violations.
5. Add the necessary break-in material to the front of the PB.
   - The scheduler manually selects slabs appropriate for the break-in portion of the PB.
   - These slabs are then attached to the front of the PB in a strictly increasing-in-width fashion.

Typically, this process takes between one-half to a full hour for the scheduler and must be repeated for each product block required in the scheduling time horizon.

Time was spent working with the hot mill schedulers to understand their work-processes in detail. It became clear that the human scheduler can optimize on one or two factors at most; typically, these are coil width with some consideration given to coil thickness. This quite reasonable limitation of human schedulers is also noted by Cowling (2003) in his work on commercial hot mill scheduling systems. After evaluating the work practices and processes of AMD’s hot mill schedulers it was determined that while they can always be relied upon to build PBs of acceptable quality, and are skilled at managing unforeseen production disturbances, as humans they cannot be expected to account for all commercial, logistical, or production objectives which may be required in an optimal PB design. It was concluded that great benefits could be realised in the application of combinatorial optimization methods to the product block sequencing problem and in developing a formulation and solution methodology which could be applied to AMD’s hot rolling operations.

4.2 Solution Formulation of the Product Block Sequencing Model

The Product Block Sequencing Model (PBSM) is an expansion of the heuristic process by which the hot mill schedulers sequence slabs within a product block. This evolution of the initial heuristic attempts to collate the knowledge and experience of the scheduler, the available documented sequencing rules, as well as all necessary production related objectives known by AMD, into a model through which mathematical optimization techniques can be applied. One significant assumption was made in the construction of the PBSM which was that the lot of slabs has already been allocated to the PB prior to sequencing optimization taking place. Slabs cannot be added to the sequence nor can they be removed from the sequence. Focusing the scope of research at this level in the initial phase was at the request of AMD management. Management had a goal for proof-of-concept of a sequencing decision support tool which could be further developed and provided to the hot mill scheduler.

As the product block sequencing problem is known to be combinatorial in nature the basis of the PBSM can be modelled as a graph theoretic network, specifically as an undirected complete weighted graph $G = (N, A)$ where N represents the set of nodes and A represents the set of arcs. In this imagining of the problem the nodes represent slabs within the PB and the arcs represent transitions between pairs of slabs. The basic PBSM graph has three special conditions. Firstly, it is undirected meaning the arcs have no orientation and thus can be traversed in either direction. Secondly, it is complete meaning each pair of nodes is connected by an arc and all possible arcs are present. Thirdly, it is weighted meaning the arcs have a numerical value associated with them. Figure 4.1 provides an illustration of a theoretical simple product block consisting of six slabs where only two variables (thickness and width) are considered and thus represented in two-dimensional space for ease of visualization.

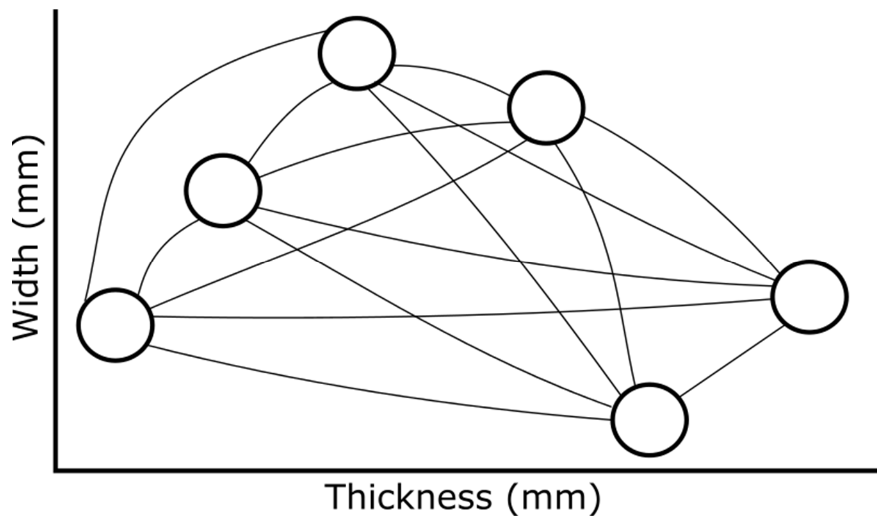

Figure 4.1 – A Visualization of the Graph Representation of a Product Block

In order to solve the combinatorial optimization problem of product block sequencing the well known Travelling Salesman Problem (TSP) formulation can be applied. Application of the TSP formulation to the product block sequencing problem utilizes the basic graph formulation previously described and applies customizations via common and problem-specific TSP techniques. These customizations extend the standard TSP formulation and allow the PBSM to accurately reflect hot rolling operational requirements within the scope of this intra-PB problem.

In the TSP formulation for the PBSM the graph network represents the slabs assigned to a product block with arc weights representing the transition cost c_{ij} of moving between slab i and slab j in the PB sequence. Following the TSP methodology, a function which calculates the cost of transition and thus defines each arc value of c_{ij} was developed and is comprised of the key variables required when considering an optimal PB sequence. A number of modifications to the traditional TSP had to be implemented in order to accurately describe the PBSM as a representation of the hot rolling process. The primary consideration is that arc weights are not necessarily identical, or symmetric, in both directions of travel between two slabs. For example, transitioning from a slab with a final coil thickness of 5mm to one of 2.5mm final thickness carries a higher cost than the reverse transition. Due to this requirement the TSP representation of the PBSM is modified to be an Asymmetric Travelling Salesman Problem (ATSP) where the cost c_{ij} of moving from slab i to slab j in the sequence may be different from the cost c_{ij} of moving from slab j to slab i. A second consideration in the PBSM is that the break-in material assigned to the product block should be maintained according to its original sequence. This is normally a small number of slabs with specific characteristics hand selected by the scheduler and as the scope of the PBSM is to re-sequence a pre-existing PB the provided break-in slab sequence must be maintained. As a result of this constraint only the body portion of the PB undergoes sequencing optimization which somewhat invalidates the completeness of the graph representation. However, the PBSM can be thought of as two unique sub-graphs: the break-in portion as a fully directed graph with a defined sequence and the body portion as the originally described undirected, complete, weighted graph. Therefore, the problem space of the PBSM can be thought of as reduced to only the body portion of slabs in the PB as the break-in sequence must be maintained. Figure 4.2 provides an illustration of a simple theoretical product block, similar to Figure 4.1, but with the noted modifications to the traditional TSP for the ATSP PBSM formulation.

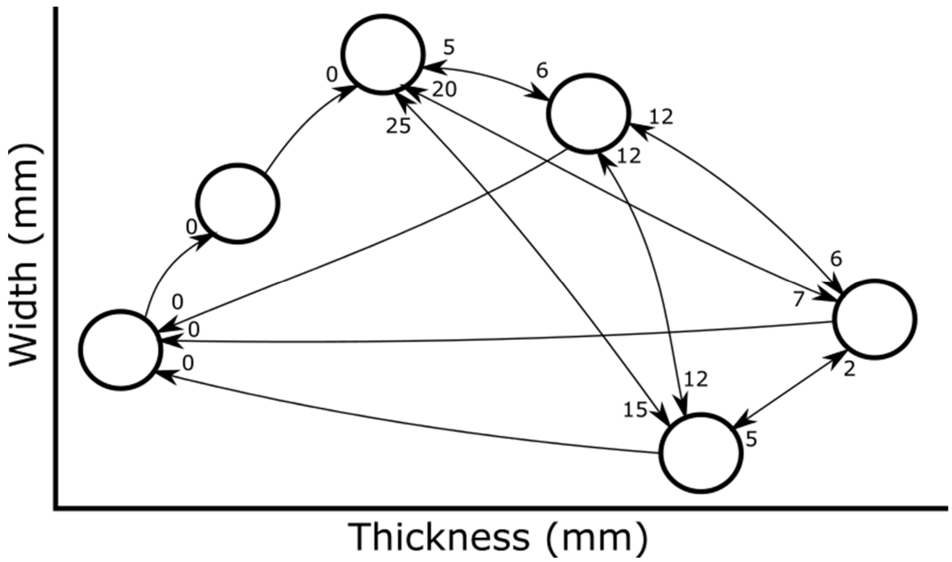

Figure 4.2 – A Visualization of Graph Representation of the ATSP PBSM

Solving the ATSP formulation for the PBSM utilizes a methodology traditional to the travelling salesman problem. The overall goal is to construct a sequence or tour, visiting each node in the graph, which minimizes the cumulative arc transition cost. This is represented by the general objective function provided in Equation 4.1.

$$min \sum_{i=0}^{n} \sum_{j \neq i, j=0}^{n} c_{ij} x_{ij} \tag{4.1}$$

This equation states that the goal is to minimize the arc costs c_{ij} when creating a sequence through all nodes (slabs) in the graph (product block) where x_{ij} represents the connection of two nodes by an arc (slab-to-slab transition). Equation 4.2 defines that x_{ij}

must be either 1 or 0 which indicates that an arc is either included or excluded in the overall sequence.

$$x_{ij} \in \{0,1\}, \qquad \forall\, i,j \tag{4.2}$$

Equations 4.3 and 4.4 respectively represent the constraints that within the PB sequence a slab is only arrived at from exactly one other slab, and that from a slab there is a departure to exactly one other slab.

$$\sum_{i=0}^{n} x_{ij} = 1, \ \ \forall\, j \tag{4.3}$$

$$\sum_{j=0}^{n} x_{ij} = 1, \ \ \forall\, i \tag{4.4}$$

These constraints allow the construction of a single sequence, or graph cycle, between all slabs in the product block without loops or backtracking to previously sequenced slabs. Additionally, it is required that the graph contains only a single cycle, or tour, through the nodes and not two or more separate tours which only collectively cover the set of nodes. Statement 4.5 outlines this requirement.

$$G = (N, A)\ must\ contain\ a\ single\ cycle\ C\ such\ that\ the\ length\ of\ C\ is \geq 2 \tag{4.5}$$

The formulation and equations described above outline only the generic basis for the PBSM defined as a TSP-like problem. The detailed PBSM objective function and PBSM constraints are outlined in sections 4.2.1 and 4.2.2 which build upon Equations 4.1 through 4.5. The specific solution methodology used to solve the PBSM for industrial hot rolling problems is outlined in section 4.2.3.

4.2.1 Objective Function

In the context of the problem described by the PBSM the primary objective is to minimize the cost of a sequence which includes all slabs in the product block where each slab-to-slab transition is assigned a cost of c_{ij}. While Equation 4.1 describes the objective function in generic terms the calculation of the arc weights is highly critical in the overall PBSM. Therefore, a detailed function was developed such that each arc $a \in A$ in $G = (N, A)$ is assigned a weight $w(a)$ representing the slab-to-slab transition cost c_{ij}.

This function was developed in collaboration with AMD, specifically the technical specialists from the hot rolling operations group. These engineers have extensive knowledge and experience of the hot rolling process and their input was highly valuable in development of the function. When the transition cost function was first investigated there was concern that the different hot mill sub-processes would have conflicting objectives in the parameters of interest and that an aggregate cost function could not be developed for the entire process. However, research into the individual sub-process and consultation with the AMD experts revealed that this is not the case. The hot rolling sub-processes of reheating furnace, roughing mill, finishing mill, and coiling equipment all benefit from having smooth slab-to-slab transitions in the same process variables within the overall PB sequence.

The function which calculates the arc weight values, known as a cost function, is an aggregation of the four primary parameters of consideration in slab-to-slab sequencing for hot rolling operations: (1) thickness, (2) width, (3) reheating furnace efficiency, and (4) metallurgical steel grade. The individual parameters in the aggregate cost function are calculated as the difference in absolute magnitude of the variable between slab i and slab j where absolute magnitude is the variable's level as a percentage of its maximum. Normalizing all variables in this fashion allows for summation of the different parameters such that a single cost or weight may be assigned to each arc in the graph. The general concept is to smooth the transitions of slabs within a PB as best as possible according to these four parameters. Calculation of the arc weight as a function of each of the four parameters when transitioning from slab i to slab j is defined by the following equations. Each of these equations follows a similar formula which is shown first.

The generic formula for the calculation an individual parameter's transition cost when moving from slab i to slab j is shown in Figure 4.6.

$$Cost\ of\ Parameter = \left| \frac{Parameter\ Value_i}{Max\ Parameter\ Value} - \frac{Parameter\ Value_j}{Max\ Parameter\ Value} \right| \tag{4.6}$$

This equation allows the four main parameters to be normalized as a percentage of their maximum value and thus considered together in a summation to calculate the final transition cost value and arc weight.

Equations 4.7 through 4.10 show the calculation of the individual parameter costs for a slab transition. Equation 4.7 shows the calculation of transition cost for a change in numerical thickness of the final coil. 16 millimeters is the maximum thickness of a coil produced by AMD's hot mill.

$$dThk = \left| \frac{Thickness_i}{16} - \frac{Thickness_j}{16} \right| \tag{4.7}$$

Equation 4.8 shows the calculation of transition cost for a change in numerical width of the final coil. 1600 millimeters is the maximum width of a coil produced by AMD's hot mill.

$$dWid = \left| \frac{Width_i}{1600} - \frac{Width_j}{1600} \right| \tag{4.8}$$

Equation 4.9 shows the calculation of transition cost for a change in theoretical heating efficiency of a slab within the reheating furnaces. 24 is the maximum value of heating efficiency index at AMD's hot mill.

$$dHIN = \left|\frac{Heating\ Efficiency_i}{24} - \frac{Heating\ Efficiency_j}{24}\right| \tag{4.9}$$

Equation 4.10 shows the calculation of transition cost for a change in metallurgical steel grade. 8 is the maximum value of the AMD grade family index.

$$dGrd = \left|\frac{Metallurgical\ Grade\ Index_i}{8} - \frac{Metalurgical\ Grade\ Index_j}{8}\right| \tag{4.10}$$

These four individual parameter costs are then combined into an aggregate transition cost function ATC_{ij} shown in Equation 4.11. This aggregate transition cost function (ATCF) calculates the value ATC_{ij} for a slab i to slab j transition and defines the value of c_{ij} (4.12) in the objective function (4.1) for each possible slab-to-slab transition in the PB.

$$\begin{gathered} ATC_{ij} = a\ \cdot dThk_{ij} + b \cdot dWid^2{}_{ij} + c \cdot dHIN_{ij} + d \cdot dGrd_{ij} \\ Where\ a, b, c, d = 1 \end{gathered} \tag{4.11}$$

$$c_{ij} = \ ATC_{ij} \tag{4.12}$$

The aggregate transition cost function ATC_{ij} contains two important elements. First, the cost of transition in numerical width $dWid$ of the final coil is included as squared term. This squared term, in conjunction with constraints outlined in the following section, allows for PB sequences where coil width is not strictly decreasing from wide to narrow. Highly penalizing large width changes via the squared $dWid$ term allows the width to both increase and decrease gradually such that other parameters may be optimized. An overall transition from the widest slabs to the narrowest is maintained, however this formulation does not require that the slabs in the PB body section be strictly decreasing in width. This allowance of a slightly floating width in the PB body is one of the core differences between this work and previous research as all existing literature regarding hot rolling sequencing constrains the PB body to be strictly decreasing in width. Secondly, weighting factors a, b, c, d have been included in the aggregate transition cost function. These factors allow for either priority/goal weighting to be placed on the different objective function parameters or for the application of currency-based cost values such that the sequencing optimization has a monetary based objective. Each weighting factor was assigned a value of 1 so that all parameters would be considered equal for this research.

4.2.2 Constraints

In order to accurately represent AMD's operational requirements in the PBSM the basic constraints of the ATSP formulation must be extended with constraints specific to the hot rolling process. These constraints are both steel hot rolling and AMD domain specific constraints and were defined with the assistance of AMD's technical specialists. These constraints represent the core set of rules currently employed by the hot mill schedulers.

The constraints defined here for the PBSM are primarily concerned with limiting the magnitude of change in certain parameters during discrete slab-to-slab transitions.

In addition to numerical thickness AMD also uses a set of thickness groups called $GRTs$ which represent the operational range of coil thickness in 16 unique bins. Equation 4.13 defines a constraint which disallows a slab-to-slab transition where the GRT index change is greater than 3. This constraint is applicable only on non-Tinplate customer orders and on material greater than 1.8mm in thickness. Equation 4.14 defines a similar constraint however this constraint limits a downward change in GRT index to 2 and an upward GRT change to 3. This constraint is applicable on tinplate customer orders and material less than or equal to 1.8mm in thickness both of which are considered special material and are more sensitive to decreasing thickness.

$$\left| GRT_i - GRT_j \right| \leq 3 \tag{4.13}$$

$$-3 \leq GRT_i - GRT_j \leq 2 \tag{4.14}$$

These constraints are primarily to support the optimization of process and equipment stability within the hot mill. Large changes in thickness may destabilize rolling mill equipment and increase equipment setup times as well as decrease heating efficiency within the reheating furnaces. While Equation 4.13 results in a symmetric cost, Equation 4.14 results in an asymmetric cost which drives the ATSP formulation requirement.

The change in reheating furnace efficiency HIN is also limited in the discrete slab-to-slab transitions. This is to improve heating efficiency and thus energy consumption within the reheating furnaces. Equation 4.15 represents this constraint on HIN.

$$\left|HIN_i - HIN_j\right| \leq 4 \tag{4.15}$$

This constraint states that a change in HIN of greater than 4 is disallowed in a single slab-to-slab transition. This constraint is symmetric in both directions of change.

Aggregate force, which is a measure of the physical force exerted on the rolling mill equipment for a slab, is also constrained within the discrete slab-to-slab transitions. This constraint is critical for rolling mill equipment stability as too large a change in aggregate force during a transition can cause critical equipment issues resulting in quality defects or delay time. Equation 4.16 outlines this constraint.

$$\left|AggForce_i - AggForce_j\right| \leq 2000\ Tonnes \tag{4.16}$$

This constraint states that an increase or decrease in aggregate force must be equal to or less than 2000 metric tonnes between two consecutive slabs.

To facilitate a sequence where width is allowed to vary slightly rather than be forced to follow a strictly decreasing profile a constraint is applied which allows for small increases in width and greater decreases in width during slab-to-slab transitions. The constraint shown in Equation 4.17 allows for such a sequence.

$$-50 \leq Wid_i - Wid_j \leq 200 \qquad (4.17)$$

This constraints states that an increase in width of 50mm and a decrease in width of 200mm will be permitted. This constraint combined with the squared term on $dWid$ in the aggregate transition cost function allows for small but reasonable increases in width while following an overall decreasing width profile. Allowing the width to float within this range over the gradual transition from wide slabs to narrow slabs provides three benefits. First, the constraint maintains stability in the finishing and roughing mills by not allowing large changes in width to cause operational disturbances or long equipment setup times. Second, smooth transitions in width within the reheating furnaces allows for more uniform heating and thus improved heating efficiency and lower energy usage. Third, allowing some variance in width provides the opportunity for optimization on other parameters in the objective function for a more globally optimal solution. This constraint represents an asymmetric transition cost and is another driver for the ATSP formulation.

As the break-in slabs assigned to a product block within the scope of the PBSM have been hand selected by the hot mill scheduler, their original sequence must be maintained. This constraint is expressed by Equation 4.18. In graph theoretic terms this constraint states that the path representing the break-in material from the original sequence, from starting node n_1 to terminal node n_{i+1}, must be maintained in the solution sequence.

$$Path_{original} = \big((n_1, n_2), (n_2, n_3) \dots (n_i, n_{i+1})\big) = Path_{optimized} \tag{4.18}$$

In context of the PBSM this equation states that the sequence of the break-in slabs within the original PB sequence must be equal to the sequence of break-in slabs in the optimized PB sequence; starting from the first break-in slab and ending with the final break-in slab.

4.2.3 PBSM Solution Methodology

As the PBSM is formulated as an ATSP, which is known to be an NP-hard problem, selection of a high performance optimization solver or solution algorithm was critical to meet the industrial goals of this research. AMD's desire to develop a decision support tool which would run in a production environment as well as an academic interest in finding exact solutions to the PBSM directed the search to the Concorde TSP solver rather than the meta-heuristic algorithms exclusively utilized in the research literature.

