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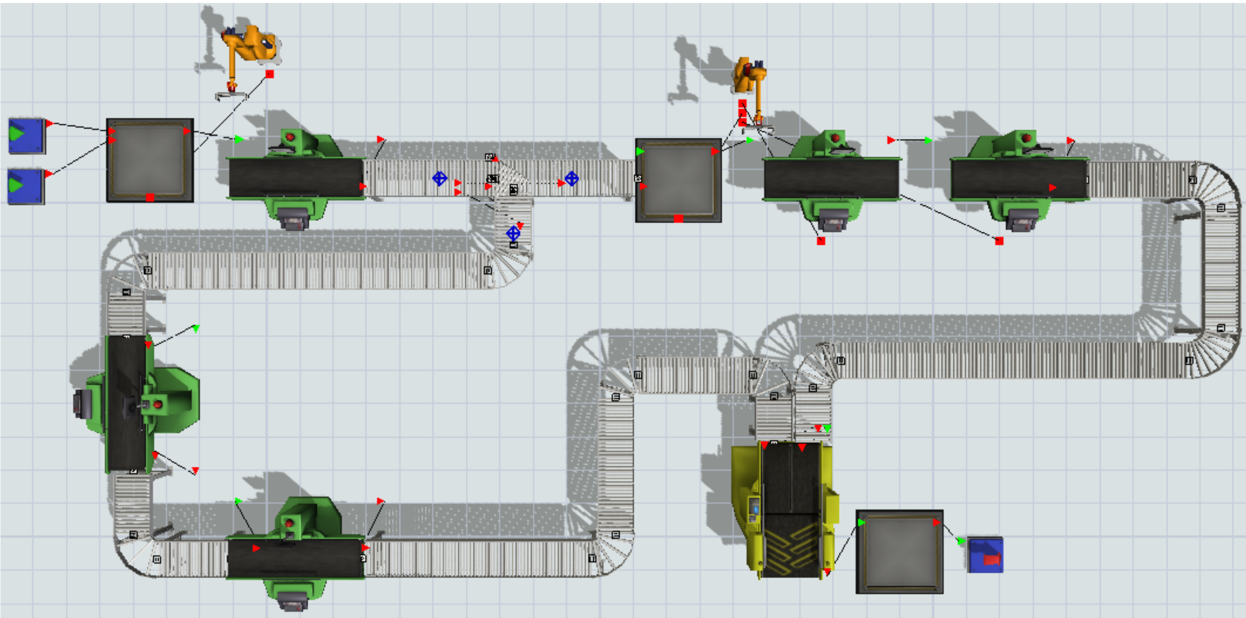

DYNAMIC CO_2 EMISSION EVALUATION

Application of Discrete Event Simulation (DES) for emission evaluation in a pump production line.

Master's thesis in Production Engineering

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# Abstract

As companies across the globe are transitioning towards net-zero manufacturing practices, applying smart data-driven solutions to the complex production systems is paramount. This thesis presents a Discrete Event Simulation (DES) based approach to quantify and reduce the CO_2 emissions for a process within the pump manufacturing line at Grundfos. Utilising DES, the study replicates the manufacturing line to study real-world operations needed for a complete product, capturing production specifications like resource utilisation, idle times and energy usage. This data is also used to calculate the CO_2 emissions from the line dynamically.

The model was developed using the DES software, FlexSim. The data used was validated against one day of previously recorded factory data and from the feedback from experts at Grundfos. Multiple scenarios were contemplated to evaluate their effects on CO_2 emission reduction. Results highlight the key inefficiencies of the current manufacturing setup and showcase how data-driven improvements can allow for a significant reduction in energy usage and emissions with consistent output.

Finally, the study supports Grundfos's sustainability goals and also facilitates a framework for integration of DES with sustainable manufacturing. The findings from the thesis lay the foundation of a shift towards smart production systems, committing to low carbon emissions, and demonstrating the power of DES.

Keywords:
Discrete Event Simulation (DES), Sustainable Manufacturing, CO_2 Emissions Assessment, Energy Consumption, Scope 2 emissions, CO_2 Intensity, Python, Scenario Analysis.

Acknowledgements

We want to thank all contributors and stakeholders for their valuable contributions towards the completion of this thesis. We would also like to thank our industrial supervisor and Grundfos Holdings for their special efforts and for facilitating the opportunity to apply advanced tools to tackle modern day industrial problems. Finally, we would like to thank our supervisor and examiner at Chalmers University of Technology for their guidance and understanding.

Lateef Afolabi Oladosu and Parth Prasad Paranjpe, Gothenburg, June 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis.

AGV	Automated Guided Vehicle
AI	Artificial Intelligence
API	Application Programming Interface
CO_2	Carbon Di-oxide
DES	Discrete Event Simulation
EMS	Energy Management Systems
ERP	Enterprise resource planning
EPE	Embodied Product Energy
ESM	Energy Simulation Model
EU	European Union
GDM	Generic Data Management
GHG	Green House Gasses
IOT	Internet Of Things
KPI	Key Performance Indicator
KWh	Kilo Watt hour
LCA	Life Cycle Assessment
MCDA	Multi-criteria decision analysis
MTBF	Mean Time Before Failure
MTTR	Mean Time To Repair
OEE	Overall Equipment Effectiveness
RCA	Root Cause Analysis
UN	United nations
WIP	Work In Progress

Nomenclature

Below is the nomenclature of variables that have been used throughout this thesis.

Variables

$CO2_{\text{base}}$	Base model CO_2 emissions base model
$CO2_{\text{pt}}$	CO_2 emissions per part
$CO2_{\text{scn}}$	CO_2 emissions from scenario
$CO2_{\text{scn}}$ avg	Average CO_2 emissions from scenario
$CO2_{\text{d}}$ %	CO_2 emissions difference %
$CO2_{\text{gd}}$	Grid CO_2 emissions
E_{base}	Base model energy
E_{pt}	Energy per part
E_{scn}	Energy from scenario
E_{scn} avg	Average energy from scenario
E_{d} %	Energy difference %
E_{busy}	Energy busy
E_{idle}	Energy idle
I_{base} %	Base idle time
I_{bat} %	Batching idle time
I_{d} %	Change in idle time
TP_{base}	Throughput base
TP_{scn}	Throughput scenario

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1 Disclaimer

The data used throughout this thesis were normalised to protect sensitive company information owned by Grundfos Holdings A/S.

2
Introduction

The first chapter introduces the background, thesis topic, and the structure of the thesis.

2.1 Background

The first industrial revolution began in the 1830s. Following the revolution, humans rapidly began using resources from various environmental sources and converting them into products (Shekhawat, Juyal, & Rathore, 2023). This marked a significant shift in the pace of production. The industrial revolution gave birth to mass production, which was the need of the present. However, with its benefits came dire consequences for the environment. The effects of emissions were not observed and contemplated until the late 19th century. The increase in the demand for raw materials like coal, iron, and wood resulted in deforestation, mining, and the utilisation of resources on a massive scale. The burning of wood and coal resulted in the release of vast amounts of carbon dioxide (CO_2) and various other pollutants into the environment, which laid the pathway for chronic degradation and harm to the environment (Agnoletti & Neri Serneri, 2014; Shekhawat et al., 2023)

By the late 19th and early 20th century, these effects on the environment became explicit. The accelerated use of fossil fuels and natural resources in the 2nd industrial Revolution increased greenhouse gas emissions exponentially, raising global temperatures. Alongside rising temperatures, the effects of climate change were observed, which had the capability of causing damage to the planet and the ecosystem (Anderson, 2024; Saxena, 2025). The depletion of resources caused an imbalance in environmental well-being. Technological advancements brought us efficiency and economic growth worldwide, but also contributed to growing carbon emissions (Anderson, 2024).

In modern times, the effects of industrialisation are still looming. After the third and fourth industrial revolutions, with the addition of new and advanced technologies, industries are still contributing to carbon emissions on a large scale. Today, amidst technological progress and environmental challenges, it is paramount to reduce the effects of carbon emissions and to transition to a carbon-neutral state to mitigate damage caused to the environment (Skilton & Hovsepian, 2018).

As the world faces the overwhelming challenges of climate change head-on, every sector and industry is under increased pressure to address their environmental issues. The manufacturing industry, being the pioneer of the world's economic and infrastructural development, is also one of the major contributors to Greenhouse Gas Emissions (GHG), bringing significant implications for the environment (Panagiotopoulou, Stavropoulos, & Chryssolouris, 2022). The reduction and reversal of environmental damage from these industries require promising initiatives and concrete efforts from the global community that are implemented at the right time to gain success in such endeavours(Issa & In'airat, 2024).

A complete understanding of the causes and sources of emissions at every significant step of the production process is crucial to achieving these goals. The traditional methods often fail to address the ever-changing and dynamic manufacturing processes (Wang, Zhang, Zhang, & Wang, 2015). To address this issue, advanced tools like Discrete Event Simulation (DES) can be integrated to obtain accurate results. DES models the manufacturing system in a sequential format, which allows for the observation and analysis of the manufacturing setup, which ultimately helps to optimise the process flow and utilise the resource usage (Goti, 2010). Approaching these problems with the DES provides a dynamic solution to study and improve production systems (Huynh, Akhtar, & Li, 2020).

Presently, the Nordics show the results of concrete efforts towards achieving the globally desired carbon neutrality goals. As of 2022, 78% of electricity in the Nordic countries is free from fossil fuels(Norden, 2022). Promising projects further into sustainability and renewable clean green energy strengthen the energy infrastructure. However, from the Figure 2.1, it can be observed that further efforts are still expected to attain the desired environmental targets in the announced timelines (Klaus Skytte, 2025; Stengel, 2025).

