Master’s Thesis

Interdisciplinary and Innovative Engineering Master’s

AI Based State Observer for Optimal Process Control: Application to Digital Twins of Manufacturing Plants

Keywords: Optimal Process Control, State Observer, Artificial Intelligence (AI), Digital Twin (DT), Smart Manufacturing, Discrete Event Simulation (DES), Key Performance Indicator (KPI)

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Convocation: July 2022

Abstract

Manufacturing plants are subject to dynamic constrains requiring robust optimization methods for improved performance and efficiency. A novel AI based optimal control system for a Digital Twin of a manufacturing plant is presented in this report. The proposed system implements an AI based state observer to predict the internal state of a highly uncertain and non-linear process model, such as a real production system. A multi-objective optimization function is used to control production parameters and keeps the process running at an optimal condition. The AI Optimization Control method was implemented on a study case on a steel manufacturing plant. The performance of the system was evaluated using the relevant manufacturing KPIs such as the equipment utilization and productivity rates of the process. The use of the AI optimal control system successfully improves the process KPIs and could potentially reduce production costs.

Resumen

Les plantes de fabricació estan subjectes a restriccions dinàmiques que requereixen una optimització robusta per millorar el rendiment i l' eficiència del sistema. En aquest projecte es presenta un nou sistema de control òptim basat en IA per a un bessó digital d' una planta de fabricació. El sistema proposat implementa un observador d' estat basat en IA per predir l' estat intern d' un model de procés altament incert i no lineal, tal com seria un sistema de producció real. Una funció d' optimització multi-objectiu es utilitzada per controlar els paràmetres de producció i mantenir el procés funcionant en condicions òptimes. El mètode d'Optimització del Control basat en AI es va implementar en un cas d'estudi d'una planta de fabricació d'acer. El rendiment del sistema es va avaluar utilitzant els KPIs de fabricació rellevants, com ara les taxes d'utilització i productivitat de l'equip del procés. L'ús de sistema de control optimitzat via AI millora amb èxit els KPIs de procés i potencialment podria reduir els costos de producció.

Resume

Las plantas de fabricación están sujetas a restricciones dinámicas que requieren una optimización robusta para mejorar el rendimiento y la eficiencia. En este informe se presenta un nuevo sistema de control óptimo basado en IA para un gemelo digital de una planta de fabricación. El sistema propuesto implementa un observador de estado basado en IA para predecir el estado interno de un modelo de proceso altamente incierto y no lineal, tal y como sería un sistema de producción real. Una función de optimización multiobjetivo es utilizada para controlar los parámetros de producción y mantener el proceso funcionando en condiciones óptimas. El método de Optimización del Control basado en AI se implementó en un caso de estudio de una planta de fabricación de acero. El rendimiento del sistema se evaluó utilizando los KPIs de fabricación relevantes, como la utilización del equipo y las tasas de productividad del proceso. El uso del sistema de control óptimo de IA mejora los KPIs del proceso y podría reducir potencialmente los costos de producción.

Acknowledgement

Special individuals were instrumental is supporting me throughout the course of pursuing my master's degree. I would like to express my sincere gratitude for their help and support.

First, I would like to thank my dear husband for supporting me and always standing by my side. Without his patience and encouragements, this project would not have been possible. My family has always provided me with vast love and support. I would like to thank my mother, my father, and my siblings for their unfaltering support in my personal life and my professional endeavors.

I would like to acknowledge the help and support of Oscar Salgado, Raul Benitez, and Jone Uribetxebarria, whom I dearly thank for their technical support and academic guidance. They had a major impact on the successful completion of this work.

I would like to acknowledge the financial and technical support provided by IKERLAN. I am very grateful for this opportunity to research and develop a project that was truly inspiring for me. I am grateful for the kind people in my team who were always helpful and welcoming.

Preface

Companies today need to be competitive in today's rapidly changing market. The long-term sustainability of most businesses is hinged on their ability to stay competitive and adopt emerging technologies that have a high impact on their success. And digital transformation is, arguably, the most influential technology at present times.

With the strong believe that digitalization is the way of the future, I find myself compelled by the new advancements in information technology and digital simulations. The new technology brough on by Industry 4.0 has enabled the development of various industries and allowed them to join-in on the digital transformation trend.

With this research, my aim is to contribute to the development and advancement in the digital transformation of the industrial sector.

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List of Abbreviations

AI: Artificial Intelligence

API: Application Programming Interface

BOF: Basic Oxygen Furnace

CAS: Composition Adjustment by Sealed Argon Bubbling

CCM: Continuous Casting Machine

CENIT: Communications Networks and Information Technologies

CNN: Convolutional Neural Network

CPS: Cyber-Physical Systems

DC: Direct Current

DeC: Decarburization Converter

DeP: Dephosphorization Converter

DES: Discrete Event Simulation

DT: Digital Twins

EAF: Electric Arc Furnace

FFN: Feed Forward Network

IoT: Internet of Things

KPI: Key Performance Indicator

LF: Ladle Furnace

MHE: Moving Horizon Estimator

ML: Machine Learning

MLP: Multilayer Perceptron

MPC: Model Predictive Control

NN: Neural Networks

RH: Ruhr Stahl-Heraeus

RNN: Recurrent Neural Network

SGJT: Shougang Jingtang United Iron Steel Co. Ltd

SysDT: System Digital Twin

VAD: Vacuum Arc Degasser

1 Introduction

The first industrial revolution started in the late 18^{th} century, enabling mass production by means of machinery. In the second industrial revolution, assembly lines and electric power generators brought a new level of efficiency to the manufacturing industry. By the 20^{th} century, a third revolution started, led by advanced computers and programmable logic controllers which promoted automated control and increased industrial productivity (IBM, Industry 4.0).

We are now facing the fourth industrial revolution, commonly referred to as Industry 4.0. The term "*Industrie 4.0*" was initially cited by the German government as a high-tech strategy for the purpose of maintaining global competitiveness in the manufacturing industry (Federal Ministry for Economic Affairs and Energy, 2021). This revolution involves IoT technology, Artificial Intelligence (AI) and smart manufacturing which provide intelligent architectures for flexible production.

One of the emerging technologies of Industry 4.0 is the application of Digital Twins (DT) of production systems. They consist of virtual simulations designed to reflect physical counterparts in the real world. They typically evolve with their physical counterpart throughout its life cycle, from design to end-of-service (IBM, Digital Twins). DT simulations are considered a novel concept with high potential for enhancing manufacturing efficiency through automated process control. They are also reputable for enabling process optimization, evaluating production scenarios, and detecting anomalies in the production process.

The conducted research on Digital Twin applications for manufacturing plant simulation and optimization is presented in this thesis report. This research introduces a novel application of an AI predictive control system used to optimize a steel manufacturing process. The aptness of the AI Optimization Control system is investigated by use of a Digital Twin simulation.

1.1. An Introduction to Digital Twins

The first concept of a Digital Twin was introduced by David Gelernter in 1991. However, the first concept of applying DTs to manufacturing processes was introduced by Dr. Michael Grieves in 2002. Grieves defined the DT as "a set of virtual information constructs that fully describes a potential or actual physical manufactured product … any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin" (Grieves, 2002).

In the manufacturing industry, DTs can encompass various levels of product details. A part DT is the smallest example of a DT, representing a single component. A unit DT is a higher level of virtual representation, consisting of different assets that form a functioning system. And, at a macro level, a process DT provides insight on the entire production process. The latter requires a high abstraction level of detail to model the system (IBM, Digital Twins).

The most promising applications for DTs in manufacturing plants consist of evaluating system performance, predicting maintenance schedules, and optimizing energy consumption. However, one of the biggest challenges of DT applications is the concept of real-time synchronization and adaptiveness to a dynamic environment. In the future, the widespread use IoT sensors and smart gateway communication networks in smart factories can enable continuous real-time connections for DT applications in manufacturing.

1.2. An Introduction to Steel Manufacturing

The ramped production of steel was led by the increased development of infrastructure projects and the growing global consumption. In 2021, the global production of crude steel has surpassed 1.95 billion tons. Today, steel production is one of the most energy and material intensive industries. Thus, many companies are developing new strategies to improve resource efficiency and achieve sustainable growth (WorldSteel, 2021).

Steel manufacturing relies on two main processes: using the Basic Oxygen Furnace (BOF) and using the Electric Arc Furnace (EAF). Most of the produced steel (70%) follows the BOF steelmaking route. In this process, iron ore is reduced to pig iron before being converted to steel. Alternatively, the EAF process uses electricity to melt steel. Then, alloys are added to adjust the chemical composition required for strength and quality (WorldSteel, 2021).

Secondary refining processes are performed on liquid steel, commonly refer to as metallurgical refining processes. In secondary refining, impurities are removed, and the chemical composition of steel is adjusted. Secondary refining takes place in a vessel compartment, called a ladle. Secondary refining processes include the Ladle Furnace (LF), the Ruhr Stahl-Heraeus (RH) process, and the Vacuum Arc Degasser (VAD) (Sumitomo Metal Ind., 2009).

Following the secondary refining process, liquid steel is continuously casted using the Continuous Casting Machines (CCM). This process allows the metal to solidify at a slow rate, producing a semi-finished slab metal part. The continuous casting process requires continuous metal flow; a ladle exchange system provides continuous pouring of the molten steel. The tundish, illustrated in Figure 1, controls the pouring speed and allows the removal of slag and other impurities before the steel casting process. (Calmat, Continuous Casting)

Finally, the semi-finished metal slabs are hot rolled at high temperature in order to produce high quality steel products. Hot rolling is a cost-effectiveness and simple manufacturing process that produces high quality steel at very low production costs. (Masteel, 2018)

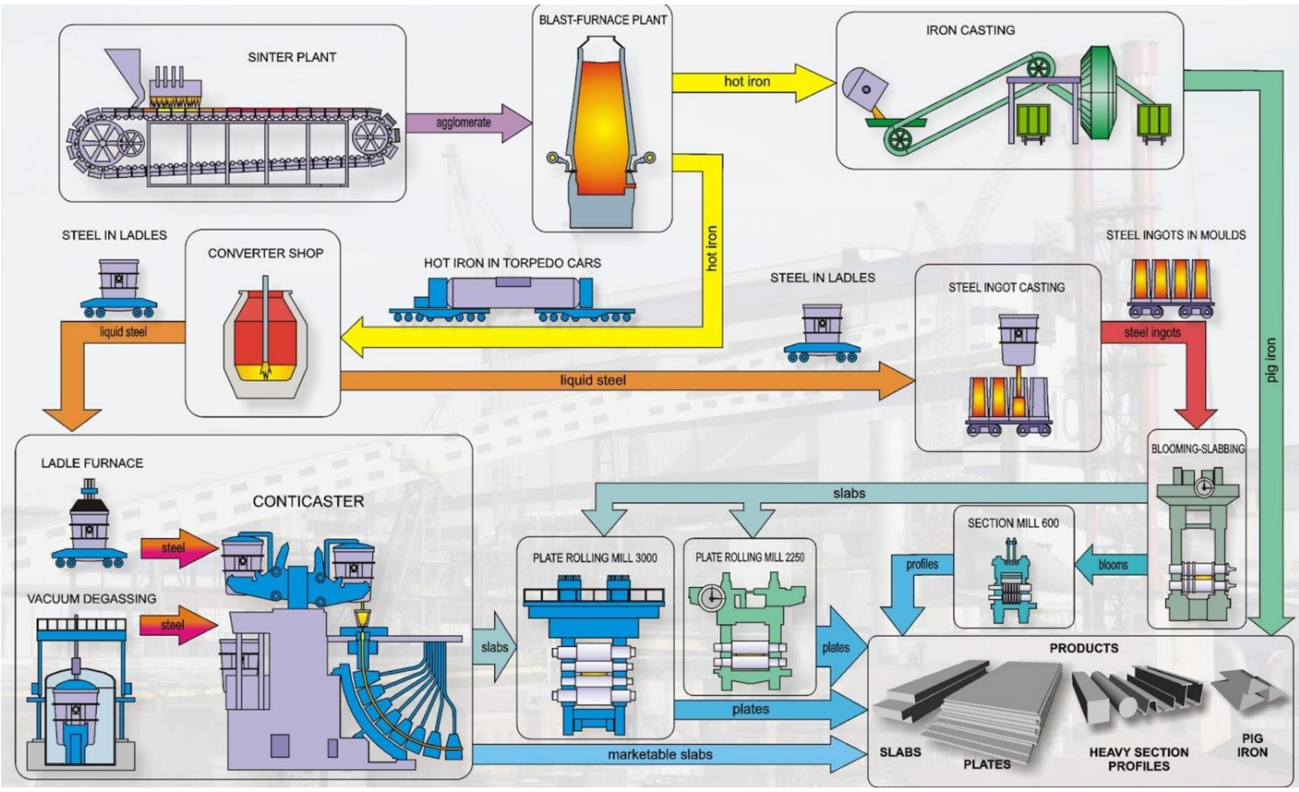


Figure 1: The Steel Manufacturing Process (Alchevsk Iron &Steel Works, n.d.)

The research conducted in this project will be presented as follows. The Analysis section will present the development of the Digital Twin model of a steel manufacturing plant. This section will cover the implementation of optimization process methods, including the development of the AI based state observer for this manufacturing process. Subsequently, the Results section will summaries the results obtained for the implemented process optimization methods. Then, the Environmental Impact is presented, followed by final remarks in the Discussion section.

2 Literature Review

The concept of Digital Twins was introduced many years ago, and ever since, this technology has gained popularity and interest. With the overwhelming advancements brought on by Industry 4.0, simulation methods and communication networks are rapidly being developed, enabling the DT transformation in the manufacturing sector.

The literature content relevant to DT applications in manufacturing is in fact insurmountable. DT simulations of manufacturing plants are already being implemented in real-life applications. The new staggering research pertinent to this technology cannot be fully covered in this text. Hence, this literature survey only highlights a few topics that are relevant to this project.

The literature review will be sectioned in the following manner. The first section will refer to DT application in the manufacturing industry. The subsequent section will focus on advanced optimization techniques for the steel manufacturing industry. And the final section will address Model Predictive Control (MPC) and the use of AI and ML.

2.1. Digital Twins in Manufacturing

Digital Twins of manufacturing plants are the virtual component of a cyber-physical system (CPS). They replicate the real system and encapsulates and model its behavior. In manufacturing systems, DTs consist of cooperative elements and subsystems representing multi-levels of production: machines, processes and logistics networks (Elmarghy et al, 2021). Presently, virtual simulators are being used in the building phases of manufacturing systems, in order to validate designs and perform what-if scenario evaluations. Yet, there is a gap between the initial simulation of a production plant and its commissioning and real-time connectivity during manufacturing (Morabito et al, 2021).

Manufacturing process simulations often rely on Discrete Event Simulation (DES) models, which are used to simulate production logistics and identify bottlenecks. There are few study cases for the development of DTs in manufacturing using combined DES models and continuous real-time models. Some simulation tools, such as Simulink, provide the functionality of integrating DES models with continuous time models, for the purpose of mirroring real physical equipment. (Vachalek et al, 2017). A Digital Twin application based on DES simulation was implemented on two assembly lines of the Comau plant in Italy. Morabito and others proposed a methodology on the use of a DES simulation as a virtual counterpart for the DT. The DES simulation (using FlexSim software) was connected to the physical machinery and was able to extract data relevant to the plant performance, effectively closing the loop on communication between the virtual and real system. The implemented DT model was able to predict the production performance and detect anomalous behavior of the physical plant (Morabito et al, 2021).

Another worthy application of DTs is the System Digital Twin (SysDT), which was presented by Magnanini et al. This system was based on a Markovian representation of system interactions using a stochastic parametric model for evaluating the performance of the manufacturing process. The SysDT method was implemented in a rail-way manufacturing company. A product tracking system, using IoT sensors, was used to collect data on machine cycles, failure occurrences and repair instances. The SysDT was responsive to variations in the production plan, allowing managers to make better decisions (Magnanini and Tullio, 2021).

2.2. Steel Manufacturing Optimization

The steel industry is an energy and resource intensive business. Companies are actively looking to improve their process efficiency and integrate advanced technology with high potential for economic benefits. Simulation optimization methods are gaining a lot of attention, which include the use of DTs, IoT sensors, and AI / ML techniques. The industrial efforts in optimizing the steelmaking process focus on the following: Planning and Scheduling, Real-Time Optimization and Control, and Energy Sustainability (Backman et al, 2019).

2.2.1 Planning and Scheduling

Planning and scheduling are a challenging problem for the steelmaking industry, considering their reliance on batch production processing (continuous casting process). A case study involving optimal planning and scheduling for a continuous casting process was implemented in a plant in Austria (Missbaur et al, 2009). Lin et al (2016) used a model based on a multi-objective optimization targeting the hot-charge ratio of steel slabs. The multi-objective function considers utilization rates of tundishes and additional costs of technical operations. Furthermore, intelligent job scheduling was introduced by Sobaszek et al. (2018) as a solution for production disturbances and uncertainties in the system.

2.2.2 Real-Time Optimization and Control

In the steel industry, a real-time optimization system for an Electric Arc Furnace (EAF) was introduced by Shyamal and Swartz. In their research, they propose an advisory system that provides online decision-making support for the EAF plant operators, incorporating a moving horizon estimator (MHE), which is used to assess the state of the plant using current and past measurements. Shyamal and Swartz further demonstrate the potential economic benefits of implementing their real-time optimization-based advisory system by simulating study cases related to electric-arc processes in steelmaking (Shyamal and Swartz, 2018).

Monitoring of complex industrial batch processes was implemented in a steel plant in Lulea, Sweden. Basic Oxygen Furnace (BOF) control devices were installed for the purpose of developing a dynamic system for sloping predictions. Based on a multivariate data analysis, an online prediction model for the phosphorus content in steel end-of-blow was implemented. The prediction model is used to adjust and control the BOF process (Brämming et al, 2016).

Rotevatn et al (2015) implemented an MPC system for the predictive model control of a Composition Adjustment by Sealed Argon Bubbling (CAS) process. The model integrates the Cybernetica^{TM} CENIT framework for online applications, allowing for an online steel metal temperature prediction using a built-in Kalman filter and a moving horizon estimator (MHE). The presented work achieves control of the steel metal temperature before the continuous casting process, optimizing the plant for energy efficiency.

2.2.3 Sustainable Development and Energy Optimization

Regarding energy optimization and sustainable development in manufacturing "three pillars for sustainability improvement have been stated: Minimizing waste of energy and materials, maximizing the use of the renewable resources, and sustainable and efficient processing". (Fan et al. 2017)

Lu et al. (2016) addressed the issue of energy consumption in the steel and iron production industry. The authors identified that in steel-rolling, energy saving margins are limited due to the constrained process path. They suggested that increasing the sinter grade, scrap usage and lump ore usage are effective ways to reduce the energy demands of the process. Furthermore, the authors conclude that optimal routing should be adopted through advanced technological measures.

Hu et al. (2022) characterized the energy flow in a steel manufacturing plant. A dynamic optimization model was built based on an objective function and the operational efficiency indicators of the plant. A steam energy system was tested, where the dynamic optimization of steam energy was effective in reducing the plant's energy consumption.

In response to the volatility of energy sources and high price fluctuation, Gajic et al. (2017) presented an electricity optimization system that adjusts production schedules in a steel melt shop. The optimization problem is solved using a continuous-time mixed-integer linear programming model. The power optimization system was successfully implemented and adopted at a stainless-steel mill facility in Italy. The system was able to reduce electricity costs by 3%.

Another effort in sustainable manufacturing was led by Maddaloni et al. (2015) focusing on the optimal exploitation of process resources in steelmaking. Their work takes into consideration CO_2 emission savings and natural gas consumptions of the plant, aiming to improve the process gas network. The optimization model is dynamic in the sense that it can be adapted to variability in the network and changing operating conditions common to an industrial context.

2.3. MCP and AI Process Control

Model Predictive Control (MPC) is already widely employed in the oil-refining and petrochemical industries using linear dynamic models. MPC is also used in the steel industry for monitoring plant settings and process quality. However, very few nonlinear MPC models are used due to their complexity and lack of commercial availability (Backman et al, 2019). Plant-wide control of dynamic, nonlinear, and uncertain systems are novel to the manufacturing industry. Furthermore, the implementation of AI and ML for predictive control is a state-of-the-art approach.

There are various new MPC methods that are being developed for dynamic, nonlinear, and uncertain system. These methods include the Robust MPC, the Stochastic MPC for softly constrained systems, and the Adaptive MPC. However, many problems still need to be addressed regarding the dynamic stability and convergence of these systems (Mayne, 2014).

A novel concept using NN for a model prediction system was initially proposed by Sha (2008). Sha introduced the use of NN for the predictive control of unknown multiple non-linear systems. The effectiveness of the MPC control system was demonstrated using a Simulink model. The scheme of the proposed non-linear system compromising an online NN training of the system is shown in Figure 2.

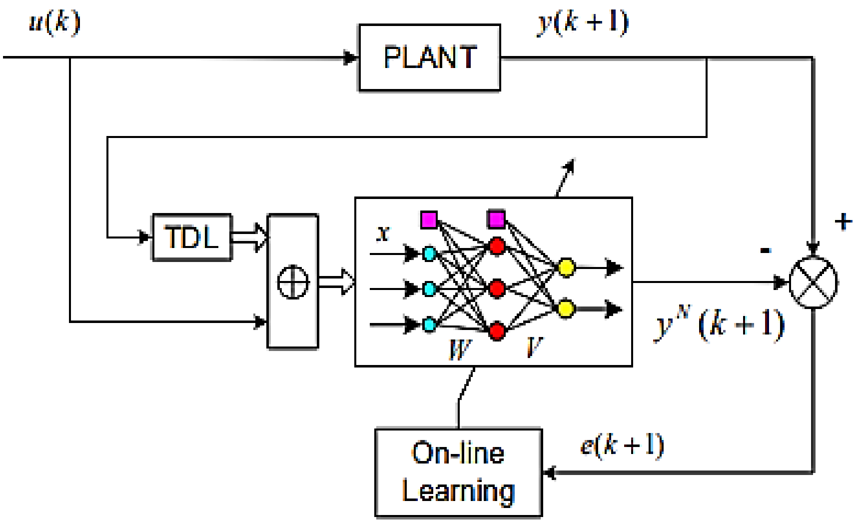


Figure 2: Modeling of a Non-Linear System by NN

Additionally, Jakovlev et al. (2013) implemented a multilayer perceptron NN for the predictive control of a radio telescope. This approach was developed for the purpose of analyzing the working conditions of a small DC motor. The NN model predicts voltage fluctuations which are used to dynamically correct the disk rotation of the radio telescope.