Concorde is a state-of-the-art exact TSP solver which utilizes the branch-and-bound methodology with cutting-plane techniques to solve large scale TSP problems and is regarded as one of the best exact TSP solvers currently available (Hahsler & Hornik, 2007). Mulder and Wunsch (2003) also describe Concorde as currently the fastest TSP solver in existence and especially useful for large-scale instances of TSP problems.

Leveraging the Concorde solver allows for both exact ATSP solutions to be generated for PBSM problems and those solutions to be returned in acceptable computation time for a production environment. It should be noted that Concorde provides only an academic research license and that if AMD wishes to pursue this solution for the production environment an industrial license for Concorde would need to be obtained.

A software framework was developed to facilitate the generation of PBSM problem instances, solving the instances via Concorde, and processing and reporting the solution results.

Software for the generation of PBSM problems was written in the Visual Basic for Applications (VBA) scripting language as an add-on component running in Microsoft Excel. The VBA component provides an interface to AMD's historical and production databases so that data can be queried and specific, scheduler constructed product blocks currently queued for rolling in the hot mill downloaded for re-sequencing. Once the slabs for a specific PB are acquired the VBA script constructs what is known as a distance, adjacency, or cost matrix D. The d_{ij} values in the matrix are computed according to the aggregate transition cost function ATC_{ij} and defined PBSM constraints for each possible slab-to-slab transition in the product block. The d_{ij} values in the cost matrix D contain values calculated by the aggregate transition cost function but also contain infeasible transitions identified as PBSM constraints. Numerically these constraints are represented in the cost matrix as some sufficiently large value approximating infinity. Output of the

VBA script for a product block is a comma separated value (CSV) file containing the cost matrix D plus a CSV file containing the original scheduler constructed PB sequence.

Once the VBA script has completed, an R program is automatically called to solve the PBSM problem. This R program leverages the TSP R library developed by Hahsler and Hornik (2007) which provides useful functions for handling TSP-like problems as well as an interface to the Concorde solver. To begin, the two CSV files constructed by the VBA script are read into the program. As Concorde is only able to solve symmetric instances of TSP problems the ATSP formulated PBSM and its associated asymmetric cost matrix must be converted to a symmetric cost matrix. This is accomplished with a function available in the TSP library called **reformulate_ATSP_as_TSP()**. This function completes the traditional technique as described by Jonker and Volgenat (1983) of asymmetric to symmetric cost matrix conversion whereby dummy nodes are inserted into the graph representation of the problem. This procedure facilitates the use of asymmetric transition costs although it greatly increases the complexity of the problem as the graph has now doubled in size to $2n$. In order to illustrate the asymmetric to symmetric conversion a simple theoretical 3 slab PB is defined and represented in graph form in Figure 4.3 with the associated cost matrix shown in Table 4.1. Conversion of the theoretical PB to its equivalent symmetric form results in the graph shown in Figure 4.4 and the associated cost matrix shown in Table 4.2. Conversion to symmetric form results in an identical problem and identical optimal solution as the asymmetric form however the problem has now doubled in both size and complexity. The example provided below illustrates the same operation performed on the PSBM problem instances prior to submission to the Concorde solver. However, the PBSM problem instances are much larger than the simple example shown here.

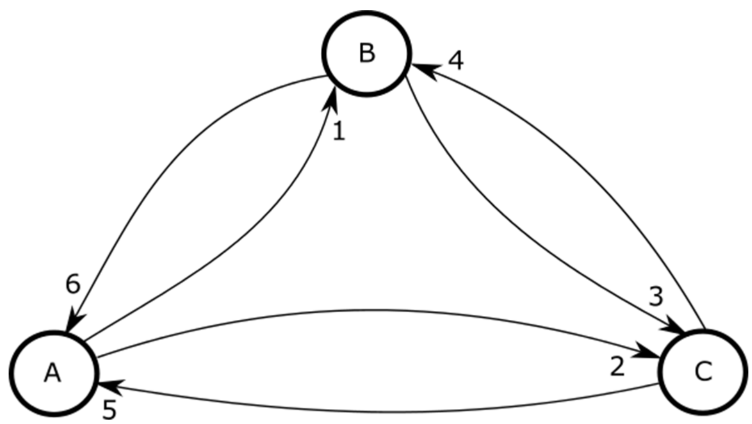

Figure 4.3 – 3 Slab Example Asymmetric Product Block Graph

	A	**B**	**C**
A	0	1	2
B	6	0	3
C	5	4	0

Table 4.1 – 3 Slab Example Asymmetric Cost Matrix

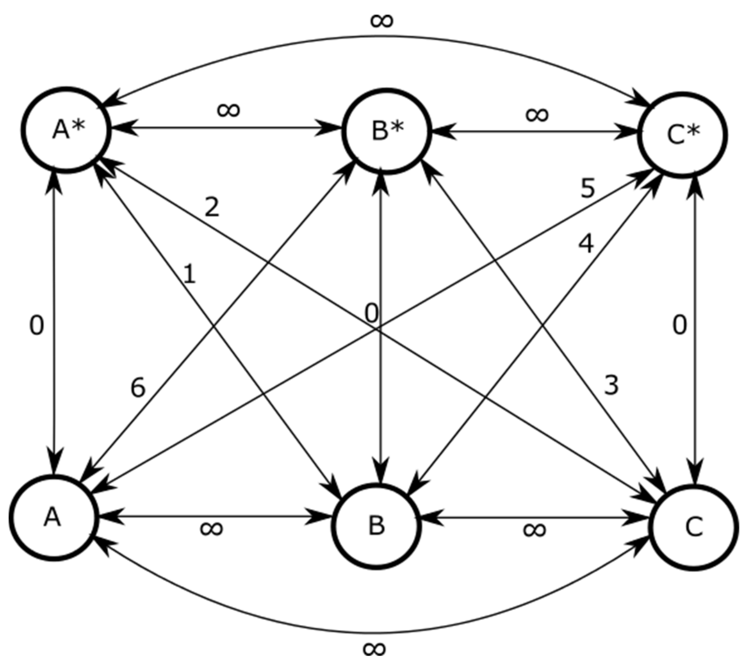

Figure 4.4 – 3 Slab Example PB Converted to a Symmetric Graph

	A	**B**	**C**	**A***	**B***	**C***
A	∞	∞	∞	0	6	5
B	∞	∞	∞	1	0	4
C	∞	∞	∞	2	3	0
A*	0	1	2	∞	∞	∞
B*	6	0	3	∞	∞	∞
C*	5	4	0	∞	∞	∞

Table 4.2 – 3 Slab Example PB Converted to Symmetric Cost Matrix

The converted cost matrix is then submitted to the Concorde solver and an optimized product block sequence is returned. The PB solution sequence returned by the solver is a re-sequencing of the original numerical slab order. In order to provide a more valuable output the CSV file containing the original sequence is reordered into the optimal sequence returned by the Concorde solver. This product block solution sequence file is then saved for further processing.

Once Concorde has returned an optimized product block sequence a second VBA scripting component processes the PB solution sequence file and performs a performance comparison. This performance comparison evaluates the new product block sequence returned by the Concorde solver versus the original product block sequence constructed by the hot mill schedulers. A number of key performance metrics and PB evaluation criteria are calculated and a summary Excel sheet is generated. The AMD hot rolling specialists provided input on the performance metrics of greatest interest and consequence which were included in this summary sheet.

Solution times for the Concorde solver running against ATSP formulated PBSM problem instances are very reasonable. Table 4.3 below illustrates computation time for six different product blocks constructed by the hot mill schedulers and then re-sequenced using the PBSM optimization software framework. These six example PBs represent the three types of hot rolling product block: normal/heavy, tinplate, and super-lite. Typically, the normal/heavy PBs contain more slabs which increases the size and thus the complexity of the sequencing problem resulting in longer execution times. Tinplate and super-lite PBs normally contain fewer slabs and are far more constrained in terms of allowable slab-to-slab transitions due to the tighter stability and quality requirements of this sensitive product. PBs with lower slab count and tighter constraints reduce the solution space of the problem which results in shorter execution time for the Concorde solver. Here Concorde is using the QSopt LP solver which is provided with the Concorde executable. All computation was performed on a 32-bit i5-5300U equipped PC with 4G of RAM.

Optimization Run	**AMD PB Number**	**Problem Size (Slabs)**	**Concorde Execution Time (seconds)**	**AMD PB Type**
1	26181	194	6.58	Normal/Heavy
2	28182	104	4.98	Normal/Heavy
3	35783	122	4.23	Tinplate
4	32280	99	2.43	Super-lite
5	32284	75	1.34	Super-lite
6	26290	99	1.12	Tinplate

Table 4.3 – Execution Times for the Concorde Solver on PBSM Problem Instances

4.2.4 PBSM Testing, Simulations, and Non-Production Trials

In order to evaluate the performance of the PBSM a rigorous testing and simulation phase was conducted in cooperation with AMD's hot mill schedulers. The testing phase consisted of a number of development iterations where the PBSM was used to re-sequence AMD production product blocks in an off-line fashion. The PBSM optimized sequences were then reported out to AMD management, schedulers, and specialists for review and revisions to the PBSM where made as required. Once the PBSM was found to be complete by the AMD specialists eleven weeks of off-line, non-production trials were completed where roughly 300 production product blocks were optimized using the PBSM. The results of these off-line trials were reported out to a wide AMD audience for comments and feedback. This stage involved close collaboration with the AMD hot mill schedulers where all re-sequenced product blocks were reviewed in detail to confirm the validity of the solution sequences for production hot rolling. This intensive testing, simulation, and off-line trial phase helped to validate the performance and reliability of the PBSM to AMD management and process specialists. Confidence in the PBSM facilitated support for the industrial production trials which followed.

4.3 Production Trial Results

To prove that the PBSM formulation and solution methodology were both practical and reliable in industrial application a number of production trials were conducted at

ArcelorMittal Dofasco's hot rolling mill. These trials involved generating PBSM problem instances of product blocks which had been initially constructed by the hot mill scheduler and then solving these PBSM problem instances using the optimization software framework. The resultant re-sequenced product blocks were then issued back to the hot mill scheduler who updated the PB within AMD's production database to reflect the optimized sequence and then submitted the PB to hot mill operational management for rolling approval. These optimized product blocks were processed through AMD's hot mill and delivered to either the next AMD operation or the final customer. Seven independent trials were conducted with a minimum of two trials for each unique product block type such that AMD's entire production range was covered. The results provided below illustrate the performance of the PBSM and solution methodology as well as the benefits provided to AMD's hot rolling operations. To reinforce the industrial application of this research a selection of the customers and final coil end-use are outlined for each set of trials.

4.3.1 Description of Performance Metrics

To evaluate the performance of the PBSM optimization trials a set of key performance metrics were selected such that the optimized PB sequence could be compared to the original PB sequence constructed by the scheduler. A description of each of these metrics is provided below.

Primary Metrics of Interest

Model (MDL) Change Count – A metric which identifies a change in the discrete model points used by the reheat furnace, roughing mill, and finishing mill setup and control models. A change in MDL indicates a change in at least one of the GRT, WID, or FAM indices which define the operating regions and specific parameterization of the mill models and results in a disturbance to the overall hot rolling process.

Heating Index Number (HIN) Change Count – A metric which identifies a change in the heating efficiency classifier used by the reheating furnaces. A change in HIN identifies two dissimilar slabs from a heating perspective which results in greater energy usage and potentially uneven or inadequate reheating of the slab.

Total Transition Cost – A metric which calculates the total sequence cost for the product block. The total transition cost can be viewed as a holistic comparison of performance between an optimized and original product block sequence.

Aggregate Force Transition Sum – A metric which tracks the total aggregate force change within a product block sequence. Although aggregate force is not a parameter in the PBSM objective function, smoothing of the objective parameters typically leads to improved aggregate force transitions. This metric was added at the request of AMD.

Absolute Thickness Change – A metric which calculates the sum of thickness changes in millimeters over the entire product block sequence. This is a highly useful metric as it provides a numerical value representing the overall smoothness of thickness for a product block sequence. This metric was added at the request of AMD.

Slab Thick Change Count – A metric which counts the number of times the slab thickness changes in a product block sequence. Tracking of this metric is critical as transitions between different sized slabs can cause heating inefficiencies in the reheating furnaces.

Benefits which can be realized from improvements in these primary metrics are:

- Improvements in final product quality.
- Improvements in process throughput and capacity.
- Reduction in energy usage.
- Reduction in yield loss.

Secondary Metrics of Interest

Average Width Change – A metric which calculates the average width change based on each transition in the product block.

Average Thickness Change – A metric which calculates the average thickness change based on each transition in the product block.

Thickness Change Count – A metric which counts the number of times thickness changes during a transition in the product block sequence. This metric was added at the request of AMD.

4.3.2 Production Trial Set 1 – Heavy Product Blocks

Heavy product blocks, as they are known at AMD, are the most common PB type and comprise the majority of material rolled in the hot mill. These product blocks produce coils with less strict customer requirements and less challenging final coil attributes and are therefore normally easier to process. As the material in these heavy PBs is less prone to quality or operational issues the heavy PBs typically contain more slabs and thus present a more challenging sequencing problem. Two production trials were conducted for heavy type product blocks. The computed performance metrics comparing the optimized PB sequence against the original PB sequence are shown in Tables 4.4 and 4.5. Figures 4.5 and 4.6 present width and thickness profiles for both the original and optimized PB sequences to illustrate visually the improvements and the overall transition smoothing effect achieved by the PBSM.

PB26181 194 Slabs	Original PB Sequence	Optimized PB Sequence	Percentage Improvement
MDL Change Count	31	27	12.90%
HIN Change Count	28	24	14.29%
Total Transition Cost	834.1815099	749.0726464	10.20%
Agg. Force Transition Sum	28156	23324	17.16%
Abs. Thickness Change	25.05	17.55	29.94%
Slab Thick Chng Cnt.	1.00	1.00	0.00%
Avg. Width Change	7.28	8.31	-14.01%
Avg. Thickness Change	0.12	0.09	29.94%
Thickness Change Cnt.	37.00	38.00	-2.70%

Table 4.4 – Performance Results for Heavy Trial 1 (PB26181)

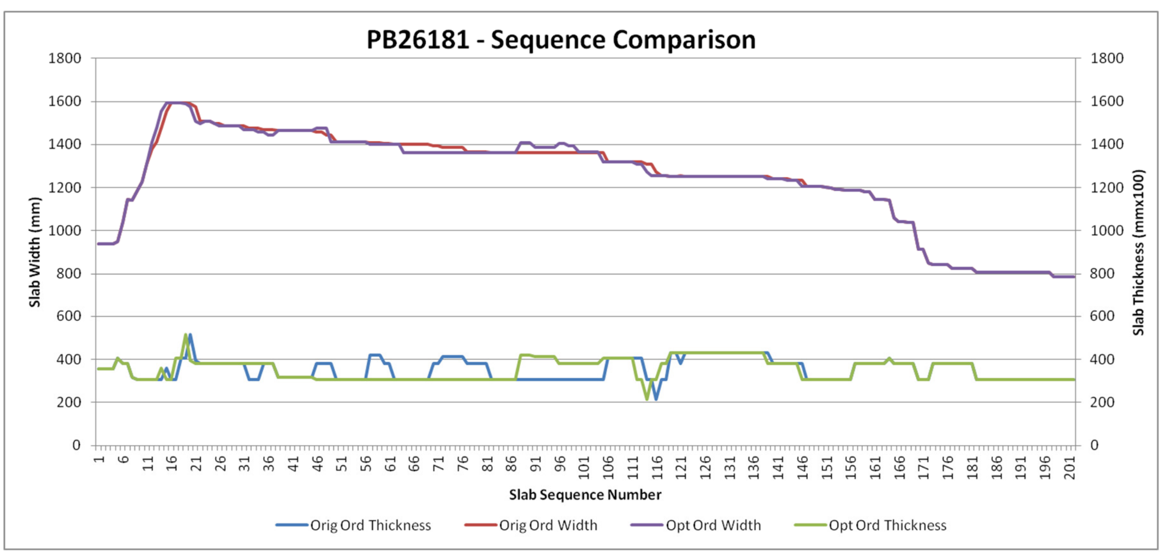

Figure 4.5 – Sequence Comparison of Width and Thickness for Heavy Trial 1 (PB26181)

PB28182 104 Slabs	Original PB Sequence	Optimized PB Sequence	Percentage Improvement
MDL Change Count	30	23	23.33%
HIN Change Count	30	17	43.33%
Total Transition Cost	1844.007915	1383.859813	24.95%
Agg. Force Transition Sum	20613	18010	12.63%
Abs. Thickness Change	23.37	15.54	33.50%
Slab Thick Chng Cnt.	22.00	17.00	22.73%
Avg. Width Change	6.56	7.21	-9.93%
Avg. Thickness Change	0.22	0.15	33.50%
Thickness Change Cnt.	33.00	33.00	0.00%

Table 4.5 – Performance Results for Heavy Trial 2 (PB28182)

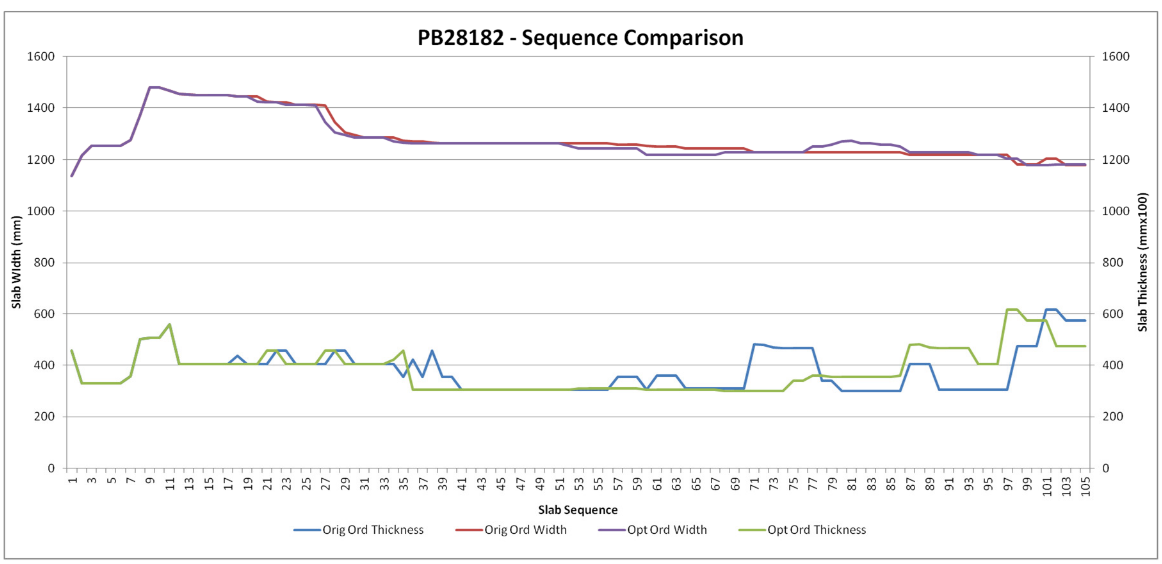

Figure 4.6 – Sequence Comparison of Width and Thickness for Heavy Trial 2 (PB28162)

Coils produced from these two product blocks were used in the following applications:

- Automotive parts for Ford and General Motors vehicles. Specifically structural chassis components, paneling, and accelerator pedal brackets.
- Steel decking for the Canam Group Ltd used in specialized construction projects.
- Spun pulleys for Maksteel.

4.3.3 Production Trial Set 2 – Tin Product Blocks

Tin product blocks are a special type of product block rolled at AMD with specific constraints and characteristics. These PBs contain 40 coils or more which are destined for further value-added processing via tinplating. These coils have more challenging final product attributes and stricter customer requirements. Due to the tighter constraints on slab-to-slab transitions in tin PBs the problem is less complex as the solution space is reduced. However, this also limits the possible improvements which can be obtained through sequencing optimization. Two production trials were conducted for tin type product blocks. The computed performance metrics comparing the optimized PB sequence against the original PB sequence are shown in Tables 4.6 and 4.7. Width and thickness profiles for both the original and optimized PB sequences are provided in Figures 4.7 and 4.8 for the two trials.