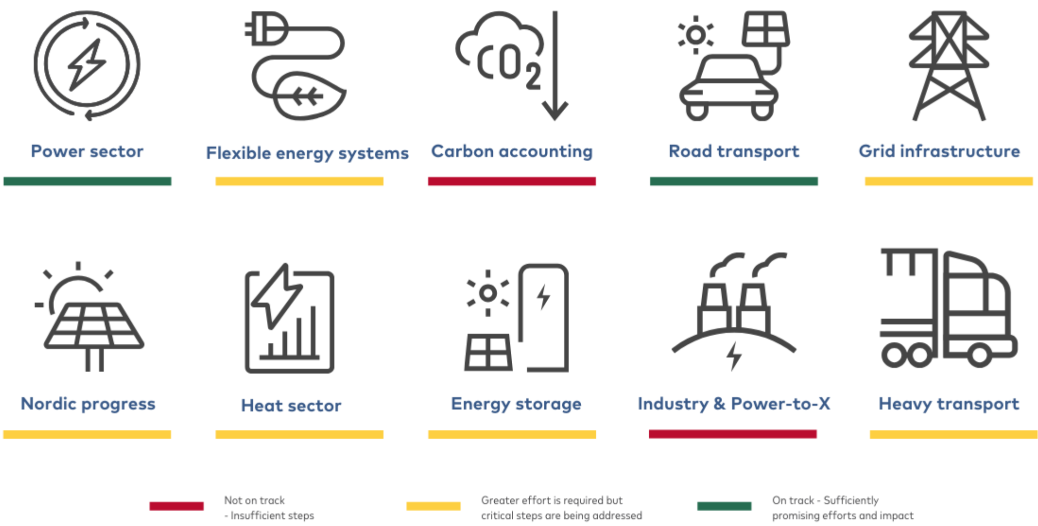

Figure 2.1: Progress of Nordic countries towards net zero emission goals (Stengel, 2025)

On the global scale, in recent times, the net-zero emission mission has gained momentum. The set targets now represent about 88% of the total global greenhouse gas emissions. The UN has highlighted the urgency to reduce emissions by 45% by 2030 and to achieve net-zero emissions by 2050, which would limit the rise in global temperature to only 1.5°C above pre-industrial levels (United Nations, 2024). The current climate plans are insufficient, indicating the need to develop promising plans that align with these goals.

2.2 Purpose

This thesis is aligned towards the application of DES to a process within pump manufacturing. The aim is to develop a simulation model which accurately represents the selected production process and to quantify the CO_2 emissions caused by the production of a pump, identifying the major contributors to the emissions. The simulation model will be used as a tool to explore various strategies targeted towards emission reduction. These strategies include process optimisation, enforcing energy-efficient equipment, and emphasising the use of green and renewable energy sources.

Grundfos, a Denmark-based company, is the world's largest pump manufacturing company. The company has committed to reducing the environmental impact caused by their various operations, setting the target to reduce their scope 1 and 2 greenhouse gas emissions by 50% and the scope 3 emissions by 30% by the year 2030. Grundfos has set the aim to achieve net zero carbon emissions by 2050 (Grundfos, 2025). These visions from Grundfos align with the climate strategies and targets of the European Union (EU) commission, the European climate law, and the European Green Deal (Grundfos, 2025) (Directorate-General for Climate Action (European Commission), 2019). The results of this thesis will assist Grundfos in achieving the set sustainability goals discussed earlier and in developing sustainable production processes (Grundfos, 2025).

In the advanced world where environmental conservation has become crucial, the use of modern and comprehensive tools such as DES serves as a progressive and advanced technique for achieving sustainable standards. Using this methodology, companies can make changes in their process that help to balance both economic growth and environmental well-being. This thesis project explores how these strategies can lay the foundation for a net-zero emission future. This thesis explains how such integrative strategies can drive meaningful progress towards a sustainable, net-zero future in the production sector.

2.3 Aim

The primary aim of this thesis is to develop a DES model capable of accurately representing the complete selected production process. The model will be used to dynamically identify and assess the significant sources of emissions, ultimately providing suggestions to lower them. The insights gained from the results of this study will help in exploring and implementing production solutions and strategies which will assist Grundfos in achieving the net-zero emission goals envisioned by 2050. On a broader scale, the thesis also aims to contribute to the global sustainability movement by showcasing the benefits of digital tools like DES in optimising production processes and achieving sustainable operational strategies.

2.4 Research Questions

Listed below are the research questions curated to address the aims and objectives of the study:

1. How can Discrete Event Simulation (DES) be used to dynamically identify and quantify CO_2 hotspots in the selected production line at Grundfos?
2. What are the scenario-based strategies for reducing CO_2 and how much impact they have on the most important KPIs of the system?
3. To what extent does integrating Python with FlexSim improve the precision, real-time responsiveness, and optimisation capabilities of discrete event simulation models for assessing and reducing production-related CO_2 emissions?

2.5 Delimitations

Towards the realisation of this thesis project, the following are the identified delimitations of the study:

- The study will focus on scope 2 emissions (gate-to-gate) related to direct energy use in the selected production line.
- The modelling of the production line will consider processes only as a means to spend the process time, and does not perform the actual processes.
- The simulation will be validated against one-day production data, to ensure realistic energy consumption and emission outputs.
- The CO_2 intensity factor used for emission calculation is assumed to be varying only throughout the day. Seasonal intensity variations are not considered.

These delimitations are required to ensure a focused, clear and achievable research scope while identifying areas for future investigations in real-time emissions tracking for sustainable production.

2.6 Outline of the Thesis

This project report is structured to follow a logical progression from problem identification to solution development and evaluation. Chapter 1 presents the background, the current global standing and efforts towards emission reduction, along with the importance of this thesis. Chapter 2 reviews existing literature and theories on sustainable production, future trends and drivers, DES and its significance on energy consumption and emissions modelling, FlexSim-Python Integration, Data Management in DES. Chapter 3 outlines the research design, data collection methods, and simulation modelling framework. Chapter 4 presents the simulation results along with an exploration of various possible strategies for emission reduction. Chapter 5 discusses the interpretation of results and provides recommendations to implement the strategies to lower the emission levels. Chapter 6 is the final chapter summarising key findings and highlighting research contributions.

3
Theoretical background

This second chapter delves into sustainable production, the potential sustainable business practices drivers and DES simulation.

3.1 Sustainable Production

3.1.1 History of sustainability and sustainable production

The concept of sustainability has been around for centuries in some form. Since the industrial revolution, the extent of sustainability has risen due to the extensive use of resources and adverse effects on the environment, ultimately triggering concerns about its impacts on the environment in the long run. Earliest efforts in sustainability were made by the late 19th and early 20th century on account of forest and wildlife conservation, but it gained special attention much later. The mid-20th century was the epicentre of major environmental movements, which led to significant events like the UN conference at Stockholm in 1972, which emphasised the need to ensure the balance of conservation and protection of the environment while achieving industrial growth (Canan, 2023).

The significant shift towards sustainable production gained momentum when industries recognised the benefits of reducing environmental harm. This recognition paved the way for strict environmental policies like targets to reduce emissions and sustainability commitments. Over time, concepts like Life Cycle Assessment (LCA) , circular economy, carbon neutrality and energy efficiency gained shape and provided guidelines for reducing their carbon footprint. Now, sustainability and sustainable production are hot topics for companies which are driven by rising climate change consequences, advanced technological requirements, and the global goal of achieving carbon neutrality (Despeisse, Mbaye, Ball, & Levers, 2012).

3.1.2 Sustainable Production Drivers

Sustainable production is about creating products with minimal environmental, social or economic impact, ensuring service viability (Garetti & Taisch, 2012). There are numerous drivers, including strict regulations, consumer expectations for eco-friendly products and efficiency. Furthermore, advanced technologies like Artificial Intelligence (AI), Internet of Things (IoT), and simulations help to improve production processes and reduce resource wastage (Li, Lu, Zhang, & Tanasescu, 2025).

The circular economy is a major driver where products are designed to be recycled and reused while pushing for reduced materials usage. Rising pressure for public sustainability reports pushes companies to shift to greener and cleaner production. Global collaboration and research in new sustainable materials that also contribute better to sustainable production (Trevisan, Boscarato, Acerbi, Terzi, & Sassanelli, 2025) (Moktadir, Rahman, Rahman, Ali, & Paul, 2018).

Various circular economy principles can also be utilised, such as remanufacture, reuse, and recycling of materials, to reduce the emissions potential significantly by reducing the need for new resources. Eco-friendly logistics, like electric and hydrogen vehicles and efficient supply chains, can lower emissions across the whole value chain of production. Afforestation programs or investments in green technologies can help compensate for unavoidable emissions (Bressanelli & Saccani, 2025).

The government plays a major role in driving sustainable production by establishing a legal framework which makes companies reduce the environmental impact of their operations. These laws and regulations include adhering to standards for emissions, waste disposal rules and resource conservation standards, which help to reduce pollution and promote energy efficiency (Genossar, 2024). Often, governments provide incentives like tax benefits and subsidies for companies which adopt these practices and show compliance with the policies. Regulations like carbon pricing encourage companies to comply with the standards. These rules and regulations encourage companies to shift to an approach which is aligned towards sustainability (Genossar, 2024).

Emission reduction strategies include various techniques that minimise energy consumption, the carbon footprint and the environmental impact. Energy efficiency is a major factor. Companies invest in advanced machines and optimised production processes, and smart manufacturing technology to reduce energy wastage. Using renewable energy like solar and wind helps to reduce dependence on fossil fuels. These energy sources are entirely emission-free, cutting greenhouse gas emissions (Afonso, 2024).