3 Problem Statement

Steel manufacturing is a complex process that relies on batch processing and optimal process control for the continuous casting of steel. The challenging optimization problem pertinent to steel manufacturing requires effective resource management and production planning tools. In real production systems, the steel making process is subject to dynamic constrains that can pose a significant problem for production engineers and human controllers. Therefore, the steel making industry is considering dynamic system models that can help in decision making in critical time-sensitive applications.

Digital Twins provide a dynamic simulation that can respond to abrupt changes in external/internal constraints. DTs can implement automated process control, requiring minimal human interventions. DT models are constantly up to date with the dynamic constrains imposed on the manufacturing process. The objective of this research is to leverage the DT simulation of a manufacturing plant for the purpose of automating and controlling the process. Presented in Figure 3, the conventional manufacturing process control is compared to the DT manufacturing concept.

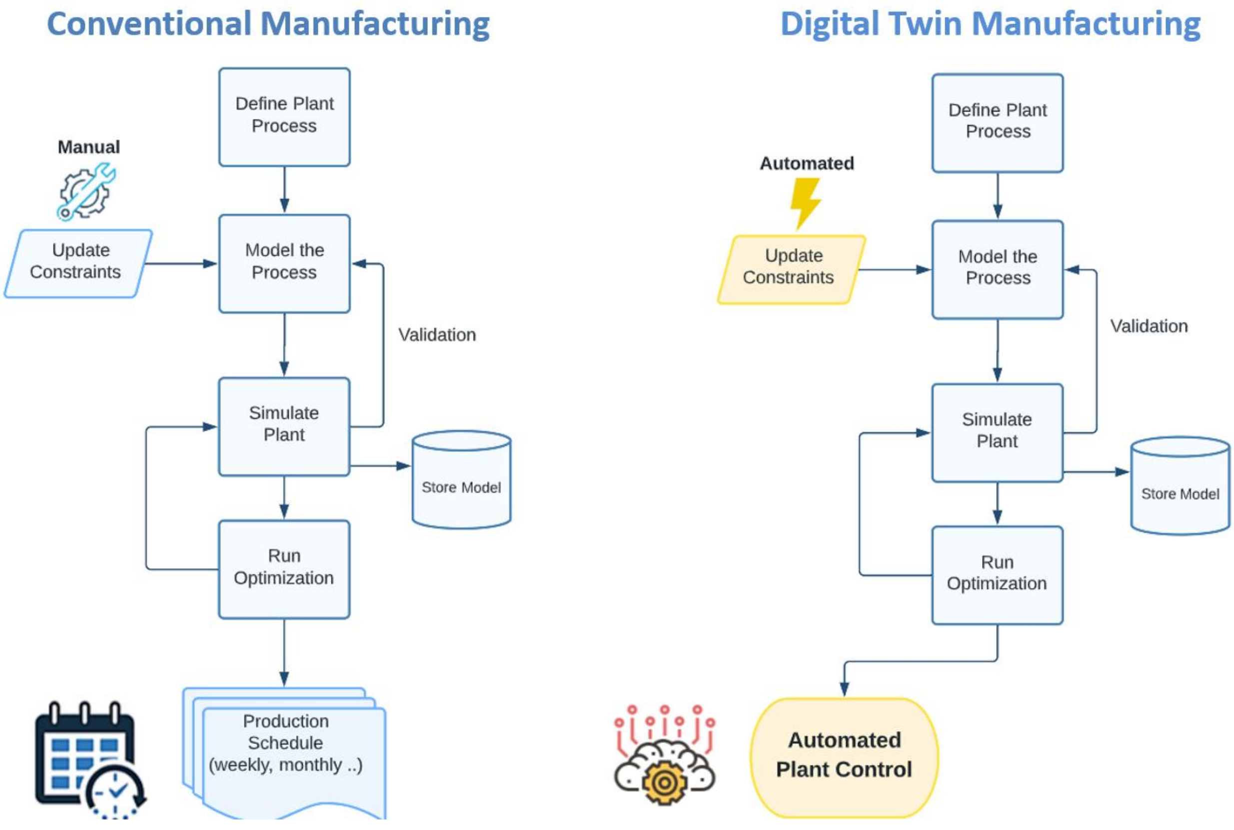


Figure 3: Conventional Manufacturing vs Digital Twin Manufacturing Concept for Automated Plant Control

As shown above, the design of DTs for manufacturing can provide a dynamic update of constraints, effectively reducing manual interactions. Furthermore, DTs can provide automatic process optimization and control, reflecting the current state and objectives of the industry.

The conducted research on a DT application for an AI based optimal control is presented in the following Analysis section. First, a use-case of a steel manufacturing plant is presented. Then, the development and validation of the DT simulation models are demonstrated. Afterwards, the optimization of the steel manufacturing plant was achieved using the following two methods: a steady OptQuest optimization, and a dynamic AI based optimization. The obtained results are documented in the following text.

4 Analysis

4.1. Use-Case: Steel Continuous Casting Process

The Shougang Jingtang United Iron Steel Co. Ltd (SGJT) is one of China's major steel producers, aggregating an annual output of 9.7 Mt of steel and 9.13 Mt of steel products. The company deploys large-scale equipment, including 5,500 cubic meters burning furnaces, in conjunction with 300t capacity steel converters. The steel manufacturing plant is located on the coast of Tangshan China, where a main seaport is situated within its vicinity (Shougang, 2022).

A study was conducted by Shuai Deng et al. (2018) apropos the production logistics of SGJT, examining the equipment efficiency under different production modes of the converters. The current steel production relies on three types of smelting processes: the dephosphorization converter (DeP), the decarburization converter (DeC), and the duplex process (DeP + DeC). In their paper, Shuai Deng et al propose an optimized solution based on adjusting the ratio from 33% to 100% employment of the duplex (DeP + DeC) converter process. The authors compared their simulation results against production statistics from collected field data pertaining to the SGJT steel manufacturing plant.

Shuai Deng et al. (2018) used the Tecnomatix Plant Simulation software, developed by Siemens, to create discrete-event modeling using object-oriented programming. A single steel ladle was defined as the base unit for the simulated process, and the ladle turnover control logic was implemented using SimTalk language.

Figure 4: Shougang Jingtang United Iron Steel Co. Ltd Facility, Tangshan China

4.1.1 Steel Manufacturing Process & Equipment

The production of crude steel consists of three main steps: 1-The Converter Process, 2-The Secondary Refining Process, and 3-The Continuous Casting Process. Depending on the steel application and steel grade, each method entails different process specifications for smelting, refining and casting. The plant contains two DeP converters and three DeC converters, each of which has a 300t capacity. In secondary refining, the plant deploys one LF (Ladle Furnace), two RH (Ruhr Stahl-Heraeus) refining furnaces, and one CAS (Composition Adjustment by Sealed Argon) refining furnace. Subsequently, continuous casting of steel ladles is carried out over four CCMs (Continuous Casting Machines). Table 1 summarizes the list of equipment used by SGJT. (Deng et al, 2018)

Table 1: A List of Equipments in the Steel Manufacturing Plant

List of Equipments				
Name	**Type**	**Discription**	**Capacity**	**Count**
KR	Reactor	Kanbara Reactor Hot Metal Desulfurization	-	4
DeC	Converter	Dephosphorization Smelting Process	300t	2
DeP	Converter	Decarburisation Smelting Porcess	300t	3
RH	Refining	Ruhrstahl-Heraeus - Secondary Metalurgical Refining Process	300t	2
LF	Refining	Ladle Furnace - Secondary Metalurgical Refining Process	300t	1
CAS	Refining	Refining Process	300t	1
CCM	Contious Casting	Steel Solidification by Continous Casting	-	4

4.1.2 Steel Production Methods

SGJT produces both low-carbon steel and ultra-low-carbon steel, with a proportion of 85% and 15% respectively. Each ladle is assigned a process path based on the required steel properties, which depend on customer orders. Process paths 1-12 produce low-carbon steel, while paths 13 and 14 produce ultra-low carbon steel. Table 2 presents the field data pertaining to SGJT's production orders. Table 3 presents information regarding each process path and its respective frequency of production. Within the 14 process methods, there are 6 methods that involve the duplex converting process. Particularly high-end steel entails duplex smelting, while the majority of steel undergoes a conventional smelting routine. (Deng et al, 2018)

Table 2: Historical Data on Production Orders.

Steel Order	
Steel Grade	Ratio
Low-Carbon	85%
Ultra Low-Carbon	15%

Table 3: Descriptions of Each Process Method and their Frequency Distribution.

Method	Steel Grade	Process Flow	# Furnaces	Frequency %
1	Low- C	DeP–DeC–RH–CC	1466	11.69%
2	Low- C	DeP–DeC–LF–CC	214	1.71%
3	Low- C	DeP–DeC–CAS–CC	182	1.45%
4	Low- C	DeP–RH–CC	936	7.46%
5	Low- C	DeP–LF–CC	740	5.90%
6	Low- C	DeP–CAS–CC	1007	8.03%
7	Low- C	DeC–RH–CC	3051	24.33%
8	Low- C	DeC–LF–CC	836	6.67%
9	Low- C	DeC–CAS–CC	1393	11.11%
10	Low- C	DeP–DeC–LF–RH-CC	485	3.87%
11	Low- C	DeP–LF–RH-CC	94	0.75%
12	Low- C	DeC–LF–RH-CC	307	2.45%
13	Ulow-C	DeP–DeC–RH–CC	1784	14.23%
14	Ulow-C	DeP–DeC–LF–RH-CC	44	0.35%

4.1.3 Processing Time & Inter-Process Conveying Time

The field statistics pertaining to the SGJT plant provide the processing times of each equipment. The processing time is normally distributed, and the maximum, minimum, mean, and standard deviation values are shown in Table 4, Table 5 and Table 6 . The reported statistics regarding the CCM equipment make a distinction between CCM 1&2 and CCM 3&4. For the purpose of simplifying the model, a cumulative average was calculated as presented in Table 5. (Deng et al, 2018)

Table 4: Historical Statistical Data on the Converting Process

Converter Process										
Methods	**Grade**	**DeP**				**DeC**				
		Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.
4, 5, 6, 11	Low-C	46.43	33.05	38.35	3.14	-	-	-	-
7, 8, 9, 12	Low-C	-	-	-	-	45.32	30.17	35.54	2.84
		Duplex - DeP				**Duplex - DeC**			
		Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.
1, 2, 3, 10	Low-C	30.80	17.17	22.45	3.13	37.93	27.03	30.94	2.26
13, 14	Ulow-C	30.80	17.17	22.45	3.13	37.93	27.03	30.94	2.26

Table 5: Historical Statistical Data on the Continuous Casting Process

Continuous Casting Process													
Methods	**Grade**	**CC1, CC2**				**CC3, CC4**				**Average All CCMs ***			
		Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.
1 - 12	Low-C	52.00	39.00	43.76	3.31	66.00	39.00	46.62	5.78	66.00	39.00	45.19	4.55
13, 14	Ulow-C	52.00	39.00	43.76	3.31	66.00	39.00	46.62	5.78	66.00	39.00	45.19	4.55

* The cumulative average is calculated from the reported statistics of CC1,CC2 and CC3,CC4.

Table 6: Historical Statistical Data on the Secondary Refining Process

Secondary Refining													
Methods	**Grade**	**LF**				**RH**				**CAS**			
		Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.	Max (min)	Min (min)	Mean	Stdv.
2, 5, 8	Low-C	65.23	35.40	48.71	6.78	-	-	-	-	-	-	-	-
1, 4, 7	Low-C	-	-	-	-	34.00	20.00	24.96	2.93	-	-	-	-
13	Ulow-C	-	-	-	-	43.00	25.00	32.50	4.58	-	-	-	-
3, 6, 9	Low-C	-	-	-	-	-	-	-	-	47.67	23.92	32.34	5.12
10, 11, 12	Low-C	65.23	35.40	48.71	6.78	34.00	20.00	24.96	2.93	-	-	-	-
14	Ulow-C	65.23	35.40	48.71	6.78	43.00	25.00	32.50	4.58	-	-	-	-

In addition to the equipment processing times, the field statistics also report the conveying time of ladles from one equipment to another. The conveying time is directly related to the plant layout and path distances between the equipment. However, no information was provided on the adopted transportation mechanism (cranes, forklifts, conveyor-belts or transport-carts). Table 7 presents the total waiting and transporting times between the equipment in the SGJT plant. (Deng et al, 2018)

Table 7: Historical Statistical Data on Inter-Process Conveying Times

Conveying Time (min)													
	DeP 1	DeP 2	DeC 1	DeC 2	DeC 3	RH 1	RH 2	LF	CAS	CCM 1	CCM 2	CCM 3	CCM 4
DeP 1	-	-	22.0	22.3	23.3	-	-	22.6	-	-	-	-	-
DeP 2	-	-	18.9	20.7	25.7	10.4	11.0	16.1	13.3	-	-	-	-
DeC 1	-	-	-	-	-	7.4	7.7	8.6	9.0	-	-	-	-
DeC 2	-	-	-	-	-	9.1	8.3	9.6	10.0	-	-	-	-
DeC 3	-	-	-	-	-	8.6	7.0	9.2	7.9	-	-	-	-
RH 1	-	-	-	-	-	-	-	-	-	9.1	9.4	10.8	11.8
RH 2	-	-	-	-	-	-	-	-	-	12.2	10.8	8.0	7.7
LF	-	-	-	-	-	10.3	13.2	-	-	6.0	7.7	9.0	9.9
CAS	-	-	-	-	-	-	-	-	-	9.1	10.2	6.1	7.3

4.1.4 Continuous Casting Process

The continuous flow of molten steel is of high importance in the continuous casting process. In a typical casting process, molten steel flows out from the ladle, through a tundish, then into the mold, where the tundish provides continuous flow when the ladles are being exchanged. In the plant simulation developed by Deng et al. (2018), 8 ladles are continuously casted together. For this research, a similar approach will be adopted when simulating the process. The SGJT steel plant outputs 572 ladles/week. Additional field statistics on production logistics and equipment utilization rate will be reported in the subsequent sections.

The following section is dedicated to the development of a Baseline Steel Plant Model.

4.2. Modeling Software

Process simulation relies on software tools that can describe physical, chemical, biological or operational relationships between interacting units. Discrete-event simulation (DES) is a prevalent method used in modeling production and logistics systems. A discrete-event model depends on asynchronous discrete incidents which control the advancement of entities in a queue system or in state charts. Hence, DES is a suitable modeling approach for the above-mentioned steel manufacturing process. (Cassandras and Lafortune, 2010)

Although many simulation programs are commercially available, particular ones provide added programming flexibility, real-time connections, and API modeling. Additionally, AI and ML techniques deliver an outstanding advantage in Smart-Manufacturing and Digital Twin models.

AnyLogic: The AnyLogic software was identified for its convenience in multi-method modeling, ease-of-use, and programming flexibility. AnyLogic simulation combines three modeling approaches: Dynamic Systems, Agent-Based, and DES modeling. The tool also provides 2D and 3D graphics for animated simulations, open API programming and ML/RL. (AnyLogic, n.d.)

MATLAB Simulink: Simulink is a general-purpose modeling tool that integrates MATLAB algorithms and programming flexibility. In particular, SimEvents is a component library that provides DES modeling and combines time-based simulation with discrete-event systems. (MathWorks, n.d.)

Table 8 lists several software applications, both commercial and openly sourced, that are commonly used for process modeling and manufacturing plant simulations.

Table 8 : Steel Plant Baseline Model Validation with Respect to the Actual Plant Statistical Data

Software	Availability	Modeling Capabilities	Animation
AnyLogic by The AnyLogic Company	Commercial	DES, agent-based, system dynamics	2D, 3D
Simulink MATLAB by MathWorks	Commercial	DES, multi-domain, dynamic systems	2D
FlexSim by FlexSim Soft. Products, Inc.	Commercial	DES	2D, 3D
Arena by Rockwell Automation	Commercial	DES	2D, 3D
Plant Simulation by Siemens PLM	Commercial	DES	2D, 3D
SimPy (python)	Open Source	DES	-
Sim.JS (JavaScript)	Open Source	DES	-

4.3. Baseline Steel Plant Model

A baseline model refers to a well-determined / current state of the process. The baseline serves as a benchmark point against which performance improvements are measured. The most important characteristic in a baseline model is the capability of reproducing empirical observations that match the actual system. Performing tests on the real system serves to calibrate the prediction accuracy of the baseline mode, validating the system for analytical use, and further re-engineering and re-design.

Two baseline models were created in parallel, using the AnyLogic software and MATLAB Simulink. Both models were created using an identical modeling approach and a uniform database corresponding to the steel manufacturing plant. The duplication of two models aims to eliminate bias and reduce uncertainty with respect to the used software tool. In case one model falls short in reproducing verifiable results, the second model serves as a fallback option to continue with this research project.

Firstly, the AnyLogic simulation is presented. An interactive user-interface is designed for dynamic visualization and convenient navigation. The created model consists of three viewing areas: the Parameters view, the Process view and the Control Panel view.

4.3.1 Parameters View (AnyLogic)

The Parameters View is displayed upon start-up of the simulation. It allows the user to adjust the production parameters and displays the input constraints of the steel manufacturing process. The Parameter View is presented in Figure 5. This research narrows on a particular subset of critical production parameters, only those are enabled for manual adjustment by the user.

The following list provides a detailed description of these parameters.

- Incoming Rate: The incoming flow rate of steel ladles where the arrival rate is defined by a time interval (in minutes) between ladle creation.
- Low Carbon Steel: The percentage value of low carbon steel orders with respect to the cumulative total of steel orders.
- Ultra-Low Carbon Steel: A percentage value representing the orders of ultra-low carbon steel with respect to the cumulative total of steel orders.

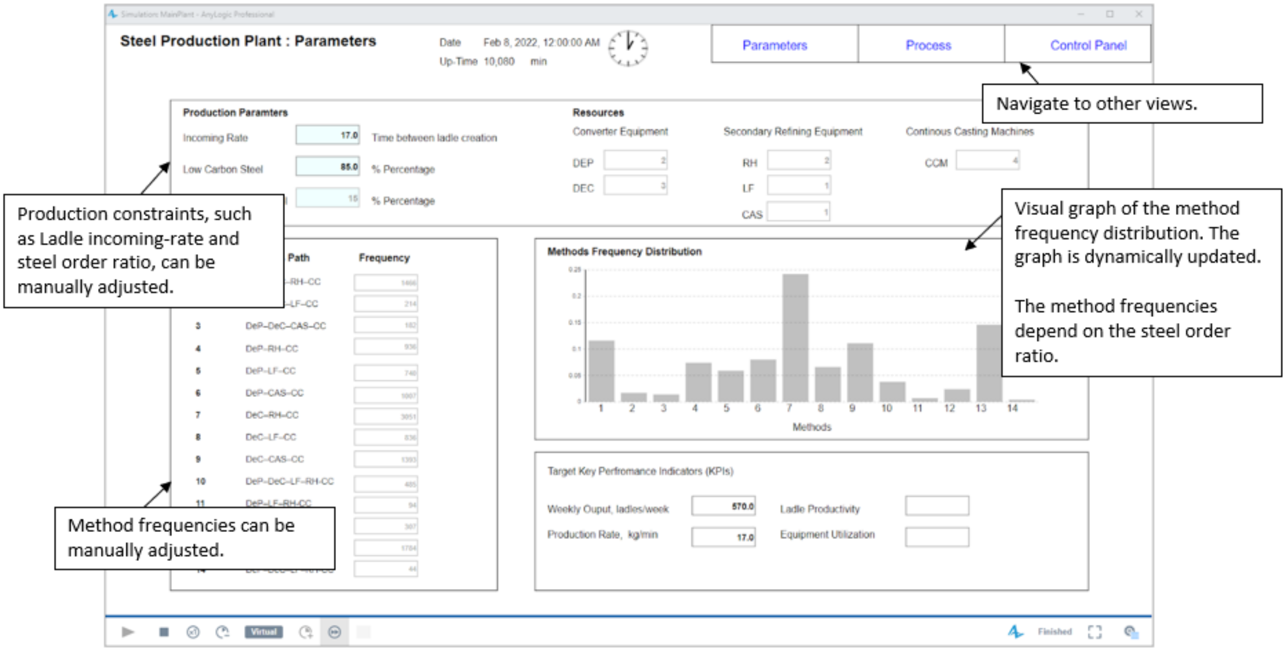


Figure 5:Parameter View - Steel Plant Simulation in AnyLogic

4.3.2 Process View (AnyLogic)

The Process View displays the processes implemented in the steel manufacturing plant. This view is accessed using the navigation button at the top right corner. The different processes are grouped in designated areas, as shown in Figure 6. Each type of equipment is modeled using a 'resource pool' block with a defined capacity representing the number of available machines. The processing of each equipment is modeled using a 'service block' with a delay function (normally distributed delay function, as explained previously). When a ladle enters the process, a machine equipment is acquired, then released upon completion of the process. During the continuous casting process, 8 ladles are batched, then simultaneously casted. Before casting, the ladles are split-up by steel grade. Lastly, inter-process transportation is modeled using a 'delay' block.