PB26290 **99 Slabs**	**Original PB** **Sequence**	**Optimized PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	16	11	31.25%
HIN Change Count	20	15	25.00%
Total Transition Cost	808.1027745	704.2448189	12.85%
Agg. Force Transition Sum	8733	6771	22.47%
Abs. Thickness Change	8.89	5.33	40.04%
Slab Thick Chng Cnt.	8.00	7.00	12.50%
Avg. Width Change	5.70	6.10	-7.10%
Avg. Thickness Change	0.09	0.05	40.04%
Thickness Change Cnt.	17.00	18.00	-5.88%

Table 4.6 – Performance Results for Tin Trial 1 (PB26290)

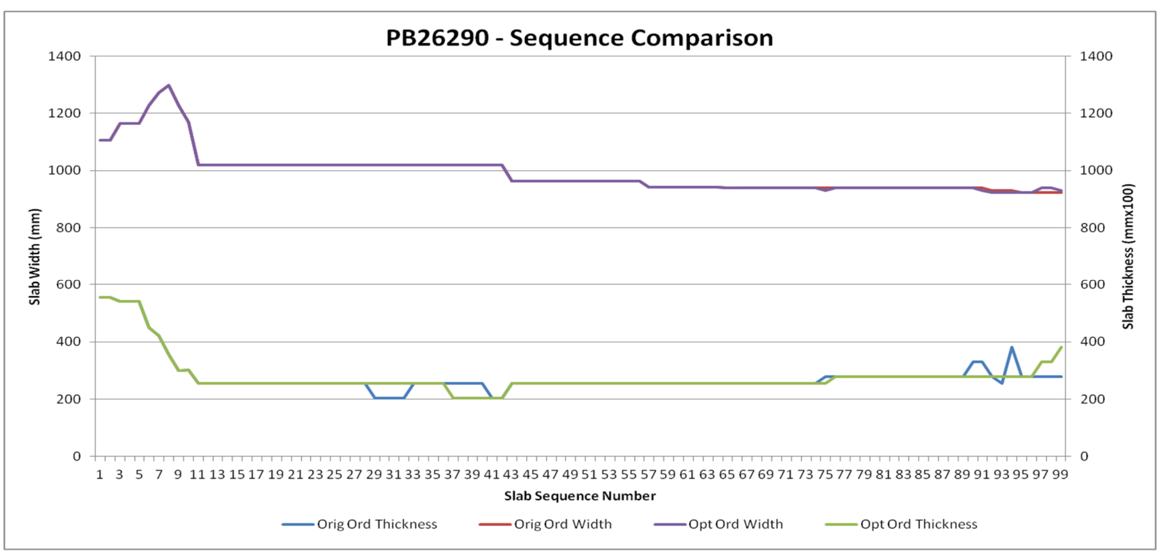

Figure 4.7 - Sequence Comparison of Width and Thickness for Tin Trial 1 (PB26290)

PB35783 111 Slabs	Original PB Sequence	Optimized PB Sequence	Percentage Improvement
MDL Change Count	19	19	0.00%
HIN Change Count	17	11	35.29%
Total Transition Cost	987.8345148	870.821788	11.85%
Agg. Force Transition Sum	13050	12392	5.04%
Abs. Thickness Change	8.67	8.73	-0.69%
Slab Thick Chng Cnt.	9.00	7.00	22.22%
Avg. Width Change	12.72	10.83	14.84%
Avg. Thickness Change	0.08	0.08	-0.69%
Thickness Change Cnt.	21.00	18.00	14.29%

Table 4.7 – Performance Results for Tin Trial 2 (PB35783)

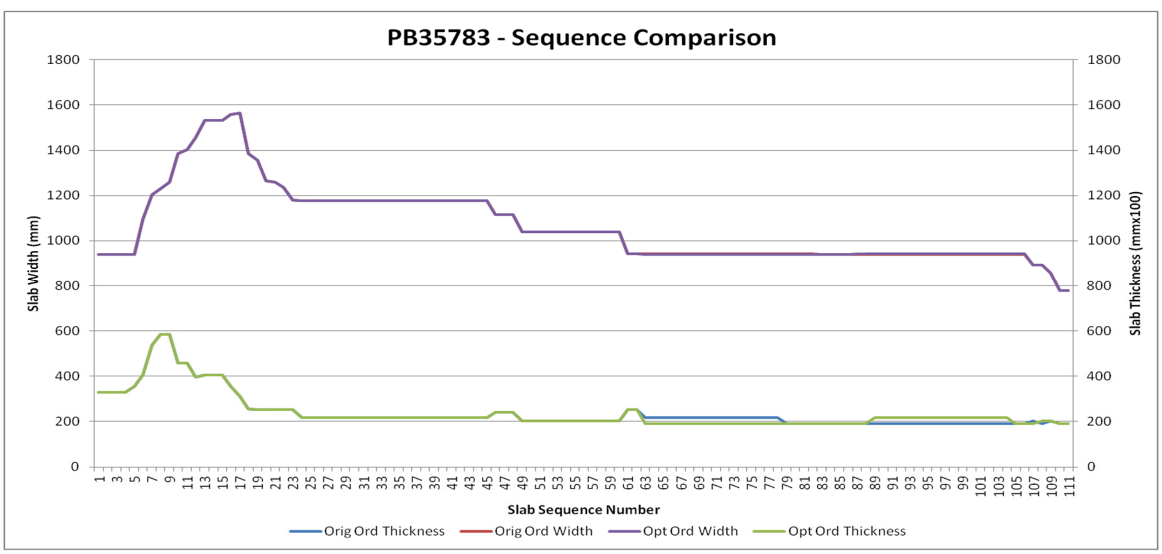

Figure 4.8 - Sequence Comparison of Width and Thickness for Tin Trial 2 (PB35783)

Coils produced from these two product blocks were used in the following applications:

- Steel roofing sheet and cladding for the Roll Form Group and the Ideal Roofing Company.
- Steel for food and beverage cans used by the Can Corporation of America and Crown Cork and Seal USA Inc.
- Painted and exposed steel used in office furniture by Concorde Steel Center Ltd.
- Painted ceiling grids by Ryerson Procurement Corporation.

4.3.4 Production Trial Set 3 –Super-lite Product Blocks

Super-lite product blocks are the third type of product block rolled at AMD's hot mill. Similar to the tin PB type super-lite product blocks have specific characteristics and constraints. Super-lite product blocks contain 10 or more slabs with a final coil thickness of less than 1.85mm with all possible metallurgical grades of steel applicable. Due to the extremely low thickness of the coils produced in a super-lite PB the quality and customer requirements are very strict and the hot rolling process is highly susceptible to disturbances. Therefore, the constraints on super-lite PBs are much the same as tin PBs which results in a less complex sequencing problem as the solution space is highly constrained. Much like tin PBs, this limits the possible improvements which can be obtained through sequencing optimization on a product block with pre-allocated material. Three production trials were conducted for super-lite type product blocks. The computed performance metrics comparing the optimized PB sequence against the original PB sequence are shown in Tables 4.8, 4.9, and 4.10. Width and thickness profiles for both the original and optimized PB sequences are provided in Figures 4.9 to 4.11 for the three trials.

PB27582 **65 Slabs**	**Original PB** **Sequence**	**Optimized PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	12	12	0.00%
HIN Change Count	17	14	17.65%
Total Transition Cost	666.0103234	491.1974234	26.25%
Agg. Force Transition Sum	12015	10769	10.37%
Abs. Thickness Change	4.11	5.15	-25.30%
Slab Thick Chng Cnt.	7.00	5.00	28.57%
Avg. Width Change	9.80	8.38	14.49%
Avg. Thickness Change	0.06	0.08	-25.30%
Thickness Change Cnt.	14.00	15.00	-7.14%

Table 4.8 – Performance Results for Super-lite Trial 1 (PB27582)

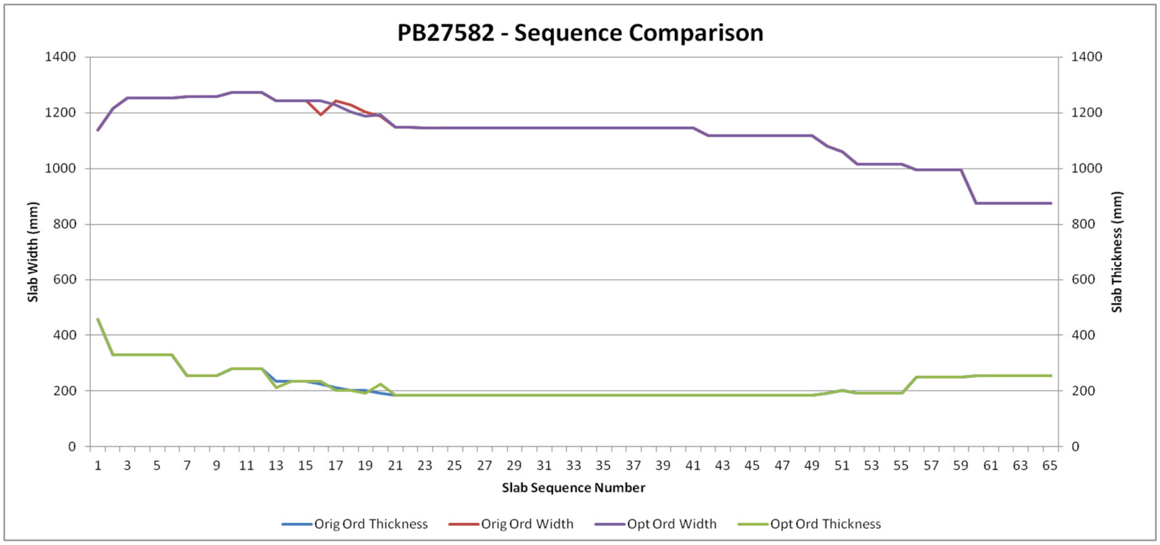

Figure 4.9 - Sequence Comparison of Width and Thickness for Super-lite Trial 1 (PB27582)

PB32280 **89 Slabs**	**Original PB** **Sequence**	**Optimized PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	19	20	-5.26%
HIN Change Count	25	20	20.00%
Total Transition Cost	945.763552	922.1716652	2.49%
Agg. Force Transition Sum	11823	11935	-0.95%
Abs. Thickness Change	5.61	5.61	0.00%
Slab Thick Chng Cnt.	7.00	9.00	-28.57%
Avg. Width Change	7.65	7.77	-1.49%
Avg. Thickness Change	0.06	0.06	0.00%
Thickness Change Cnt.	22.00	23.00	-4.55%

Table 4.9 – Performance Results for Super-lite Trial 2 (PB32280)

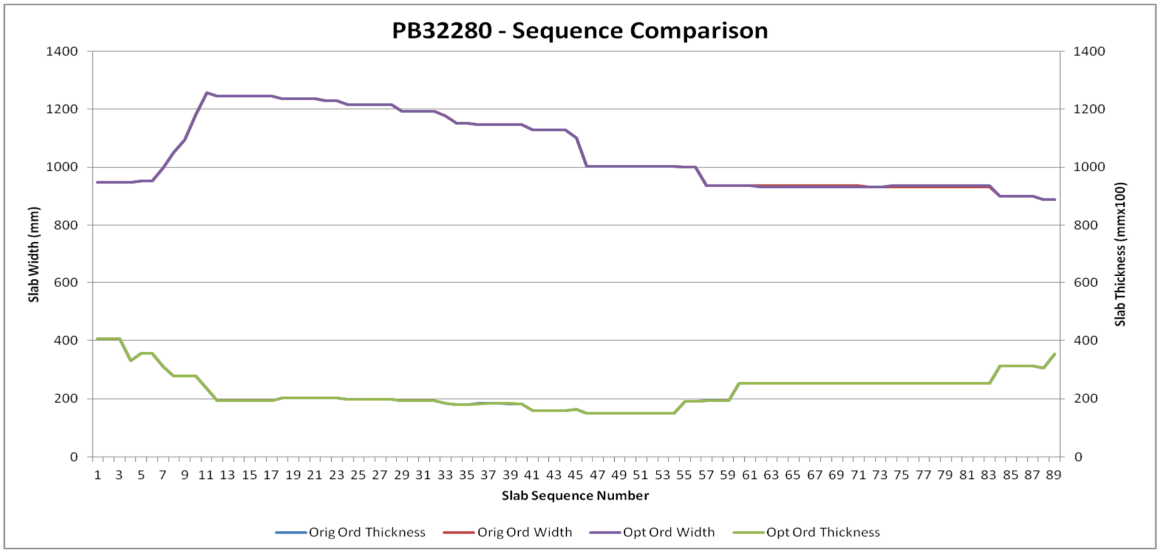

Figure 4.10 - Sequence Comparison of Width and Thickness for Super-lite Trial 2 (PB32280)

PB32284 75 Slabs	Original PB Sequence	Optimized PB Sequence	Percentage Improvement
MDL Change Count	17	17	0.00%
HIN Change Count	14	12	14.29%
Total Transition Cost	693.8790035	685.5456702	1.20%
Agg. Force Transition Sum	15739	14771	6.15%
Abs. Thickness Change	4.93	4.93	0.00%
Slab Thick Chng Cnt.	7.00	7.00	0.00%
Avg. Width Change	9.45	9.45	0.00%
Avg. Thickness Change	0.07	0.07	0.00%
Thickness Change Cnt.	20.00	21.00	-5.00%

Table 4.10 – Performance Results for Super-lite Trial 3 (PB32284)

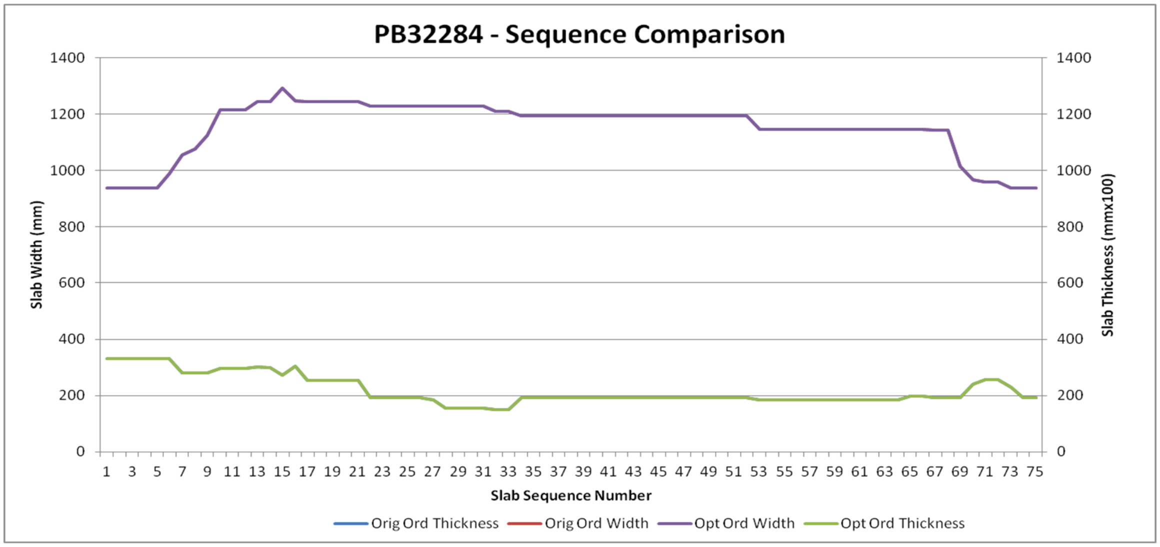

Figure 4.11 - Sequence Comparison of Width and Thickness for Super-lite Trial 3 (PB32284)

Coils produced from these two product blocks were used in the following applications:

- Brake shoes for Janco Steel Ltd. and Nova Steel Inc.
- Garage doors for Metal Koting.
- Welded tubing for the Bull Moose Tube Company.
- Steed studding for Super Stud Building Products Inc.

4.3.5 Summary of Production Trial Results

The percentage improvement figures calculated for the production trial PBs (Tables 4.4 through 4.9) all show considerable improvements in key performance metrics as a result of sequencing optimization via the PBSM. The greatest benefits are noted for the heavy product block types as the solution space is far less constrained than that of the tin and super-lite PBs, however the tin and super-lite PBs also show good performance improvements.

Improvements in key performance metrics for the heavy PB trial blocks range from 12.90% to 44.33% with the total sequence improvement ranging from 10.2% for the first trial PB to 24.95% for the second trial PB. Improvements in overall smoothness of thickness transitions in these trial PBs are very good at 29.94% and 33.50% which indicates the benefits of allowing width to vary within the PB body section. Only positive improvements have been made in the set of primary metrics and no infeasible sequences were generated. The heavy PB trial results are all excellent and show the considerable benefit of the PBSM.

The tin trial product blocks showed very good improvements in performance metrics although they were slightly lower than those of the heavy PBs. The majority of key performance metrics showed positive improvements however in the second trial PB the model point change count remained the same between the original and optimized sequences, and the absolute thickness change decreased very slightly. All other primary metrics showed improvements between 5.04% and 40.04% in the two trial blocks. No improvement in metrics such as the model point or HIN change is not of great concern. The decrease in the absolute thickness metric is not ideal however numerically there is only a very slight difference between the original sequence at 8.67mm and the optimized sequence at 8.73mm. No infeasible sequences were generated for the tin trial product blocks and overall the performance improvements were excellent.

The super-lite trial product blocks showed similar results to the tin trial PBs although improvement percentages were lower on average. A number of the primary metrics showed little to no improvements with a few metrics showing small decreases. Again, no improvement in a metric is not great cause for concern, especially in the case of the super-lite PB type where the problem is highly constrained from the outset. Performance metric decreases are not ideal however the decreases came as the result of only one additional model point change and two additional slab thickness transitions in PB32280 only. These small additional disturbances are not cause for concern especially if it results in an overall improved product block sequence which is the case for PB32280 as evidenced by the positive overall improvement in the sequence cost. Once again no infeasible sequences were generated for the super-lite trials and the performance improvements overall are good. From these trials it was concluded that the super-lite product block type is the most highly constrained PB type and that the benefits provided by sequencing optimization may be limited. These trials also illustrated the limitations of re-sequencing a pre-allocated set of slabs without the ability to add, delete, or swap from available slab inventory.

As AMD’s hot mill is already a highly efficient and high performance operation improvement figures of the magnitudes returned for these production trials are exceptionally good. AMD management was quite surprised and pleased by these results. The success of these industrial production trials, in addition to collaborating with the hot mill schedulers to create good rapport and buy-in, helped to confirm the performance, quality, and reliability of the PBSM in industrial application.

4.4 Findings and Issues Encountered

Through a substantial number of off-line simulations and the set of industrial production trials, the PBSM and associated solution methodology were proven to provide highly beneficial performance improvements on existing product block sequences in a fashion that was both reliable and practical for hot rolling operations. The PBSM could be adopted by AMD with relative ease and integrated into the existing proprietary scheduling software to provide a product block optimization and decision support tool for the hot mill scheduling team. Leveraging the mathematical optimization techniques of the PBSM to assist the schedulers would provide product block sequences of quality and performance far beyond what can be reasonably expected of a human. Based on the performance metrics derived from the production trials, sustained utilization of PBSM optimization would result in benefits to stability, quality, capacity, and energy usage within AMDs hot rolling operations. These findings were discussed in detail with AMD management and the performance benefits provided by the PBSM fully acknowledged.

Over the course of this initial phase of research two key issues and areas for improvement were noted.

Original Research Scope

The requested scope of the original research presented a significant constraint in that the PBSM only considered the re-sequencing of an existing product block. This limited the ability to improve on an existing PB sequence through addition, deletion, and swapping of slabs between product blocks as well as into and out of slab inventory. This also meant that if the scheduler had knowingly created a constraint violation by design in the original PB sequence, it may be impossible to resolve in the PBSM.