Process optimisation can be applied to various industries with approaches like lean manufacturing, increased automation and real-time process monitoring to reduce inefficiencies throughout the process, leading to lower emissions. Using recycled materials helps reduce environmental impact due to material extraction. Carbon capture can be applied to reduce emissions from entering the atmosphere (Output Industries Limited, 2024).

Industry 4.0, AI optimisation, digital twins, smart factories, IoT will be the factors that drive the future of sustainable production. Integration of IoT and automation, and real-time data analytics, enhances the efficiency of production systems. AI can be used to optimise energy usage and predictive maintenance. Digital twins allow for real-time simulation, reducing wastage and improving production system design. Smart factories use these technologies to improve operational efficiency and minimise resource consumption (Leng et al., 2021) (Jamwal, Agrawal, Sharma, & Giallanza, 2021)

3.2 Discrete Event Simulation (DES)

3.2.1 Introduction to DES and Its Role in Decision-Making

Given the environmental challenges outlined in Chapter 2, industries must adopt advanced decision-support tools like DES in conjunction with Industry 4.0 technologies to strengthen sustainability efforts. Discrete Event Simulation (DES) has emerged as a vital decision-support tool, providing a systematic approach to modelling, analysing, and optimising production processes (Babulak & Wang, 2008).
Ingalls (2011) described the power of DES in its ability to replicate the dynamics of a real system. A more comprehensive simulation definition was also presented in the paper, where it is described as "the process of designing a dynamic model of an actual dynamic system for either understanding the behaviour of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system" (Ingalls, 2011). By simulating discrete events within a system, DES enables manufacturers to explore different operational scenarios, optimise resource utilisation, and reduce environmental impacts such as CO_2 emissions.

3.2.2 Overview of Discrete Event Simulation

As a decision support tool, it could be applied at different production phases e.g; product/system/operation or during operation for the critical evaluation to achieve optimal solutions to reduce the capital and investment waste (Heilala et al., 2008). DES enables researchers and industry professionals to simulate discrete changes in a system over time, allowing for the analysis of system performance, resource allocation, and environmental impacts. It is one of the best methods to pinpoint problems in the system and try different means (scenarios) like resource utilisation, labour and machine scheduling, throughput under average and peak load until the desired system is achieved without incurring production waste and investment loss (Heilala et al., 2008).

DES structure that comprises entities, resources, events, global variables, random number generators, calendar, statistics collectors, and systems state variables was comprehensively discussed in (Ingalls, 2011). DES as a tool or in combination with other systems like VSM of lean manufacturing are used in the identification and reduction of production wastes (Heilala et al., 2008).

Heilala et al. (2008) presented a project called SIMTER that combines environmental impact analysis with DES. It was designed to support decision-making by combining data and models to identify and solve problems within production systems and promote sustainable production. Though the project has not been successfully executed, it is expected to be of great importance in sustainable production, where environmental impact will be assessed (LCA) in combination with DES.

Ito, Ylipää, Skoogh, and Gullander (2021) In their paper considered production disturbances as an undesired and unplanned event that causes the production not to perform as planned. It was confirmed that 50% Overall Equipment Effectiveness (OEE) is lost to production disturbances, which also have a negative effect on environmental and social parts of sustainability, with a significant impact on financial performance (Ylipää, Skoogh, Bokrantz, & Gopalakrishnan, 2017). A six-stage production disturbance method was established, where Industry 4.0 happens to be the backbone. The simulation method as part of Industry 4.0 was identified as part of the supporting technology for the prevention and mitigation stages (Ito et al., 2021).

3.2.3 Advantages of DES in Decision-Making

1. The power to accurately replicate complex systems: DES enables dynamic modelling of production processes in simulation (Ingalls, 2011).
2. Scenario analysis: The ability to imitate real real-life production system makes it possible to try alternative strategies to achieve emission reduction(Zhou, Wang, & Ma, 2024)
3. Resource optimisation: With DES, inefficiencies in energy consumption and machine utilisation can be identified and improved. Like bottlenecks identification and RCA in production disturbance reduction (Ito et al., 2021).
4. Experimentation without disturbing the real production systems: DES are carried out in parallel with production, with little to no disturbance to the production processes (Babulak & Wang, 2008) (Heilala et al., 2008).
5. Cost savings: High financial performance through cost savings and an optimised system can be achieved through DES. Reduction of disturbances and elimination of trial by error that causes production waste are some clear means to achieving this (Ylipää et al., 2017).

Table 3.1: Comparative Review of Selected Studies Using DES for Emissions Evaluation

Author and Year	Sector	Methodology	Contribution	Identified Gaps	How This Study Adds Value
Zhang (2015)	Construction	DES	Estimated emission using load factors during the earthwork activities	Lacked dynamic optimisation: not factory-focused	This study adopted Python-flexsim dynamic optimisation in a factory-focused context.
Oliveira et al.2025	Steel Plant	JaaSim(Open Source)	Used station additions to evaluate energy and productivity gains	Fully focused on energy, not direct CO_2 quantification	This study focused mainly on CO_2 emissions and dynamic multi-scenarios simulation
Hong and Lü (2022)	Construction	DES+IoT data	Used IoT-based real-time energy readings to improve accuracy	Outside manufacturing context	Applies IoT data integration and automation to discrete manufacturing settings
Seow et al. (2013)	Manufacturing	ESM + DES	Categorised energy into direct/indirect, integrated with EMS	Limited to static energy categorisation	This study worked with dynamic emission modelling and scenario evaluation
Borbolla et al.2024	Manufacturing	DES+Python	Scenrios-based analysis of emissions in stamping processes	No optimsation	Extends to multi-machines, energy scenarios and process redesign

3.2.4 DES for Energy Consumption and Emissions Modelling

The pursuit of net-zero emissions through different emissions reduction methods can be highly effective and impactful, with a correct emission calculation and evaluation. (Zhang, 2015) highlighted the inability to integrate uncertainties affects the credibility of emission evaluation results. DES was presented as a solution to achieve high credibility in emission calculations to support the emission reduction decision in construction processes. One of the main aims of the (Zhang, 2015) is to use the DES modelling method to achieve an easy and economical emission-evaluation plan by removing the gap between emissions and emission-reduction methods and addressing the current approach of emission-evaluation for construction processes. Four cases of load factors were considered in the DES emission-evaluation methods, and 200 simulation runs were carried out for each case to achieve 95% confidence interval. The result was able to identify the activities that generated the highest emissions (hauling, digging and returning) and suggested emission reduction plan should be focused on those areas for an impactful effort(Zhang, 2015).

Another research work by (Seow et al., 2013) presented how simulation can be used in achieving energy efficiency, emission-reduction and high economic performance by understanding parameters that contribute to high energy consumption in the production of a product. The ability of DES to capture dynamics of a system and options for "what-if" scenarios analysis gave it an edge over energy consumption analytical and evaluation tools like LCA and Energy Management Systems (EMS), which are static (Seow et al., 2013). The paper adopted the Embodied Product Energy (EPE) framework for its energy simulation model by summing up direct and indirect energy. The Figure 3.1 further simplified the ESM and simulation model process flow and their components.

The Table 3.1 compares past studies that have demonstrated the viability and capability of DES in evaluating emissions within various domains. Most of these studies typically lacked dynamic optimisation integration or direct application to a complex line like the pump production line. This thesis project addresses most of the gaps highlighted in the table by implementing a FlexSim-Python integrated DES model for energy use, CO_2 quantification and emission-reduction strategy evaluation in a pump production context.

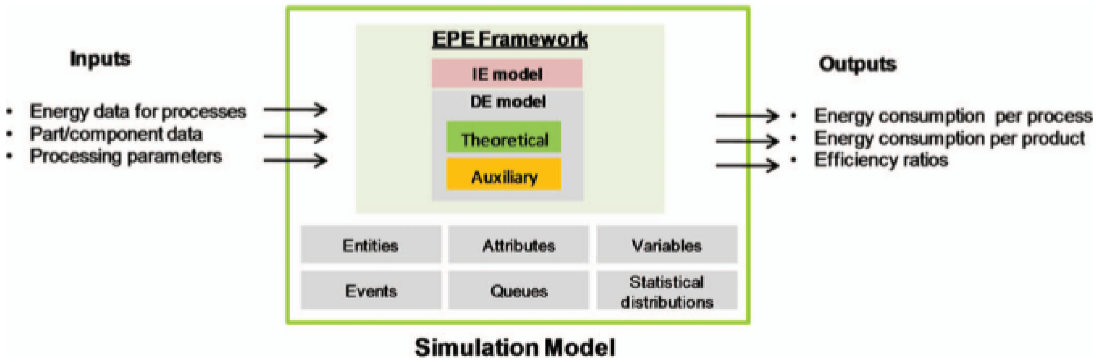

Figure 3.1: Inputs and outputs energy categorisation for Energy Simulation Model (Seow et al., 2013)

3.2.5 Data Management in DES

DES is highly dependent on data, not just data, but quality and reliable data to achieve high accuracy in results and performance. To achieve the desired results in this project, there must be high consistency in data input. A study carried out by (Skoogh & Johansson, 2008) shows 31% of simulation modelling time is used on data input. To reduce this time and improve the quality of data input, (Skoogh & Johansson, 2008) proposed a methodology to improve credibility and reduce the time of input data management. The input data management includes quality data preparation, simulation-adapted data, identification of relevant data input, collection of and transformation of raw data for simulation modelling and documentation of data for future re-use. Figure 3.2 illustrates the method in which high accuracy and speed could be achieved through the input data management methodology(Skoogh & Johansson, 2008).