4.3.3 Output Statistics (AnyLogic)

The Control Panel View is shown in Figure 7. This view displays the collected statistics on steel ladles and machine equipment. The top left section displays the Ladle Statistics, consisting of results on lead time, idle time, processing time, and transporting time. The bottom section is dedicated to Equipment Statistics, which displays the equipment utilization rates per machine type. In the bottom left-corner, the simulation weekly statistics are summarized for added user-functionality.

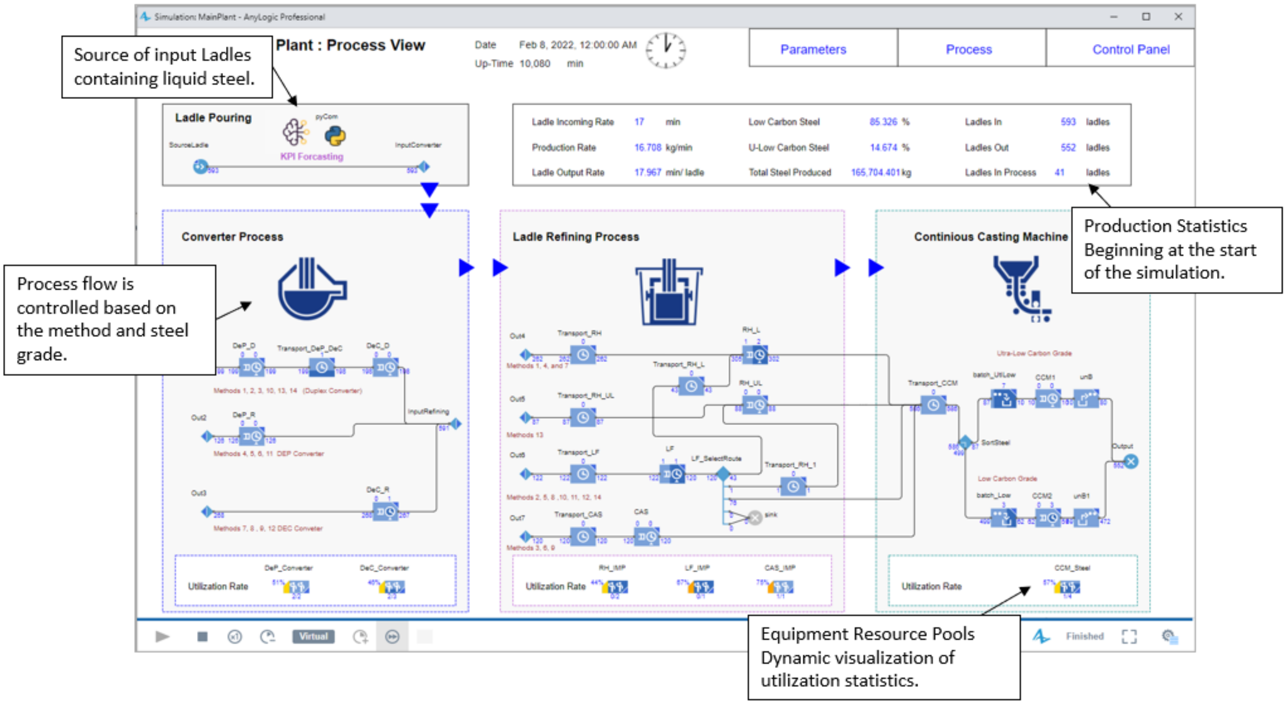


Figure 6: Process View - Steel Plant Simulation in AnyLogic

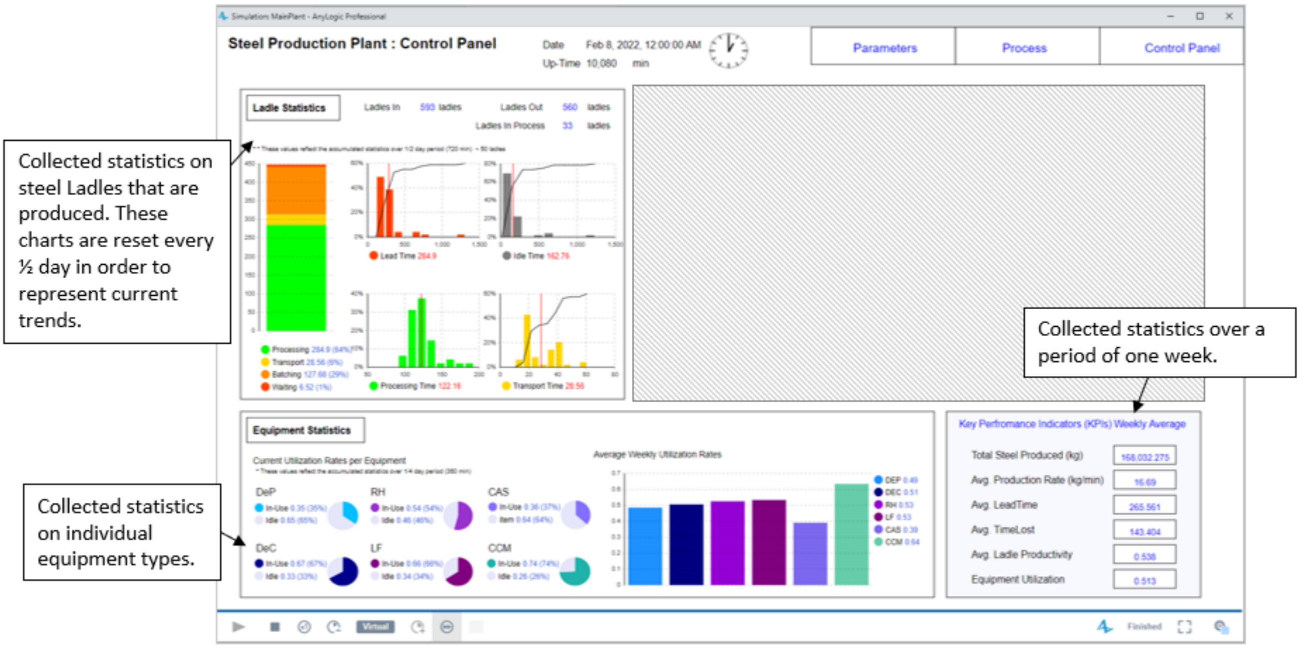


Figure 7: Control Panel View - Steel Plant Simulation in AnyLogic

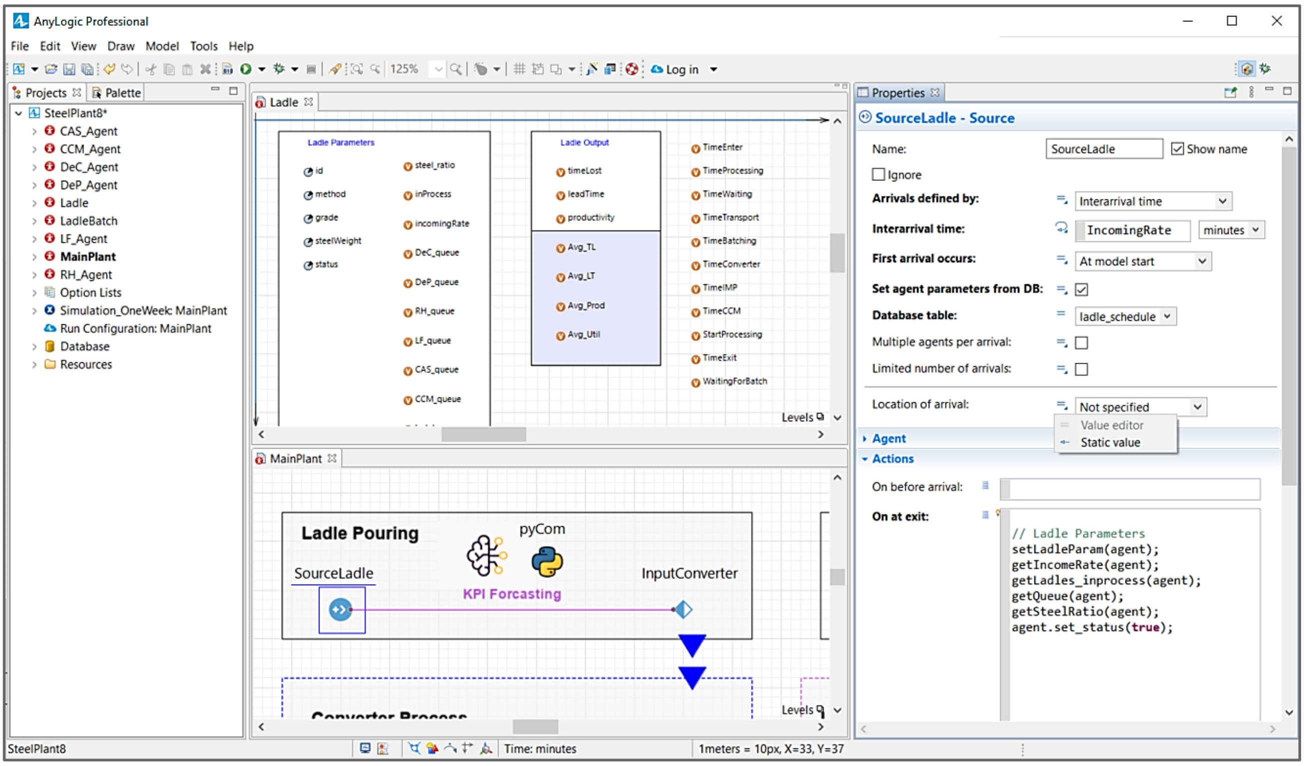


Figure 8: Graphical Interphase - Steel Plant Simulation in AnyLogic

The Simulink baseline model is presented in the following paragraphs.

4.3.4 Process Overview (Simulink)

In Simulink, the SimEvent library was used to model the steel production process. Here, the different processes were similarly grouped in designated areas, as shown in Figure 9. The source of steel ladles modeled using an ‘Entity Generator’ block, and the ladle incoming rate is defined by the user. Each generated entity (ladle) contains attached attributes that define an assigned method and a corresponding process path, as shown in Figure 10.

Similar to the methodology implemented in AnyLogic, the steel ladles are collected in batches of 8 units before passing to the conscious casting machine. A splitting port (OutPort 5) is used to separate the low steel and ultra-low steel ladles before casting. Finally, ladles exit the plant into a sink block.

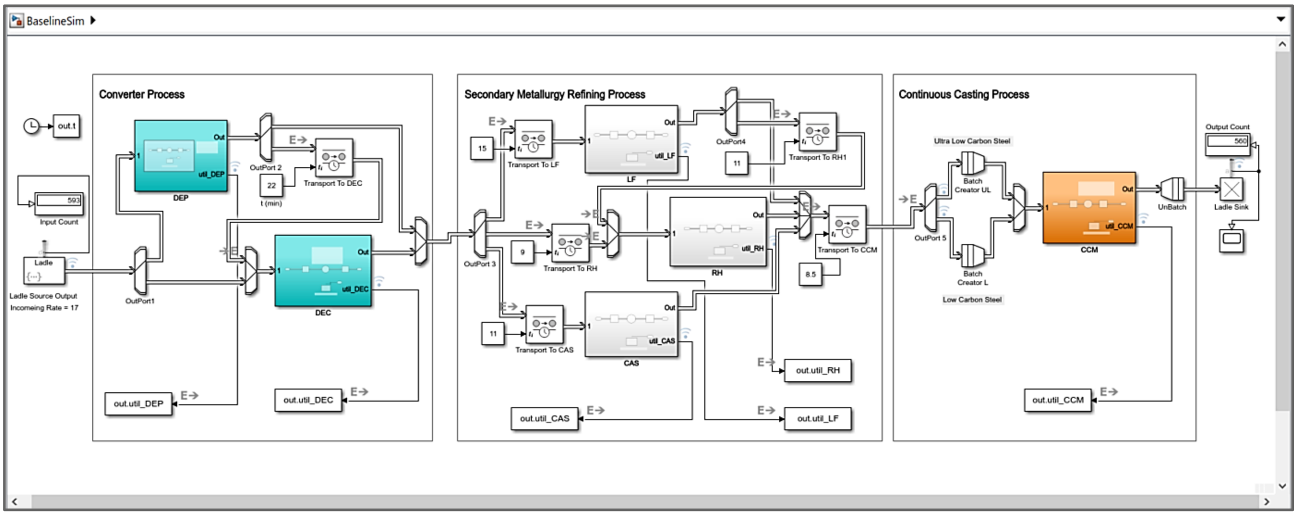


Figure 9: Process Overview - Steel Plant Simulink Diagram

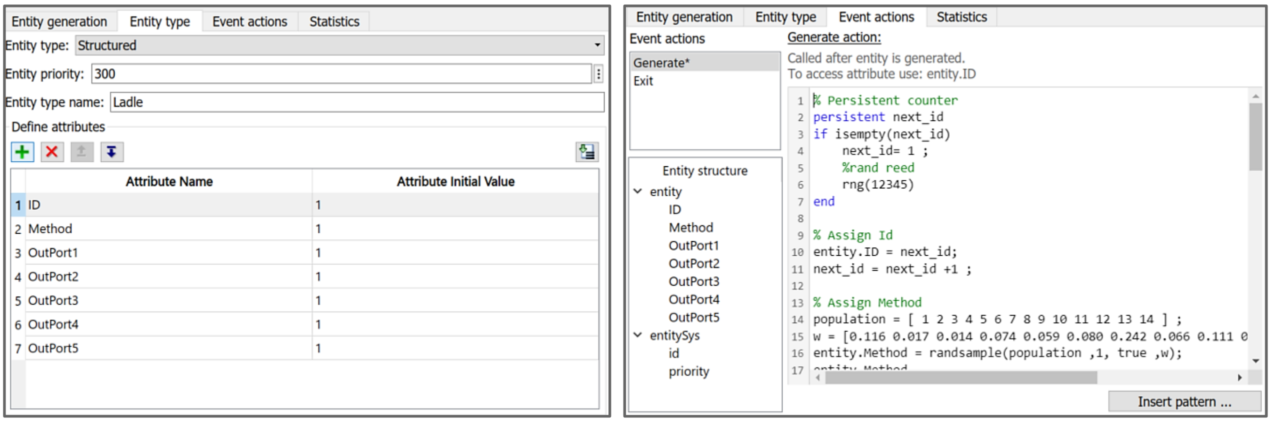


Figure 10: Entity Generator Block Properties - Steel Plant Simulink Diagram

Each equipment type was modeled in a subsystem, as shown in Figure 11. The ‘Resource Pool’ block is used for equipment acquisition / release. The ‘Entity Server’ block is used to simulate the processing of each ladle, where the ladle method controls the processing time consumed by this block. The ‘Time Delay’ block is used to model inter-process conveying.

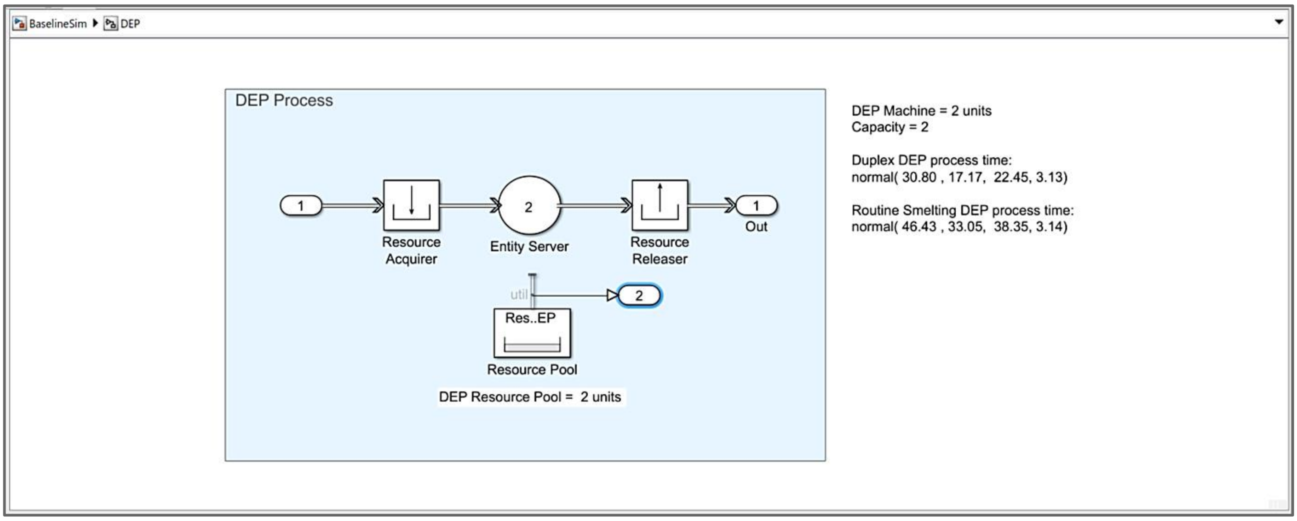


Figure 11: DeP Process - Steel Plant Simulink Diagram (Subsystem)

4.3.5 Output Statistics (Simulink)

The output results of the Simulink model are graphically represented in Figure 12. A MATLAB code was programmed to set-up production parameters and run the simulation. The code generates summary plots describing the utilization statistics of each equipment type. Figure 12 presents the simulation results of the Simulink baseline model over a one-week period.

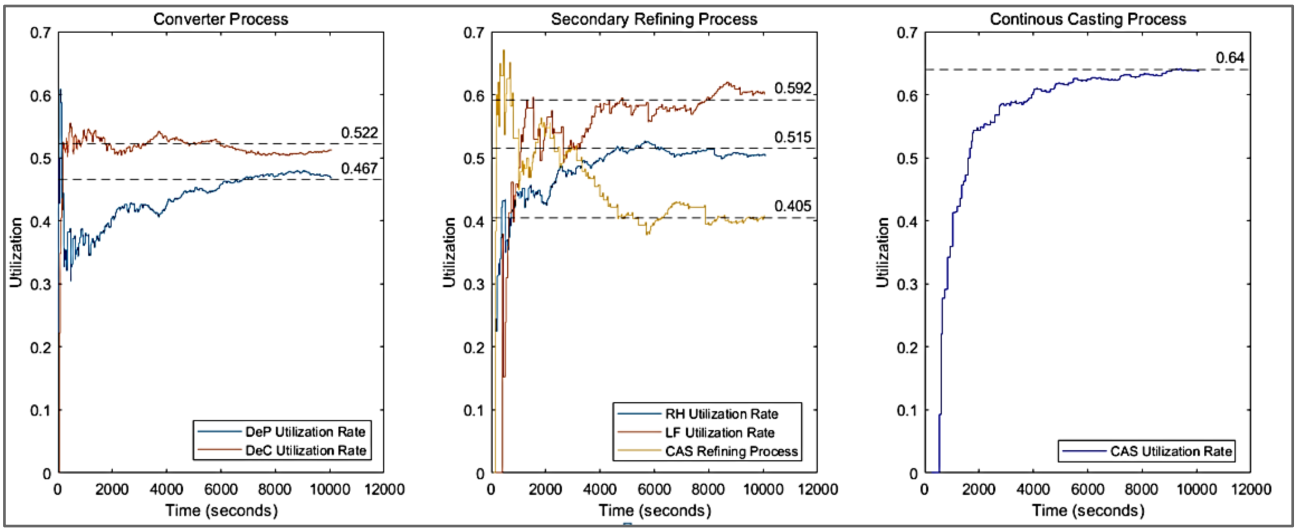


Figure 12: Equipment Utilization Rates - Steel Plant Simulink Model

4.4. Baseline Model Validation

In Digital Twin applications, historical data is crucial for validating the accuracy and reliability of the virtual simulation. Conveniently, the SGJT steel plant presents an extensive amount of field statistics, making it a suitable case-study that can be tested and validated. The historical data from the SGJT plant was adopted for a baseline simulation model. Two baseline models were built, using AnyLogic and Simulink. The results obtained from the baseline models are compared against the collected field statistics on equipment utilization, production rates, and steel grade ratios.

Statistical variability is an intrinsic property of both baseline simulations due to the variability in model inputs. Hence, an average of 5 simulation runs was considered a more sensible result. The average values for equipment utilization rates, production output rates, and steel grade ratios are summarized in Table 9. [consult Appendix II – Baseline Simulation Data Results] SGJT's field statistics include the utilization rates for each individual unit. However, in the simulations, each equipment is modeled as a resource pool, therefore, the statistics represent the average utilization rate per equipment type. For this reason, only the average utilization rates per equipment type are compared herein.

The obtained results from AnyLogic and Simulink are nearly identical, determining that both software tools have congruent design methodologies. Moreover, both simulation results are consistent with the actual field statistics of the plant and the error falls within an acceptable range [< ± 5 %]. A better prediction accuracy can possibly be achieved through additional refining of the model, however, for the purpose of this research project, the model's accuracy is satisfactory.

Table 9: Steel Plant Baseline Model Validation with Respect to the Actual Plant Statistical Data.

Baseline Model Validation						
		Plant Statistics	**AnyLogic Simulation ***	**% Error**	**MATLAB Simulation ***	**% Error**
Ladle Output Rate (min/Ladle)		**17.04**	17.81	**4 %**	17.71	**4 %**
Equipment Utilization Rate	DeP_D	0.48	-		-	
	DeP_E	0.55	-		-	
	DeP Avg.	**0.51**	0.46	**-5 %**	0.47	**-5 %**
	DeC_A	0.53	-		-	
	DeC_B	0.54	-		-	
	DeC_C	0.51	-		-	
	DeC Avg.	**0.53**	0.52	**-1 %**	0.52	**-1 %**
	LF	no data	0.59		0.59	
	RH	no data	0.52		0.52	
	CAS	no data	0.40		0.41	
	CCM Avg.	**0.64**	0.64	**0 %**	0.64	**0 %**
Steel Grade	Low Carbon	85.00%	84.85%	0 %	85%	**0 %**
	Ultra-Low Carbo	15.00%	15.15%	0 %	15%	**0 %**

4.5. Sensitivity Analysis

A sensitivity analysis determines the impact of uncertainties of one or more input variables, and their impact on the overall uncertainty of the model. In other words, it is a study that investigates the model's response to changes in an input variable. This is an essential part of process modeling which identifies priority parameters that have the highest influence on the system outputs.