Expanding the scope of research to consider multiple product blocks, slab allocation, and slab inventory would allow for greater global optimality in product block sequences over the scheduling horizon as well as the benefits of constructing multiple product blocks simultaneously.

Width Constraints

AMD's hot rolling operation has a unique consideration in that the width of slabs in a product block body section does not have to follow a strictly decreasing coffin-shape profile. This special allowance provides AMD the ability to smooth or optimize other parameters in the PB sequence while allowing the width to vary slightly in both an increasing and decreasing fashion. The constraints around this consideration involve integrating parameters over multiple slabs which is somewhat complex and proved to be difficult to implement for Concorde due to its specific design as a traditional TSP solver. In order to accommodate AMD's width constraints in the PBSM the asymmetric width constraint (4.17) and the quadratic penalization of width in the objective function (4.11) were implemented as an approximation. These two elements provided similar allowances to the AMD design requirements however they had the unfortunate effect of over-constraining width transitions to some degree.

Additionally, AMD's chief hot rolling specialist had developed a concept called a width-group (WG). Width-groups are sections of a product block where no constraints are placed on the width changes of slab-to-slab transitions. The idea is that a PB consists of multiple WGs and within each WG width is not constrained in any way such that the transitions of other objective parameters may be optimized instead. WGs are a relatively unknown and rather theoretical concept in hot rolling mill research globally and even AMD's schedulers do not make use of the practice (A. Ianos, Personal Communication, September 2016).

By incorporating the concept of width-groups within the PBSM it was postulated that AMD's complex width constraints could be greatly relaxed resulting in a more optimal sequence found for the other objective function parameters. There was also interest in investigating a solution which utilized the width-grouping concept as this would be a novel development in steel hot rolling mill production optimization and something which could provide a competitive advantage for AMD.

In order to apply the width-grouping concept properly product blocks should be constructed using a WG design during the slab allocation phase. Therefore, expanding the research to investigate the higher level scheduling and allocation problem would be a necessary enabler for applying the width-grouping concept. These two primary areas of enhancement of the initial PBSM, scope expansion and width-group design, motivated the second phase of research into production scheduling and sequencing optimization for AMD’s hot mill.

Chapter 5

Integrated Scheduling and Sequencing Optimization for Hot Rolling Mill Production

This chapter presents the second phase of research into production scheduling and sequencing optimization in collaboration with ArcelorMittal Dofasco's hot rolling operations. This work builds upon the knowledge gained from the initial research and expands the research scope to cover scheduling and allocation in addition to sequencing. The objective is to present the newly realized problems resultant from the expanded scope, in context of AMD's operations, and outline the formulations and solution methodologies which have been applied. A prototype software application is described as well as its application in conducting a series of trials using AMD production data. Performance results are illustrated through these trials with collaboration and feedback from AMD hot mill schedulers and specialists. Finally, issues and findings gained from this second phase of work are reviewed.

5.1 An Overview of the Problem in Context

While the initial phase of research was successful in achieving AMD management's goal for a proof-of-concept sequencing optimization tool, it was clear significant improvements could be made by expanding the original research scope to include scheduling in addition to sequencing. Expanding the problem scope to include the scheduling and allocation of slabs into product blocks as well as the sequencing of those slabs within the product blocks allows a number of new concepts to be applied. First, the inventory of slabs must now be considered as the product blocks are constructed by allocating slabs from this inventory into a set of specific PBs required for the planning horizon. Control over the scheduling and selection of specific slabs into specific product blocks allows for more optimal product block sequences as the PBs can be designed with an overarching objective in-mind. Second, by controlling the allocation of slabs and construction of the product blocks AMD's width-group concept can be applied as a component of the PB design. The proposed WG design philosophy should help to facilitate constraint relaxation at the sequencing level and generate PB sequences with higher quality and more optimal operational performance overall. Third, now that the slab inventory and scheduling of slabs is considered, multiple product blocks can be constructed simultaneously rather than a single PB at a time. Automated construction of product blocks for the entire 4-day hot mill planning horizon would significantly reduce the monotonous tasks performed by the schedulers. This would allow them to focus on higher value work such as performing more specific or unique (hot mill or market condition related) optimizations to the PB sequences, running "what-if" type analysis on PB designs, or quickly rescheduling due to process disturbances. With these benefits in mind it was clear that expanding the research scope to include both scheduling and sequence of slabs would provide high value for AMD as well as allow for investigation into areas not currently discussed in the available research literature.

Chapter 4, specifically section 4.1, provides a detailed description of the work-flow AMD hot mill schedulers use when constructing a product block. This work-flow is still applicable in this second phase of research. As the construction of product blocks over the planning horizon is now in focus, the following tasks currently performed by the schedulers must be addressed and integrated with the problems addressed in the first phase of research:

1. Determine the types and number of product blocks required over the current planning horizon.
   - Determined based on both customer due dates and finishing operational capacity requirements.
2. Collect a population of slabs from the available inventory.
   - These slabs could be physical slabs available in existing inventory or virtual slabs with a casting date which makes them available for the planning horizon.
3. Construct the required product blocks by allocating slabs from the available population using a PB design methodology.

- The schedulers utilize some heuristics in an attempt to create product blocks composed of slabs with similar characteristics; primarily grouping slabs based on thickness.
- The width-group-based product block design concept is not currently employed by AMD's hot mill schedulers.

When the hot mill scheduler constructs product blocks for the complete 4-day planning horizon it takes six to eight hours of effort.

The ultimate goal for this second phase of research was to develop a model formulation and solution methodology for optimization of the scheduling of slabs into product blocks such that the necessary product blocks can be generated for the required hot mill planning horizon. This slab scheduling model could then be integrated with the product block sequencing model developed during the initial phase of research which would allow the allocated slabs in each generated product block to be rearranged into an optimal PB sequence. The integration of these two models would provide a complete scheduling-sequencing optimization framework which could then be applied to AMD's 4-day hot mill operational planning process.

While AMD management did have interest in this second phase of research they provided no overall goals or requirements as they did in the initial phase. As a result, the focus and direction of the second research phase was primarily driven by an academic interest in developing an integrated scheduling-sequencing solution for AMD's hot rolling operations. The primary objective was a scheduling-sequencing optimization framework which integrated a scheduling model using width-group-based product block design with the previously developed sequencing model. A solution composed of these features would be a novel development and could potentially deliver significant competitive advantage to AMD.

5.2 Solution Architecture

To develop a complete scheduling-sequencing optimization solution for AMD's hot rolling operations the PBSM developed during the initial phase of research would be integrated with a new optimization model formulated to solve the product block slab scheduling problem; henceforth known as the slab scheduling and allocation model (SSAM). As the PBSM and SSAM complete two unique tasks it was decided to decompose the overall scheduling-sequencing problem into two distinct layers within the optimization framework. The upper layer would perform the necessary data collection and preprocessing as well as the slab scheduling optimization and allocation using the SSAM to schedule and construct the required product blocks. The constructed product blocks would then be passed to the lower layer where the slab sequences within each PB would be optimized using the PBSM. Figure 5.1 illustrates the design and architecture of the AMD hot rolling scheduling-sequencing optimization framework at a high level.

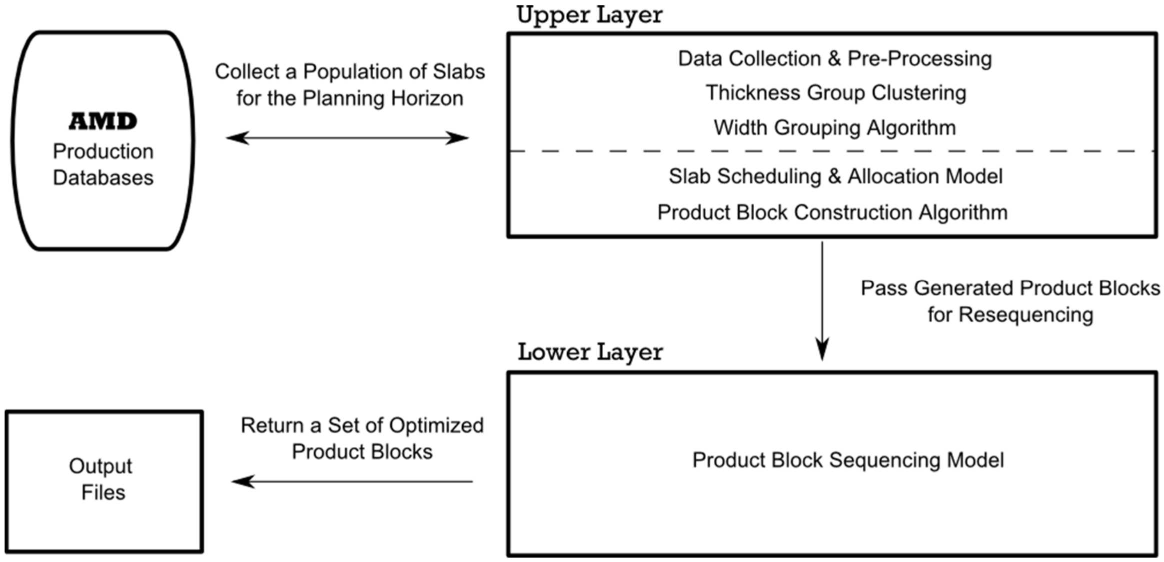

Figure 5.1 – AMD Scheduling-Sequencing Optimization Framework Architecture

Decomposition of the problem into these two distinct layers provides a number of benefits. First, it provides the ability to continue with the initial research goal of finding exact solutions to the hot rolling optimization problems of scheduling and sequencing. As the SSAM can be approximated by traditional scheduling models a Linear Programming (LP) formulation can be developed and exact solutions found by a wide range of LP solvers. The PBSM, as described in Chapter 4, can continue to be solved using the Concorde exact TSP solver. Second, decomposition allows for encapsulation of the two separate optimization problems from a software architecture perspective. This encapsulation enables exchange of models, solution methodologies, application or business logic within one layer without affecting the other layer in any way. Third, it allows for easier maintainability and extensibility of both the optimization software and application software when deployed in a production environment. Considerations for ease of maintenance and modification are important when optimization solutions are deployed in production as an organization may not have the specialized knowledge or resources to support these complex tools.

While there are advantages in decomposing the problem the primary concession is in the possibility that because of the decoupling between scheduling and sequencing the resultant product blocks generated for the planning horizon may not be globally optimal. Fortunately, as this research is primarily focused on industrial application results which are not true globally optimal solutions or cannot be proven as such are of little consequence. Reliable high quality product blocks and product block sequences as well as an optimization framework which allows for fast iteration by the schedulers are of more importance to AMD than true globally optimal solutions to the combined SSAM and PBSM. Additionally, if the objectives are properly formulated at each level of the decomposition and the overall optimization framework is designed with the decomposition in mind, then the solutions returned should be approaching global optimality. It should also be noted that the contemporary research literature does focus on formulations where the two problems are integrated and solved simultaneously; however, all examples of this type of formulation employ meta-heuristic optimization algorithms for which true optimality cannot be proven either. As the primary goal of this second phase was to develop a scheduling-sequencing optimization solution which integrated the width-group design methodology and provided a proof-of-concept for industrial application, decomposition of the problem into two distinct layers provided valuable benefits with no significant drawbacks within the scope of this research.

5.3 Upper Layer Formulation –Scheduling & Allocation of Material

The upper layer of the integrated scheduling-sequencing optimization framework encompasses the core of new development in this second research phase. The upper layer is comprised of five main components which in cooperation result in the construction of a set of required product blocks for the desired planning horizon. The first three tasks completed by the upper layer are primarily data collection and preprocessing steps required to organize and align the slab population for the subsequent scheduling step. The fourth and principle task of the upper layer utilizes the SSAM and generates an optimized allocation schedule which provides a plan for slab assignment. The fifth and final task algorithmically constructs production product blocks based on the allocation schedule returned from the SSAM. These generated product blocks will then be passed to the lower layer for slab sequencing optimization by a revised PBSM. The following sections describe in detail the five main components of the upper layer.

As the scheduling-sequence optimization framework is intended for industrial use at AMD's hot rolling operations, the overall design follows that of the human-machine interaction paradigm. From the beginning, the intent had been to develop the optimization framework described here into a software application through which the hot mill schedulers would interact to construct product blocks for a desired planning horizon. As human-machine interaction is the objective by design, the work-flow of the framework involves decisions to be made by a human user at a number of steps. Full automation of scheduling and sequencing for hot rolling operations over a planning horizon would be possible with modifications to the framework design.

5.3.1 Data Collection and Preprocessing

The first stage of the upper layer obtains the complete population of available slabs for the required hot mill planning horizon. These could be physical slabs currently available in inventory or virtual slabs which have yet to be produced but are confirmed to be available in time for hot rolling. Slabs for both the body section of the PB and the break-in section of the PB are collected at this time. Body section slabs may vary greatly in their attributes while break-in section slabs are highly specific and explicitly selected for their intended purpose. The procedure for this stage replicates the heuristics and business logic used by AMD and the hot mill schedulers.

AMD does not necessarily prioritize customer due dates when selecting the population of slabs for the planning horizon. Instead, a combination of customer due dates and capacity requirements of downstream operations are used. In some cases, on-time delivery to the next operation for one product may be sacrificed if by providing another product to a certain production line will allow that line to continue operation and not shut down. Conveniently, AMD calculates and assigns what is known as a dynamic-delivery date to each slab which considers both the on-time delivery and operational capacity requirements. Using this dynamic-delivery date the required number of slabs with the nearest dynamic-delivery date can be selected and obtained for the planning horizon slab population.

There is a great deal of flexibility at the data preprocessing stage. The population of slabs could be selected based on either a specific product block type the scheduler wishes to generate for the planning horizon or a generic population which covers all product block types required for the horizon. In the scope of this research the data preprocessing stage was designed with human-machine interaction in mind where the scheduler is required to identify a specific product block type they wish to construct PBs for over the current planning horizon.

From a system-integration perspective there is also flexibility as the data preprocessing stage could operate in two unique modes. One mode could be as implemented here in this research where the manual heuristics of the scheduler and AMD business logic are automated and the slab population is queried from a production database. Alternatively, the data preprocessing stage could act as an interface to higher level planning components of a plant-wide optimization system and receive the planned population of slabs for the current rolling horizon. The overall goal of the data preprocessing stage is to collect and organize the slab population so that it is ready for optimization regardless of the origin of the data.

5.3.2 Thickness Group Clustering

Once the slab population has been collected and an inventory of slabs is generated the second stage of the upper layer may proceed. The second stage involves partitioning the slab population into a set of clusters. This clustering is performed in order to generate near homogeneous product blocks with contiguous ranges of thickness as well as to allocate material such that the operational capacity of the hot mill is maximized by the set of PBs. Creating homogeneous clusters with contiguous ranges of thickness ensures that during sequencing optimization the slabs are not so dissimilar that extremely costly slab-to-slab transitions occur. Creating clusters with material distributions which maximize operational capacity and continuous rolling time of the mill (before consumables must be changed) ensures feasible and capacity-optimal PBs are constructed from each cluster.

These clusters separate the slab population based on the distribution of both coil thickness by GRT index and work-roll wear effect known as wear kilometers (WKM). Partitioning the slab population to create clusters based on thickness using the GRT index is a relatively straightforward concept; it is ideal to partition the population such that clusters with relatively normal thickness distributions are resultant. The wear kilometer concept however is more abstract. Wear kilometers indicate the amount of physical wear applied to the work-rolls in the rolling mills for a slab of steel. Wear kilometers provide an accurate measure of the impact a slab of steel has on the mill equipment as the WKM value considers many factors including thickness and metallurgical hardness. The wear effect of a certain slab and thus its WKM value can vary greatly depending on the coil thickness and metallurgical grade of steel. Therefore, wear kilometers are an important consideration when constructing PBs as certain thicknesses or grades may allow for more or less of those slabs in a certain PB. AMD product blocks have limitations on the minimum and maximum number of WKM a PB can be allocated and in most operational situations this amount is maximized to benefit throughput. Consideration of both thickness distribution and distribution of wear kilometers allows for the partitioning of the slab population into clusters which provide ideal product blocks from a thickness perspective and a process capacity and throughput perspective. It is therefore critical to consider both of these parameters simultaneously when clustering the slab population.

As the AMD hot mill schedulers construct one product block at a time they employ a rough estimation of the clustering concept in their work-processes. When building a product block sequence, the schedulers whenever possible try and select a set of slabs from inventory that fall within one of three GRT ranges: GRT 1-6, GRT 6-10, or GRT 10-16. This heuristic attempts to create homogeneity within the thickness distribution of a PB, although it is not guaranteed. Additionally, the schedulers attempt to maximize the total wear kilometers of slabs assigned to a product block but only as a final check in their work-flow. They do not actively consider wear kilometers when allocating slabs to a PB.

In the scope of this research the thickness clustering stage was once again designed according to the human-machine paradigm. The clustering is performed using data visualization techniques provided to the user. The user is then able to determine using their expert knowledge where the optimal partitions are for the slab population based on the distributions of both thickness and wear kilometers. Figure 5.2 below illustrates an example of a slab population taken from AMD production data. This figure shows a population of heavy type material where three ideal clusters have been selected and are outlined in red, blue, and green.

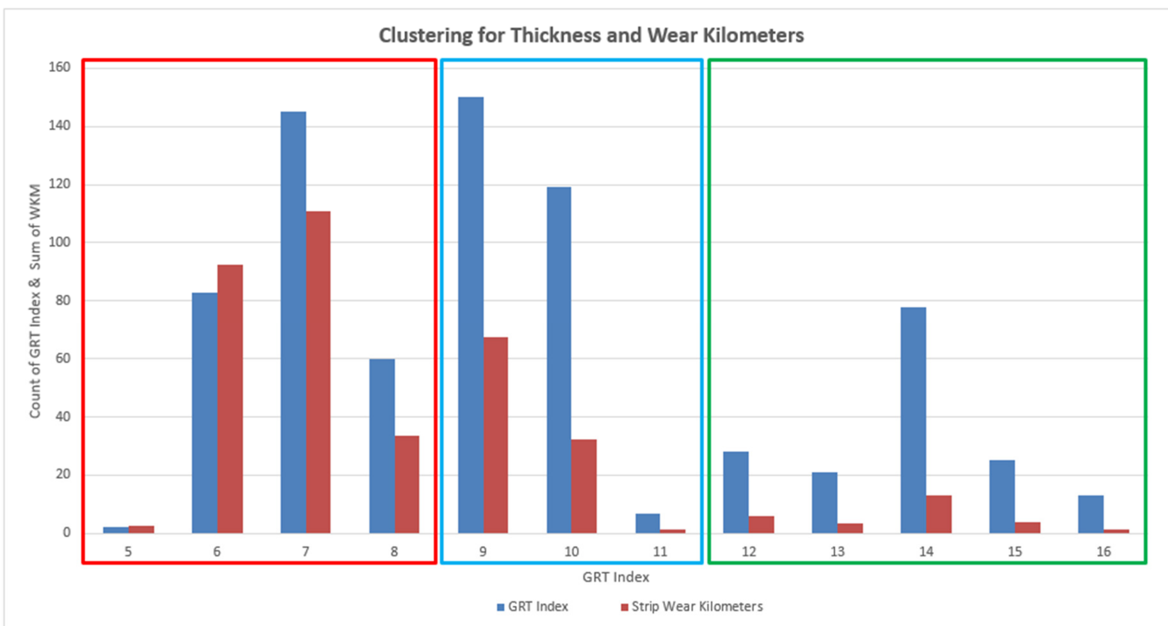

Figure 5.2 – An Example of Slab Population Clustering

If required, this clustering operation could be implemented in an automatic fashion using a variety of clustering and mode finding algorithms. There is however value in leveraging the human-machine paradigm for the clustering stage as the user, likely the hot mill scheduler, will have valuable real-time expert knowledge of the status of the hot rolling operation and can select clusters based on the current operational objectives. These objectives frequently change depending on both market and operational conditions and may be revised on a day-to-day or even hour-to-hour basis.