In further research on input data management, Skoogh et al. (2012)suggested a solution that took away total reliance of simulation models on data from Enterprise Resource Planning (ERP). Sometimes, the input data needed for modelling might

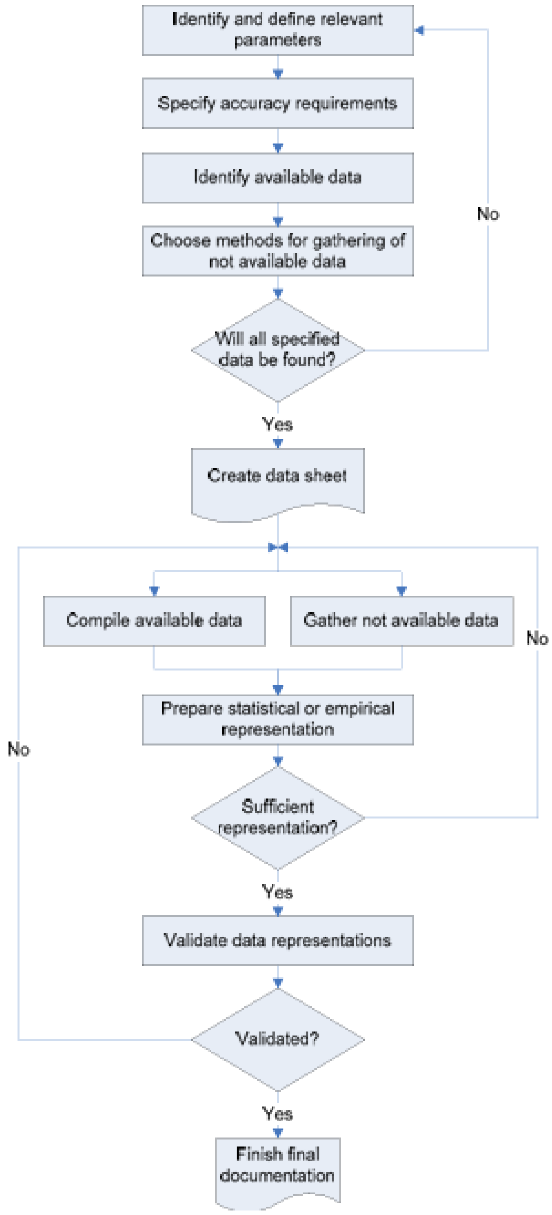

Figure 3.2: Proposed methodology for increased precision and rapidity in input data management (Skoogh & Johansson, 2008)

not be fully captured by ERP, and manual input will be needed to complement it. This takes time and needs to be solved. This solution was achieved through a software solution called Generic Data Management Tool (GDM-Tool)(Skoogh et al., 2012), see Figure 3.3. It automates raw data extraction from different sources, transforms to a usable format for different simulation software. Data goes through some processes before becoming useful for simulation models (contextualisation, categorisation, correction, calculation, and condensation)(Skoogh et al., 2012). For ease of use and applicability of the software for different modelling software, a standardised data presentation format for the simulation model called CMSD was developed in 2010 to achieve smooth automated data handling. The results from the conventional data input management and GDM-Tool show a significant 78% time reduction from the conventional method. This is a great improvement in the simulation field(Skoogh et al., 2012).

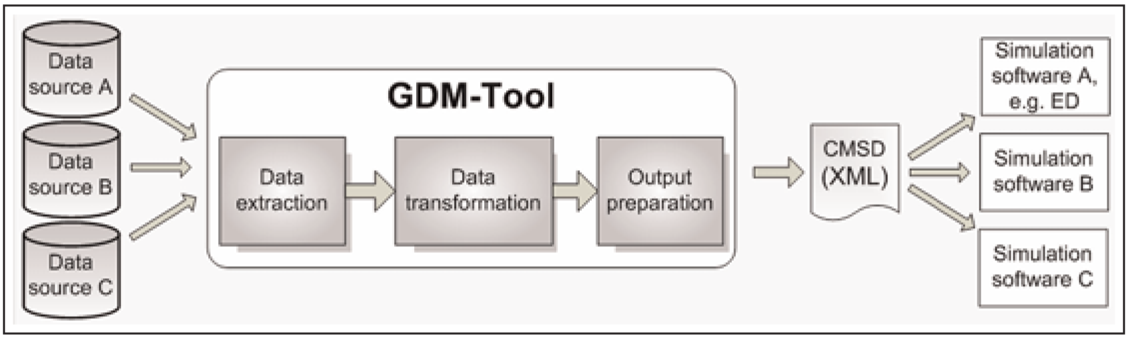

Figure 3.3: Schematic illustration of data management process using a Generic Data Management Tool (GDM-Tool) (Skoogh et al., 2012)

3.2.6 Verification and Validation in DES

As a decision-making support and problem-solving tool, simulation is expected to exhibit some specific degree of accuracy in its results while replicating the real-world system. This can be achieved through verification and validation as discussed in the simulation conference paper by (Robert G. Sargent, 2010). To verify the simulation validity, the paper (Robert G. Sargent, 2010) discussed four approaches, which include:

1. Scoring model
2. Independent verification and validation
3. Model user validity
4. Model developer validity

In the Figure 3.4 below, Robert G. Sargent (2010) presented a modelling process that shows how verification and validation are carried out in the simulation process, in a very simplified way.

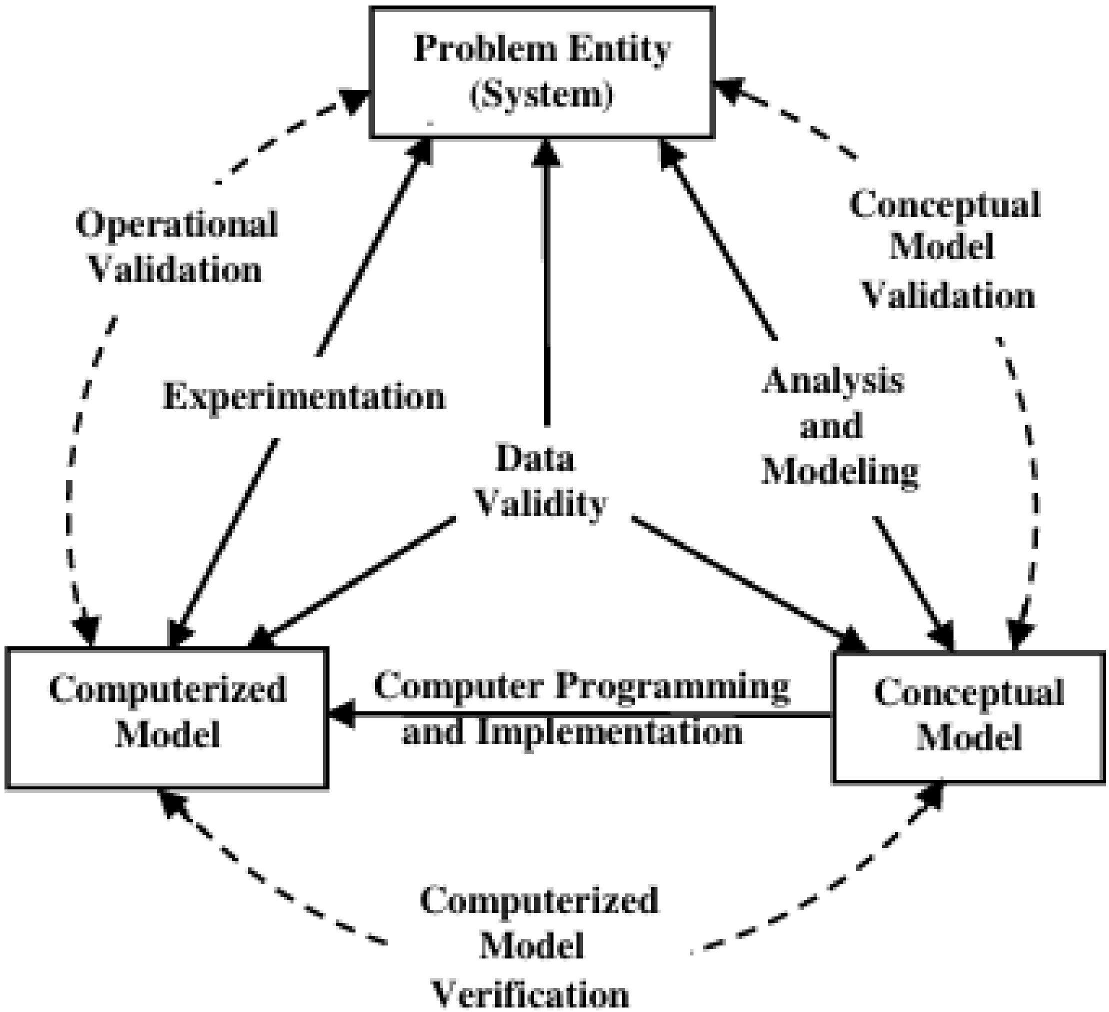

Figure 3.4: A Simplified Version of the Modelling Process (Robert G. Sargent, 2010)

For the modelling validation, different techniques were discussed, like animation, comparison to other models, degenerate tests, event validity, extreme condition tests, face validity, historical data validation and Turing tests (Robert G. Sargent, 2010). Computerised model verification is the process to ensure that both the conceptual model and the computer models are correct. On the other hand, conceptual model validation is about ensuring that theories and assumptions underlying the conceptual model are correct and a reasonable model representation of the problem entity and structure are for the intended purpose of the model (Robert G. Sargent, 2010).

For the selected production line, validation will be performed by comparing DES outputs with real-time energy consumption and emissions data from Grundfos's production facilities.

3.2.7 Scenario Analysis for Net-Zero Manufacturing

3.2.7.1 Evaluating Carbon Reduction Strategies

The capability of DES to capture the dynamics of a system and integrate it into the external environment for modelling, making it suitable for emission evaluation and reduction strategies (Seow et al., 2013). Using DES scenario analysis, different net-zero emission strategies will be assessed.