Apropos the adopted use case of the SGJT steel manufacturing plant, key performance indicators (KPIs) ought to be deliberately decided beforehand. KPI's are subjective measures that aim to quantitatively and qualitatively assess the performance of the process. These KPI's are contingent on the company's goals, the type of industry, and their customer needs. Different manufacturing processes may have distinctly unique KPIs to measure performance attributes.

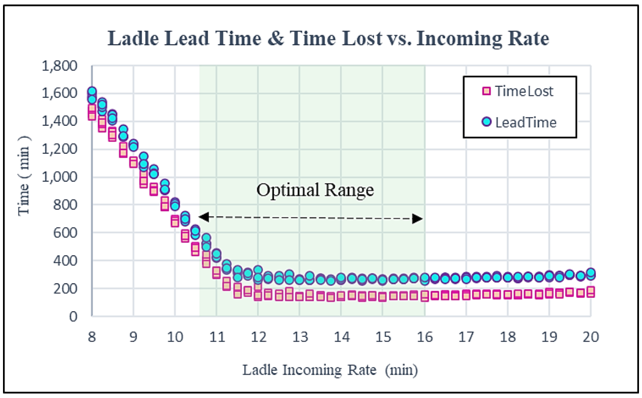
In this research, the focus will be on four quantifiable KPIs that correspond to steel manufacturing. These KPIs reflect the objectives of a steel manufacturing process, which aim to increase revenue and cut back on energy losses, without compromising overall costs. Therefore, the four selected KPIs, pertinent to steel manufacturing and continuous casting, are the following:

- **KPI #1- Lead Time**: This is a measure of the cumulative time that a steel ladle spends in the process before exiting the manufacturing line. This measure reflects the energy, time and manpower required to produce the ladle. Lower expenditures are achieved by reducing the average lead time per ladle within the manufacturing process.
- **KPI #2 Time Lost**: This is a measure of the cumulative time that a ladle wastes in 'idle' state, that is, without having value added. This measure reflects the energy losses of the system as ladles dissipate heat and require energy to be heated again. An efficient process aims to reduce the average time lost per ladle.
- **KPI #3-Productivity Rate**: The productivity rate of a ladle is the ratio of processing time to total lead time. This is another measure that reflects the efficiency of the process. A higher productivity rate means that less time is lost per ladle.
- **KPI #4 Utilization Rate**: The utilization rate is a measure of how much time each equipment is being 'in-use' versus being 'idle'. A higher utilization rate usually reflects a higher revenue and a higher return on investment. Furthermore, higher utilization means that less energy is consumed to reheat the equipment. Usually, a higher utilization rate is a desired objective within a manufacturing process.

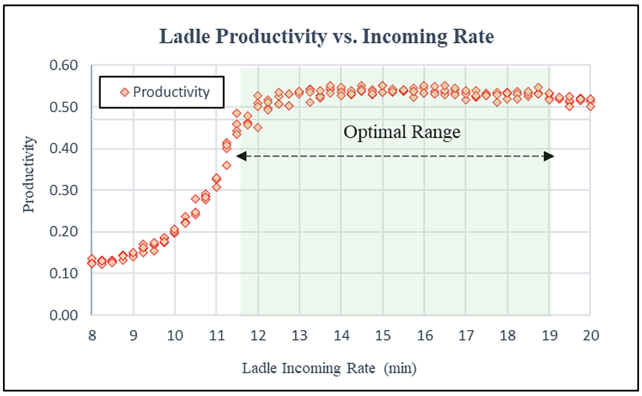
A sensitivity study is carried out on the baseline model built in AnyLogic. The sensitivity analysis investigates the relationship between the critical production parameters (the ladle incoming rate and steel order ratio) and the KPIs mentioned above. The analysis consists of varying one parameter input, while keeping all other parameters at a constant state, and observing the change in the simulation output results.

4.5.1 KPIs Sensitivity to Ladle Incoming Rate

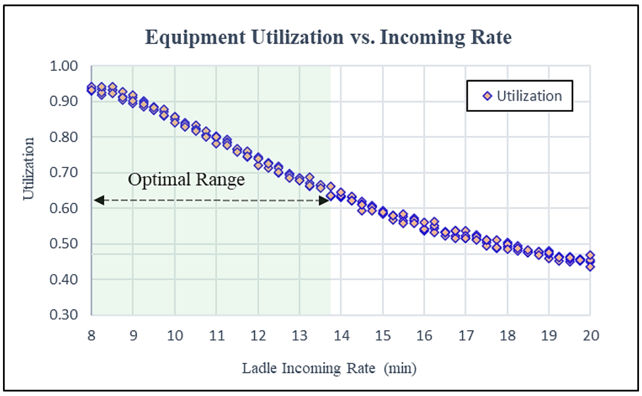
First, the ladle incoming rate is studied. A sensitivity experiment is carried out, by varying the incoming rate (time between incoming ladles) from 8 minutes to 20 minutes, with a step of 25 seconds. The steel grade ratio is kept constant at 85% low carbon steel and 15 % percent ultra-low carbon steel. The simulation results are shown in Figure 13. The KPIs, LeadTime, TimeLost, Productivity and Utilization are measured in response to the varying incoming rate. The sensitivity analysis indicates that some KPIs present conflicting trends, such that a slower incoming rate (increased time interval) leads to better ladle productivity, yet decreased utilization rates. The optimal range of ladle incoming rate is highlighted on the graphs as shown in the Figure 13.



a) KPIs #1&2 : Lead Time and Time Lost (Ladle)



b) KPI #3 : Productivity Rate (Ladle)

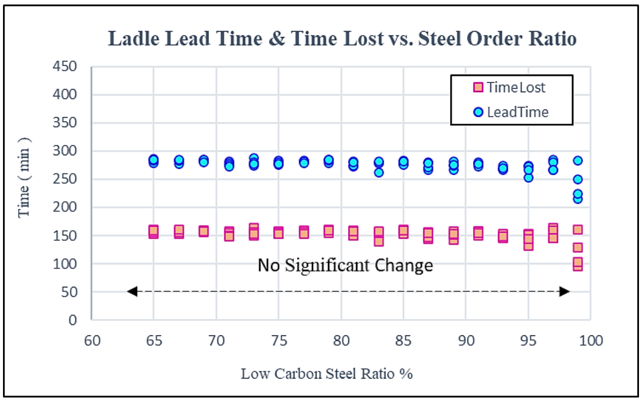


b) KPI #4 : Utilization Rate

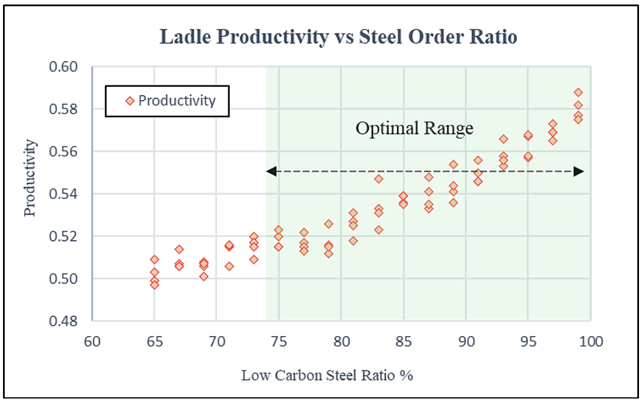
Figure 13: Baseline Model KPI Sensitivity to the Incoming Rate Parameter

4.5.2 KPI Sensitivity to Steel Order Ratio

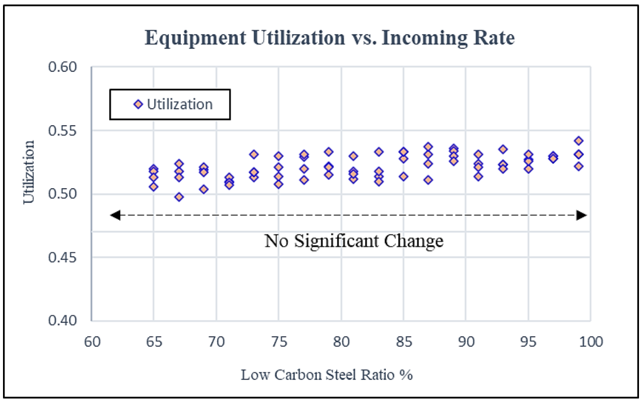
Subsequently, the sensitivity of the steel order ratio is investigated. Another sensitivity experiment was built in AnyLogic, where the varying parameter was the low carbon steel percentage. The ratio was varied between 50% and 100% of low carbon steel, while the ultra-low counterpart was adjusted accordingly. The incoming rate was fixed at a constant value of 17 min between incoming ladles. The results of the experiment are presented in Figure 14. Only the ladle Productivity is sensitive to the steel grade ratio, as a higher proportion of low carbon steel indicates a better productivity rate. However, the other KPI measures were not significantly impacted by the variation in steel grade ratio.



a) KPIs #1&2 : Lead Time and Time Lost (Ladle)



b) KPI #3 : Productivity Rate (Ladle)



b) KPI #4 : Utilization Rate(Equipment)

Figure 14: Baseline Model KPI Sensitivity to the Steel Order Ratio

The results obtained in the sensitivity analysis show that the incoming rate parameter has more impact on the performance of the steel plant. Therefore, the incoming rate between ladle creation has a higher potential for effectively optimizing the process. In contrast, the steel grade parameter only impacts the productivity output. Therefore, the control of steel grade ratio will not be highly beneficial for this process. Also, the steel grade ratio is an external constraint that is imposed by customer orders. For this reason, this project will only focus on optimizing the incoming rate parameter to achieve an improved performance of the manufacturing plant.

In the following section, the ladle incoming rate will be considered the control variable. Further analysis will be carried out with respect to this production parameter, in aims of achieving better performance with respect to the baseline model.

4.6. Steel Plant Optimization

In the past, manufacturing plant optimization relied on industrial experts and conducting experiments on the physical process. These optimization methods are economically burdensome and unreliable for dynamic systems. Alternatively, optimal process control is a cost-effective solution that requires little investment and can potentially achieve better optimization of the manufacturing plant.

In this section, the DT simulation of the steel manufacturing plant is used for implementing an optimal process control system. Two optimization methods are compared: a steady-state optimization of a process variable, and a dynamic optimal process control using an AI state observer. The advantage of the DT simulation is providing a limitless testing environment for various scenarios of the production system. The DT simulation of the manufacturing plant allows for the evaluation of these optimization methods. The simulation provides extensive data on the measured performance of the system and the KPIs pertinent to steel production.

Process optimization is a discipline that quantitively searches for the optimal solution for a process model. Various optimization methods are presently used, depending on the system constrains and the nature of the problem. For example, linear programming is a deterministic algorithm that solves an optimization problem by solving a linear objective function. Where as, other stochastic algorithms are more suited for unconstrained and nonlinear process models (Fikar and Kostur, 2012).

Furthermore, an optimization model adheres to the following basic classifications: constrained vs unconstrained, linear vs non-linear, and single-objective vs multi-objective. The presented steel manufacturing plant exhibits non-linear characteristics with indeterministic outputs. Although an objective function depends on the company’s goals, a multi-objective function is used to optimize the plant.

A stochastic optimization engine is provided in the AnyLogic software, called the OptQuest Engine.

OptQuest Optimization Engine: OptTek is specialized in providing optimization solutions for complex systems. One of their leading products is the OptQuest Engine, which is dedicated for optimization in simulation environments. The algorithm implements a sophisticated, stochastic searching technique based on evolutionary methods. It is highly efficient for complex problems involving elements of uncertainty (OptTek, 2022).

4.6.1 Multi-Objective Function

The objectives of a steel manufacturing process are maximizing efficiency and productivity, while minimizing energy costs. A multi-objective function considers these conflicting objectives (representing the steel plant KPIs). Certainly, a multi-objective function is subjective to the company's goals. Depending on the industry, the company and the external economic factors that are imposed, the multi-objective function reflects priorities that are unique to the organization.

The KPIs presented for this steel manufacturing plant are inter-dependent. It is imminent that the Productivity of ladles is dependent on the attained lead times and processing times. It is not simple to define an objective function that relates these dependencies, without consulting the actual company. In fact, this research does not focus on the multi-objective function, perse, but focuses on implementing a methodology using a multi-objective function for optimal control of the system. Considering the simulation results obtained in the sensitivity analysis, a relationship was deduced relating the KPI outputs. Using the obtained data, the measured outputs are fitted in three forms of equations: a linear model, a weighted linear model, and a nonlinear model.

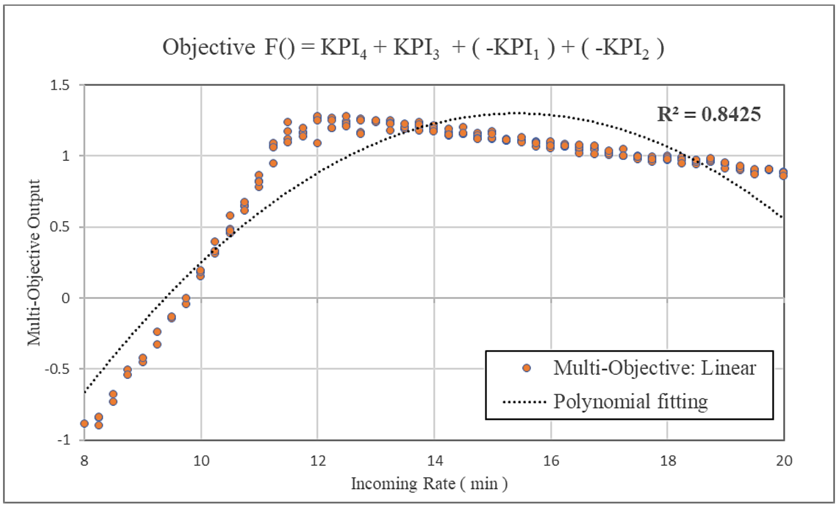
Normalization: The KPIs (Lead Time, Time Lost, Productivity, and Utilization) are on different scales. Normalizing these variables is necessary to have a uniform scale that varies from 0-1. The scaling is performed using the minimum-maximum scaling formula, as described in Eq. 1, where x_i' is the scaled data variable.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad \text{Eq. 1}$$

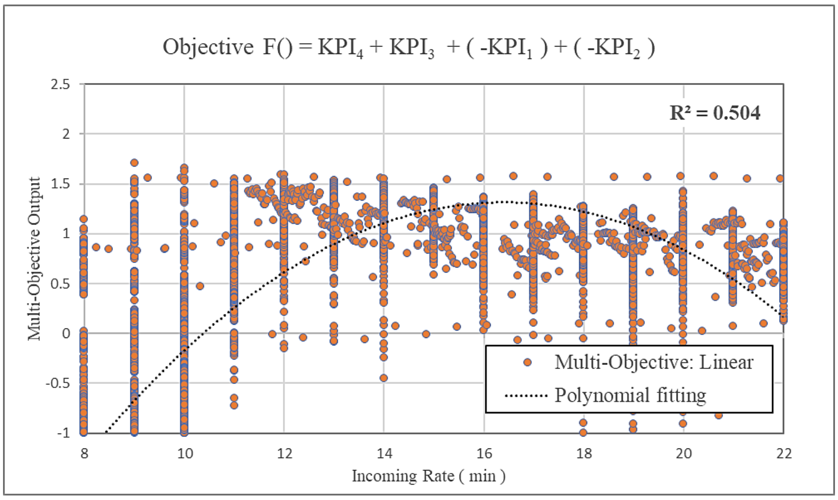
KPI Sampling Frequency: The statistics collected on ladles and equipment can be sampled on a weekly basis, as shown in the sensitivity analysis, or they can be sampled at a higher frequency rate. Given that the average processing time of ladles is around 5 hours, it is sensible to collect KPIs at a sampling rate that captures this dynamic system. Therefore, a sampling rate ¼ day (6 hours) was used to collect the KPI statistics reflecting the dynamic response of the system to changes in the plant. On the other hand, a the one-week sampling rate represents the steady-state response of the process.

The first equation is a linear model that relates the normalized KPIs in equal proportions. KPIs 3 and 4, referring to the Utilization and Productivity rates, respectively, are in positive correlation of the objective output. Whereas KPIs 1 and 2, referring to the Lead Time and Time Lost, respectively, are in a negative correlation with respect to the function output. Therefore, maximizing the objective output reflects higher Utilization and Productivity, and lower Lead Time and Time Lost. The linear multi-objective function is presented in Eq.2.

$$Linear\ Function = KPI'_4 + KPI'_3 - KPI'_1 - KPI'_2 \qquad \text{Eq. 2}$$



a) Weekly Sampling Rate - Steady-State Response



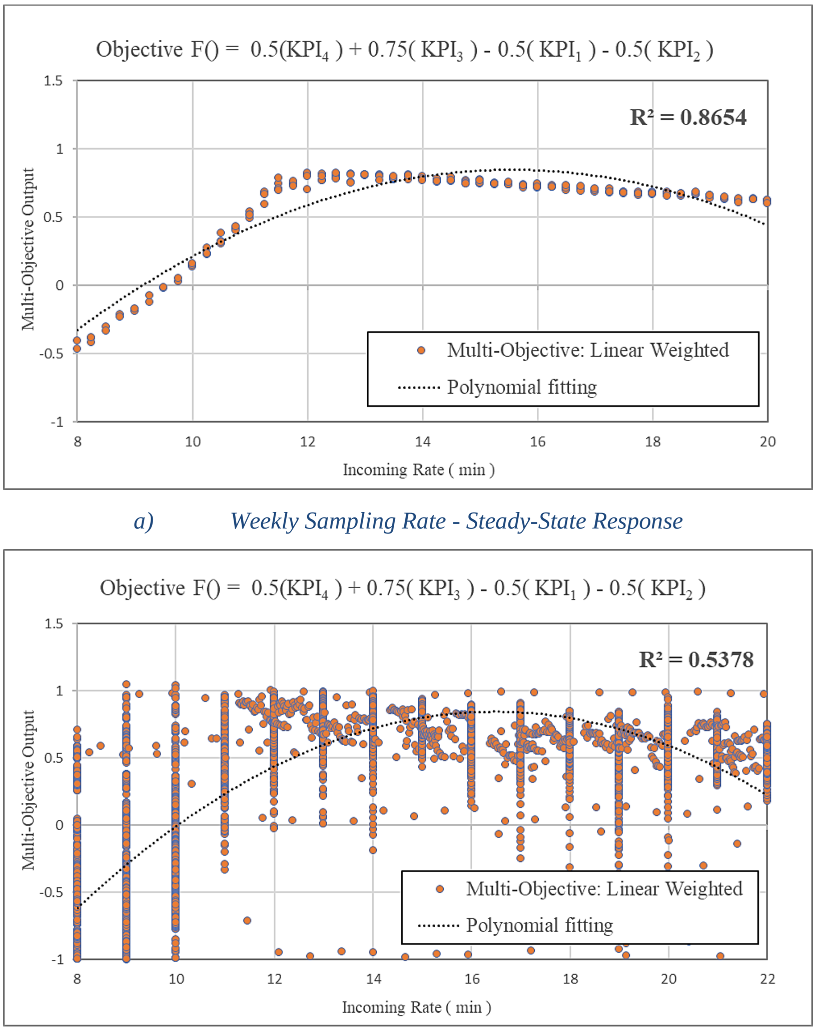
b) ¼ Day Sampling rate - Dynamic Response

Figure 15: Fitting of A Linear Multi-Objective Function

Figure 15 presents the fitting of the simulation data using Eq.2. Subplot a) presents fitting of data sampled after one week of plant up-time. Subplot b) present the fitting of data sampled every ¼ day. Evidently, b) portrays a higher scatter reflecting the dynamic response of the system. While the data in a) is closely fitted, representing the steady-state response of the system. A polynomial fitting of the data is performed to compare the models. The polynomial fitting yields better a coefficient of determination (R-squared) for the steady-state model in graph a).