Once the thickness group clusters have been determined each cluster of slabs, or sub-population, is submitted sequentially to the remaining stages of the scheduling-sequencing framework. Product blocks for each cluster may then be scheduled, constructed, and sequenced.

5.3.3 Width Grouping Algorithm

The clusters defined by the previous slab population partitioning are iteratively processed by the remaining stages of the scheduling-sequencing framework in sequential order. The next stage in the upper layer performs a set of calculation tasks algorithmically which define the problem and strategy employed during scheduling optimization. These tasks are completed by the Width Grouping Algorithm (WGA).

In order to construct product blocks through the allocation of specific slabs an overall PB design and objective must be defined. Here the product block design is based on the AMD proposed concept of width-groups. A product block is organized into a series of width-groups where the length of the WG must not exceed 40 wear kilometers and the overall width change within the WG must not exceed 40 millimeters. Figure 5.3

illustrates a theoretical product block constructed using the WG design. The benefit of applying the width-group concept to PB design is that it completely removes the complex width constraints required by the original PBSM formulation at the sequencing layer. Within a product block sequence where WG design has been applied, the only width constraints are that the order of the WGs must be maintained and that the slabs assigned to a WG must stay within that WG. This relaxation allows for greater freedom in the optimization of PB sequences with full adherence to AMD's width constraint requirements. In order to achieve these relaxations at the sequencing layer the width-group-based PB design must be applied at the scheduling layer as part of the slab scheduling and allocation process. Section 5.4 presents a revised PBSM which considers and accounts for the allowances provided by width-group-based PB design within the scheduling layer.

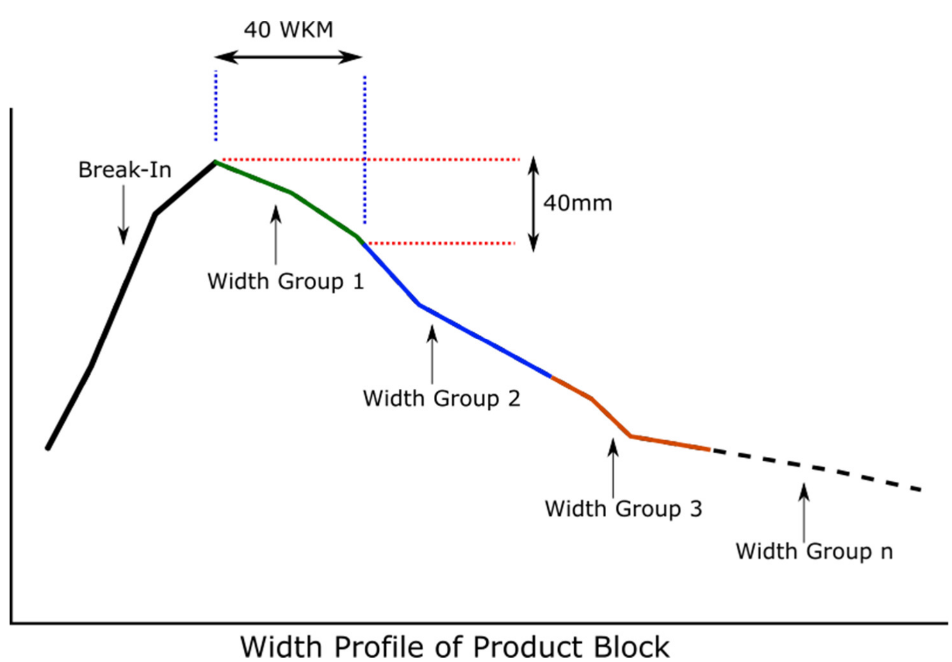

Figure 5.3 – Example of a Width-Group Designed Product Block

To determine the optimal width-group design for a population of slabs the Width Grouping Algorithm is employed. The WGA is a novel development of this research which fully realises and extends AMD's original width-group concept into a functional algorithm. The WGA processes the current cluster and creates a width-group PB design based on the width composition of the cluster aggregate slab population. Pseudo-code for the Width Grouping Algorithm is provided in Figure 5.4 below.

```
"Width Grouping Algorithm"
REPEAT
        CALCULATE startingWidth(startingRow)
        endWidth = startingWidth - 40
        CALCULATE endRow(startRow, endWidth, numRows)
        CALCULATE wkmLimitCheck(startRow,endRow,maxWKM,numProdBlocks)
        IF wkmLimitCheck != ok THEN
                endRow = wkmLimitCheck
        ENDIF
        IF endRow != 0 THEN
                WRITE widthGroupNumbers
        ELSE
                WRITE widthGroupNumbers
                stoppingFlag = TRUE
        ENDIF
        startRow = endRow
        widthGroupNumber += widthGroupNumber
UNTIL stoppingFlag
```

Figure 5.4 – Pseudo-code for the Width Grouping Algorithm

The general operation of the WGA proceeds as follows:

1. Calculate the number of required product blocks from the cluster.
2. Sort the cluster on width from wide to narrow.
3. Select $i = 1$ slab's width as the starting width of the WG and calculate the ending width using the allowable width range defined for a WG.
4. Iterate through the cluster and find the slab j which corresponds to the ending width.
    a. If the sum of WKM from starting slab i to ending slab j **does not violate** the WKM constraint, then assign all slabs within the range WG identifier k.
    b. If the sum of WKM from starting slab i to ending slab j **does violate** the WKM constraint, then set the ending slab j of the WG to the slab which sets the total WKM of the WG to the defined maximum allowable WKM. Assign all slabs within the range WG identifier k.
    c. Set the starting slab equal to the ending slab for the next iteration: $i = j$.
5. Iterate until the entire cluster has been assigned a WG identifier.
6. Calculate and return the required parameter values.

The algorithm takes the current cluster and computes the following parameters based on the aggregate population of slabs within the cluster:

1. Total number of required product blocks.
2. Total number of slabs required in each product block.
3. Total number of width-groups in the width-group design based on the aggregate population.
4. Total number of slabs available from each width-group of the aggregate population.
5. Boundaries of each width-group.
6. Proportion of slabs within each width-group compared to the total slab population of the current cluster. (Recipe)

Using the aggregate population of slabs from the cluster a width-group-based generic product block design is generated. This generic design can then be applied as the basic design for all product blocks which will be constructed from the cluster. The output parameters calculated by the WGA are required for the subsequent slab scheduling optimization stage. Items 1 through 5 of the above list provide the generic width-group design and slab population parameters which will be used to construct all product blocks for the current cluster of slabs. Item 6 provides a recipe which will form the basis for the scheduling optimization objective function.

5.3.4 Slab Scheduling & Allocation Model

Once the generic product block design has been generated by the Width Grouping Algorithm and the required parameters are calculated and available, the penultimate stage of the upper layer may be performed. This stage involves the generation of a slab allocation schedule for the set of required product blocks using the parameters calculated by the WGA. This scheduling optimization is completed using the generic product block design calculated by the WGA as a basis for the objective function employed by the Slab Scheduling and Allocation Model. The optimized allocation schedule returned by the SSAM is leveraged by the final stage of the upper layer to algorithmically construct the set of required production product blocks.

5.3.4.1 SSAM Solution Formulation

As this second phase of research considers production optimization for a medium to large inventory of slabs over an extended planning horizon, the SSAM must be formulated in a fashion which enables the construction of multiple product blocks using slabs allocated from a cluster's population. To achieve this goal, the generic width-group-based product block design calculated in the previous stage by the WGA provides a formula, or recipe, for the basic profile of each PB which will be constructed from the cluster. Figure 5.5 below illustrates this concept of designing all required PBs based on the generic width-group design of the aggregate cluster population. This recipe provides a mechanism which facilitates simultaneous creation of multiple PBs by scheduling slabs such that all product blocks are nearly identical in their width profiles. Using this formulation, the objective of slab scheduling optimization then becomes to minimize the deviations from this generic recipe for all product blocks constructed from the slab cluster.

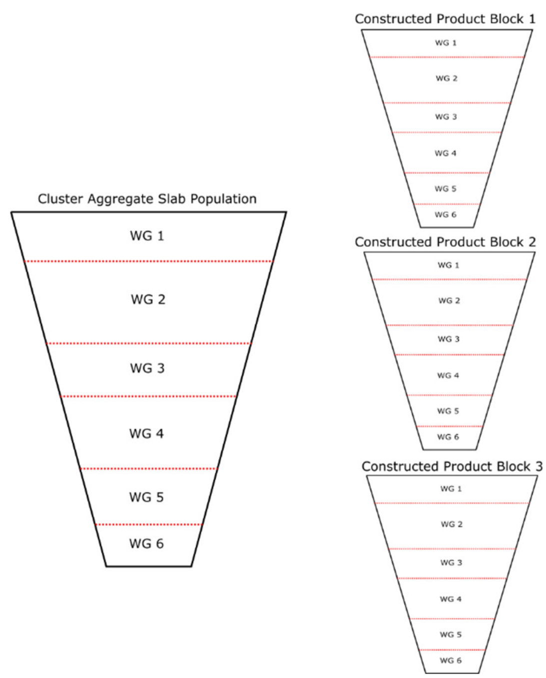

Figure 5.5 – Generic Width-Group Design Applied to All Constructed Product Blocks

The overarching objective to construct all product blocks for a cluster using a generic width-group design recipe was selected based on the assumption that for AMD's hot rolling operation it is ideal to have product blocks as similar as possible in width-group composition. There is benefit for AMD in having minimal deviation between product block composition from the perspective of control system stability and adaptation as well as operational benefits due to the prior knowledge that all PBs will have roughly the same structure. It should be noted that while this overarching objective does provide benefit to AMD it may not be applicable to other hot rolling steel mills. Additionally, there may be more appropriate overarching objectives which would provide a similar mechanism for multi-product block construction.

As the SSAM is essentially a scheduling problem it can be formulated as a Linear Program more specifically as a Mixed Integer Linear Program (MILP) as the slabs are discrete units and thus a solution which contains integer values is of practical interest. The MILP formulation of the SSAM assigns slabs from the set of slabs of each width-group $s \in S_{wg}$ to the set of product blocks $p \in P$ such that deviation from the generic width-group design recipe is minimized. This minimization is completed for all width-groups in the set of width-groups $w \in WG$ and for all product blocks in the set of product blocks $p \in P$. The solution to the MILP formulation of the SSAM is an optimized allocation schedule which indicates the number of slabs of a certain width-group to assign to each width-group within each product block.

It must be noted that the SSAM does not consider or allocate specific slabs to the various width-groups of each product block. The SSAM considers the available number of generic slabs within each width-group of the aggregate cluster slab population and assigns these generic slabs to the WGs of each product block in a fashion which minimizes deviation from the calculated width-group-based design recipe. The result of the SSAM MILP problem is an allocation schedule which informs the Product Block Construction

Algorithm (PBCA) on how to assign unique slabs to the width-groups of the resultant product blocks. Selection of specific slabs to construct the actual PBs is managed by the logistic strategies of the subsequent and final stage of the upper layer: the PBCA. The SSAM scheduling optimization stage is deliberately formulated in a high level manner such that optimization of the product block allocation schedule and assignment of specific slabs are decomposed into two separate tasks. This allows the pure optimization problem of slab scheduling to be managed separately from the business and logistical problem of priority slab assignment. Decomposing these two tasks allows for different assignment strategies to be employed by the PBCA without reformulating the entire SSAM MILP. This decomposition also helps with the extensibility and maintainability of the overall optimization framework when deployed in production.

The following sections provide a detailed description of the MILP formulated SSAM as it was implemented in this research.

5.3.4.2 SSAM Objective Function

In the context of the problem described by the SSAM the objective function defines the minimization of the deviation between the width-group-based design recipe calculated by the WGA for the aggregate slab population of the cluster and the final width-group composition of each resultant product block. Optimization of the slab allocation schedule, and thus the solution to an SSAM problem instance, is achieved by allocating slabs from the cluster population to each PB such that this deviation-based objective function is minimized.

This objective function formulated as an MILP and as implemented in this research is defined by Equation 5.1.

$$Min \left| RCPE_w - \frac{X_{p,w}}{PBT_p} \right| \quad \forall\, p \in P, \forall\, w \in W \tag{5.1}$$

Equation 5.1 states that the objective of the SSAM MILP is to minimize the absolute deviation between the width-group-based design recipe and the final allocated width-group composition for each width-group of each product block required from the cluster.

The recipe for each width group and the total number of slabs which should be allocated to each product block are known prior to solving the SSAM. The absolute deviation between recipe and actual width-group composition is required such that the solution does not incorporate potentially large positive and negative deviations which result in a cumulative minimization of the problem.

5.3.4.3 SSAM Constraints

Constraints required by the SSAM are primarily related to ensuring feasibility of the solution.

Equation 5.2 outlines the standard non-negativity constraint required by most LP and MILP problems. This constraint provides the logical requirement that the variables pertaining to the number of slabs allocated to a certain width-group of a certain product block must be either zero or greater than zero. It is impossible to allocate a negative number of slabs to a width-group.

$$X_{p,w} \geq 0 \quad \forall\, p \in P, \forall\, w \in W \tag{5.2}$$

Equation 5.3 outlines a constraint ensuring material availability from the aggregate width-groups is adhered to. This constraint ensures that no more than the available number of slabs from a certain width-group of the aggregate cluster population can be allocated to a width-group of a constructed product block.

$$\sum_{1}^{p} X_{p,w} \leq WGT_w \quad \forall\, w \in W \tag{5.3}$$

Equation 5.4 outlines a constraint ensuring the pre-calculated product block size is not exceeded. This constraint ensures that the number of slabs allocated to a specific product block does not exceed the total size of that PB as pre-calculated by the WGA.

$$\sum_{1}^{w} X_{p,w} \leq PBT_p \quad \forall\, p \in P \tag{5.4}$$

Equation 5.5 outlines a constraint ensuring the SSAM solution contains all slabs available in the current cluster population. This ensures that the SSAM solution is both feasible in that not too many or too few slabs have been allocated and that the entire slab population from the cluster has been utilized.

$$\sum_{1}^{p}\sum_{1}^{w} X_{p,w} = TP \tag{5.5}$$

Equation 5.6 defines the SSAM to be an integer variable problem. This constrains the solution variables of the SSAM to be integers only and ensures that practical solutions to the problem are realized.

$$X_{P,W} \in \mathbb{Z} \tag{5.6}$$

5.3.4.4 SSAM Solution Methodology

As the SSAM is formulated as an MILP a wide range of LP modelling languages and LP solvers could be employed to solve problem instances. From an optimization performance perspective, the relatively small size of the SSAM means that most conventional LP solvers will return solutions in times which are more than acceptable for the intended industrial application of this research.

In this research the GAMS modelling language was used to develop the SSAM with the CPLEX solver used to solve the MILP formulated SSAM problem instances. The GAMS model of the SSAM was developed in a generic fashion so that an input parameter file could be automatically populated with the required parameters calculated by the WGA. Specific SSAM problem instances could then be constructed using this file just prior to optimization. Additionally, an SSAM solution results file is generated which contains the optimized slab allocation schedule to be used by the PBCA in the selection and assignment of specific slabs to the required product blocks.

These specific design elements of the SSAM implementation in GAMS facilitate the dynamic generation of SSAM problem instances and the automatic construction of multiple product blocks over the planning horizon.

5.3.4.5 SSAM Nomenclature

Indices

$p \in P - \mathit{The\ number\ of\ product\ blocks}$

$w \in W - \mathit{The\ number\ of\ width\ groups}$

Parameters

$WGT_W - \mathit{The\ total\ pieces\ in\ each\ aggregate\ width\ group}$

$PBT_P - \mathit{The\ total\ pieces\ in\ each\ product\ block}$

$TP - \mathit{The\ total\ number\ of\ pieces\ in\ the\ aggregate\ problem}$

$RCPE_W - \mathit{Percentage\ of\ pieces\ in\ a\ width\ group\ of\ the\ aggregate\ problem}\ (\mathit{Recipe})$

Variables

$X_{P,W} - Allocation\ Schedule\ of\ Slabs$

5.3.5 Product Block Construction Algorithm

Once an optimized allocation schedule is returned from the SSAM, specific slabs may be selected and allocated to the PB set. This final stage of the upper layer utilizes the optimized allocation schedule returned from the SSAM and the Product Block Construction Algorithm to construct the required number of PBs from the cluster slab population. The PBCA selects and assigns unique slabs from the cluster into specific product blocks using a defined logistical strategy. These resultant product blocks are now production feasible but not yet optimal and still require sequencing optimization by the revised PBSM.

The PBCA as implemented in this research leverages a priority queue design for construction of the specific product blocks. A priority queue is built for each of the width-groups of the aggregate slab population. The AMD dynamic-delivery date is used as the priority key for the queues in order to select and assign slabs into product blocks based on the allocation schedule returned by the SSAM. For each width-group of each product block in the allocation schedule, specific slabs are iteratively selected and de-queued by priority and assigned into the associated width-group of a production product block. The required unique break-in slabs are then selected using AMD-specific heuristics and assigned in a strictly increasing-in-width sequence prior to the first width-group. The general process of the PBCA is illustrated in Figure 5.6.

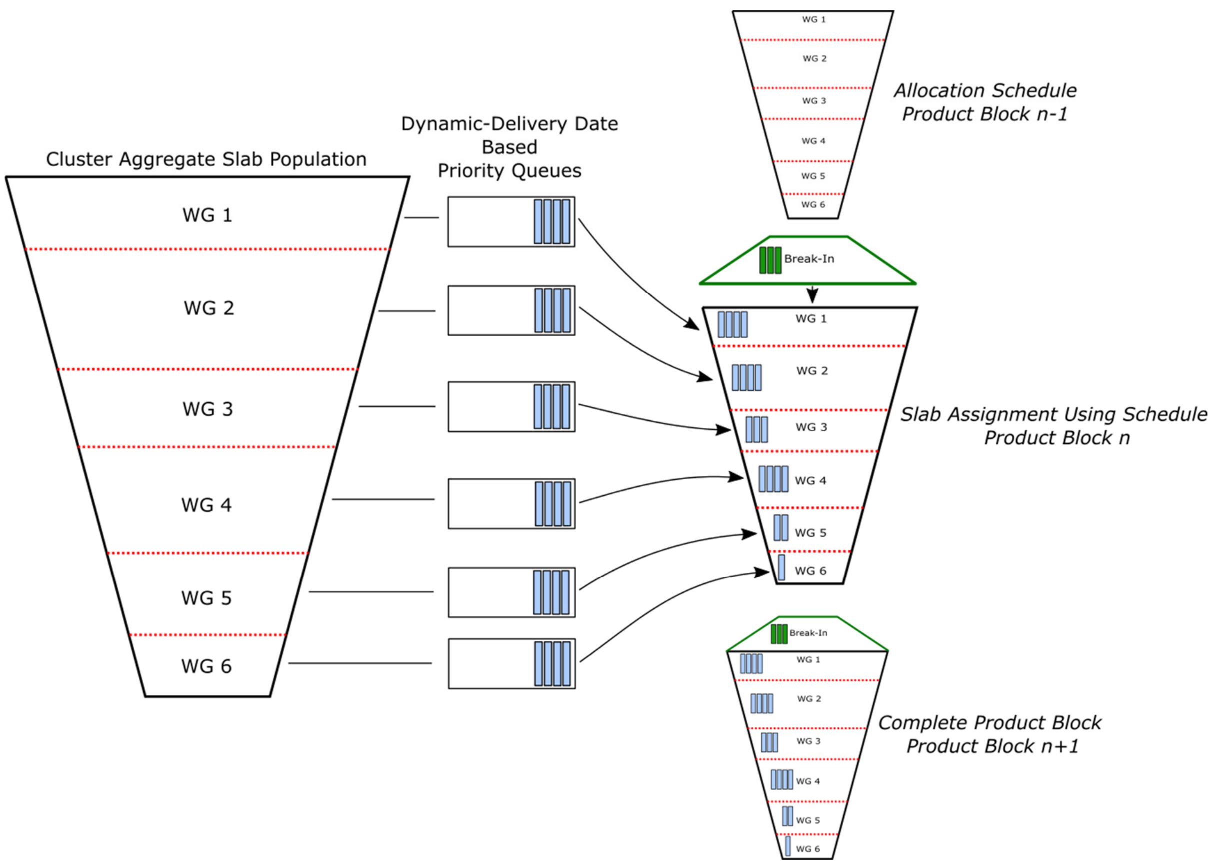

Figure 5.6 – Product Block Construction Algorithm Process

The PBCA priority queue design results in the construction of a set of product blocks where the slab composition in each PB, and thus the PBs themselves, are associated with dynamic-delivery date priority. As the dynamic-delivery date is a composite value describing both the required customer and downstream operation delivery date the resultant product blocks can then be ordered in a sequence which supports timely material flow as well as customer delivery.