1. Machine upgrade: simulation of energy-efficient machinery to quantify CO_2 reductions.
2. Optimised scheduling: using the insight from the energy consumption to plan production, like adjusting machine schedules to minimise peak energy demands and emissions
3. Process Reorganisation: evaluating the impact of altering workflows to enhance energy efficiency and reduce carbon footprints

3.2.7.2 Research Findings on Scenario Analysis for Energy and Emission Reduction

1. Bottlenecks detection: Production disturbances are known to have a significant impact on energy consumption and emission in production systems (Ito et al., 2021). Different scenarios can be simulated to identify bottlenecks for improvement actions and optimisation.
2. Optimised scheduling: with the option to use various "what if" scenarios, the Energy Simulation Model can be used for improvement and optimisation in energy efficiency for production application (Seow et al., 2013). This is possible when the production planners and engineers understand various "what-if" scenarios to plan production operations accordingly. This method was also used in achieving 8.1% GHG emissions reduction (Hong & Lü, 2022).
3. Process optimisation: bottlenecks removal by addition of new testing stations and increase of utilisations of key machines in a DES project of a steel plant led to 87% production increase, 38.2% total energy savings and 71.2 metric tons of CO_2 emission avoided (Oliveira et al., 2025).

4

Methods

This chapter discusses the method used for DES modelling and emission assessment

4.1 Research Design

In 2022, Grundfos became the first company in the water solutions sector to receive validation from the Science-Based Targets Initiative organisation for its 2050 net-zero emissions target. To address carbon emissions, Grundfos is focusing on enhancing product efficiency and durability, exploring alternative business models, increasing renewable energy usage, and collaborating with suppliers to solve sustainability problems. The company is making special efforts to integrate the circular economy into its principles to shift its business model to reduce emissions. These initiatives are part of Grundfos's strategy to lead the sector in terms of sustainability (Grundfos, 2025).

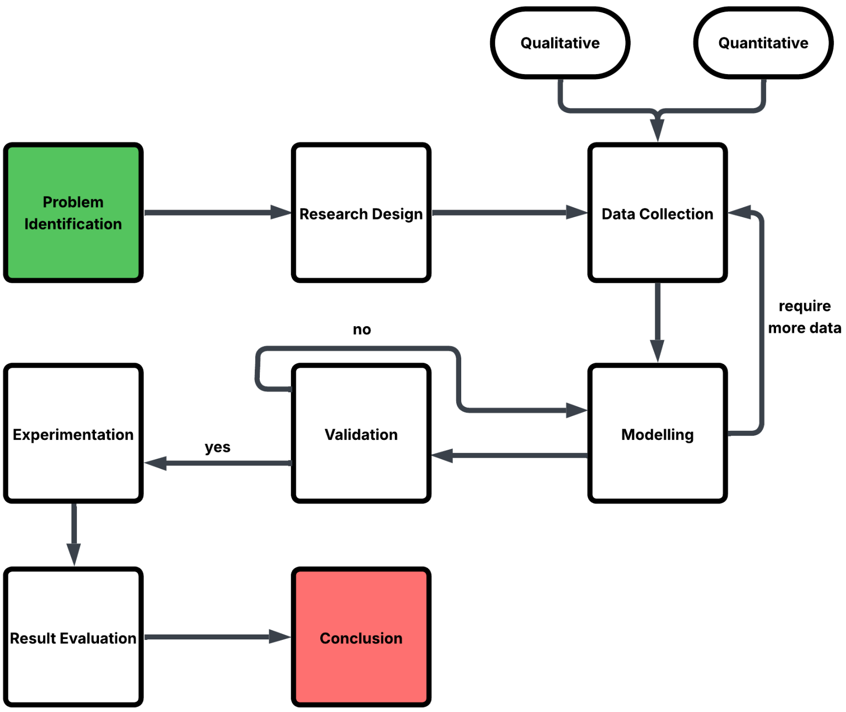

Figure 4.1: Research methodology flow with project milestones

The Figure 4.1, depicts the approach towards conducting this thesis in detail. The research began with the problem identification, here the objectives, aim and research question for the thesis were identified and focused on. In the research design phase, various pre-existing tools were studied and compared to assess current state of emission evaluation tools and practices. Here, the approach towards project realisation was decided. Afterwards, data collection was started to gather data in order to generate a realistic model. Qualitative and quantitative data were obtained from the company in various ways like industrial visit, company records, power logs, historical consumption data. Once sufficient data was gathered, the modelling phase began. In the modelling phase, the base model of the system was established. the model had to be accurate to real life setting. Subsequently, the model was validated against various factors like face validity, gathered data, expert reviews.

If the model did not meet the expectation, new data was gathered and the model was validating again making this process iterative. After the validation phase, the model gave valuable results reflecting he current emission levels of the system. The base model results were obtained and recorded establishing base level for comparison and strategy generation. The experimentation phase, implemented various scenarios for emission reduction to check their effects of the level of emission, aiming for reduction. After several experiments were run, the results from those scenarios were compared with the base level of emission to provide with valuable insights to devise an emission reduction strategy. The project was concluded after this phase, solidifying the outcome from the research.

4.1.1 Literature Review

To achieve the aim of the thesis, it was crucial to assess the emission assessment tools with DES already present in the industry. This methodology expanded on the framework from these pre-existing tools.

The databases used to obtain technical papers included databases like Scopus, Science Direct, Research Gate and Google Scholar. The Boolean searching methods of AND, OR and NOT were applied to narrow down the search results. Keywords applied to detect important papers include Sustainability, manufacturing, emission assessment, Discrete Event Simulation, DES, Process improvement, sustainable manufacturing, CO_2 emission.

These papers were from various sectors like construction, manufacturing, and healthcare. Each study was examined to reveal its contributions towards assessment, gaps, and uniqueness. This study worked by identifying the gaps in the existing methods to assess emissions dynamically. Out of all the papers examined, 4 papers used DES simulation for emission assessment with integration of other technologies; the paper by (Borbolla et al., 2024; Hong & Lü, 2022; Seow et al., 2013; Zhang, 2015) was the most relevant with the use of DES. These papers were finalised due to their close resemblance to the thesis topic and methodology.
This thesis used a mixed study for research purposes. It integrated the qualitative

and quantitative study, ensuring a complete data-driven evaluation for the selected production line at Grundfos. The two methodologies served different purposes. The quantitative study helped gather numerical data, which was essential to develop a Discrete Event Simulation (DES) model using historical production data, energy consumption and downtime records to simulate the model to evaluate the CO_2 emissions. On the other hand, the qualitative study for data delved into gathering insightful information from subject domain experts, like professionals from the sustainability and production team of the company. This information helped to ensure that the model represented the production process accurately in real-life scenarios and circumstances, guaranteeing its validity for real-world applications.

A strict quantitative study provides numerical insights but may fail to consider practical things like contextual factors, production constraints and time/process-specific considerations. Likewise, a pure qualitative study lacks the data-driven precision to accurately generate a model to analyse the emissions. A robust and practical study was ensured by integrating both of these studies. The combination of the two allowed this research to create a practical decision-aiding tool. This tool will enable Grundfos to compare different strategies for CO_2 emission reduction and to select the best possible study (Grundfos, 2025).

4.1.2 Quantitative Study for Data Collection

This component of the quantitative study included gathering important numerical data related to production specifications for the selected production line. This data was quantified for Key Performance Indicators (KPI) like -

1. Throughput rate and cycle times
2. Energy (electricity) consumption in kWh
3. CO_2 intensity (kg/kWh)
4. CO_2 emissions from the energy use (kg)
5. Process inefficiency impact like failures, changeover times, idle times and breaks

The simulation model was ran several times to create different scenarios to assess how enhancements like scheduling, machine and resource utilisation and process modification affect the emission rate. The results from these scenarios will provide meaningful insights which benefit decision-making.

4.1.3 Qualitative study for data collection

In contrast, the qualitative component included collecting insights from industry professionals and practices.

1. Question-based interviews with experts to discuss real-world sustainability and production problems, challenges and initiatives.
2. Validation of the simulation model for assumptions and accuracy.
3. Comparison with standard practices within the industry to guarantee effective and practical emission reduction strategies.

This ensured the harmony between the DES model and real-life industrial operations, enhancing practicality.

4.2 Data Sources and Collection Methods

This study used historical records of production data, energy consumption logs and operational performance records to create and maintain an accurate DES model. The process used for data collection supports emission assessment and the optimisation strategy in a way that the process is complete, consistent and relevant to the research topic.

4.2.1 Historical production data

This study used the following data sources:

1. Historical production logs: The records for the 1 day of throughput rates, cycle times and operational shifts were utilised to provide insights on factors like average production capacity, variability and efficiency losses for the respective production line.
2. Energy (electricity) consumption record: energy use in terms of kWh in the important phases of the production cycle revealed variation in energy consumption across different machines and processes.
3. Downtime and maintenance logs: Information about production inefficiencies like unforeseen stoppages, breakdowns and scheduled maintenance events. The use of this dataset was to parameterise downtime events for the production process.

These datasets were preprocessed for the removal of inconsistent data, normalising the data and ensuring compatibility with the DES model.

4.2.2 Data Sources

For this study, several sources were used for the data collection, as mentioned above:

1. Production monitoring systems provided historical and real-time records of throughput, machine and resource utilisation and energy use.
2. Observation of the factory floor and discussions with domain experts helped validate the data and record valuable operational specifications.
3. Literature and standard industry benchmarks supported CO_2 emission and energy estimations.

A combination of company datasets and standard industry benchmarks enabled this study to ensure the accuracy of the DES model.