Alternatively, a weighted linear multi-objective function can be used to model the KPIs, as expressed in Eq. 3. In this model, the equation variables are multiplied by weights, such that higher priority is given to KPI 3, reflecting a higher priority for increased ladle Productivity. The weighted linear model slightly reduced the scatter of the data, resulting in improved R-squared values, as shown in Figure 16.

$$Weighted\ \ Function = 0.5 \cdot KPI'_4 + \ 0.75 \cdot KPI'_3 - 0.5 \cdot KPI'_1 - 0.5 \cdot KPI'_2 \qquad \text{Eq. 3}$$



a) Weekly Sampling Rate - Steady-State Response

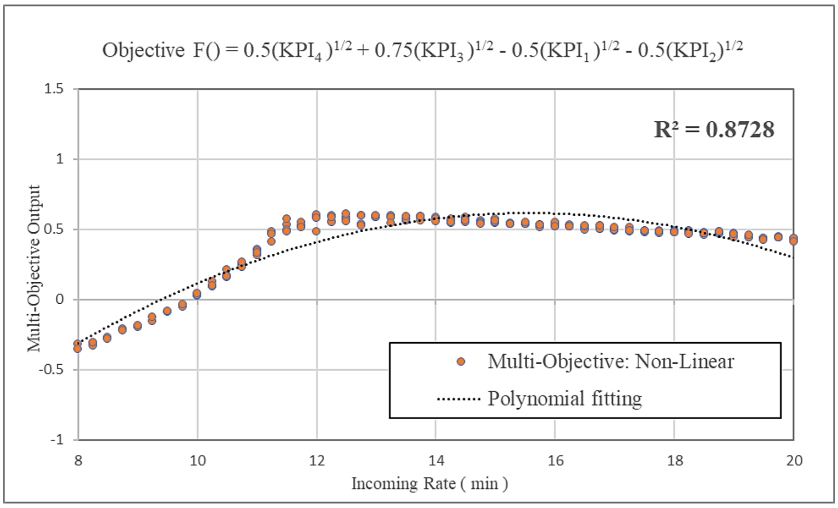
b) ¼ Day Sampling rate - Dynamic Response

Figure 16: Fitting of Linear-Weighted Multi-Objective Function

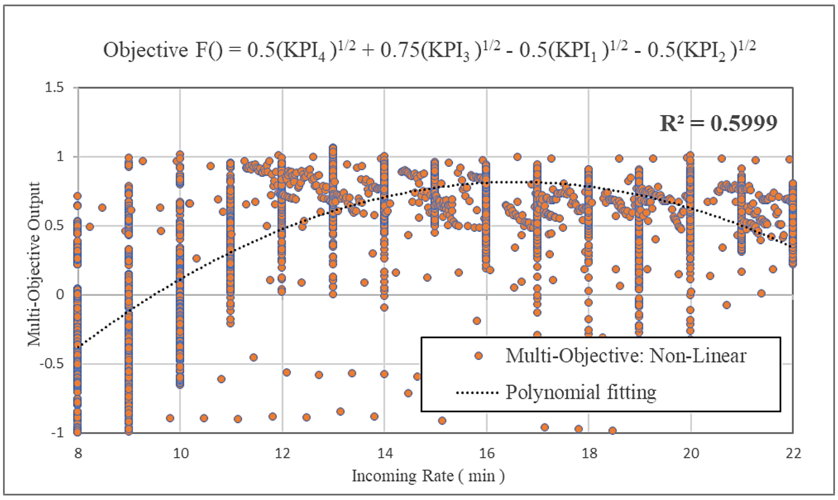
Lastly, a nonlinear model is used as multi-objective function relating the KPIs for an optimal output. The nonlinear multi-objective function is expressed in Eq. 4.

$$Nonlinear\ Function = 0.5(KPI'_4)^{1/2} + 0.75(KPI'_3)^{1/2} - 0.5(KPI'_1)^{1/2} - 0.5(KPI'_2)^{1/2} \quad \text{Eq. 4}$$

Figure 17 presents the data fitting applied to the nonlinear model. Compared with the previously presented linear models, the nonlinear multi-objective function yields the best results in terms of reduced scatter and R-squared values obtained for the polynomial fitting of the data.



a) Weekly Sampling Rate - Steady-State Response



b) ¼ Day Sampling rate - Dynamic Response

Figure 17: Fitting of A Nonlinear-Weighted Multi-Objective Function

In summary, the optimization function can be adjusted depending on the desired objectives of the process. It is a subjective evaluation that models the relationship of a system's outputs with respect to its performance. Based on the analysis presented above, it can be presumed that the non-linear model is the most appropriate for this steel manufacturing process. The non-linear model produces the best fitting of the data and reduces scatter.

4.6.2 OptQuest Optimization

As previously stated, the OptQuest Engine provides a robust search based on stochastic and metaheuristic techniques. OptQuest is integrated in AnyLogic and can control simulation runs as well as manipulate input parameters. The algorithm implements a smart search for a continuous or discrete variables. After every iteration, the objective function is used to evaluate the fitness of the solution. The objective of the experiment is to maximize the multi-objective function, as explained in the previous section. The program code tracks the BestObjective value, the BestIteration, and the BestSolution of the experiment. The BestSolution refers to the optimal incoming rate parameter, while the BestObjective refers to the output of the defined optimization function. The experiment was programmed using Java script [consult Appendix I – Optimization Code (OptQuest)]. The maximum number of iterations was set to 150 simulations. Figure 18 presents the user-interface of the OptQuest Optimization experiment.

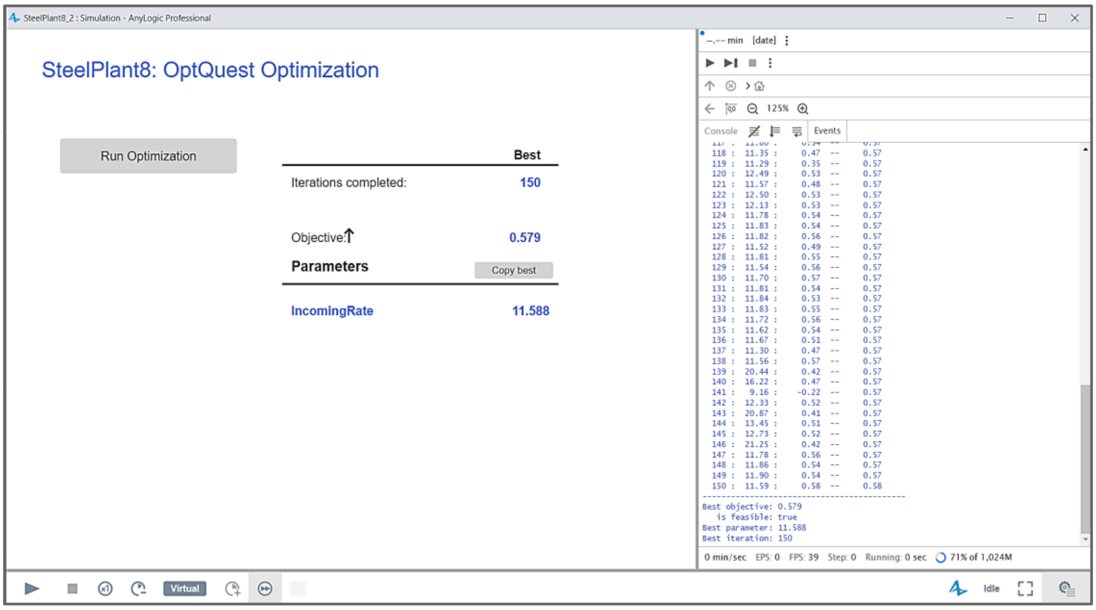


Figure 18: Steel Plant KPI with respect to each replication run.

The OptQuest algorithm is attempted for the optimization of the incoming rate parameter. In Figure 19, the output results of one experiment are presented. The Objective value is plotted against the iteration runs, indicating the stochastic search property of this algorithm. The BestObjective was encountered after 45 iteration runs, for which a multi-objective value of 0.585 was obtained.

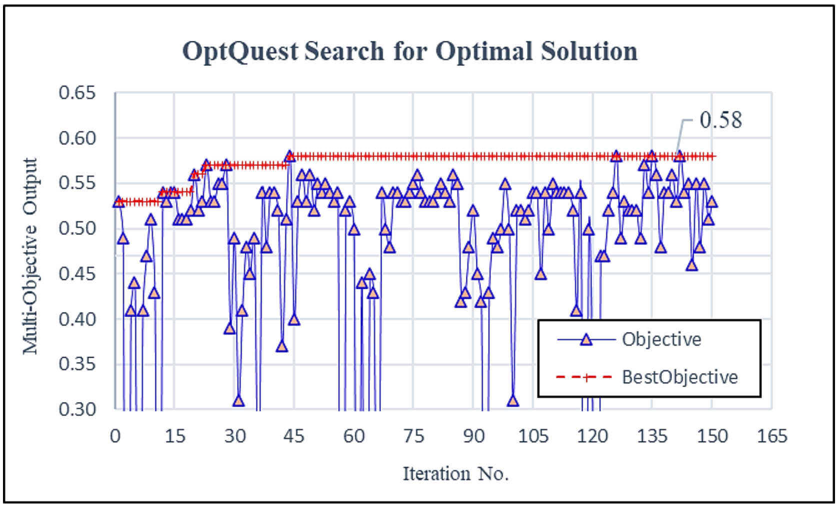


Figure 19: OptQuest Optimization Performance

Evidently, the stochastic nature of the algorithm does not yield a nondeterministic solution. Different optimization experiments produce unique solutions. This can be seen in Figure 20 showing the output variability between three OptQuest experiments. The optimal solutions for the incoming rate were 12.12, 12.38, and 11.52 min. The average value of the optimal solution is 12.08 min, which is consistent with the results of the sensitivity analysis previously performed on the baseline model.

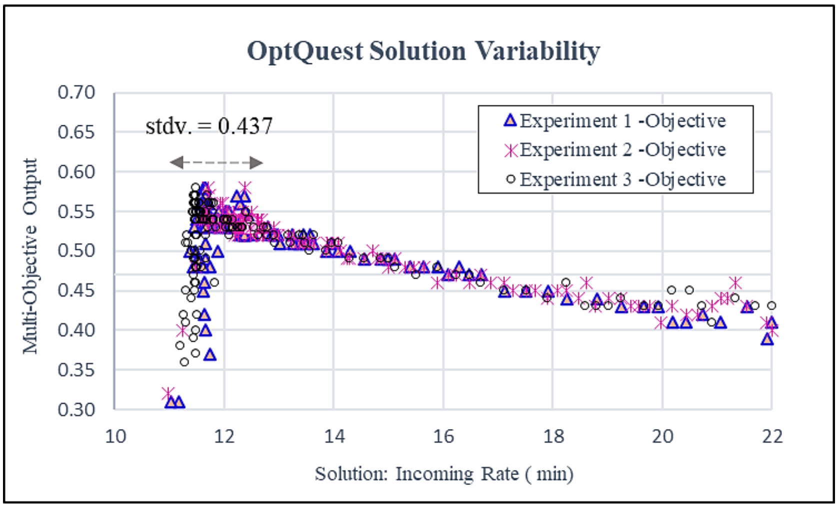


Figure 20: Stochastic Nature of the OptQuest Optimization Algorithm

To conclude, the OptQuest algorithm offers an efficient optimization tool applicable to plant simulations. This optimization method provides a steady-state optimal variable that can potentially improve the performance of the process. The results obtained for this process improvement method are presented later in the Results Section.

In the following section, an AI based process control is implemented.

4.7. AI Optimization Control

AI Optimization Control is based on the Model Predictive Control (MPC) concept which is reputable for high performance and minimal intervention from human controllers. In MPC applications, the control problem emanates from optimizing system dynamics subject to high uncertainties in real-time processes. In contrast with deterministic systems, the control of uncertain systems requires a feedback signal which was historically challenging to implement in large-scale plants (Morari, Garcia, and Prett, 1998). Yet, technological advancements have made great strides in developing communication networks and IoT sensors in the manufacturing industry. Therefore, the future of manufacturing can effectively rely on adapted MPC methods to control complex processes.

MPC is commonly applied to process plants with slow control, due to the high computational cost required for solving the optimization problem. In more recent years, embedded MPC processors have integrated micro-controllers that can be applied to fast dynamic systems. Robust control using MPC has been a high-interest research topic, especially with regard to achieving sufficient stability against internal and external disturbances. Various MPC algorithms have been introduced in the literature for nondeterministic systems, such as tube based MPC, adaptive MPC and stochastic MPC, however, real applications of these algorithms are scarcely implemented. (Chalupa et al, 2013)

In this research project, an optimization control algorithm was inspired from the MPC concept. In this control method, an AI predictor is trained to provide an early forecast of the process outputs. The predicted outputs provide an estimate on the current state of the plant, which are considered by the optimization control algorithm, essentially achieving a feedback loop to control the process. Figure 21 presents a process control diagram representing the AI Optimization Control method.

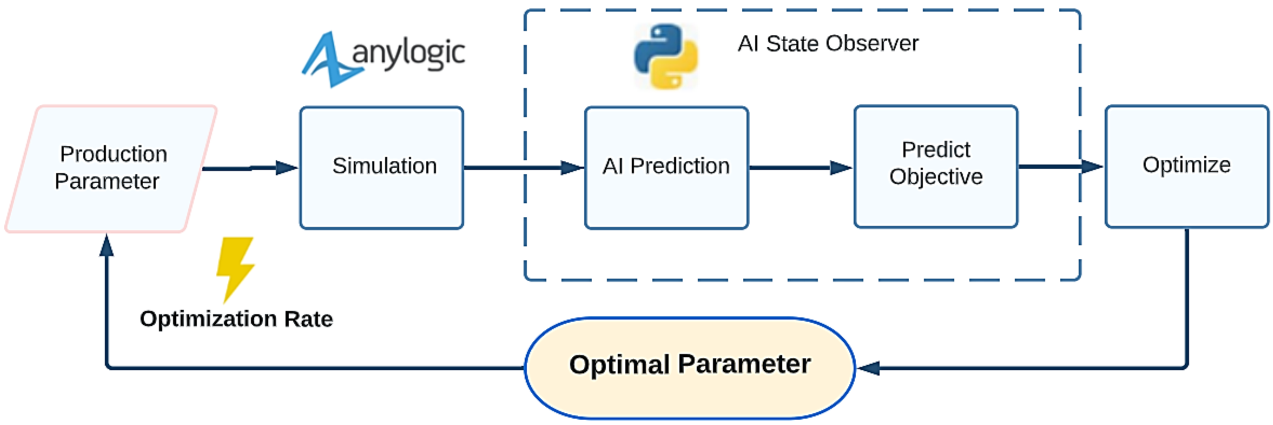


Figure 21: AI Optimization Control System

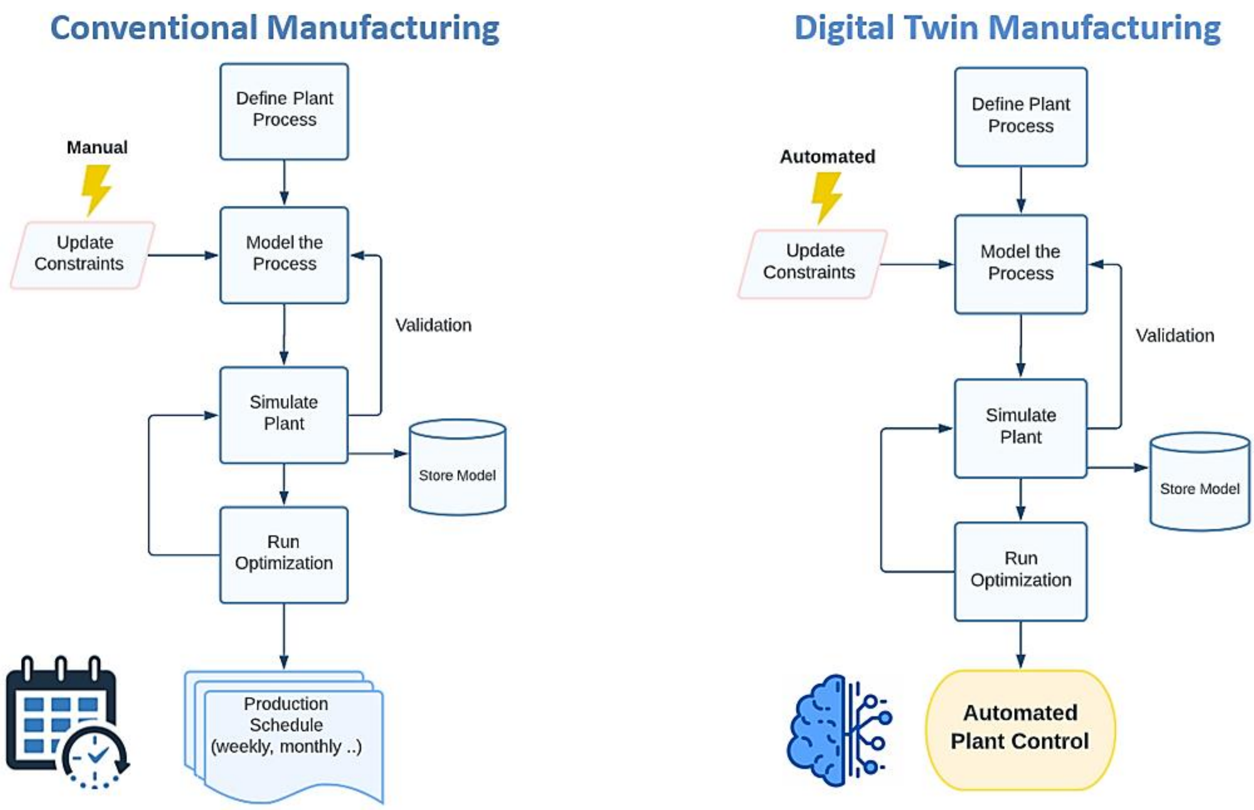


Figure 22: Conventional Manufacturing vs Digital Twin Manufacturing Concept for Automated Plant Control

In large-scale production, significant cost saving, and process optimization can be achieved by means of automation. Specifically in relation to steel manufacturing, which involves a high volume of materials, energy consumption and process complexity, the industry is actively looking for sustainable ways to optimize energy and manage resources. The industry has a lot to gain from automated process control that can adapt quickly to volatile changes in internal and external constraints. A potential application for DTs in manufacturing is enabling automated control through the simulation environment. In Figure 22, the conventional manufacturing process control is compared against the Digital Twin concept for automated plant control. On the right side, the conventional process relies on manual updates for constraints and objectives, resulting in a slow rate of optimization for plans and schedules (daily, weekly or monthly basis). Comparatively, a Digital Twin plant allows for a dynamic update of constraints. Further, the latter can provide automated control using the innovative AI Optimization Controller, which is introduced in this research thesis.

The following text is dedicated to explaining the AI Optimization Control methodology. First, the AI state observer (AI Predictor) is introduced. Then, the various NN models implemented in the AI state observer are compared. Finally, the AI Optimization Control algorithm is explained.

4.7.1 AI State Observer

In control theory, the state-observer is a computer implementation that estimates the internal state of a system. Sometimes, systems have immeasurable states, for which a state observer is used to provide feedback at each control step. The knowledge of the current state of the system is crucial for closed-loop process control, as it is utilized to optimize the future course of the plant. A popular state observer is based on the Kalman filter for stochastic systems. The Kalman filter infers the current state from previous observations and the initial state of the plant. However, the drawback of the Kalman filter is that convergence is inadequate in nonlinear systems (Chalupa et al, 2013).

Artificial Intelligence (AI) and Machine Learning (ML) algorithms have been successfully implemented in forecasting applications for diverse industrial fields. Similar to a state observer in a control system, AI/ML models can serve to predict the state of an immeasurable system. Following this logic, and with enough training data, an AI predictor can be used to accurately represent the current state of a manufacturing plant. The AI model can be trained to forecast production KPIs, given knowledge about the manufacturing process from its previous and current states.

The aim of this research project is to implement an AI state observer to control and optimize the steel manufacturing plant. The created baseline model represents a virtual replication of the process, which can be exploited for training data. Since the reliability of the mode is validated, the DT simulation can be effectively consulted to generate an infinite amount of data points to be used for AI training. In fact, it is mainly for this purpose that DTs of manufacturing plants are the most potentially groundbreaking technology for the manufacturing industry. The purpose of a DT model is to provide a reliable source of additional data relevant to the plant, which is otherwise very expensive to obtain through testing.

Synthetic Data: As mentioned, the baseline model provides a reliable source of data pertaining to the steel manufacturing plant. Select parameters are identified, which can serve to represent the current state of the plant. The simulation model was adapted for additional data collection. First, the ladle parameters are presented in the following list:

- Id: A sequential ID number referring to each ladle.
- Method: [1-12] referring to the process path.
- SteelWeight: The steel weight in a ladle is randomly sampled from a normal distribution.
- Grade: [0 = Low Carbon Steel, 1 =Ultra-Low Carbon Steel]
- Status: [0 = Processing, 1= Processing Completed]

Secondly, the predictor variables are collected at the time the ladle enters into the process:

- Steel_Ratio: The ratio Low-Carbon/Ultra-Low Carbon steel that is currently being processed in the plant.
- In_Process: The number of ladles currently being processed in the plant.
- Incoming Rate: The average incoming rate of ladles with respect to the last 40 ladles that entered the process.
- DeC_Queue: The current queue size of the DeC equipment.
- DeP_Queue: The current queue size of the DeP equipment.
- RH_Queue: The current queue size of the RH equipment.
- LF_Queue: The current queue size of the LF equipment.
- CAS_Queue: The current queue size of the CAS equipment.
- Batch_Queue: The current size of the collected batch, depending on the steel grade.

Finally, the output variables (KPIs) to be predicted, are collected when the ladle exits the process. Therefore, the data effectively collects information at the initial state of ladle creation, to be correlated with the KPI outputs at the final state of the process. In order to represent the dynamic state of the process, the KPIs were sampled at ¼ day rate (every 6 hours).

All the ladle parameters, predictor variables and KPI outputs can be seen in Figure 23, presenting the graphical editor of the ladle agent in AnyLogic.

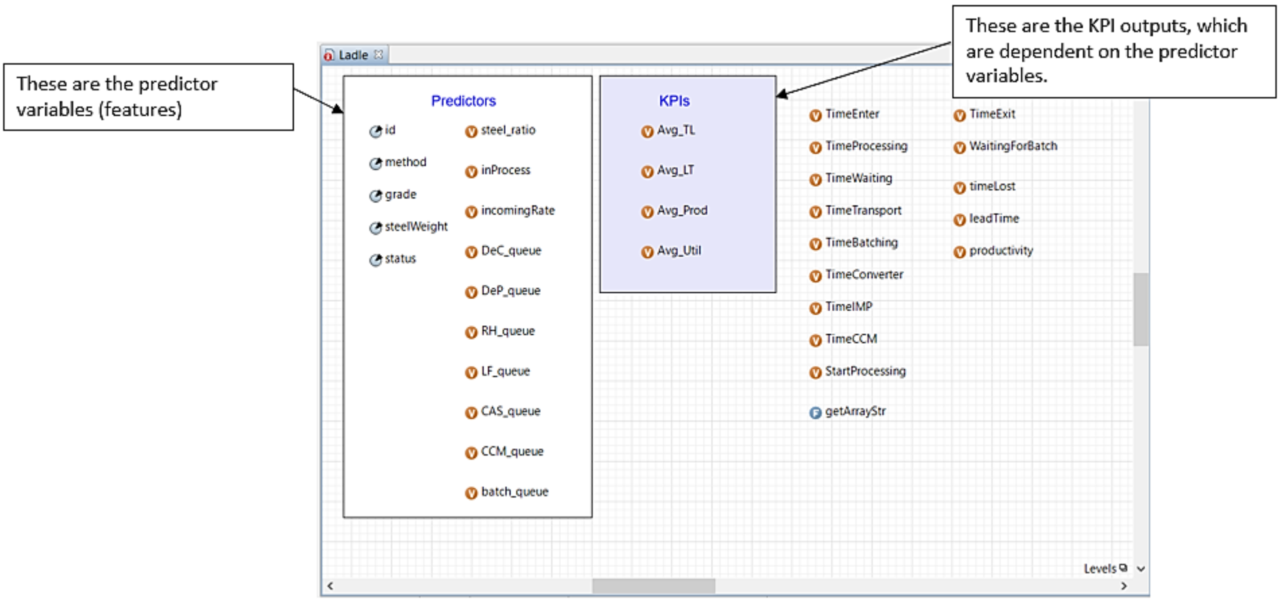


Figure 23: AnyLogic Graphical Editor - Ladle Parameters and Variables

In order to create a synthetic database for training, the simulation model was operated at various incoming rates. Some outliers were introduced in the simulation in order to prevent over-fitting. The data was collected from simulating 635,040 minutes (equivalent to 63 weeks) of plant up-time. The dataset consists of 44,665 ladles each representing one data point.