The decoupling of the SSAM and PBCA allows for this nearest dynamic-delivery date strategy to be exchanged for any business or logistic strategy required by AMD without reformulating the SSAM.

On completion of the PBCA a set of unique and production feasible, but not optimal, product blocks are generated. These product blocks have been constructed using a width-group-based design and allocated with unique AMD slabs from the cluster population. The upper layer of the optimization framework is now complete and these product blocks may be submitted to the lower layer for sequencing optimization by the revised PBSM.

5.4 Lower Layer Formulation – Sequencing of Material

Once the upper layer has constructed the set of required production product blocks for the current cluster, a refined version of the initial PBSM is utilized to optimize the slab sequence within each of these product blocks. This refined PBSM contains modifications to the original PBSM design from the initial research phase which leverage the width-group-based product block design applied in the scheduling stage of the upper layer. Through consideration of the width-group PB design the complex constraints required in the original PBSM formulation may be greatly relaxed. The benefits provided by a combination of the width-group-based design employed by the SSAM in the upper layer and the refined PBSM in the lower layer allow for greater performance and quality of the resultant optimized product blocks.

The following sections outline the details of the Refined Product Block Sequencing Model (R-PBSM) as formulated in the second phase of research.

5.4.1 Solution Formulation of the Revised Product Block Sequencing Model

The Product Block Sequencing Model described in Chapter 4 contained a number of complex constraints and objective function considerations in order to meet AMD's specification for allowable width change within a product block sequence. While these constraints met AMD's requirements they did not align well with the Concorde solver and were found to unnecessarily over-constrain the width transitions within a product block sequence. Through the construction of product blocks generated using a width-group-based design the need for these complex and difficult-to-implement constraints on width transitions are completely relaxed and fully removed from the PBSM formulation. This second phase of research takes the complete initial formulation of the PBSM and makes a number of modifications which result in the R-PBSM. The R-PBSM maintains the same graph-theoretic ATSP formulation as the PBSM but with revisions made to components of the objective function and certain constraints which pertain to width and width transitions, as well as the addition of new width-group-related constraints.

The original width constraints are replaced with a set of easily implemented and more straightforward constraints on both intra and inter width-group sequences. The asymmetric slab-to-slab transition constraint on numerical width, described by Equation 4.17, is removed entirely. The objective function of the R-PBSM also simplifies as a result of the width constraint relaxations resulting in the squared width transition cost term, described in Equation 4.11, being removed from the aggregate transition cost function. The original slab-to-slab width transition constraints are replaced with constraints on the width-groups themselves. In the R-PBSM the only constraints on width are that the sequence of width-groups must be maintained and that the slabs allocated to a width-group must stay within that width-group. Slabs may be re-sequenced within their width-group without any restriction on slab-to-slab width transitions allowing the remaining parameters in the ATCF to take precedence in the determination of an optimal sequence. Width becomes far less of a constraint on the overall product block sequencing problem as a result of this reformulation. The width-group-based PB design and optimization of the both the scheduling and sequencing of PBs now results in full adherence to AMD's width transition requirements without the over-constraint of the initial PBSM formulation. The R-PBSM formulation should ultimately provide product blocks of greater quality and operational performance when processed by the hot rolling mill.

5.4.2 R-PBSM Objective Function

As a result of the width constraint relaxations provided by the width-group-based product block design, the objective function of the R-PBSM contains a modified version of the original aggregate transition cost function of the PBSM. Equation 5.7 illustrates the new aggregate transition cost function with Equations 5.8 and 5.9 outlining the same basic objective function formulation for the R-PBSM as in the original PBSM. All remaining conceptualizations and equations pertaining to the original PBSM objective function continue to apply to the R-PBSM formulation.

$$ATC_{ij} = a \cdot dThk_{ij} + b \cdot dHIN_{ij} + c \cdot dGrd_{ij} \tag{5.7}$$

$$Where\ a, b, c = 1$$

$$c_{ij} = ATC_{ij} \tag{5.8}$$

$$min \sum_{i=0}^{n} \sum_{j \neq i, j=0}^{n} c_{ij} x_{ij} \qquad x_{ij} \begin{cases} 1\ nodes\ i\ and\ j\ are\ connected \\ 0\ otherwise \end{cases} \tag{5.9}$$

In Equation 5.7 the numerical width transition term has been completely removed compared to Equation 4.11 of the original PBSM. No longer must difference in numerical slab width be considered in the cost of slab-to-slab transitions or the overall cost of a product block sequence. Width-groups however must be considered in both slab-to-slab transitions and the overall PB sequence although only through constraints as will be illustrated in the following section. Once again coefficients are applied to the ATCF parameters for future application of priority/goal weightings, or monetary-based cost values. This research considered all coefficients to have a value of 1 and thus equal weighting of all parameters within the ATCF.

5.4.3 R-PBSM Constraints

The R-PBSM formulation of the product block sequencing problem contains nearly the same set of constraints as the original PBSM. The constraints described by Equations 4.14 through 4.18 in Chapter 4 remain in the R-PBSM formulation with the exception of the slab-to-slab width transition constraint described by Equation 4.17 which is removed entirely. In place of the slab-to-slab transition constrain on numerical width a set of new constraints on width-groups are created for the R-PBSM.

The first new constraint of the R-PBSM constrains the set of slabs within a specific width-group to remain within that width-group. This is expressed by Equation 5.10.

$$WG_{original} = \{s_1, s_2, s_3, \dots s_n\} = WG_{optimized} \qquad \forall\, WG \tag{5.10}$$

Equation 5.10 states that the set of slabs which were allocated to a width-group of the product block must stay within that width-group in the optimized product block sequence. Slabs assigned to a width-group may not move outside of their assigned width-group.

The order of the set of slabs within a width-group however does not need to be maintained.

The second new constraint of the R-PBSM constrains the order of the width-group sequence to remain as originally planned by the width-group design. This is expressed by Equation 5.11.

$$WGS_{original} = (WG_1, WG_2, WG_3, \dots WG_n) = WGS_{optimized} \tag{5.11}$$

Equation 5.11 states that the ordered sequence of width-groups, from the original product block design, must be maintained in the solution sequence of the optimized product block. Here the ordered sequence of the width-groups is indeed the constraint and must be maintained.

5.5 A Prototype Decision Support Tool

In order for the hot rolling scheduling-sequencing optimization framework described here to be evaluated for performance of results, potential industrial application, and to ensure acceptable design for a production environment, a prototype of the framework had to be developed. It was decided to develop a software application containing the full feature set and framework design, both upper and lower layers, as developed in the second phase of research. As the application was intended only as a proof-of-concept for performance evaluation it was decided to rapidly develop a piece of software which could then be ported to a production application at a later time. To accomplish this rapid development an alpha-stage application was produced over the course of three days and developed in VBA such that components from the initial phase of research could be leveraged for reuse. The intent of this process was that once performance of the scheduling-sequencing optimization framework had been proven using AMD production data the application, if desired by AMD management, would be ported to a modern software language.

Using VBA an Excel-based decision support tool was created following the framework design and optimization model formulations described in the second phase of research. This decision support tool incorporated the human-machine interaction design paradigm such that the hot mill scheduler is integrated into the scheduling and sequencing process for the desired planning horizon. This combination of human and software enables greater performance in the dynamic construction of product blocks by augmenting the real-time operational knowledge of the hot mill scheduler and the power of rigorous optimization models and algorithmic processing. The hot mill scheduler is able to select and specify certain parameters and conditions for the scheduling and sequencing models through a user interface such that the models reflect the current operational status of the hot mill. Interfaces were developed to gather the required data from AMD's production databases to create the initial slab population for the planning horizon. All required algorithms, including the WGA and PBCA, were developed as encapsulated functions in VBA to facilitate ease of porting in the future. The core optimization models of the GAMS-based SSAM MILP and the R-based R-PBSM ATSP are called from the VBA decision support tool however they are executed by their respective native applications. All movement and transfer of data between VBA, GAMS, and R is achieved through CSV files. The decision support tool, upon completion, returns an Excel Workbook with individual Worksheets containing the optimized product blocks, composed of specific AMD slabs, as generated by the scheduling-sequencing optimization framework.

The following outlines the work-flow of the prototype decision support tool when the scheduler wishes to generate a set of product blocks for a certain time horizon.

1. The hot mill scheduler selects the type of scheduling run to be performed (either a general run or a specific product block type run) and the length of the planning period.
    - AMD production databases are then queried and the required slab data is returned.
    - This creates the initial slab population for the planning period.
2. A visualization of the thickness and wear kilometer distribution for the slab population is presented to the scheduler. The scheduler then partitions the slab population into up to three clusters based on the distributions of thickness and wear kilometers as well as current operational objectives.
    - These clusters are then submitted sequentially to the remaining stages of the framework.

3. The Width Grouping Algorithm receives a cluster and algorithmically creates a width-group-based product block design based on the cluster's slab population.
    - The WGA output parameters are calculated and an input file for GAMS is generated to enable dynamic construction of an SSAM problem instance for the current cluster.
4. The VBA application then calls the external GAMS implemented Slab Scheduling and Allocation Model to generate an optimized allocation schedule using the width-group-based PB design.
    - The input file is used by GAMS to generate the SSAM problem instance for the current cluster.
    - CPLEX is used by GAMS to solve the SSAM MILP problem.
    - An output file is generated by GAMS which provides the optimized allocation schedule.
5. The Product Block Construction Algorithm utilizes the optimized allocation schedule, returned by GAMS, to construct the set of required product blocks for the current cluster.
    - The PBCA selects and assigns specific slabs to each product block based on a priority determined by dynamic-delivery date.
    - Specific break-in material is assigned to the front of the constructed product blocks.
    - A CSV file representing each unique product block generated by the PBCA is constructed.

6. The VBA application then calls the external R implemented R-PBSM which creates and solves R-PBSM problem instances for each of the product blocks in the current cluster.
    - From the CSV file containing each product block a cost matrix representation of the PB is generated using the aggregate transition cost function of the R-PBSM.
    - The cost matrix in ATSP form is converted to symmetric TSP form.
    - The reformulated cost matrix is then submitted to the Concorde solver and the solution sequence is used to generate an output CSV file.
7. Once each cluster of the initial slab population is processed an Excel Workbook is generated with individual Worksheets showing the optimized product blocks for the specified planning horizon.

The prototype decision support tool outlined here facilities the generation of a set of optimized product blocks for a certain planning horizon using the scheduling-sequencing optimization framework developed during this research. As the prototype interfaces directly to AMD's production databases, industrially practical and production-ready product blocks are returned from a run of the application. As a result, this prototype enabled a series of industrial trials to be conducted using real AMD production data to generate a set of optimal product blocks for the hot rolling operation. These trials allowed for a performance comparison between PBs generated by the hot mill schedulers for a certain planning period and those generated by the prototype for the same horizon.

5.6 Non-Production Trial Results

With a prototype decision support tool now available, a series of trials were conducted at AMD to evaluate the performance of the scheduling-sequencing optimization framework and the applicability of the overall design to a production environment. These trials were non-production or offline trials where real AMD slab inventory and production data was supplied to the prototype and used to construct a set of product blocks for a specified planning horizon. Unlike the trials conducted during the first research phase these generated product blocks were not supplied back to the AMD production database and were not physically processed through the hot mill. The product blocks returned by the prototype for these trials were however evaluated by both AMD hot mill schedulers and technical specialists to ensure feasibility for practical hot rolling. Modifications to AMD’s proprietary planning software to allow the submission of the generated PBs would have enabled the execution of true production trials; however, this work was outside the scope of this research and would have required additional time and resource commitments from AMD.

To compare the performance of the scheduling-sequencing optimization framework against that of the scheduler the same slab population used by the scheduler to plan the hot rolling operations for a certain time horizon was provided to the prototype. This allowed the product blocks created by the scheduler and the product blocks returned from the optimization framework to be evaluated for performance on a near equal level. The product blocks constructed by the scheduler and those returned by the prototype were compared based on a set of key performance metrics for both scheduling and sequencing. Scheduling performance was evaluated on process capacity utilization determined by the maximization of product block wear kilometers, as well as general uniformity in product block composition of slab attributes. Sequencing performance was evaluated using the same set of primary key performance indicators employed in the PBSM production trials from the initial research phase.

It must be noted here that direct 1:1 comparison between product blocks created by the hot mill scheduler and those created by the prototype are impossible. As the scheduler and the prototype may have allocated entirely different sets of slabs into their respective product blocks a direct evaluation between a scheduler PB and a prototype PB does not provide an equal or fair comparison. This is especially true for sequencing performance. In spite of this technical difficulty, an attempt has been made to match and compare the most similar product blocks in order to impart a general idea of the realized performance improvements. Making these comparisons also helps to provide some industrial context for the improvements provided by the optimization framework. A holistic view of performance is also provided which compares the two sets of product blocks created for the planning horizon on important overall metrics such as number of total PBs, maximization of WKMs, and aggregate sequencing metrics for the entire set of PBs.

The following sections present the individual trials of the scheduling-sequencing framework and provide performance results and noted observations for each specific trial. Feedback from AMD management collected during presentation of these trial results is summarized and presented to illustrate the industrial applicability of the optimization framework.

5.6.1 Trial 1 - Scheduling and Sequencing of Heavy Material for a 4 Day Horizon

Trial 1 involved the construction of a set of heavy-type product blocks over the standard 4-day planning horizon for the hot rolling mill: September 9th to September 13th 2016. A set of four product blocks created by the scheduler were evaluated against the set of product blocks created by the prototype when the same aggregate slab population was submitted to the optimization framework as the operational plan for the scheduling horizon. Table 5.1 illustrates the composition of the aggregate slab population as well as the original product blocks from which it was created.

Heavy-Type Product Block Scheduling & Sequencing September 9th to September 13th 2016			
Original Hot Mill PB	**Number of Slabs**	**Sum of Wear Kilometers**	**Material Type**
36783	176	31	Heavy – HSLA
37180	175	140	Heavy - HSLA
37281	180	63	Heavy - HSLA
37280	213	123	Heavy - HSLA
Aggregate Slab Population Totals	**744**	**357**	**Heavy - HSLA**

Table 5.1 – Framework Trial 1: Aggregate Slab Population Composition

Figure 5.7 illustrates the distributions of both coil thickness by GRT index and wear kilometers for the aggregate slab population as well as the selected cluster partitions. Three clusters were chosen based on a visualization of these distributions attempting to create homogeneity in thickness and balance the number of slabs and cumulative wear kilometers in each cluster. These clusters were then submitted to the scheduling-sequencing optimization framework and a set of optimal product blocks were constructed in a fully automated fashion.

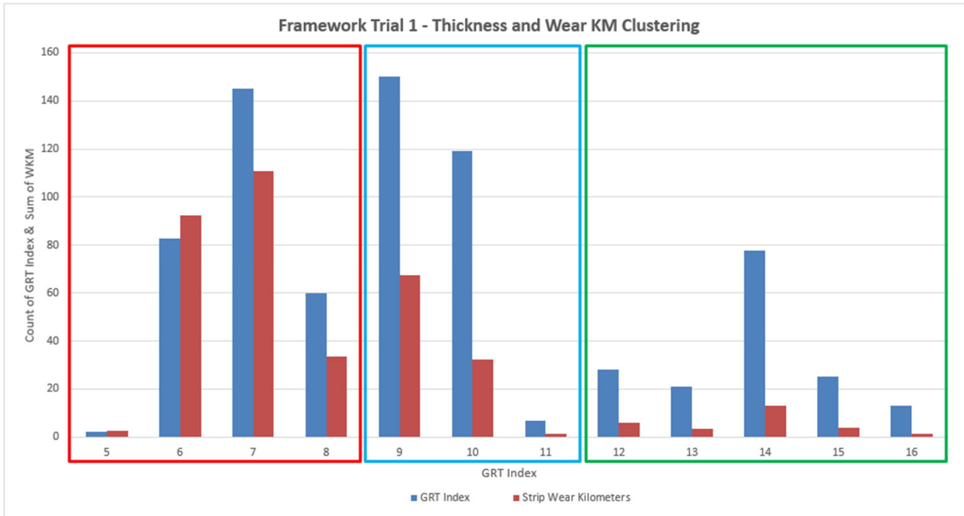

Figure 5.7 – Framework Trial 1 Cluster Selection

Once the prototype had returned the set of optimized product blocks an evaluation was completed for both scheduling and sequencing performance. Comparisons were made between the set of product blocks generated by the hot mill scheduler and the set of product blocks returned by the prototype. Table 5.2 provides a scheduling performance metric comparison between the two PB sets. Tables 5.3 through 5.6 provide sequencing performance metric comparisons where the most similar PBs in the two PB sets were matched and evaluated. Table 5.7 provides a sequencing performance metric comparison when the metrics for each set of product blocks are aggregated together.

Scheduling Performance

Performance Comparison		
	Scheduler Solution	**Prototype Solution**
Number of Resultant PBs	4	4
Median Number of Slabs per Product Block	174.5	158.5
Median Total Wear Kilometers per Product Block	92.31	107.09
Prototype Settings		
Max WKM per PB: 130	Min WKM per PB: 60	Max WKM per WG: 50

Table 5.2 – Framework Trial 1: Summary of Scheduling Performance Metrics

Scheduling performance of the optimized PBs shows reasonable improvements over the scheduler generated PBs. Although both the scheduler and the prototype returned four product blocks, the median wear kilometer value of the four optimized product blocks is higher than that of the scheduler's product blocks. This results in greater operational capacity utilization of the hot rolling mill as the optimized product blocks provide greater production rates before delay time is incurred to replace consumables; primarily finishing mill work-rolls.

Sequencing Performance

As the number of slabs and cumulative amount of wear kilometers varied between clusters, the number of product blocks generated by each cluster is different. Cluster 1 generated two resultant product blocks. Clusters 2 and 3 generated one resultant product block each.