4.2.3 Data Management and Preparation

To ensure data usability and quality, the following method in the Table 4.1 was used for data storing, handling and structuring. The collected database was compiled into a repository with the fields below.

Table 4.1: Key data storing structure

Data Field	Description
Resource ID	Unique identifier for each machine
Machine Cycle Time	Processing time per unit
Energy Usage	energy consumed per operation
Downtime Events	Number of breakdowns per shift
Throughput Rate	Units processed per hour

4.3 DES Model Development

The development of the DES model stated above followed a methodical and structured approach, making the model comparable to a real-life production setting. This promised accuracy and applicability to numerous other applications. In this DES model, production flow, electricity consumption quantification, and CO_2 emission evaluation were facilitated, revealing process inefficiencies and possible improvement areas.

4.3.1 Conceptual Model

The conceptual model was the ideology behind the model stated before the development of the actual DES model. It established system boundaries, key entities, process flow logic and considerations (assumptions) about the model used in the DES model. Figure 4.2 of the conceptual model provides a pictorial view of the production process of the investigated production line.

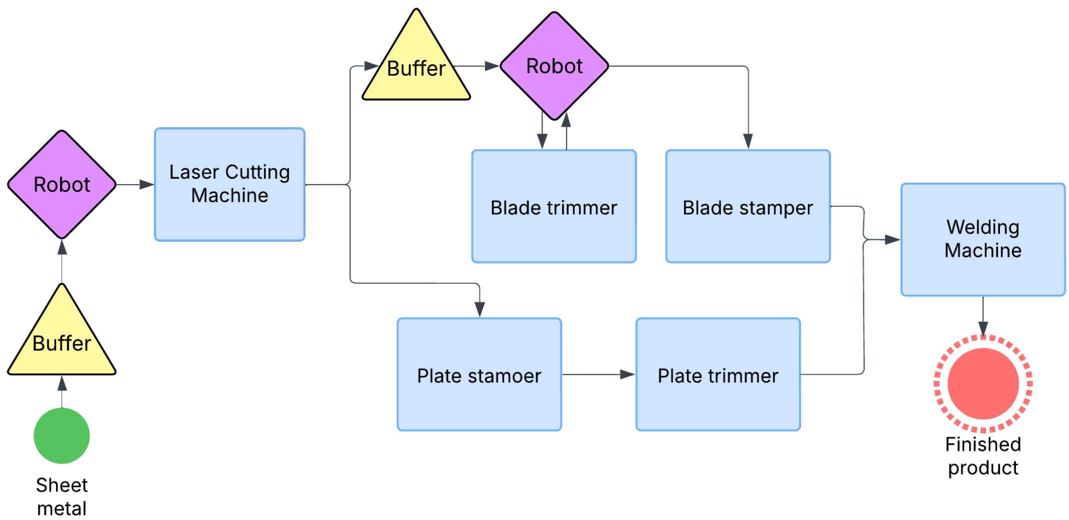

Figure 4.2: Conceptual model

The conceptual model begins with the supply of raw materials for fabricating the components of the pump parts. The raw material is supplied in the form of sheet metal from the warehouse indicated as a green circle. A buffer is provided for temporary storage from which the robot arm loads raw material onto a laser cutting machine. At the laser cutting, the raw material is converted into two variants of plates and one variant of the blade. After laser cutting, the flow splits. Blades move upwards toward another buffer. Another robot arm picks up the blades and loads them into the blade trimming to trim the excess material. Again, the robot arm picks up the blades and loads them into the blade stamper for shaping the blades. The blades are ready for welding at this stage and wait until the plates have finished their parallel processing.

On the other hand, from the laser cutting machine, after the split, the plates move directly downwards to the plate stamping machine, which shapes the plates as required. Subsequently, the plates are loaded onto the plate trimming machine to make the hole and trim away excess material. After this step, the plates reach the welding machine, where they are joined together with the blades by welding to yield the finished product indicated by red.

4.3.1.1 System Boundaries

The model featured a gate-to-gate production process for the selected production, considering the following.

1. The product flow goes from inventory to main process, then sub-process to the outward storage as finished product.
2. Scope 2 emissions, which were the direct electricity consumption by machines and sub-processes, were focused on.
3. Dynamic CO_2 intensity factor was integrated to provide accurate emission tracking.

4.3.1.2 Entities and Resources

1. Entities were product units which served as the products flowing through the production line, called flow items.
2. Resources included the machines, robot arms, conveyor belts used in the model.

4.3.1.3 Event Logic

1. Historical production parameters like throughput, real-time energy consumption and downtime event specification were set in the model.
2. Each unit flowed from one machine to the other through the production line, consuming energy at each process.

4.3.2 Model development

1. Flow items were each unit of the pump parts treated as an entity moving through the pre-determined path.
2. Pertinent details on machine levels like cycle times, energy consumption and downtime events were provided as input based on historical data.

3. Events like idle state, setup time and breakdown states were factored into the simulation.
4. Each activity that consumed electricity and contributed to emissions was tracked in the model.

4.3.2.1 Verification and Validation

To guarantee an accurate and reliable model replicating a real-life production setup, the model was validated in multiple steps.

1. Face validation was carried out in the form of a discussion with production engineers at Grundfos to confirm reliability.
2. Comparison with one day historical data was used to cross-verify and compare the output from the model in terms of energy usage, throughput and emissions.
3. After comparison, the model parameters were adjusted to adequately align the model with real factory conditions.

4.4 Assumptions for DES model

Several assumptions were made to lower the complexity of the DES model. These assumptions helped complete the model, ensuring a reliable output matching real-life data.

1. Constant Processing times - Each machine, which was part of the DES model, was considered to have process times which are exact and non-varying.
2. No machine failure - The machines did not fail like in real life. The only phase when the machines did not work was after the shift ended and during the breaks in between. Also, throughout the operating hours, the machines were fully working up to their standard speed.
3. Energy consumption and Time - The energy consumption of each of the machine was based on the processing and idle time that the machine spends during the work hours and off-shift.
4. Negligible warm-up time - Time required for start up (warm-up) of the machines was not factored into the model. The machines began processing immediately as the shift began and shut down immediately as the shift ended.
5. Material availability - The raw material was always provided at the exact time, matching the throughput perfectly, taking away the possibility of under- and overproduction.
6. Single processing - Every machine was only designed to process one flow item at a time. The line was not dedicated to parallel production.
7. Demand consideration - The orders for the products were assumed to be always present during the entire simulation time of the model.
8. No external logistics - The model was designed to end after the welding station, yielding a product at the exit. Further processes like its cleaning, treatment, assembly, material handling and storage were not modelled.
9. Workload distribution - The total yearly throughput was divided into shifts, allocating the load uniformly. Each shift was considered to only produce the targeted throughput to match yearly data.

10. Emissions sources - The six machines were the main contributors to the emissions for the selected process. Entities like robot arms and conveyors had minimal emissions, relative to the main contributors and the whole production line.

4.5 FlexSim-Python Integration Using FlexSimPy

4.5.1 Overview of FlexSim-Python Integration

Reliability and dependability were crucial to dynamic emission evaluation while using a tool like DES. To strengthen this and gain confidence of the system, this study came up with a solution that integrated the FlexSim model with Python using FlexSimPy, a Python API designed for external control, automation, and optimisation of simulation models (FlexSim, 2025). By enabling real-time data exchange between FlexSim's simulation environment and Python's computational libraries (e.g., NumPy, Pandas, SciPy), the selected production line was examined for CO_2 emissions, energy consumption, and throughput under varying process conditions. This outstanding solution brought ease of use, a higher limit of sensitivity analysis and speed in achieving net-zero emissions assessment.

4.5.2 Implementation in FlexSimPy

The FlexSimPy solution is designed to give direct control and manipulation of FlexSim nodes and simulation elements through Python. A successfully compiled FlexSimPy permits to use 'import FlexSimPy' Python command to launch and control FlexSim (FlexSim, 2025). The workflow for integrating Python with FlexSim using FlexSimPy API is illustrated Figure 4.3, and a working Python code of the solution can be found in Appendix D.

4.5.3 FlexSim-Python Interaction Process using FlexSimPy

The Python-FlexSim integration follows a client-server paradigm in which Python acts as the external controller and FlexSim serves as the simulation engine:

1. Scenario Parameter Transmission - Python passes scenario-specific parameters, such as shift schedules, process times, and energy consumption factors, to FlexSim.
2. DES Model Execution - FlexSim executes these scenarios by processing discrete events in the selected production line, tracking energy usage, throughput, and downtime.
3. FlexSim-Python Data Exchange - After the completion of the simulation run, FlexSim returns simulation outcomes (e.g., CO_2 emissions, energy consumed, production rate) to Python for logging, analysis, and potential optimisation.

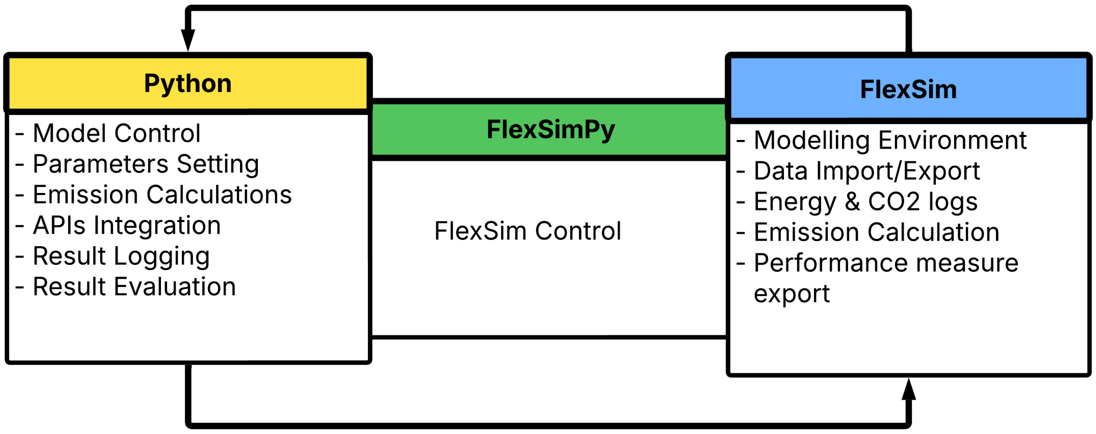

Figure 4.3: FlexSim-Python Process Logic

4.5.3.1 Workflow of FlexSim-Python Integration

The Table 4.2 provided a brief description of the responsibilities of each of the tools that make up the solution, in a chronological manner. A process logic for the FlexSim-Python is represented in the Figure 4.3, which in combination with Table 4.2, provides a clearer view of process communications and applications of tools within the FlexSim-Python integrated solution.