Correlation Analysis: Before training the AI Predictor model, a correlation analysis was performed to evaluate the relationship between the predictors and output variables (KPIs). The first is the Pearson correlation coefficient which evaluates the linear relationship between the variables. The second is the Spearman correlation coefficient, which evaluates the nonlinear correlation between the variables. The results are summarized in Table 10 and Table 11 . Based on the results of the correlation analysis, the variables having insignificant linear and nonlinear correlations will be omitted in the AI training. This ensures that the trained model is not subject to random sporadic correlations. The variables with high correlation coefficients are highlighted in green, as shown in the tables below.

Table 10: Correlation Analysis Results: Pearson Coefficient Matrix (Linear)

Pearson Coefficient Matrix				
Predictors / Ouput Variables	**Time Lost**	**Lead Time**	**Productivity**	**Utilization**
id	-0.069	-0.068	0.082	-0.031
method	0.056	0.058	-0.052	0.007
grade	0.076	0.078	-0.069	-0.006
steelWeight	0.006	0.006	-0.004	0.010
steel_ratio	-0.042	-0.040	0.003	-0.050
inProcess	**0.9234**	**0.9218**	**-0.8581**	**0.6454**
incomingRate	**-0.3087**	**-0.3073**	**0.4198**	**-0.8744**
DeC_queue	**0.7062**	**0.7044**	**-0.5724**	**0.4384**
DeP_queue	**0.4981**	**0.4962**	**-0.4202**	**0.3533**
RH_queue	**0.4332**	**0.4321**	**-0.4739**	**0.4452**
LF_queue	**0.8027**	**0.8018**	**-0.7435**	**0.5314**
CAS_queue	**0.2403**	**0.2391**	**-0.2786**	**0.3613**
CCM_queue	**0.9258**	**0.9243**	**-0.8283**	**0.4513**
batch_queue	0.003	0.003	-0.018	-0.005

The queue size of each machine equipment has the highest correlations with respect to the output variables (KPIs). On the other hand, the 'id' variable is randomly assigned, and the 'steelWeight' is randomly sampled from a normal distribution. Therefore, it is expected to see no correlation with respect to these variables. Consistent with the sensitivity analysis on steel order ratio, the 'steel_ratio' variable also exhibits little correlation with respect to the outputs. To conclude, 10 predictor variables are selected, which are highlighted in green in Table 11.

Table 11: Correlation Analysis Results: Spearman Coefficient Matrix (Nonlinear)

Spearman Coefficient Matrix				
Predictors / Ouput Variables	**Time Lost**	**Lead Time**	**Productivity**	**Utilization**
id	-0.073	-0.071	0.082	-0.028
method	**0.1312**	**0.1330**	-0.065	0.008
grade	**0.1904**	**0.1913**	-0.093	-0.007
steelWeight	**0.0029**	**0.0032**	-0.003	0.010
steel_ratio	0.080	0.082	-0.083	-0.022
inProcess	**0.6316**	**0.6307**	**-0.6599**	**0.8296**
incomingRate	**-0.3622**	**-0.3614**	**0.4005**	**-0.8886**
DeC_queue	**0.4895**	**0.4883**	**-0.5136**	**0.5888**
DeP_queue	**0.4091**	**0.4081**	**-0.4227**	**0.4754**
RH_queue	**0.3696**	**0.3690**	**-0.3924**	**0.4753**
LF_queue	**0.5744**	**0.5775**	**-0.5882**	**0.6437**
CAS_queue	**0.1941**	**0.1925**	**-0.2098**	**0.3394**
CCM_queue	**0.7252**	**0.7229**	**-0.7524**	**0.5865**
batch_queue	0.020	0.018	-0.032	-0.006

4.7.2 Neural Network Models

Neural Networks (NN) are prevalent in regression problems and can be applied to both supervised and unsupervised learning. The concept of NN is derived from the biological interactions of neuron cells. NN models are composed of interconnected nodes each with an associated weight and threshold value, adapting to flow of input data. There is a comprehensive list of NN model types designed to serve various problem-solving objectives. Researchers are actively testing and developing new NN models to solve complex problems.

In this research project, three NN architectures are investigated. The first architecture is the Feed Forward Neural Network (FFN), also known as the multi-layer perceptron. The second architecture type is the Convolutional Neural Network (CNN). And the third architecture, which particularly implements a feedback loop, is called the Recurrent Neural Network (RNN).

Feed Forward Neural Network (FFN): This architecture is the most conventional and simple to use. It consists of an input layer, a number of hidden-layers and a final output layer. The input layer takes multiple values (predictor variables) and the output layer produces multiple values (KPIs). A deeper network contains a higher number of hidden layers between the input and output layers. (IBM, Neural Networks)

Convolutional Neural Network (CNN): CNNS are widely used in image recognition and computer vision applications. CNNs implement matrix multiplications that are useful for feature extractions. A CNN architecture consists of a convolutional layer, a pooling layer, a fully connected layer, and finally an output layer similar to FFN models. More CNN layers translate to higher model complexity, which is useful for identifying more features. (IBM, Convolutional Neural Networks)

The CNN architecture can be applied to extract information from the previous states, such as time series datasets. For this, the collected data from the steel plant simulation needs to be rearranged from an array of [44,665 x 10] to an array of [44,665 - L x L x 10], where L is the temporal lookback step. This is illustrated in Figure 24 below. Given the fact that an average of 30 ladles are usually present in the process, the temporal timestep L was selected to be 24. That means that for every output variable (KPI), the previous 24 incoming ladles are considered in the input.

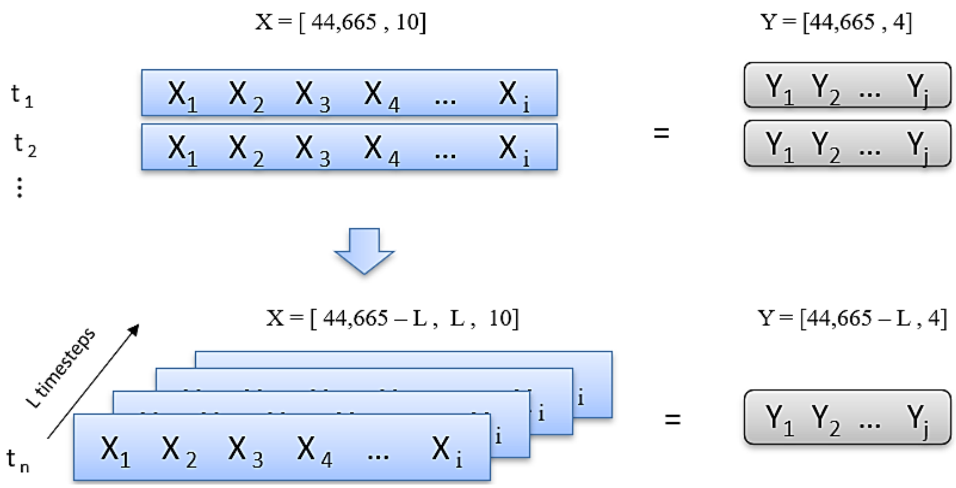


Figure 24: Rearranging The Dataset for a Temporal Representation

Recurrent Neural Network (RNN): The RNN architecture is considered to be a more novel application of NNs. It is commonly used for speech recognition as well as ordinal temporal problems. Long Short-TermMemory (LSTM) are distinguishable networks, having a memory property that takes previous information into consideration. LSTMs were introduced by Sepp Hochreiter and Juergen Shmidhuber to solve the problem of the vanishing gradients pertinent to RNNs. LSTMs have three gates in their hidden layers, the input gate, the output gate and the ‘forget’ gate. These gates control the flow of input data, as needed, in order to achieve better prediction models. (IBM, Recurrent Neural Networks)

The implementation of LSTM networks for this project also entails the rearrangement of the dataset to consider a lookback time step. The arrangement of the data follows the same format as the one presented in Figure 24. The same temporal frame is implemented, where 24 previous ladles are considered for each output variable.

Data Preprocessing: AI algorithms are usually highly sensitive to the training data. Hence, it is essential to clean and preprocess the data before implementing it in the training process. Furthermore, the data needs to be normalized in order to obtain reasonable results. The normalization of this dataset was achieved by applying a minimum-maximum scaling, as previously presented in Eq_. This scaling method is only applicable to ordinal variables. A one-hot encoding algorithm was used to normalize the categorical variables.

Moreover, the dataset was split into two separate sections, one used for training, while the other was used for validating the prediction model. In addition to this, a separate smaller dataset was collected from the steel plant simulation, to be used for testing purposes.

The three datasets are the following:

1. Training Data = 33, 499 data points (75% split)
2. Validation Data = 11,166 data points (25% split)
3. Testing Data = 2, 087 data points (from a separate simulation)

Training Parameters: The parameters used in NN training algorithms are subject to tuning, depending on the problem. For this application the ‘relu’ activation function was used for all NN because of the regression nature of the predictions. The NN models were trained using 30 epochs and a batch size equal to 64. The loss function is based on the mean-squared error, which is evaluated for each iteration.

NN Performance Evaluation Measures: Regression evaluation metrics are assumed for comparing the performance of each NN model. These metrics include the Mean Absolute Error (MAE), the Root Mean Squared Error (RMSE), the R-squared adjusted parameter, and the Explained Variance. The R-squared adjusted metric evaluates how well the model is fitted to the data. It is not an accuracy score, yet it can indicate how well the variance is explained. The difference between R-squared and the Explained Variance is that the latter does not consider the mean absolute error of the data.

The results of the NN model performances are summarized in Table 12. The best performing models are highlighted in green.

Table 12: Evaluation of Neural Network Model Performances

Neural Network Model Performance											
Neural Network Model	**Parameters**	**Stepsize**	**Computation Cost**	**MAE**		**RMSE**		**R2_adjusted**		**Explained Variance**	
				Validation	**Test**	**Validation**	**Test**	**Validation**	**Test**	**Validation**	**Test**
FeedForward Network (FFN)											
1. FFN (n=0 linear)	44		307us/step	0.0464	0.0458	0.0662	0.0669	0.8718	0.5579	0.8767	0.5770
2. FFN_32 (n=1)	484		430us/step	0.0405	0.0435	0.0603	**0.0640**	0.8932	**0.5986**	0.8941	0.6058
3. FFN (n=7)	1,878		700us/step	0.0458	0.0475	0.0703	0.0688	0.8508	0.5418	0.8523	0.5519
Convolutional (CNN)											
4. CNN_16 (n=1)	948	24	4ms/step	0.0393	0.0413	0.0596	0.0620	0.8951	0.5897	0.8954	0.5945
5. CNN_32 (n=1)	1,892	24	4ms/step	0.0391	**0.0413**	0.0597	**0.0623**	0.8949	**0.5822**	0.8962	0.5858
Recurrent (RNN)											
6. LSTM_8 (n=1)	644	24	7ms/step	0.0411	**0.0420**	0.0622	0.0643	0.8850	0.5581	0.8943	0.5809
7. LSTM_16 (n=1)	1,796	24	12ms/step	0.0424	0.0432	0.0639	0.0656	0.8780	0.5467	0.8932	0.5872
8. LSTM_4_4 (n=2)	1,188	24	13ms/step	0.0596	0.0575	0.0837	0.0814	0.7679	0.4611	0.8554	0.5581
CNN_LSTM											
9. CNN_32_LSTM_4 (n=2)	964	24	7ms/step	0.0388	**0.0408**	0.0602	**0.0629**	0.8923	**0.5683**	0.8940	0.5849

The training of various NN models to predict KPI outputs of the steel plant was successful, by evidence of the results presented above. The MAE and RMSE values are below 0.05 and 0.07, respectively, indicating the good prediction accuracy of the models. The values of MAE and RMSE of both the validating and testing datasets are comparable. The R-squared value is around 0.89 which is considerably excellent for the validation set. This value drops to 0.58 for the testing set, considering that less data points are fitted, and less scatter is explained by the data. In summation, the presented NN prediction models perform very well overall, and the NN models do not exhibit over-fitting issues.

Figure 25, Figure 26, and Figure 27 present the predicted versus actual KPI outputs for the FFN_model, the CNN_32 model, and the LSTM_8 model.

It can be seen that the CNN and LSTM models predict a more stable output that is less affected by the high statistical variability of the process. As shown in Figure 25, the lead time and time lost averages collected over ¼ day (6 hours) are highly irregular. This is expected for most production lines. Contrarily, the measured utilization rates are less prone to this erratic behavior. Arguably, it is not important to follow these irregular peaks, and it is more important to closely follow the trend of the observed KPIs. Furthermore, the steady output of the AI perdition model will help in achieving a stable AI based control system in the next step of this project.

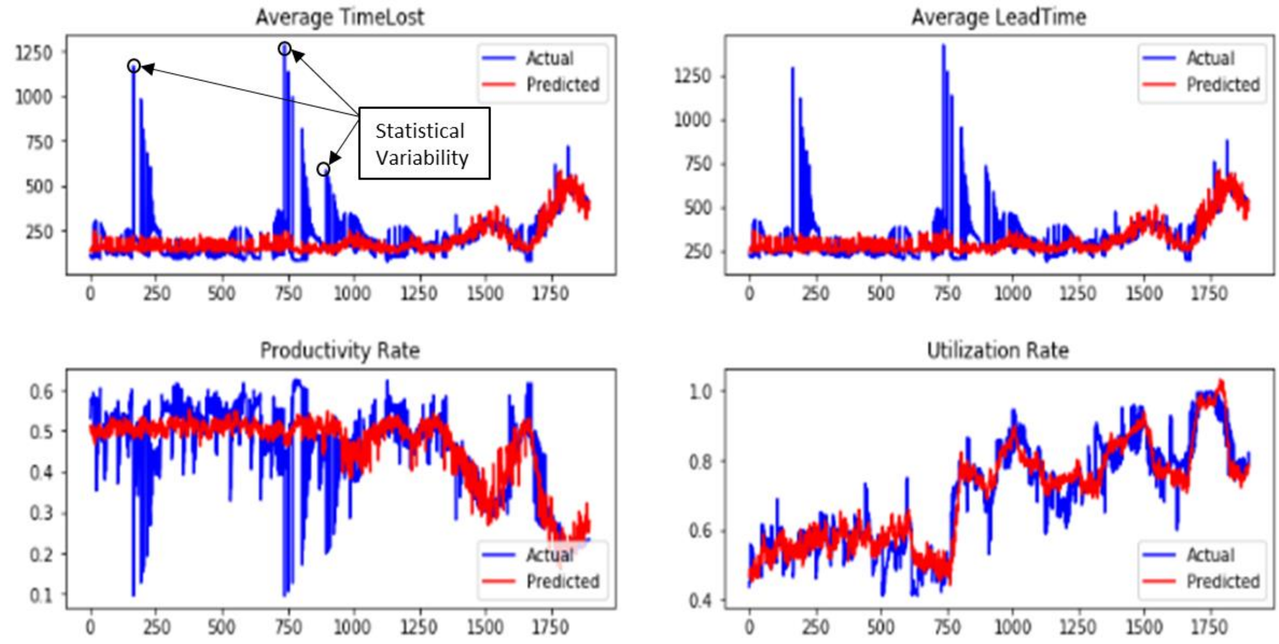


Figure 25: Predicted vs. Actual KPIs Using the FFN_32 (n = 1) Model

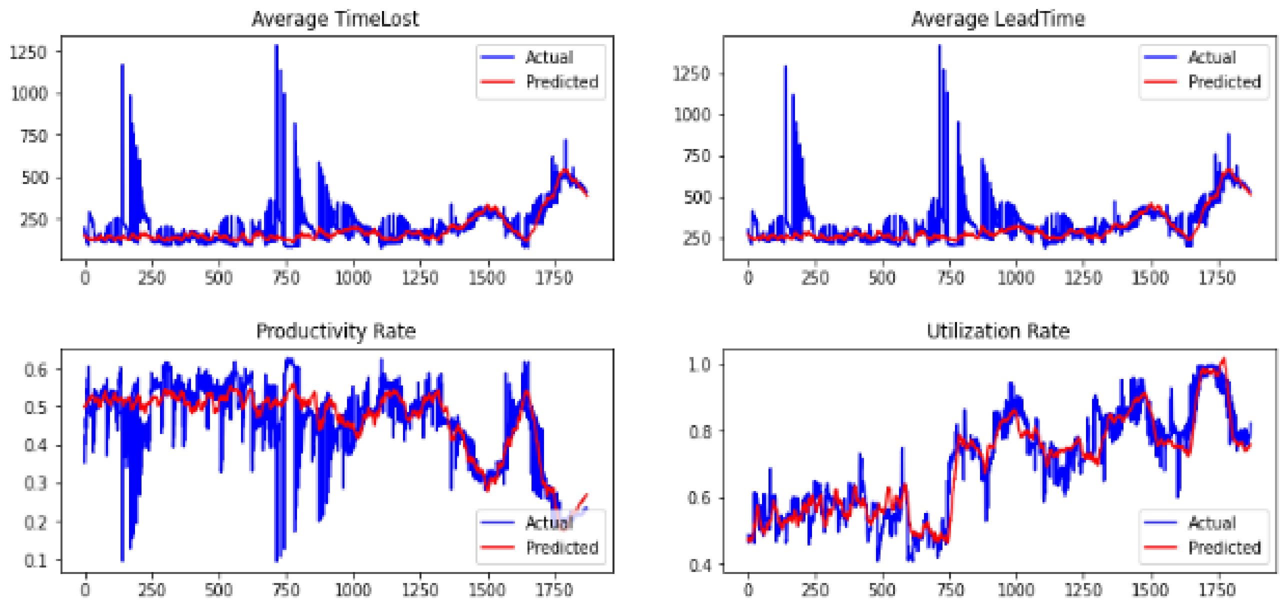


Figure 26: Predicted vs. Actual KPIs Using the CNN_32 (n = 1) Model

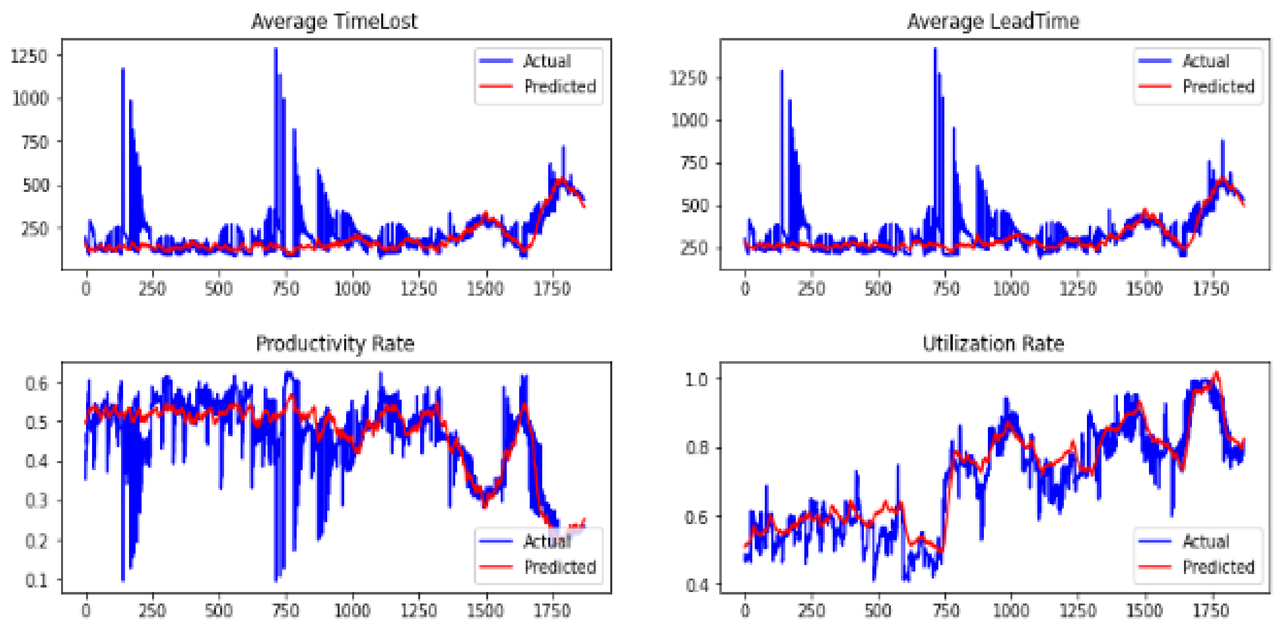


Figure 27: Predicted vs. Actual KPIs Using the LSTM_8 (n = 1) Model

As previously mentioned, it is not highly important to predict the erratic nature of lead time and time lost KPIs, instead it is more important that the trend is accurately predicted. When comparing the NN models, the best performance is observed using the CCN architecture [# 5 CNN_32]. This assessment was made based on the obtained results for MAE and RMSE scores. Furthermore, the CNN prediction model has the most closely fitted and stable output. Therefore, this was the model that was chosen to be implemented in the AI based state observer for the control system.