Cluster 1 (GRT 1-8) **PB 1 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	46	34	26.09%
HIN Change Count	51	30	41.18%
Total Transition Cost	1780.717448	1247.809896	29.93%
Agg. Force Transition Sum	43260	29940	30.79%
Abs. Thickness Change	34.15	13.91	59.27%
Slab Thick Chng Cnt.	6.00	11.00	-83.33%

Table 5.3 – Framework Trial 1: PB1 of Cluster 1 Sequencing Performance Comparison

Cluster 1 (GRT 1-8) **PB 2 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	30	46	-53.33%
HIN Change Count	45	30	33.33%
Total Transition Cost	1421.076823	1248.950521	12.11%
Agg. Force Transition Sum	25367	34545	-36.18%
Abs. Thickness Change	28.17	16.68	40.79%
Slab Thick Chng Cnt.	6.00	13.00	-116.67%

Table 5.4 – Framework Trial 1: PB2 of Cluster 1 Sequencing Performance Comparison

Cluster 2 (GRT 9-10) **PB 1 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	31	18	41.94%
HIN Change Count	35	15	57.14%
Total Transition Cost	1594.619792	705.9205729	55.73%
Agg. Force Transition Sum	25577	22171	13.32%
Abs. Thickness Change	27.78	9.97	64.11%
Slab Thick Chng Cnt.	3.00	2.00	33.33%

Table 5.5– Framework Trial 1: PB1 of Cluster 2 Sequencing Performance Comparison

Cluster 3 (GRT 11-16) PB 1 Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	38	20	47.37%
HIN Change Count	21	16	23.81%
Total Transition Cost	1826.68099	1078.674479	40.95%
Agg. Force Transition Sum	38851	30023	22.72%
Abs. Thickness Change	62.5	40.71	34.86%
Slab Thick Chng Cnt.	11.00	6.00	45.45%

Table 5.6 – Framework Trial 1: PB1 of Cluster 3 Sequencing Performance Metrics

Aggregate Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	145	118	18.62%
HIN Change Count	152	91	40.13%
Total Transition Cost	6623.10	4281.40	35.36%
Agg. Force Transition Sum	133055	116679	12.31%
Abs. Thickness Change	152.6	81.27	46.74%
Slab Thick Chng Cnt.	26	32	-23.08%

Table 5.7 – Framework Trial 1: Aggregate Sequencing Performance Comparison

Sequencing performance of the optimized PBs shows significant improvements over the scheduler generated PBs. With the exception of the second PB generated from cluster 2, each of the individual product block comparisons show large percentage improvements in all sequencing performance metrics. While the second PB generated from cluster 2 does show performance decreases in some metrics, the absolute thickness change metric still shows a large improvement as do the HIN and overall transition cost metrics. Once again, these direct comparisons are difficult to make as the slab composition of the two PBs selected for evaluation may be unfairly dissimilar.

The aggregate sequencing comparison provides an overall performance comparison between the set of PBs generated by the scheduler and those generated by the prototype. This evaluation provides a more accurate performance comparison however some of the industrial relevance is lost as the individual product blocks which would be physically processed are not considered. This cumulative comparison once again shows significant improvements in all primary sequencing performance metrics with the exception of slab thickness changes. An increase in the number of slab thickness changes, while not ideal, is not detrimental as long as the PBs are still feasible for hot rolling. This was confirmed for all four PBs returned by the prototype. These improvements, especially the near 50% increase in overall smoothing of thickness, are extremely impressive considering the performance of AMD's scheduling team is already world-class when compared against other ISPs.

Prototype Execution Performance

Table 5.8 below illustrates performance of the scheduling-sequencing optimization framework, as implemented in the prototype, in terms of execution times for Trial 1. Total execution time of the prototype to construct the optimal product blocks for Trial 1 is provided as well as execution times for the individual optimization solver components.

Prototype Performance	Problem Size (Slabs)	Total Prototype Execution Time (seconds)	CPLEX Execution Time (seconds)	Concorde Execution Time (seconds)
Cluster 1	293	46.78	0.007	3.93
Cluster 2	281	51.68	0.02	17.27
Cluster 3	170	33.41	0.02	3.25
Total Execution Time		131.87	0.047	24.45

Table 5.8 – Framework Trial 1: Prototype Execution Times

The set of product blocks for Trial 1 is generated in 2 minutes and 20 seconds by the prototype compared to the 2 hours it would take the hot mill scheduler. This is a considerable time saving.

These performance figures also illustrate the speed of execution for both the SSAM and R-PBSM problems solved in CPLEX and Concorde respectively. The execution time of the optimization components within the prototype is only a fraction of the total running time, where the majority of execution time is comprised of data collection and processing as well as file I/O tasks. It is reasonable to assume that if the prototype was ported to a modern compiled language, rather than VBA, significant improvements would be realized in the cumulative execution time of the application.

5.6.2 Trial 2 - Scheduling and Sequencing of Tin Material for a 4 Day Horizon

Trial 2 involved the construction of a set of tin-type product blocks for a 4-day planning horizon: September 26th to September 30th 2016. Market conditions at the time of Trial 2 were challenging and thus the demand for only 2 tin-type PBs within the 4-day planning horizon was somewhat unusual. The optimized construction of tin-type PBs was of interest to confirm acceptable operation of the prototype on these PB types which contain more difficult to process material and thus typically higher cumulative PB wear kilometers as well as more restrictive constraints within sequencing. A set of two product blocks created by the scheduler were evaluated against the set of product blocks created by the prototype when the same aggregate slab population was submitted to the optimization framework as the operational plan for the scheduling horizon. Table 5.9 illustrates the composition of the aggregate slab population as well as the original product blocks from which it was created.

Tin-Type Product Block Scheduling & Sequencing **September 26th to September 30th 2016**			
Original Hot Mill PB	**Number of Slabs**	**Sum of Wear Kilometers**	**Material Type**
39480	138	140	Tinplate – Mild
39580	162	140	Tinplate – Mild
Aggregate Slab Population Total	**300**	**280**	**Tinplate – Mild**

Table 5.9 – Framework Trial 2: Aggregate Slab Population Composition

Figure 5.8 illustrates the distributions of thickness by GRT index and wear kilometers for the aggregate slab population as well as the two clusters which were selected based on this visualization. These clusters were then submitted to the scheduling-sequencing optimization framework and a set of optimal product blocks were constructed.

It must be noted that the scheduler generated product blocks for this trial actually exceeded the standard maximum cumulative wear kilometer value (130 WKM) for a product block as defined by AMD. This was almost certainly due to market and operational conditions at the time of this trial. However, it is at the scheduler's discretion to adjust this parameter and thus a maximum of 180 WKM per PB was applied to accurately reflect the decisions of the scheduler within the prototype. The ability for the user to make real-time adjustments to optimization parameters illustrates a major benefit of the human-machine interaction paradigm on which the scheduling-sequencing framework was designed.

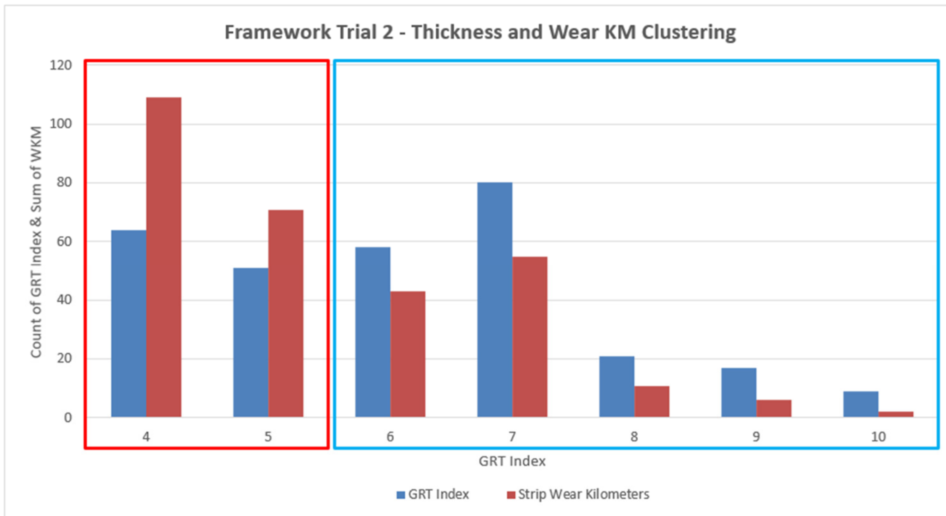

Figure 5.8 – Framework Trial 2 Cluster Selection

Once the prototype had returned the set of optimized product blocks an evaluation was completed for both scheduling and sequencing performance. Table 5.10 provides a scheduling performance metric comparison between the two PB sets. Tables 5.11 and 5.12 provide sequencing performance metric comparisons where the most similar PBs in the two PB sets were matched and evaluated. Table 5.13 provides a sequencing performance metric comparison when the metrics for each set of product blocks are aggregated together.

Scheduling Performance

Performance Comparison		
	Scheduler Solution	**Prototype Solution**
Number of Resultant PBs	2	2
Median Number of Slabs per Product Block	150	150
Median Total Wear Kilometers per Product Block	148.34	148.34
Prototype Settings		
Max WKM per PB: 180	Min WKM per PB: 60	Max WKM per WG: 50

Table 5.10 – Framework Trial 2: Summary of Scheduling Performance Metrics

A comparison of scheduling performance between the two sets of product blocks shows little difference. As there are only two resultant product blocks in both the set of scheduler generated PBs and the set of prototype generated PBs the median number of slabs and total wear kilometers are identical. Looking at the numerical values for total slabs and wear kilometers the scheduler's PBs have 138 and 162 slabs with 152.66 and 144.02 WKM respectively, while the prototype's PBs have 115 and 185 slabs and 179.92 and 116.76 WKM respectively. These two sets of product blocks are relatively balanced and comparable in their scheduling performance. A scheduling solution which reproduces the human scheduler's results is fully acceptable even though no performance improvements are realized.

Sequencing Performance

Each cluster in Trial 2 produced one resultant product block.

Cluster 1 (GRT 4-5) **PB 1 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	16	4	75.00%
HIN Change Count	25	12	52.00%
Total Transition Cost	927.0859375	596.3242188	35.68%
Agg. Force Transition Sum	11126	5997	46.10%
Abs. Thickness Change	9.43	1.13	88.02%
Slab Thick Chng Cnt.	10.00	7.00	30.00%

Table 5.11 – Framework Trial 2: PB1 of Cluster 1 Sequencing Performance Comparison

Cluster 2 (GRT 6-10) PB 1 Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	44	48	-9.09%
HIN Change Count	41	41	0.00%
Total Transition Cost	1696.002604	1444.696615	14.82%
Agg. Force Transition Sum	30798	36815	-19.54%
Abs. Thickness Change	20.68	24.54	-18.67%
Slab Thick Chng Cnt.	32.00	24.00	25.00%

Table 5.12 – Framework Trial 2: PB1 of Cluster 2 Sequencing Performance Comparison

Aggregate Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	60	52	13.33%
HIN Change Count	66	53	19.70%
Total Transition Cost	2623.088542	2041.020833	22.19%
Agg. Force Transition Sum	41924	42812	-2.12%
Abs. Thickness Change	30.11	25.67	14.75%
Slab Thick Chng Cnt.	42	31	26.19%

Table 5.13 – Framework Trial 2: Aggregate Sequencing Performance Comparison

Performance comparison results for sequencing in this second trial are quite interesting. The first product block generated by the prototype has a lower piece count but greater total wear kilometers compared to the scheduler generated PB which it was compared against. This would indicate generally more difficult to roll material and a more challenging sequencing problem in the optimized PB versus the scheduler's PB. However, the sequencing performance results show large improvements in all key metrics in the optimized PB versus the scheduler generated PB. The second product block generated by the prototype has a higher piece count but lower wear kilometer value compared to the scheduler generated PB used for evaluation. Overall this second PB has slight decreases in performance metrics. However, the percentage decreases in performance are relatively small and in some part can be attributed to the fact that there are simply a greater number of slabs in the optimized PB versus the scheduler's PB. If the metrics are adjusted to a per-slab basis, then the optimized PB performs higher in nearly all key metrics. Once again these product block comparisons are only to provide some indication of the industrial applicability of the resultant PBs.

The aggregate sequencing performance comparison shows good improvements in all key performance metrics with the exception of aggregate force which shows only a slight decrease. The improvements in sequencing performance for these tin-type product blocks are only slightly lower than the improvements seen in the heavy-type product blocks. The difference in benefits returned by the scheduling-sequencing optimization framework between heavy-type and tin-type product blocks is a result of the greater constraints applied to the tin-type blocks at the sequencing level. The results returned from the prototype for this second trial on tin-type material once again show fully production feasible product blocks with improved performance metrics when compared to the product block set constructed by the hot mill scheduler.

Prototype Execution Performance

Table 5.14 below illustrates performance of the scheduling-sequencing optimization framework, as implemented in the prototype, in terms of execution times for Trial 2. Total execution time of the prototype to construct the optimal product blocks for Trial 2 is provided as well as execution times for the individual optimization solver components.

Prototype Performance	**Problem Size (Slabs)**	**Total Prototype Execution Time (seconds)**	**CPLEX Execution Time (seconds)**	**Concorde Execution Time (seconds)**
Cluster 1	115	28.47	0.03	3.27
Cluster 2	185	35.38	0.02	3.74
Total Execution Time		63.85	0.05	7.01

Table 5.14 – Framework Trial 2: Prototype Execution Times

The set of product blocks for Trial 2 is generated in 1 minute and 6 seconds by the prototype compared to the 1 hour it would take the hot mill scheduler. This is again a considerable time saving.

As before, it can be seen that the majority of execution time is consumed not by the optimization solvers, but rather by the data collection, processing, and file I/O tasks.

5.6.3 Trial 3 - Scheduling and Sequencing Resulting in Reduced Delay Time

Trial 3 involved the construction of heavy-type product blocks over an extended time horizon of 5 days: September 22nd to September 27th 2016. Evaluating the scheduling-sequencing framework for an extended planning horizon was of interest to ensure the prototype could properly process a large slab population and generate the appropriate product blocks for such a planning period. A set of six product blocks created by the scheduler were evaluated against the set of product blocks created by the prototype when the same aggregate slab population was submitted to the optimization framework as the operational plan for the scheduling horizon. Table 5.15 illustrates the composition of the aggregate slab population as well as the original product blocks from which it was created.

Heavy-Type Product Block Scheduling & Sequencing September 22th to September 27th 2016			
Original Hot Mill PB	**Number of Slabs**	**Sum of Wear Kilometers**	**Material Type**
39183	210	76	Heavy - HSLA
39182	154	93	Heavy - HSLA
39185	155	139	Heavy - HSLA
39283	137	96	Heavy - HSLA
39184	112	56	Heavy - HSLA
39286	100	73	Heavy - HSLA
Aggregate Slab Population Total	**868**	**533**	**Heavy - HSLA**

Table 5.15 – Framework Trial 3: Aggregate Slab Population Composition

Figures 5.9 illustrates the distribution of coil thickness by GRT index and wear kilometers for the aggregate slab population and identifies the two distinct clusters which were defined for this trial. These clusters were submitted to the scheduling-sequencing optimization framework and a set of product blocks were constructed.

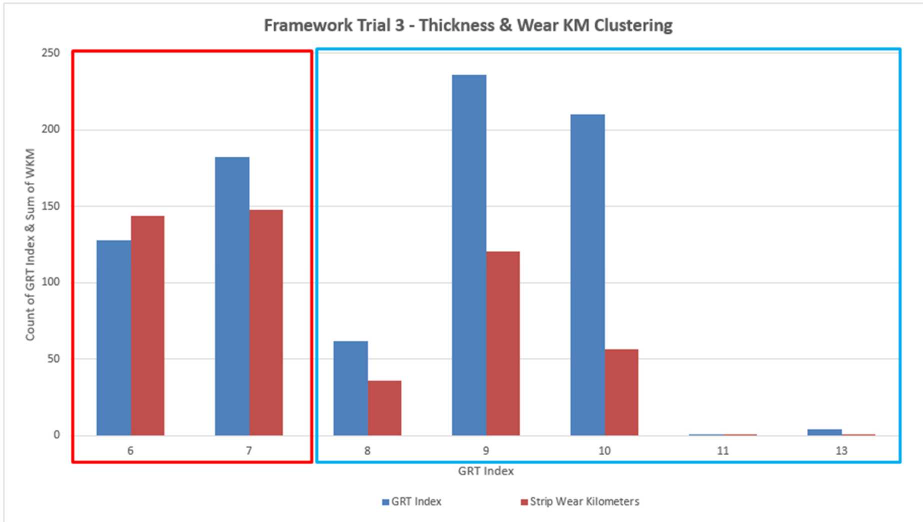

Figure 5.9 – Framework Trial 3 Cluster Selection

Scheduling Performance

Performance Comparison		
	Scheduler Solution	**Prototype Solution**
Number of Resultant PBs	6	5
Median Number of Slabs per Product Block	128	108
Median Total Wear Kilometers per Product Block	79.19	99.15
Prototype Settings		
Max WKM per PB: 130	Min WKM per PB: 60	Max WKM per WG: 50

Table 5.16 – Framework Trial 3: Summary of Scheduling Performance Metrics

A comparison of scheduling performance shows significant improvements in the set of product blocks generated by the prototype over the set of product blocks generated by the hot mill scheduler. Most significant is the reduction in total number of product blocks from six generated by the scheduler to five generated by the prototype. Reducing the total number of product blocks results in immediate benefits as one less work-roll change, and its associated delay time, is required by the hot mill. In the case of AMD where the cost of production stoppage is $1000/minute, and with a work-roll change lasting 8 minutes at a minimum, there are immediate costs savings of $8000 CAD as a result of the optimized product block scheduling. In addition to decreased delay time there are also cost savings as a result of not having to machine the worn work-rolls one additional time. Cost savings resultant from reduced machining are dependent on the number of work-rolls which require grinding and can only be determined at production time. However, at a minimum two of seven finishing mill work-rolls will need machining and thus a conservative estimate of the cost savings resultant from reduced machining is $505 CAD considering only grind-losses and not electrical or manpower costs. This figure could be considerably greater, up to a maximum of $2248 CAD per product block, depending on the work-roll machining requirements. Furthermore, the optimized product blocks have a higher median total wear kilometer value resulting in an overall greater utilization of hot mill operational capacity.

This is a tremendous result in terms of scheduling performance improvements. If even one work-roll change per day could be reduced through utilization of the scheduling-sequencing framework, theoretical annualized savings of \$2.92M could be realized considering delay time with additional savings of \$184,130 realized through decreased grind-losses. Reducing one work-roll change per shift, which is not outside the realm of reason, could result in annualized savings of \$5.84M considering delay time with additional savings of \$368,256 realized through decreased grind-losses.

Sequencing Performance

As the six product blocks generated by the scheduler were reduced to five product blocks by the prototype, cluster 1 PB 3 is a comparison between itself and two of the scheduler's original product blocks.

Cluster 1 (GRT 6-7) PB 1 Comparison	**Scheduler PB Sequence**	**Prototype PB Sequence**	**Percentage Improvement**
MDL Change Count	25	23	8.00%
HIN Change Count	22	23	-4.55%
Total Transition Cost	1509.670573	1142.013021	24.35%
Agg. Force Transition Sum	19160	27914	-45.69%
Abs. Thickness Change	18.06	9.59	46.90%
Slab Thick Chng Cnt.	5.00	7.00	-40.00%

Table 5.17 – Framework Trial 3: PB1 of Cluster 1 Sequencing Performance Comparison

Cluster 1 (GRT 6-7) **PB 2 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	24	18	25.00%
HIN Change Count	23	20	13.04%
Total Transition Cost	1506.628906	1153.441406	23.44%
Agg. Force Transition Sum	18120	24071	-32.84%
Abs. Thickness Change	16.96	9.69	42.87%
Slab Thick Chng Cnt.	6.00	10.00	-66.67%

Table 5.18 – Framework Trial 3: PB2 of Cluster 1 Sequencing Performance Comparison

Cluster 1 (GRT 6-7) **PB 3 Comparison**	**Scheduler PB** **Sequence**	**Prototype PB** **Sequence**	**Percentage** **Improvement**
MDL Change Count	54	24	55.56%
HIN Change Count	51	23	54.90%
Total Transition Cost	2881.888021	965.0716146	66.51%
Agg. Force Transition Sum	43979	22928	47.87%
Abs. Thickness Change	44.95	8.13	81.91%
Slab Thick Chng Cnt.	12	6.00	50.00%

Table 5.19 – Framework Trial 3: PB3 of Cluster 1 Sequencing Performance Comparison

Cluster 2 (GRT 8-13) PB 1 Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	40	37	7.50%
HIN Change Count	41	36	12.20%
Total Transition Cost	1978.589844	1048.914063	46.99%
Agg. Force Transition Sum	36057	54075	-49.97%
Abs. Thickness Change	37.82	24.6	34.96%
Slab Thick Chng Cnt.	11.00	12.00	-9.09%

Table 5.20 – Framework Trial 3: PB1 of Cluster 2 Sequencing Performance Comparison

Cluster 2 (GRT 8-13) PB 2 Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	31	45	-45.16%
HIN Change Count	37	42	-13.51%
Total Transition Cost	1561.251302	1314.123698	15.83%
Agg. Force Transition Sum	35624	62064	-74.22%
Abs. Thickness Change	42.04	29.06	30.88%
Slab Thick Chng Cnt.	4.00	12.00	-200.00%

Table 5.21 – Framework Trial 3: PB2 of Cluster 2 Sequencing Performance Comparison

Aggregate Comparison	Scheduler PB Sequence	Prototype PB Sequence	Percentage Improvement
MDL Change Count	174	147	15.52%
HIN Change Count	174	144	17.24%
Total Transition Cost	9438.028646	5623.563802	40.42%
Agg. Force Transition Sum	152940	191052	-24.92%
Abs. Thickness Change	159.83	83.61	47.69%
Slab Thick Chng Cnt.	38	48.00	-26.32%

Table 5.22 – Framework Trial 3: Aggregate Sequencing Performance Comparison

Sequencing performance metrics resultant from direct product block comparisons show mixed results in the third trial. Performance results from direct product block comparisons become even less relevant when the slab population is large, as it was in this trial, due to the significant dissimilarity in product block composition between the two resultant PB sets. This is especially true in the case of Trial 3 where six product blocks have been reduced to five. Nevertheless, all of the PB comparisons contain some improvements in primary metrics and the critical metric of absolute thickness change maintains high performance improvements in all compared product blocks.