Table 4.2: Tools used for various processes in FlexSim-Python interaction

Step	Process	Tools used
1	Define the DES model in FlexSim	FlexSim
2	Connect to FlexSim from Python	FlexSimPy API
3	Dynamically set simulation parameters	Python (NumPy)
4	Run the simulation model and collect data	FlexSim
5	Retrieve key performance indicators (KPIs)	FlexSim
6	Store and analyse results for optimisation	Python

4.6 Scenario Analysis

4.6.1 Scenario-Based Insights for Grundfos

The integrated solution was expected to provide valuable insights for the production line through iterative simulation and comparison, like machine speed adjustment, shift scheduling changes, process optimisation that would advance the company's efforts towards net-zero emissions by 2050.

4.6.2 Performance metrics

Table 4.3: Important performance metrics, their meaning and the units used

Metric	**Definition**	**Unit**
Total CO_2 Emissions	Greenhouse gas emissions from energy usage	kg
Energy Consumption	Total electricity consumed per shift	kWh
Production Throughput	Number of products produced per shift	Units
Resource Utilisation	Percentage of time machines are active vs. idle	%
Peak Demand Reduction	Reduction in energy use during high-cost peak hours	%

The study adopted the KPIs highlighted in the **table 4.3** above, to be able to correctly evaluate the dynamic CO_2 emission for the selected production line. These KPIs served as a further guide towards achieving the aims and objectives of the project

5
Results

This chapter presents the results obtained from the base model in Chapter 3 and its analysis.

5.1 Result Interpretation

The results include various metrics like CO_2 emissions, throughput, stay time and energy consumption by the machines in the production line. Afterwards, the different scenarios explored were presented, to identify the best possible emissions reduction strategy.

The method applied to this section of the thesis followed a simple structure. First, the interview analysis was presented, which recorded pertinent data used for the realistic model generation and how it support the "what if" scenarios exploration. Afterwards, using the FlexSim and the FlexSim-Python integrated solution, important data like energy consumption in kWh and CO_2 emissions in kg were calculated and analysed. Following this, emission reduction scenarios "what if" were applied to the base model of the selected production process, one at a time, to grasp their effects individually and collectively. This allowed for comparison of the results to pinpoint the most feasible solution for maximum emission reduction. Ultimately, the results were summarised.

5.2 Interview Analysis

A few experts working at Grundfos were interviewed at the time of the industrial visit. Several questions were framed and asked to the line operators, line managers, maintenance crew and employees in the sustainability team. These questions were structured in a way to obtain quantitative data crucial for a realistic model and to replicate all necessary events. The questions were noted along with the observations made of operators' work methods. The condensed summary of questions and answers, in the Appendix E.

From the interviews, it became clear that the selected production line, despite being automated, required human intervention in terms of supervision. Machines were automated, requiring minor setup and would run idle on breaks. The responses hinted at several bottlenecks and focus areas present within the system. According to the line manager, the bottlenecks, which are always busy processing materials, were identified. This further aligns with observations made during the industrial visit to the production area. These machines were the plate section and the welding machine. The operators shared the productive volume for the whole year, which was approximately 75000 products. The lead time for one product was nearly 2 minutes, consistent with observations made at the factory.

The maintenance standards in the factory were effective and timely. Routine check ups and preventive maintenance were present. These regular maintenance practices drastically lower the machine failure rate and unwanted breakdowns. The maintenance team has a quick response time in the event of a breakdown. The maintenance team quickly identifies the problem and solves it to resume production as soon as possible.

The machine had consistent cycle times due to automated setup. If production is slightly delayed, the materials are handled by buffers and conveyors present. These additions help to cope with uncertainties. After completing one process, the process begins immediately if the next machine performing the process is free. The products are produced on an order basis. The production is streamlined to work on one product after the other, there are negligible delays, helping meet daily demand and scheduling.

5.3 Base Model Emission Profile

The base model emissions profile includes the results obtained from the base model of the selected production line for one day. These values were observed from the simulation model and treated as the results of the real-life setup. These data were also be used as base data for validating the production model in terms of the reduction in emissions after improvements.

The energy consumed by the machines were calculated by applying a triangular distribution statistical method to capture variation in the system. This includes energy spent by the machine for the processing and while idle. This triangular factor was then multiplied by the time to get the total energy used by the machine.

5.3.1 Key Metrics and Observations

1. Total energy consumed (kWh).
2. Total CO_2 emissions (kg).
3. Breakdown of idle energy wastage as a percentage of total energy consumed.

From the base model results, the energy log from the model provided the accumulated energy consumed by each of the machines while processing and during off-shift. The energy categorisation of active and idle energy with a statistical triangular distribution was used to correctly capture this, represented with E_{base}. Real-time CO_2 intensity from the grid integrated into Python code using API was used to dynamically calculate the CO_2 emitted per machine and product produced in the form of $CO_{2\text{base}}$ and $CO_{2\text{pt}}$. All these values were presented in the Table 5.1.

Table 5.1: The obtained emission results from the Base model

Machine	E_{base}	$CO2_{\text{base}}$	Total parts	$CO2_{\text{pt}}$
Blade Stamper	79.4	3.257	212	0.015
Blade Trimmer	73.3	3.006	212	0.014
Plate Stamper	406.4	16.683	424	0.039
Plate Trimmer	424.3	17.401	424	0.041
Welding Machine	439.8	18.040	212	0.085
Laser Cutter	75.3	3.084	635	0.005

5.3.2 Emission hot spot detection

1. **Identification of machines/processes with the highest emissions.**
   From Figure 5.2, it could be observed that the machines with the highest emissions were the plate stamper, the plate trimmer and the welding machine, compared to laser cutting, the blade trimmer and stamper, using the amount of emissions produced per hour, across the day.
2. **Description of observed inefficiencies and idle times.**
   From the Figure 5.1, the plate stamper and the plate trimmer have high setup times, directly affecting the production flow and lead time for the product. The welding machine spends the majority of the time waiting for the second plate variant to reach it so the welding could begin, increasing lead time significantly.
3. ***CO_2* intensity variation**
   From the Figure 5.3, it is evident that the variation in CO_2 factor change the emission calculation significantly. the quantity of CO_2 emitted by the machines varies based on the value of CO_2 intensity factor.

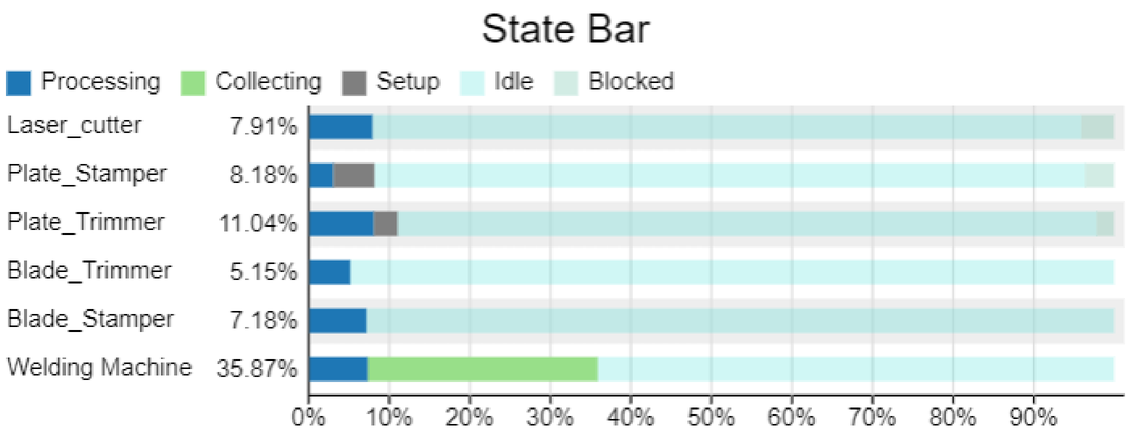

Figure 5.1: Machine activity breakdown by percentage (Time)