4.7.3 Optimization Control Algorithm

In control theory, a control algorithm governs the system inputs in order to manipulate the system towards the desired state. An ideal control algorithm provides a functional compromise between minimizing the response delay and overshoot, while achieving a fast steady-state response. In closed-loop control, various mathematical models can be used to develop the relationship between the set-point and measured feedback signal.

For this AI based optimal controller, a control algorithm was developed. The algorithm is a simple application based on the gradient of the multi-objective function. The algorithm is comparable to the gradient descent optimization method, which essentially uses the gradient function to reach an optimal solution. The algorithm achieves optimal control by governing the required input change that will lead to maximizing the multi-objective value.

The control algorithm developed for this project consists of the following steps:

Step 1: Predict KPIs using the AI state observer.

Step 2: Calculate ΔF , the gradient of the multi-objective function.

Step 3: Calculate ΔP, the gradient of the control parameter (incoming rate).

Step 4: Calculate the new parameter P_{t+1} using Eq. 5.

$$P_{t+1} = P_t + \eta_{adapted} \; (\Delta F \cdot \Delta P) \qquad \text{Eq. 5}$$

$$if\ P_t \leq 10 : \qquad P_{t+1} = 0.5\,(10 - P_t) + P_t$$

$$if\ P_t > 16 : \qquad P_{t+1} = 0.5\,(16 - P_t) + P_t$$

Step 5: Set the control parameter to the new P_{t+1} .

where $\eta_{adapted}$ is an adaptive learning rate η that regulates the momentum of the applied change.

$$\eta_{adapted} = \eta * [\ 0.57 \,/\, f(y_1, y_2, \dots y_i)\ ] \qquad \text{Eq. 6}$$

$f(y_1, y_2, \dots y_i)$ represents the obtained objective value using the predicted KPIs $(y_1, y_2, \dots y_i)$.

Function body

```
// Delta Objective
double  trend = Get_Trend() ;

//  Delta Incoming_Rate
double m = Get_m();

// Optimization Algorithm
double learning_rate = 6;

new_Rate = IncomingRate + (learning_rate*trend * m)*(0.57/pred_obj)   ;
//~ adaptive learning rate

// Limit Incoming Rate within stable range
if (new_Rate > 16)
{ new_Rate = (16-IncomingRate)*0.5 + IncomingRate ;
}
else if  (new_Rate <= 10)
{ new_Rate = (10-IncomingRate)*0.5 + IncomingRate;
}


// Update Incoming Rate
```

Figure 28: Implementation of the Control Algorithm In AnyLogic.

In order to improve the convergence and stability of the control system, it was deemed necessary to impose limitation on the control parameter when outside the stability range. Therefore, soft constraints are imposed to limit the incoming rate parameter within with 10 and 16 min. The algorithm logic was programmed in an AnyLogic function, as shown in Figure 28.

Evidently, the algorithm’s performance is highly sensitive to the tuning parameters, such as the learning rate η. The sensitivity of the control parameters was analyzed and will be presented in the Results section.

4.7.4 AI Optimization Simulation (AnyLogic)

The AI Optimization control was integrated in the Anylogic Simulation of the steel manufacturing plant. A Python connector is integrated into the simulation, where the java-based environment can interact with python code using JSON data formatting. JSON data formatting is a data exchange tool that allows different programming languages to interact.

In the Control Panel view, a visualization board is implemented which displays the KPI forecasting of Lead Time, Time Lost, ladle Productivity and equipment Utilization rates. The predicted KPIs are plotted (in red) when the ladle enters the process, while the actual KPI outputs are plotted (in blue) at a later time when the ladle exits the process.

Figure 29: KPI Forecasting and AI Optimization Control Implemented in AnyLogic

Figure 29 presents the implemented KPI forecasting plots in the Control Panel in the Anylogic simulation. By consulting this visualization board, the human-controller can access the actual state of the plant in terms of measurable performance indicators. The controller can make better decisions regarding the manufacturing plant, having these forecasted measures ahead of time.

Additionally, the AI Optimization Controller can be activated using the ON/OFF buttons to the right of the KPI Forecasting area. By activating the ON button, automatic control is implemented on the steel manufacturing plant. The optimization rate was initially set to 1 hour, with a first optimization instance occurring after 12 hours. The delay in first occurrence was necessary to ensure that the plant is operating in steady state before the initial optimization is implemented. Every 1 hour, the optimization function is triggered, and a new incoming rate is set, effectively steering the production process towards an optimal production.

Now that system is successfully implemented, the AI Optimization Control is tested and compared against other optimization techniques. In the next section of this thesis report, the analytical results pertaining to this research are presented.

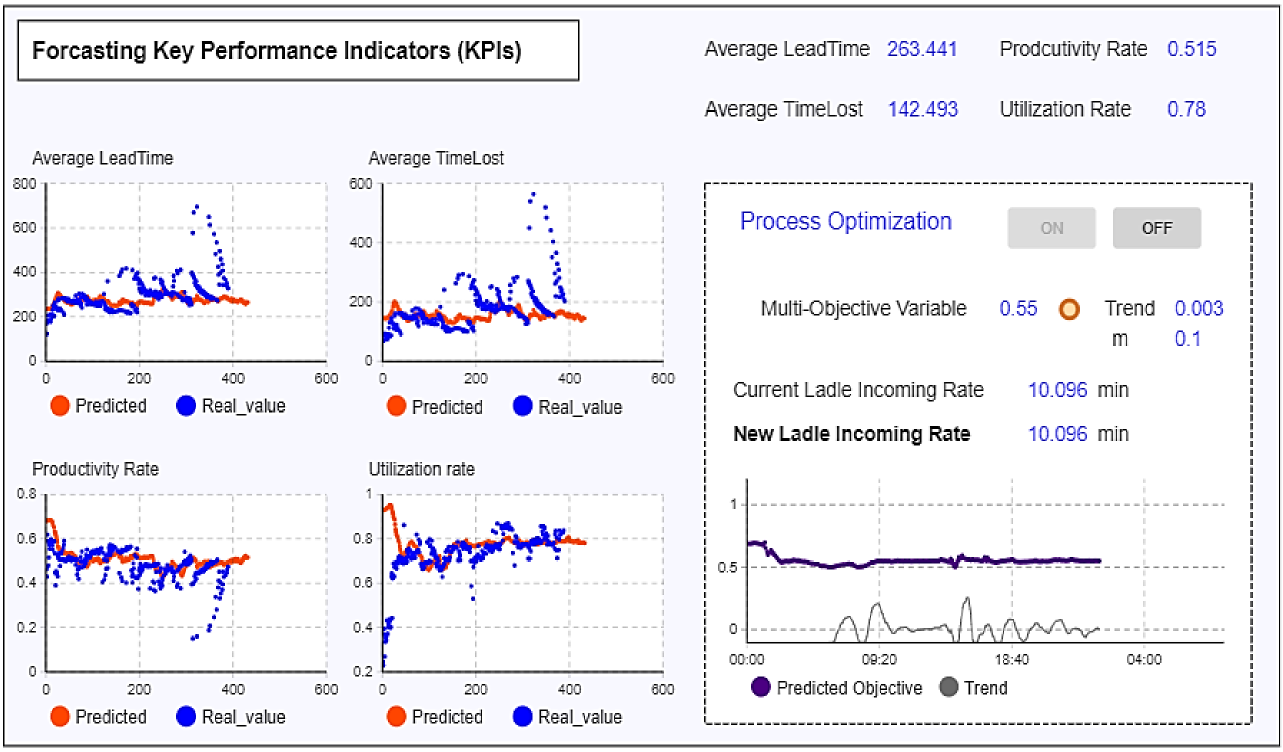


Figure 30: AI Optimization Control Interface

5 Results

The results obtained in this project are presented in this section. First, OptQuest and the AI Optimization Control methods are compared against the baseline model performance. The results of these optimization techniques are benchmarked against the previously published results by Deng et al. (2018). Second, an evaluation of the AI Optimization Control method is discussed. This evaluation investigates the potential parameter-tuning of the AI based control system for a real production environment.

5.1. Plant Optimization Results

The performance of the steel manufacturing plant is evaluated using the Key Performance Indicators (KPIs) of the steel production process. The baseline performance values are compared against the OptQuest model and the AI Optimization Control model, as shown in Table 13. Given the nondeterministic nature of these models, an average value is calculated from 5 simulation runs. Each simulation was conducted for a one-week simulation of the steel plant. The improvement is calculated with respect to the baseline model values, and the standard deviations reflect the variability in the simulation results.

Table 13: Steel Plant Optimization Results Compared Against the Baseline Model

Key Performance Indicators (KPIs)										
		Baseline Model	**OptQuest Model**	sdv.	Improvement	± 1 sdv	**AI Opt. Control Model**	sdv.	Improvement	± 1 sdv
Incoming Rate	(min)	17.00	**12.08**		-		-	-	-	
Steel Grade Ratio	%	85/15	85/15		-		85/15	-	-	
Ladles In	unit	593	833.80	0.84	41%	± 0%	782	45.29	32%	± 8%
Ladles Out	unit	560	776.00	5.66	39%	± 1%	739.4	52.62	32%	± 9%
Ladle Output Rate	(min/ladle)	17.98	12.84	0.12	29%	± 1%	13.89	0.77	23%	± 4%
Total Steel Produced	(kg)	167,966.76	232,756.85	1,647.06	39%	± 1%	216,925.15	10,123.86	29%	± 6%
Average Production Rate	(kg/min)	16.681	23.25	0.13	39%	± 1%	21.56	1.02	29%	± 6%
Average Ladle Lead Time	(min)	277.859	308.29	20.78	-11%	± 7%	278.92	6.30	0%	± 2%
Average Ladle Time Lost	(min)	155.795	185.29	20.75	-19%	± 13%	155.94	5.89	0%	± 4%
Average Ladle Productivity	rate	0.538	0.48	0.01	-5%	± 2%	0.51	0.01	-3%	± 1%
Average Equipment Utilization	rate	0.522	0.73	0.01	21%	± 1%	0.69	0.04	17%	± 8%

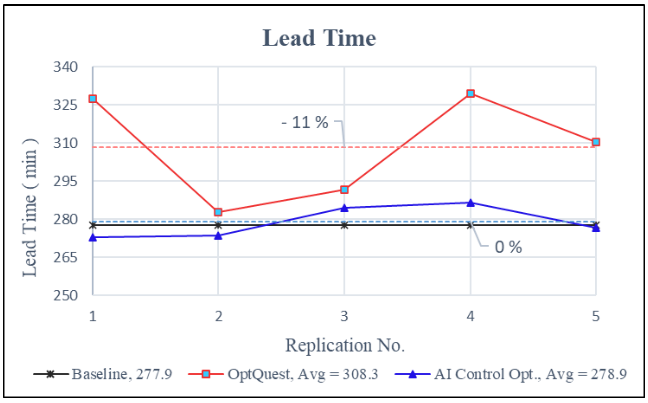
* The indicated values for the OptQuest Model and AI Opt Control Model represent the average results of 5 simulation runs.

Table 13 indicates that the OptQuest model achieves a 39% improvement on the total steel produced. Furthermore, a 21 % improvement was measured for the average utilization rate of all equipment. In contrast, a -5% decline in ladle productivity, an 11% increase in lead time, and a 19% increase in time lost were observed.

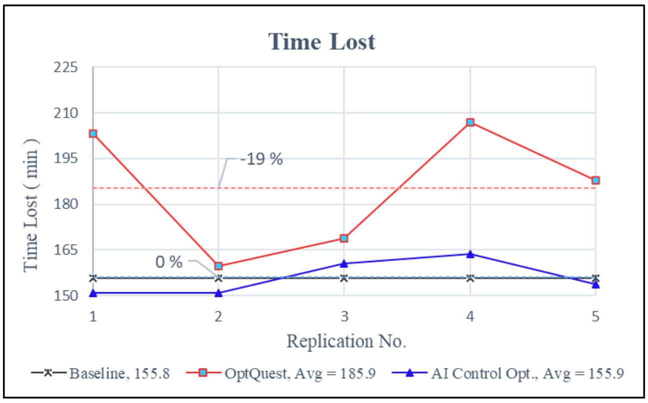
The AI Optimization Control model also achieves a significant improvement on the total output production of steel, equivalent to a 29% increase. The average utilization rate of equipment was also improved by 17%. A better outcome was achieved in relation to the productivity of the plant. Only a -3% decline was noticed for the productivity rate, and the lead time and time lost were not affected.

The KPI outcomes of each optimization method are plotted in Figure 31. As shown in the figures, the OptQuest simulation exhibits a much higher variability in lead time and time lost, in comparison to the dynamic control of the AI Optimization model.

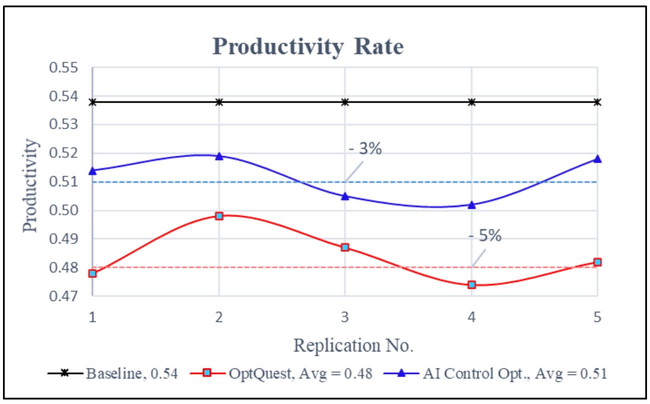
In fact, one of the significant advantages of implementing a dynamic control of the process, as done by the AI based optimal control system, is the diminution of the variability in highly scattered KPIs (specifically lead time and time lost). This is an extremely desired improvement in the process performance. Clearly, the advantage of dynamic process control is manifested in these results.



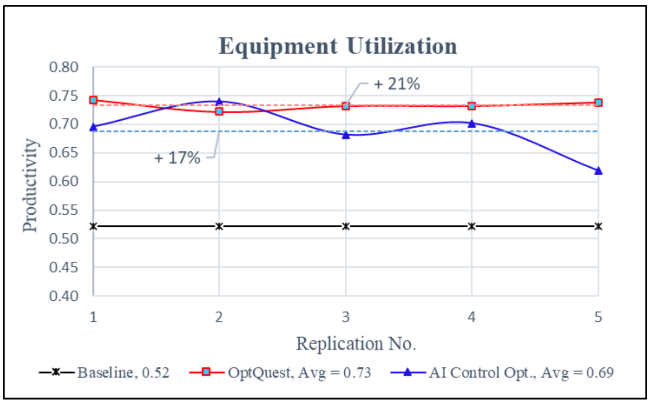
a) KPI #1 : Lead Time



b) KPI #2 :Time Lost



c) KPI #3 : Productivity Rate (Ladle)



d) KPI #4 : Utilization Rate(Equipment)

Figure 31: Steel Plant KPIs Optimization Results

Table 14 and Table 15 present the results obtained for each simulation run for both the OptQuest model and the AI Optimization Control model, respectively.

In summary, both models perform very well with respect to the baseline process of the steel plant. The AI Optimization Control model improved KPI measures without compromising the lead time and time lost. This reflects a higher productivity of the plant, as more steel is produced, with lower time and energy consumption.

Table 14: Steel Plant KPI Results of the OptQuest Optimization

OptQuest Model : Key Performance Indicators (KPIs)								
		Run no. I	Run no. II	Run no. III	Run no. IV	Run no. V	**Mean**	**Stdv.**
Incoming Rate	(min)	12.08	12.08	12.08	12.08	12.08	12.08	0
Steel Grade Ratio	%	85/15	85/15	85/15	85/15	85/15	-	-
Ladles In	unit	834	833	834	833	835	**833.80**	**0.84**
Ladles Out	unit	776	768	776	776	784	**776.00**	**5.66**
Ladle Output Rate	(min/ladle)	12.94	12.941	12.799	12.65	12.844	**12.84**	**0.12**
Total Steel Produced	(kg)	232,771.53	230,447.47	232,673.85	232,787.21	235,104.19	**232,756.85**	**1,647.06**
Average Production Rate	(kg/min)	23.18	23.187	23.427	23.103	23.347	**23.25**	**0.13**
Average Ladle Lead Time	(min)	327.264	282.901	291.701	329.367	310.229	**308.29**	**20.78**
Average Ladle Time Lost	(min)	203.28	159.613	168.917	206.841	187.806	**185.29**	**20.75**
Average Ladle Productivity	rate	0.478	0.498	0.487	0.474	0.482	**0.48**	**0.01**
Average Equipment Utilization	rate	0.742	0.722	0.732	0.732	0.738	**0.73**	**0.01**

Table 15: Steel Plant KPI Results of the AI Optimization Control Model

AI Optimized Control Model : Key Performance Indicators (KPIs)								
		Run no. I	Run no. II	Run no. III	Run no. IV	Run no. V	**Mean**	**Stdv.**
Incoming Rate	(min)	-	-	-	-	-	-	-
Steel Grade Ratio	%	85/15	85/15	85/15	85/15	85/15	-	-
Ladles In	unit	826	776	765	825	718	**782**	**45.29**
Ladles Out	unit	795	728	712	790	672	**739.40**	**52.62**
Ladle Output Rate	(min/ladle)	12.89	13.89	14.132	13.539	14.986	**13.89**	**0.77**
Total Steel Produced	(kg)	227,888.44	218,391.86	213,539.39	223,248.82	201,557.23	**216,925.15**	**10,123.86**
Average Production Rate	(kg/min)	22.688	21.709	21.223	22.164	20.014	**21.56**	**1.02**
Average Ladle Lead Time	(min)	273.029	273.573	284.56	286.614	276.808	**278.92**	**6.30**
Average Ladle Time Lost	(min)	150.856	150.931	160.559	163.744	153.61	**155.94**	**5.89**
Average Ladle Productivity	rate	0.514	0.519	0.505	0.502	0.518	**0.51**	**0.01**
Average Equipment Utilization	rate	0.696	0.74	0.682	0.702	0.619	**0.69**	**0.04**

5.1.1 Benchmarking The Performance of the Models

The obtained results in this research are benchmarked against the previously published optimized process regarding the SGJT steel manufacturing plant. In their paper, Shuai Deng et al (2018) proposed an optimization based on increasing the deployment of the duplex (DeP + DeC) converter process. Their research suggested that a 100% employment of the duplex process yields a 10-15% improvement on converter productivity and a 5% improvement on the overall equipment utilization rates (Deng et al, 2018).

The optimized process suggested by Shuai Deng et al. (2018) was simulated using the DT plant simulation. The results obtained were consistent with the claims made by Shuai Deng et al. (2018), however, these results do not outperform the plant optimization techniques that are presented in this research paper. Table 16 and Table 17 benchmark the results obtained for the OptQuest model and the AI Optimization Control model.

Table 16: Benchmarking of Steel Plant KPIs

Benchmarking Key Performance Indicators (KPIs)								
		<u>**Baseline Model**</u>	**100% Duplex Model**	Improvement	**OptQuest Model**	Improvement	**AI Opt. Control Model**	Improvement
Total Steel Produced	(kg)	167,966.76	**167,910.30**	0%	232,756.85	39%	216,925.15	<u>29%</u>
Average Production Rate	(kg/min)	16.681	16.766	1%	23.25	39%	21.56	<u>29%</u>
Average Ladle Lead Time	(min)	277.859	301.43	-8%	308.29	-11%	278.92	<u>0%</u>
Average Ladle Time Lost	(min)	155.795	166.34	-7%	185.29	-19%	155.94	<u>0%</u>
Average Ladle Productivity	rate	0.538	0.515	-2%	0.48	-5%	0.51	-3%
Average Equipment Utilization	rate	0.522	0.572	5%	0.73	21%	0.69	<u>17%</u>

Table 17: Benchmarking of Steel Plant Equipment Utilization Rates

Benchmarking Equipment Utilization Rates								
		<u>**Baseline Model**</u>	**100% Duplex Model**	Improvement	**OptQuest Model**	Improvement	**AI Opt. Control Model**	Improvement
DeP Utilization	(rate)	0.461	0.66	20%	0.65	19%	0.65	<u>19%</u>
DeC Utilization	(rate)	0.522	0.6	8%	0.73	21%	0.66	<u>14%</u>
RH Utilization	(rate)	0.519	0.5	-2%	0.65	13%	0.67	<u>15%</u>
LF Utilization	(rate)	0.590	0.6	1%	0.86	27%	0.77	<u>18%</u>
CAS Utilization	(rate)	0.400	0.43	3%	0.60	20%	0.55	15%
CCM Utilization	(rate)	0.639	0.64	0%	0.89	25%	0.86	<u>22%</u>

5.1.2 Dynamic Optimal Control

A major process improvement was attained by implementing an AI based optimal control providing a dynamic system response. The presented AI Optimization Control model can react to input changes in the incoming rate, and reactively adjust the process parameters of the plant. This indicates that the system is constantly optimized, even when unexpected changes occur in the process. Even more, the statistical variability of the process is mitigated by the dynamic control system. This dynamic response is further investigated in the following paragraphs.

5.2. AI Control System Sensitivity to the Learning Rate η

Given the scope and timeframe of this project, the AI Optimization Controller could have been further ameliorated in order to achieve better control performance. Nevertheless, this investigation aims to identify the potential improvement of the control system by means of parameter-tuning.

Parameter-tuning is essential in achieving a stable and high-performance control system. For instance, the simulation is highly sensitive to the learning rate η. For this reason, an adaptive learning rate was attempted to improve stability and response time of the system. After numerus simulations, the learning rate of η -6 was deemed suitable by means of trial and error.