Once again the aggregate sequencing performance comparison shows good improvements in all of the critical primary metrics with only slight decreases in aggregate force and slab thickness changes. These are again excellent results as all the product blocks generated by the prototype were confirmed to be fully feasible for production hot rolling and still maintained considerable improvements over the original product blocks created by the scheduler.

This third trial illustrates the significant practical and industrially relevant benefits of the optimization framework in both the scheduling and sequencing of hot rolling product blocks. This trial also proved that applying the optimization framework to longer planning horizons is not only feasible with the current optimization architecture design but has the potential to return even greater benefits than when applied to shorter planning periods.

Prototype Execution Performance

Table 5.23 below illustrates performance of the scheduling-sequencing optimization framework, as implemented in the prototype, in terms of execution times for Trial 3. Total execution time of the prototype to construct the optimal product blocks for Trial 3 is provided as well as execution times for the individual optimization solver components.

Prototype Performance	**Problem Size (Slabs)**	**Total Prototype Execution Time (seconds)**	**CPLEX Execution Time (seconds)**	**Concorde Execution Time (seconds)**
Cluster 1	333	43.4	0.01	4.87
Cluster 2	535	105.71	0.007	20.58
Total Execution Time		149.11	0.017	25.45

Table 5.23 – Framework Trial 3: Prototype Execution Times

The set of product blocks for Trial 3 is generated in 2 minutes and 48 seconds by the prototype compared to the 3 hours it would take the hot mill scheduler. Once again, this demonstrates a considerable time saving and opportunity to leverage the scheduler for more value-added activities.

Execution time for sequencing on cluster 2 was somewhat longer than what has been noted during the previous two trials. This is a result of cluster 2 containing a considerably greater number of slabs due to the reduction in total product block count, as well as the selection of the cluster partitions. In the case of cluster 2 the sequencing problem has become more complex, due to the intrinsic nature of the ATSP, and thus requires a longer time to solve.

As with the previous two trials the execution time of the optimization solvers is trivial and only a fraction of the total application running time.

5.6.4 Trial Feedback from AMD Management

The non-production trials completed using the prototype application demonstrated considerable improvement in key performance metrics versus comparable product blocks created by the hot mill schedulers. All critical metrics for both scheduling and sequencing showed excellent improvements. However, once the trials were complete and the findings compiled it was imperative to have the results reviewed by AMD in order to verify industrial applicability and compliance to all production constraints and requirements.

A rigorous and detailed review of the non-production trials conducted in this second phase of research was completed in collaboration with the hot mill schedulers and technical specialists. Performance was reviewed and the feasibility of production hot rolling for each product block generated by the prototype was confirmed.

Once the trials had been completed and performance reviewed, a presentation of the results was provided to AMD management. Management was surprised at the magnitude of performance improvements realized by the scheduling-sequencing optimization framework and acknowledged the exceptional results obtained through the trials with satisfaction. Most interesting to the managers were the fast solution times returned by the prototype, the possibility of generating more uniform product blocks, and the potential of reducing total product block count over the planning horizon.

5.7 Cost and Benefit Analysis

The trials conducted using the prototype illustrated that there are clear benefits to hot rolling process stability, throughput, and capacity utilization when width-group designed product blocks are rigorously scheduled and sequenced by the optimization framework. In addition to the process related advantages there are secondary benefits through productivity gains for the commercial group and scheduling team as well as operational benefits for the hot mill.

5.7.1 Process and Operational Monetary Benefits

The metrics used for trial evaluation were selected as they presented the greatest insight into the performance and quality of the scheduling and sequencing solutions returned by the optimization framework. These performance figures represented the improvements realized by the optimized product blocks over the original product blocks in percentage terms of the defined metrics and were useful in comparison type analysis. These evaluations however did not provide any indication of overall monetary benefit to AMD.

A considerable effort was undertaken in concert with AMD technical specialists to develop a model which would provide some indication of the monetary benefits realized by the optimized product blocks. This modelling effort proved difficult due to the high performance nature of AMD's hot mill and the low rate of quality, stability, and general performance issues. When defects do occur it is nearly impossible to correlate them directly with poor scheduling or sequencing with most instances typically resultant of mechanical or electrical equipment failures.

Ultimately, a model was constructed which calculates the cost of process stability related defects as a result of slab sequencing changes in terms of Canadian Dollars (CAD). This model applies the annualized cost of various stability related defects, defined on an event-basis, to slab-to-slab transitions in numerical thickness, width, and aggregate force. The equations describing this model are outlined in Equations 5.12 through 5.15 and were provided by AMD's chief hot rolling mill technical specialist A. Ianos via personal communication in November of 2016.

$$ForceFactor = \ 4.77^{-06} \cdot AggForce_n - AggForce_{n-1} + \ 0.00254 \tag{5.12}$$

$$WGN = \left(\frac{Width_n}{{Thickness_n}^3 \cdot Hardness_n}\right) \cdot \left(\frac{\left(\frac{Width_n}{{Thickness_n}^3 \cdot Hardness_n} - \frac{Width_{n-1}}{{Thickness_{n-1}}^3 \cdot Hardness_{n-1}}\right)}{1000}\right) \tag{5.13}$$

$$StabilityFactor = 0.000136 \cdot WGN^2 + 0.000826 \cdot WGN + 0.004883 \tag{5.14}$$

$$TransitionDollarCost = \$72 \cdot ForceFactor + \$10883 \cdot StabilityFactor \qquad (5.15)$$

For the trials conducted using the optimization framework the cumulative monetary costs of both scheduling and sequencing may be calculated and compared between the set of scheduler generated product blocks and the set of prototype generated product blocks. Table 5.24 shows the cumulative cost of sequencing, as well as the costs associated with scheduling, for the two sets of product blocks over the planning horizon of each trial. Sequencing costs are determined based on the transition cost model calculation while improvements in scheduling costs result from reductions in the total number of product blocks for the planning period.

Monetary Comparison	**Scheduler PB Seq. Cost (CAD)**	**Prototype PB Seq. Cost (CAD)**	**Sequencing Benefit (CAD)**	**Scheduling Benefit (CAD)**	**Total Benefit (CAD)**
Trial 1	39655.90	39288.68	367.23	0	367.23
Trial 2	16743.61	16221.96	521.65	0	521.65
Trial 3	44813.71	44231.64	582.07	8505.00	9087.07

Table 5.24 – Summary of Monetary Performance Benefits

Trials 1 and 2 show reasonable overall monetary improvement (\$367.23 and \$521.65 respectively) in the cost of scheduling and sequencing over the traditional 4-day planning horizon. A highly interesting result is that while sequencing optimization of tin-type PBs shows slightly lower improvements in performance metrics when compared to heavy-type PBs there appears to be considerable monetary benefit associated with optimizing the sequence of tin-type product blocks. Trial 2 shows only a slightly lower monetary improvement from optimizing the sequence of two tin-type product blocks as Trial 3 does from six heavy-type product blocks. This appears to indicate that there may be greater benefits from optimization of the tin-type product blocks; a fact not immediately apparent from review of the performance metrics. While these sequencing improvement figures may seem negligible any potential cost savings are highly valued within AMD's hot rolling mill. As a world-class hot mill with exceptionally low quality and operational issues small incremental improvements must be made to maintain operational excellence and pursue continuous improvement.

Trial 3 shows that the most significant benefits are realized through optimal scheduling of product blocks and over longer time horizons. In the case of Trial 3 whereby scheduling optimization has reduced the number of required product blocks by one complete PB, costs savings of $8505 due to reduced delay time and machining losses are realized. This scheduling benefit is then compounded with the monetary benefits of improved process stability, a value of $582.07, realized through sequencing optimization. Trial 3 illustrates the real benefits of the optimization framework developed in this research. The application of scheduling optimization has reduced the number of required product blocks by one over the planning horizon which directly increases capacity utilization and thus the throughput rate of the hot mill. Operational benefits are also associated with reduction in the total number of required product blocks through reduced machining and grind-loss of finishing mill work-rolls, resulting in cost savings between \$505 and \$2248 CAD per product block, as well as manpower which can be reallocated to other tasks. In addition, sequencing optimization has generated product block sequences which not only demonstrate improved sequencing performance metrics but also result in reduced theoretical cost of stability and quality related issues.

While the monetary benefits calculated for the three trials are valuable in providing industrial context through dollar-based cost improvement figures, the complete set of benefits may only be realized through continued application of the scheduling-sequencing optimization framework to AMD's hot rolling operations. Through continued use of the solution framework in the scheduling and sequencing of product blocks the true benefits to the hot rolling process would become apparent in the various key performance indictors which AMD tracks for the hot rolling mill. It is not unreasonable to assume that performance improvements in the metrics tracked during this research, but also in unforeseen metrics and benefits to ancillary areas would materialize from continuous application of the optimization framework to AMD's hot rolling operations.

Additionally, an accurate calculation of the true monetary benefits could only be performed in a historical fashion once the framework is implemented in the production environment. However, as it is useful in presentation and discussion to provide a quantification of the benefits generated by the proposed solution an estimate of the annual cost savings may be calculated. Using the computed monetary benefits from the trials as a baseline and assuming favorable market conditions, a conservative informal estimate of annual cost savings resultant from application of the scheduling-sequencing optimization framework is $1.2M CAD per year. This calculation makes the assumptions of an average PB sequencing benefit of $250 CAD, 1700 PBs per year, and the reduction of one PB within each planning horizon achieved through improved scheduling.

$$Annual\ Scheduling\ Benefit = \frac{365}{4}\ Horizons\ per\ Year \cdot \$8505 = \$776{,}081.25$$

$$Annual\ Sequencing\ Benefit = \ 1700\ PB\ per\ Year\ \ \cdot \$250 = \$425{,}000$$

$$Total\ Benefit = \$1{,}201{,}081.25$$

5.7.2 Scheduler Productivity and Commercial Benefits

Benefits to productivity of the AMD commercial group and a shift towards greater value-added work for the hot mill scheduling team may also be realized as a result of employing the optimization framework in a decision support application capacity.

Currently the hot mill schedulers spend considerable time performing repetitive scheduling and sequencing tasks. By leveraging the framework as a decision support tool much of the monotonous work performed by the schedulers would be handled by software in an automated fashion. Not only would low-value and tedious work no longer be required but, as has been demonstrated through this research, the scheduling and sequencing of product blocks generated by such an optimization tool would be of higher quality and operational performance than those currently constructed by the schedulers.

Freeing the schedulers from these repetitive tasks allows their time to be employed for higher value-added work which would be possible through the proposed decision support application. The schedulers would be able to produce product blocks for the required planning horizon with much faster iteration, as well as run "what-if" scenarios to determine how to best schedule the hot rolling mill for different market or operational conditions. As the optimization framework is designed with human-machine interaction in-mind the schedulers would be able to react to external demands and apply their considerable knowledge to adjust the configurable parameters of the scheduling and sequencing models to accommodate these special requests. Requests for the inclusion of new or last minute customer orders in the current planning horizon, the scheduling and sequencing of experimental grades, and customer orders which are at or exceed the limitations of the hot mill could all be managed more efficiently with a decision support tool. An enhanced ability to respond to these types of commercial requests provides considerable competitive advantage to AMD through security for existing customer orders and the ability to expand the product range of the hot mill into new areas.

Chapter 6

Conclusions and Recommendations

6.1 Conclusions

The main conclusions to be drawn from this thesis are as follows:

1. **Benefits and as well as limitations are realized when only the re-sequencing of pre-constructed product blocks is considered.** After introducing an asymmetric travelling salesman problem formulation and exact solution methodology for the product block sequencing problem sets of rigorous simulations and industrial trials were conducted. Through these simulations and production trials it was found that significant improvements, but also hindering limitations, present themselves when the scope of the optimization problem is limited to only the re-sequencing of existing product blocks. These disadvantages arise from the inability to consider the population of available slabs, design product blocks with an overarching objective, allocate specific slabs based on that objective, as well as the difficulty in implementing certain width-related constraints. The performance improvements in product block sequencing generated by the proposed model were

excellent, however it was determined that far greater benefits could be realized through optimal scheduling in addition to sequencing.

2. **Clustering of the slab population based on thickness and wear kilometers promotes higher performance within the scheduling and sequencing layers.** Early simulation with the scheduling-sequencing optimization framework illustrated the need to partition the slab population into distinct clusters such that highly dissimilar slabs would not be allocated to the same product block. Considering both thickness and wear kilometer distributions of the aggregate slab population provides optimal clusters to the optimization layers of the framework. Near-normal distributions of thickness allow for higher performance sequencing as no extreme transitions should occur within the resultant product block sequences. A distribution of wear kilometers which provides the minimum number of feasible product blocks, while maximizing the total wear kilometers allocated to each product block, improves scheduling performance and thus the operational capacity of the hot mill. The performance results and calculated improvements achieved through the non-production trials illustrated the benefit of the slab clustering methodology.

3. **A novel width-grouping algorithm enables the creation of a width-group-based product block design to form an overarching objective for scheduling optimization.** The width-group-based product block design proposed by AMD is novel within the steel and rolling mill industrial research community. However, it

was abstract in its conception and without any mechanism for application. This research extended and formalized the original theory and developed a mechanism through which width-group-based product block designs can be obtained. The width-grouping algorithm designed and developed in this research provides a computational method for generating a generic product block design from an aggregate slab population. Application of the width-group-based product block design provides an overarching objective for scheduling and allocation whereby multiple product blocks can be simultaneously constructed. This design also relaxes certain complex constraints of slab sequencing for greatly improved performance. The novel width-grouping algorithm is the enabling mechanism for the performance improvements in scheduling and sequencing illustrated by the simulation and trial results of this research.

4. **The model formulations which comprise the multi-layered scheduling-sequencing optimization framework facilitate the generation of feasible, high performance product blocks.** Findings from the first phase of research indicated that greater benefits could be realized by expanding the research scope to include both optimal scheduling and sequencing of hot rolling production. A set of algorithms were designed and a mixed integer linear programming model was formulated for optimal scheduling and allocation of slabs over a required time horizon. The original combinatorial sequencing model was revised to account for both the augmentation and relaxation of constraints resultant from the width-group-based product block designs generated by the scheduling model. An

intensive series of simulations followed by non-production trials with feedback from the schedulers and technical specialists were performed. Results from these trials illustrated the considerable process and operational improvements as well as commercial and productivity benefits of applying the scheduling-sequencing framework to hot rolling production optimization. It was found that significant improvements in process metrics and operational performance are realized when a comparison is made between the product blocks returned from the scheduling-sequencing optimization framework and those generated by the scheduling team. Furthermore, the concept of width-group-based design and the developed width-grouping algorithm were proven to be feasible in industrial application. The results obtained from the scheduling-sequencing optimization framework continuously outperformed the results obtained via manual scheduling and sequencing, in both key performance metrics and monetary benefits, on all industrial trials and simulations conducted over the course of this research.

5. **Valuable industrial and application benefits are realized by the architecture and design of the optimization framework.** The architecture of the scheduling-sequencing framework developed and implemented in the prototype application contains a number of valuable design features. Decomposition of the optimization problems into two distinct layers provides overall simplification of the models as well as the ability to modify or exchange models within one layer without negatively affecting the other. Encapsulation of software components including the optimization models, algorithms, and business logic aids in the extensibility

and maintainability of the framework. When deployed in a production environment a client can maintain necessary business or application components without requiring expert knowledge of algorithmic or optimization methods. The use of the human-machine interaction design paradigm allows the framework to be implemented as a decision support tool for the scheduling team whereby the schedulers can adjust and modify parameters in the optimization models in real-time based on market or operational conditions. This type of interaction was proven necessary and valuable during the trials where atypical market conditions required modification to operational limit parameters within the scheduling model.

6. **Obtaining exact solutions to both the scheduling and sequencing optimization problems defined in this research is feasible.** While not necessarily a primary goal in terms of industrial application, obtaining exact solutions to the scheduling and sequencing of product blocks had been a desired outcome of this work. The optimization model formulations defining both the scheduling and sequencing components of the framework facilitate the use of exact methods in their solution. A mixed integer linear programming model representing the scheduling problem was solved via CPLEX and a customized asymmetric travelling salesman problem representation of the sequencing problem was solved via Concorde. Solution times for scheduling and sequencing using the framework averaged 1.9 minutes for a typical 4-day planning horizon. As opposed to much of the contemporary research literature in this field, where meta-heuristic optimization methods are employed, the scheduling-sequencing framework proposed here provides exact

solutions in computation times which are more than acceptable for the desired industrial application.

6.2 Recommendations for Future Work

Proposed in the following list are areas for further investigation as well as logical next steps in the development of a production application:

1. **Further collaboration with an industrial partner should be pursued for continued and robust development of the scheduling and sequencing models.** The scheduling and sequencing models formulated in this research were derived for the specific operational and commercial context of AMD's hot rolling mill. While the fundamental components of the models would be directly transferable to other hot rolling mills, overall robustness of the optimization framework should be evaluated when applied to non-AMD operations. Ideally, a set of constraints and features common to all hot rolling mills would be incorporated into the models and selected-able for specific deployments via configurable parameters. Collaboration with the European and South American hot rolling mills within the ArcelorMittal group may prove to be a valuable exercise.

2. **Expansion to neighbouring levels of planning, scheduling, and sequencing.** The logical next step upon implementation of the scheduling-sequencing framework is to move upward and outward within the ISP structure building off the findings of this research. This would include long-term scheduling and production planning for the hot rolling mill, as well as optimization of upstream and downstream neighbouring processes. Examples include precise scheduling of the product block units according to the roughing mill roll campaigns, integration of scheduling with the continuous casters, and production planning for long-term time horizons. There are also considerable benefits to be realized in the area of slab sorting, organization, and sequencing within the local and remote slab inventory yards which supply material to the hot mill. An investigation into slab yard optimization would be an excellent, well defined, and nicely contained research project with the potential for significant value creation.

3. **Tabu-search or a similar meta-heuristic optimization algorithm should be investigated as a replacement for the exact solvers.** While there are benefits from the use of exact optimization solvers, licensing and financial issues may be encountered with Concorde and CPLEX. Moving to a meta-heuristic optimization algorithm would remove any licensing or fiscal issues however there may be a cost in terms of speed and quality of the resultant solutions. A comparison should be made between the performance of the exact solutions obtained in this research and those returned by a meta-heuristic. Tabu-search may be a good candidate

algorithm as it is the most prevalent meta-heuristic employed in the contemporary research literature concerning scheduling and sequencing optimization for rolling mills.

4. **The prototype should be ported to a modern language.** As performance of the scheduling-sequencing optimization framework has been proven, the prototype should be ported to a modern software language as soon as possible. Development of a proper application in a modern language will facilitate further development of the framework as either a component of a larger plant-wide optimization system or as a decision support tool. Greater buy-in from industrial partners can be expected if they are presented with a polished and high performance software application.

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