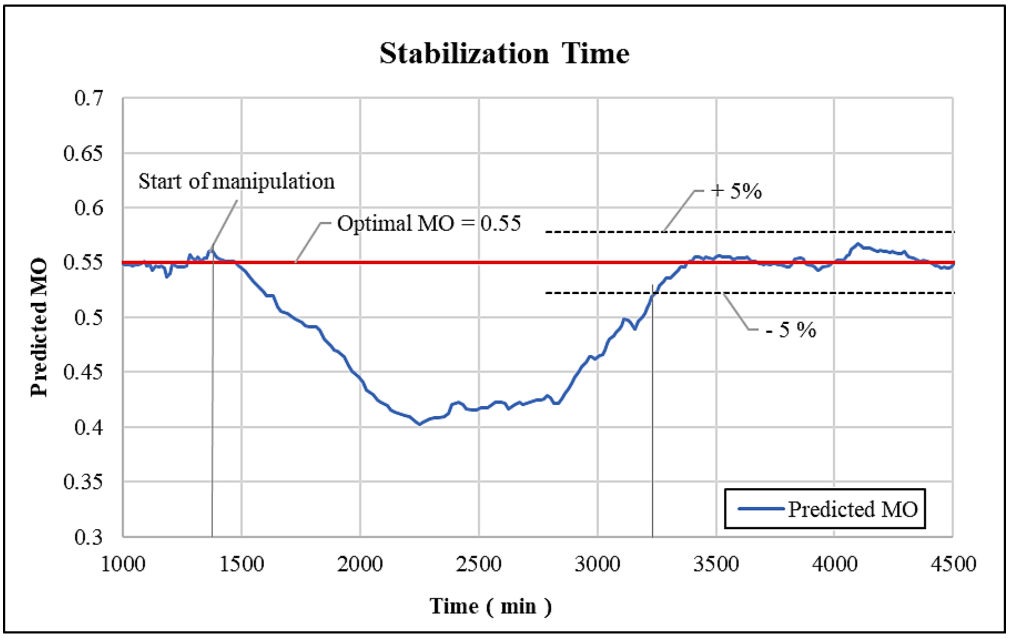


Figure 32: The Evaluation of Stabilization Time of the AI Control System

First, the stability of the system response with respect to the learning rate was investigated. In order to evaluate the stabilization time, a stimulus was applied by manipulating the incoming rate. The stimulus is applied after the system reaches a steady-state response (approximately after 12 hours of plant up-time). Then, the stimulus is applied by manipulating the incoming rate to a value outside of the optimal range (i.e. 17 min between incoming ladles). The stability of the system is observed until the system is brought back within ± 5% of its stability range. In this control system, the stability point is the optimal multi-objective function output (0.55). Figure 33 further explains the method of calculating the time to stabilization of this system.

It can be seen in Figure 33 that as the learning rate η increases, a better time response is achieved. This is because a higher momentum is used to steer the control system toward the desired range. With these results, it can be deduced that better performance is potentially feasible if the learning rate is tuned for optimal response. Further results of this analysis are tabulated below in Table 18.

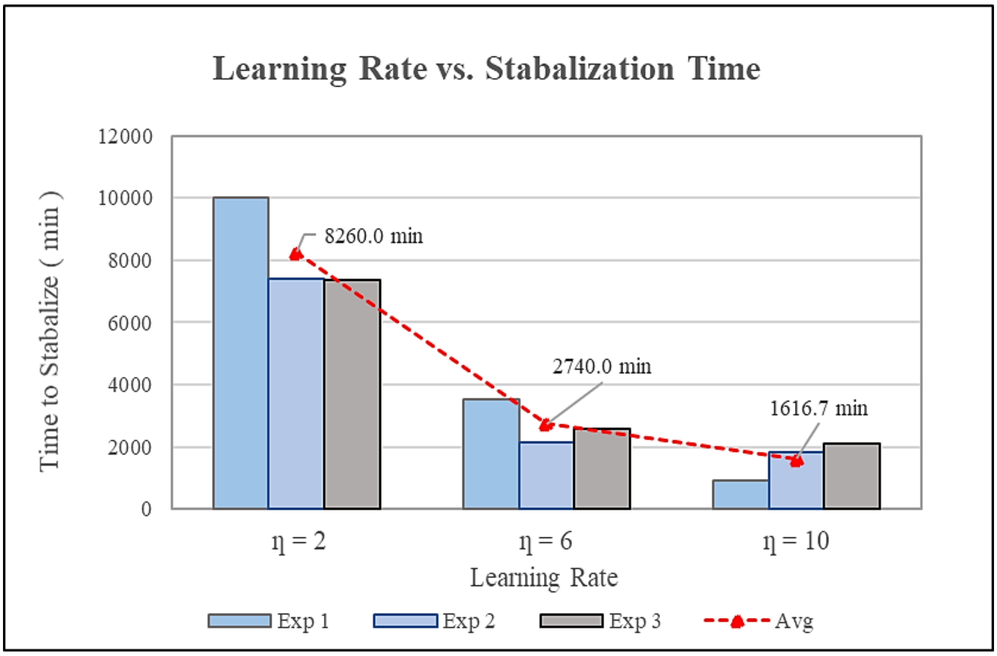


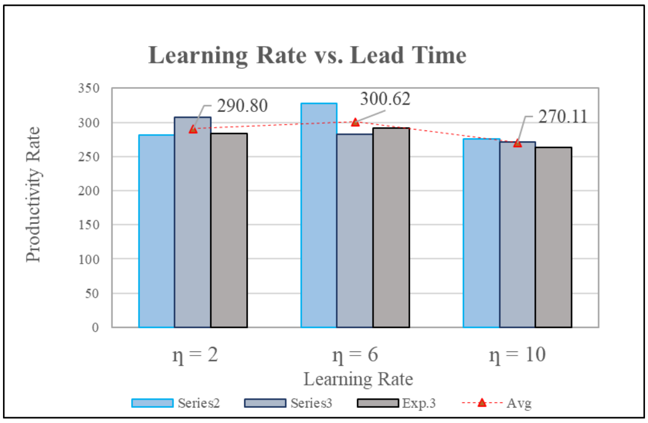
Figure 33: Sensitivity of the Learning Rate Parameter with Respect to the Stability of the AI Control System

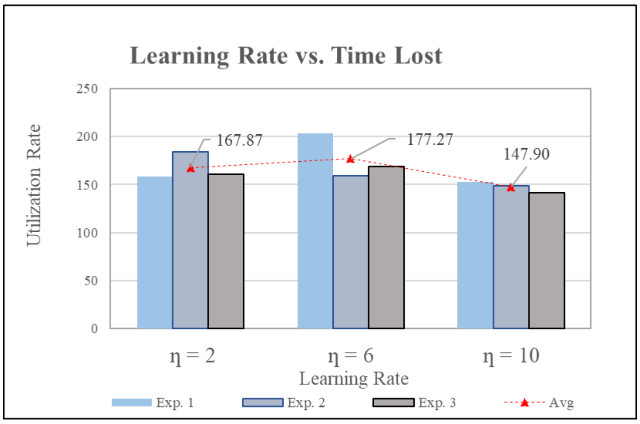
Furthermore, the impact of the learning rate η parameter on the KPIs of the manufacturing plant was investigated. Figure 34 present the steel plant KPI sensitivities with respect to the learning rate of the control system. Consistently, an improved performance is observed when the learning rate is increased.

Table 18: Steel Plant KPI Results of the AI Optimized Control Model with Respect to the Learning Rate η.

AI Optimized Control Model : Senstivity to Learning Rate η							
Learning Rate η		**η = 2**		**η = 6**		**η = 10**	
		Mean	Stdv.	Mean	Stdv.	Mean	Stdv.
Ladles In	unit	793.00	71.02	782.00	45.29	752.33	82.62
Ladles Out	unit	747.33	65.25	739.40	52.62	709.33	83.27
Ladle Output Rate	(min/ladle)	12.83	0.04	13.89	0.77	13.26	0.45
Total Steel Produced	(kg)	224014.21	19331.85	216925.15	10123.86	212786.61	24831.16
Average Production Rate	(kg/min)	22.31	1.85	21.56	1.02	21.47	2.62
Average Ladle Lead Time	(min)	290.80	14.21	278.92	6.30	270.11	5.94
Average Ladle Time Lost	(min)	167.87	14.33	155.94	5.89	147.90	5.65
Average Ladle Productivity	rate	0.50	0.03	0.51	0.01	0.52	0.00
Average Equipment Utilization	rate	0.70	0.06	0.69	0.04	0.65	0.08
Time to stabalize	(min)	8260.00	1507.02	2740.00	722.03	1616.67	627.80

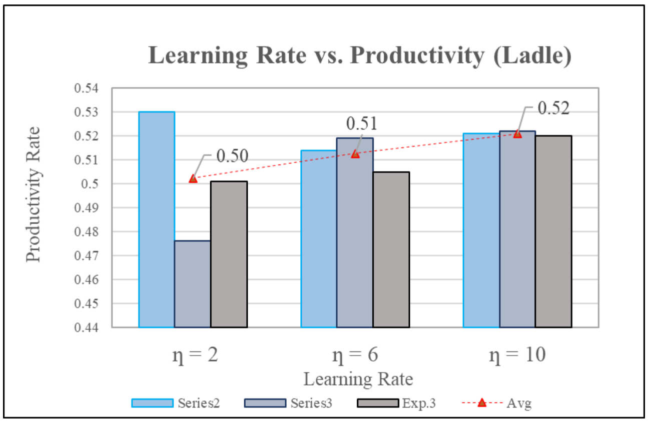
* Time to Stabilization calculated after parameter change (Incoming Rate = 17) to the time that the MO variable is stabilized within 5% of the optimal value (0.55)

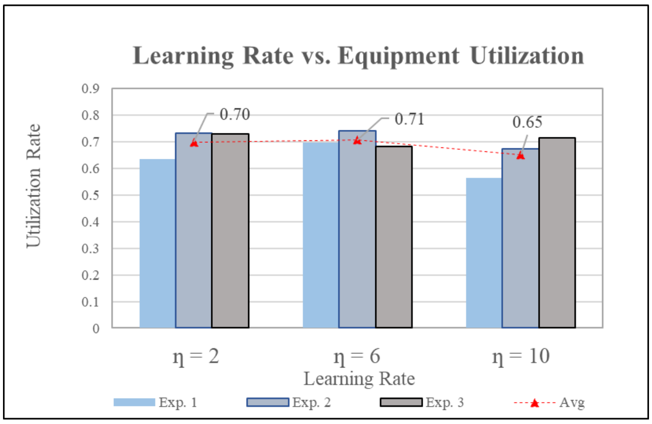




a) KPI #1 : Lead Time

b) KPI #2 :Time Lost





c) KPI #3 : Productivity Rate (Ladle)

d) KPI #4 : Utilization Rate(Equipment)

Figure 34: Steel Plant KPI Sensitivity to the Learning Rate

6 Environmental Impact

Digital Twins can be tools that guide the manufacturing industry towards better and more sustainable processes. For instance, the presented AI Optimization Control system could potentially increase resource efficiency, thus reducing costs and energy consumptions. The manufacturing KPIs used in the optimization function reflect the energy requirements and resource productivity of the manufacturing plant. By optimizing the process based on these KPI objectives, the process can be controlled to always run at the most energy-efficient state.

Implementing the AI Optimization Control system has associated risks of failure and breakdowns. It is important to consider that the control system may go into instability or fail to accurately represent the current state of the plant. In these failure scenarios, risk prevention and mitigation measures need to be implemented. For example, a disconnect switch is a risk mitigation measure that allows the controller to disengage the AI Optimization Control system if it fails. This risk mitigation approach was implemented in the AnyLogic simulation of the steel manufacturing plant using the OFF button to stop the automated control at any moment. Another risk mitigation system is the use of alarms which can go off in the event of system instability or deviation beyond the desired range. The potential environmental impact of a control system failure can be costly and detrimental to the safety of the system and its surroundings. Therefore, Digital Twin design of manufacturing plants must take these risks into consideration.

7 Discussion

The reliable use of Model Predictive Control (MPC) for optimizing manufacturing processes depends on the linearity of the model and the uncertainty level inherent to the system. For highly nonlinear models, such as batching processes, this control method is challenging to implement due to the nondeterministic nature of the system output. Additional research is required to develop effective automated control systems that can be reliable in controlling and optimizing uncertain manufacturing processes.

The development of an AI predictive control system based on Neural Networks was proposed in this research project. The AI prediction model was created based on synthetic data collected from the DT simulation of a steel manufacturing plant. The proposed methodology integrates the AI predictions with the simulation environment and achieves an optimal process control. The obtained results demonstrated an astounding improvement in performance by evaluating the KPIs related to the process. The proposed optimization method yields a better performance when compared to the benchmarked optimization methods (Deng et al, 2018).

The proposed AI based optimal control method improves the performance of the system and also achieves an automatic control that dynamically reacts to changes in the production plan. This method provides an alternative to manual control and optimization methods, and effectively minimizes interventions by human controllers. Furthermore, the dynamic control of the process reduces the variability in highly scattered KPIs as achieved by the implemented AI based optimal control system. This is an extremely desired improvement in the performance of manufacturing processes.

This research demonstrated how NN prediction models could be effectively applied to nonlinear, probabilistic systems such as manufacturing processes. However, the true reliability of NN prediction models in in real system is still in question. The NN model is highly sensitive to the quality and span of the data used to train the model. Therefore, more research and investigation are needed to identify the challenges of AI predictive control in real production environments.

There remains the challenge of online process optimization and real-time connections in DT applications. More case-studies are needed to test and validate data-driven synchronization and traceability. The feasibility and cost effectiveness of real-time solutions has been well documented in literature, however, there is a shortage of real-life applications that effectively deploy such systems in the manufacturing industry.

Future Work

- The AI Optimization Control presented in this work could be further developed for higher stability and control performance. Tuning the control parameters, such as the learning rate, can be further investigated. The analytical work presented herein demonstrated a high potential for better performance based on parameter tuning. Furthermore, more advanced control algorithms, such stochastic optimization algorithms, can be tested in this context.
- This research only focused on the overall system performance related to a steel manufacturing process. The same methodology can be applied to a smaller critical system. The methodology can be evaluated and specifically adapted for critical processes that have high economic and environmental impacts.
- In this case-study, a DES-based simulation model was considered. However, it is also possible to have agent-based or dynamic system simulations for manufacturing plants. More so, complex systems might call for a multi-method modeling approach. Therefore, further research can be dedicated to other DT simulation models to investigate the applicability of the AI Optimization Control method.
- Finally, real-life applications are needed to validate the concept of the AI based optimization control process. A feasibility study can be conducted to evaluate the applicability of this solution in a real production environment.

Conclusion

This research demonstrates the benefits of using Digital Twins for manufacturing process optimization. Complex manufacturing systems exhibit nonlinear and nondeterministic characteristics that make them challenging for implementing process control. This research present an AI based optimal control system that effectively addresses the issues of nonlinearity and uncertainties in these processes. Neural Network based predication models provide a robust tool for estimating the state of the manufacturing plant. In this research, the trained NN models demonstrated high prediction performance that could successfully be implemented as an AI based state observer for process control application.

A Digital Twin simulation of a steel manufacturing plant was used to implement the novel AI based optimal control system. This control system uses a multi-objective function relating the key performance parameters (KPIs) of the manufacturing process to dynamically adjust the production parameters. The results obtained for implementing the AI Optimization Control method proved to be outstanding with respect to the baseline model performance. The control system successfully achieves higher equipment utilization and higher process productivity. The dynamic control also reduces the high scatter that is inherent to naturally sporadic KPIs. The indicated improvement in KPIs lead to energy-cost savings and higher revenues for the manufacturing process.

In closing, the use of an AI based state observer for optimal process control of manufacturing plants has great potential for making progress in the manufacturing industry. The methodology proposed in this research should be further developed in the future, in order to bring forth digitalization and automation of manufacturing plants.

Economic Assessment

The economic assessment of this project consists of evaluating the budget allocated to finance and produce this work. The project was carried out over the course of 4 months, at the R&D facilities of Ikerlan. The company provided technical and financial support throughout the course of this research.

Given the financial support provided by Ikerlan, professional software licenses for MATLAB and AnyLogic were used. However, it is also possible to carry out this project using free software licenses available for academic research and development.

The project costs are summarized in the following Table 19.

Table 19: Project Economic Break-Down

Resource Requirements	Cost	Rate	Total Cost
Man-hours (intern rate)	6.25 €	/Hour	3,360.00 €
Equipment (Computer + Monitors)	1,500.00 €		1,500.00 €
Software			
MATLAB License	250.00 €	/ Year	85.00 €
AnyLogic Professional License	12,000.00 €	/ Year	4,000.00 €
Energy Consumption	50.00 €	/ Month	200. 00 €
Unexpected Costs (~ 10%)	1,000. 00 €		1,000. 00 €
		Total =	**10,145.00 €**

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Appendix I – Optimization Code (OptQuest)

```
try {
	// Create Engine, initialize random number generator:
	Engine engine = createEngine();

	engine.setStartTime( 0.0 );
	engine.setTimeUnit( MINUTE );
	engine.setStartDate( toDate( 2022, FEBRUARY, 28, 0, 0, 0 ) );
	engine.setStopDate( toDate( 2022, MARCH, 7, 0, 0, 0 ) );
	engine.setDefaultRandomGenerator(new java.util.Random());

	// Create optimization variable
	final COptQuestContinuousVariable v = new COptQuestContinuousVariable();
	v.SetLowerBound(8.0);
	v.SetUpperBound(22.0);

	// Create objective
	final COptQuestObjective obj = new COptQuestUserControlledObjective();
	obj.SetMaximize();

	// Create optimization engine
	final COptQuestOptimization opt =
ExperimentOptimization.createOptimization(engine, new OptimizationCallback() {

		@Override
		public void evaluate(COptQuestOptimization optimization,
				COptQuestSolution solution, Engine engine) {
			// Create new root object:
			MainPlant root = new MainPlant(engine, null, null);

			// Setup parameters of root object here
			root.Low_C_Steel = 85.0 ;


			root.setDefaultRandomGenerator(new java.util.Random());

			root.IncomingRate = solution.GetVariableValue(v);
			// Prepare Engine for simulation:
			engine.start( root );
			// Start simulation in fast mode:
			engine.runFast();
			// Process results of simulation here
			solution.SetObjectiveValue( obj, root.Objective );
			// Destroy the model:
			engine.stop();
		}

		// Trace each iteration (optional!)
		@Override
		public void monitorStatus(COptQuestOptimization optimization,
				COptQuestSolution solution, Engine engine) {
			try {
				traceln(String.format("  %3d : %6.2f : %8.2f  -- %8.2f",
					solution.GetIteration(), solution.GetVariableValue(v),
					solution.GetObjectiveValue(),
					optimization.GetBestSolution() != null ?
```

```
                                   optimization.GetBestSolution().GetObjectiveValue(obj) :
Double.NaN));
                    } catch (COptQuestException e) {
                          traceln(e.Description());
                    }
             }

      });

      // Setup optimization engine
      opt.AddVariable(v);
      opt.AddObjective(obj);
      // Set the number of iterations to run
      opt.SetMaximumIterations(150);

      // Add suggested solution (initial solution)
      COptQuestSolution suggestedSolution = opt.CreateSolution();
      suggestedSolution.SetVariableValue(v, 12.075);
      opt.AddSuggestedSolution(suggestedSolution);

      traceln(" Iter : Param  : Objective -- Best obj.");
      traceln("-------------------------------------------");
      // Perform optimization
      opt.Optimize();
      traceln("-------------------------------------------");

      // Output results
      COptQuestSolution bestSolution = opt.GetBestSolution();
      traceln("Best objective: " + format(bestSolution.GetObjectiveValue(obj)));
      traceln("   is feasible: " + format(bestSolution.IsFeasible()));
      traceln("Best parameter: " + format(bestSolution.GetVariableValue(v)));
      traceln("Best iteration: " + bestSolution.GetIteration());

      BestSolution = bestSolution.GetVariableValue(v) ;
      BestObjective = bestSolution.GetObjectiveValue(obj);
      BestIteration = bestSolution.GetIteration() ;


} catch (COptQuestException e) {
      traceln(e.Description());
}
```

Appendix II – Baseline Simulation Data Results

Table 20: Baseline Model Simulink Simulation Results

Simulink MATLAB Simulation Results								
		Run no. I	Run no. II	Run no. III	Run no. IV	Run no. V	Mean	Stdv.
Ladle Output Rate	(min/ladle)	17.93392857	17.65	17.99	17.52	17.47	**17.71**	**0.24**
DeP Utilization	rate	0.460	0.443	0.464	0.484	0.472	**0.465**	**0.02**
DeC Utilization	rate	0.528	0.533	0.533	0.504	0.513	**0.522**	**0.01**
RH Utilization	rate	0.514	0.555	0.515	0.490	0.503	**0.515**	**0.02**
LF Utilization	rate	0.628	0.584	0.566	0.581	0.603	**0.592**	**0.02**
CAS Utilization	rate	0.404	0.350	0.423	0.440	0.407	**0.405**	**0.03**
CCM Utilization	rate	0.638	0.639	0.640	0.637	0.640	**0.639**	**0.00**
All Equipment	rate	0.529	0.517	0.523	0.523	0.523	**0.523**	**0.00**

Table 21: Baseline Model AnyLogic Simulation Results

AnyLogic Simulation Results								
		Run no. I	Run no. II	Run no. III	Run no. IV	Run no. V	Mean	Stdv.
Ladle Output Rate	(min/ladle)	17.71	17.65	17.83	17.877	17.96	**17.81**	**0.13**
DeP Utilization	rate	0.484	0.413	0.486	0.473	0.450	**0.461**	**0.03**
DeC Utilization	rate	0.488	0.560	0.499	0.518	0.543	**0.522**	**0.03**
RH Utilization	rate	0.512	0.531	0.498	0.544	0.512	**0.519**	**0.02**
LF Utilization	rate	0.589	0.607	0.664	0.484	0.605	**0.590**	**0.07**
CAS Utilization	rate	0.406	0.419	0.362	0.394	0.419	**0.400**	**0.02**
CCM Utilization	rate	0.636	0.641	0.637	0.643	0.637	**0.639**	**0.00**
All Equipment	rate	0.519	0.529	0.524	0.509	0.528	**0.522**	**0.01**