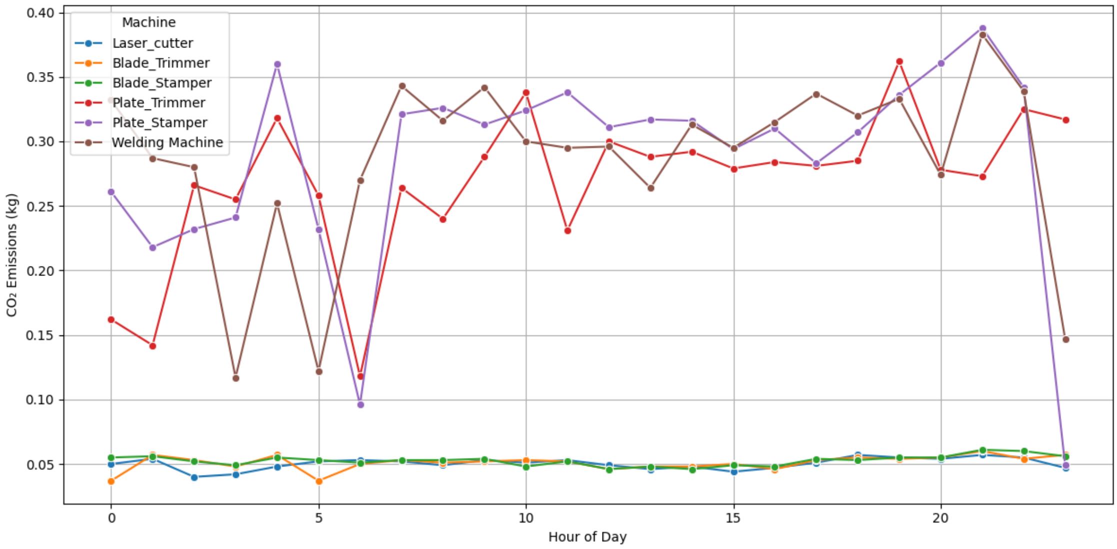

Figure 5.2: Base model CO_2 emission profile

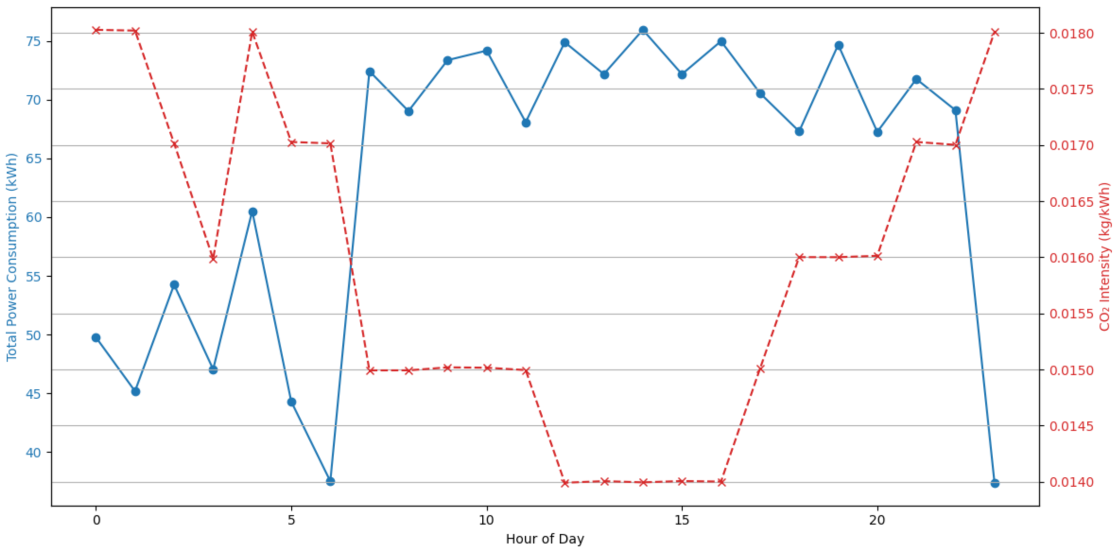

Figure 5.3: Hourly Power Consumption and CO_2 Intensity from the Grid

5.4 Scenario Analysis Results

The scenario analysis explored multiple possible methods of emission reduction, with DES as a decision support tool. Various techniques can be used to reduce the emissions from the base model results. For example, approaches like process improvement and shift scheduling in the current setup were discussed.

5.4.1 Scenario 1: Machine Upgrade

For the first scenario, the machines with the highest energy consumption (Welding machine, Plate stamper and Trimmer) were upgraded to reduce their energy usage by 10% . Statistical calculation for the 10% upgrade on paper would negate the aim of the project as utilisation value like average idle time and busy time would not be correctly captured, unlike with the DES model, where machine speed and setup time were the parameters considered for improvement.

This scenario reflected:

1. Lower total energy usage across the production flow.
2. Reduction in idle energy consumption.

Table 5.2: Energy and CO_2 emissions comparison between Baseline and Scenario 1

Machine	E_{base}	E_{scn}	$E_d\%$	CO_2^{base}	CO_2^{scn}	$CO_{2d}\%$
Blade Stamper	79.672	79.901	0.287	1.262	1.268	0.475
Blade Trimmer	77.488	75.680	-2.333	1.226	1.193	-2.692
Laser Cutter	76.450	75.555	-1.171	1.207	1.196	-0.911
Plate Stamper	440.402	412.046	-6.439	6.876	6.515	-5.250
Plate Trimmer	411.289	369.159	-10.243	6.444	5.841	-9.358
Welding Machine	413.373	377.211	-10.193	6.511	5.781	-9.383

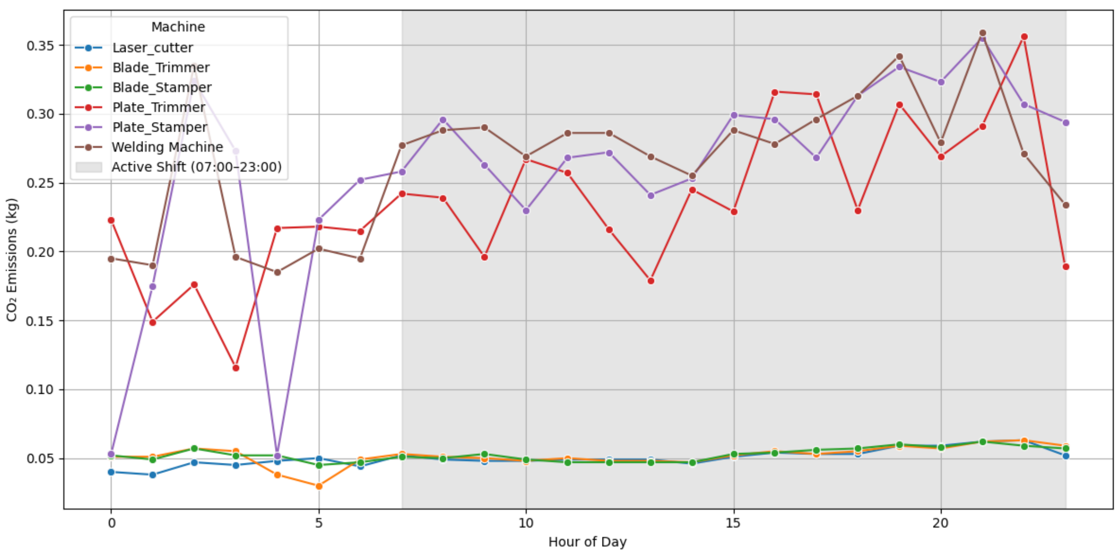

Figure 5.4: Hourly CO_2 emissions by machines after the 10% upgrade

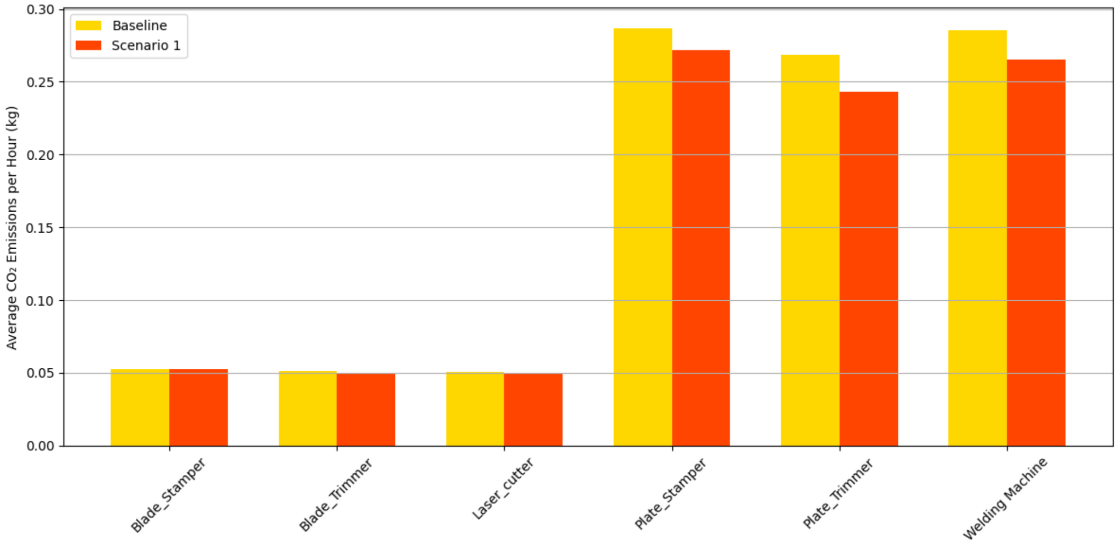

Figure 5.5: CO_2 Emission Reduction from Machine Upgrades against the Base Model

5.4.2 Scenario 2: Scheduling Optimisation

The second scenario shifted the work hours to coincide with the lowest emissions, using a day-long emission data forecast from the grid. From the Electricity maps, the changing CO_2 intensity was analysed for one day, which pointed towards the CO_2 intensity being lower from 17:00 to 09:00 every day. Therefore, the work hours were changed from 07:00-23:00 to 17:00-09:00. This essentially lowered the CO_2 emissions at the changed shift. Also, the peak energy demand for the factory during the normal work shift was reduced.

Table 5.3: Emission comparison between base model and scheduling using CO_2 intensity forecast from the grid to plan production

PM key	Metric	Base model	Scenario 2	Change(%)
Total CO_2	Total CO_2 Emitted (kg)	23.52	21.79	- 7.35
Total Energy	Total Energy used(kWh)	1498.67	1451.52	- 3.15

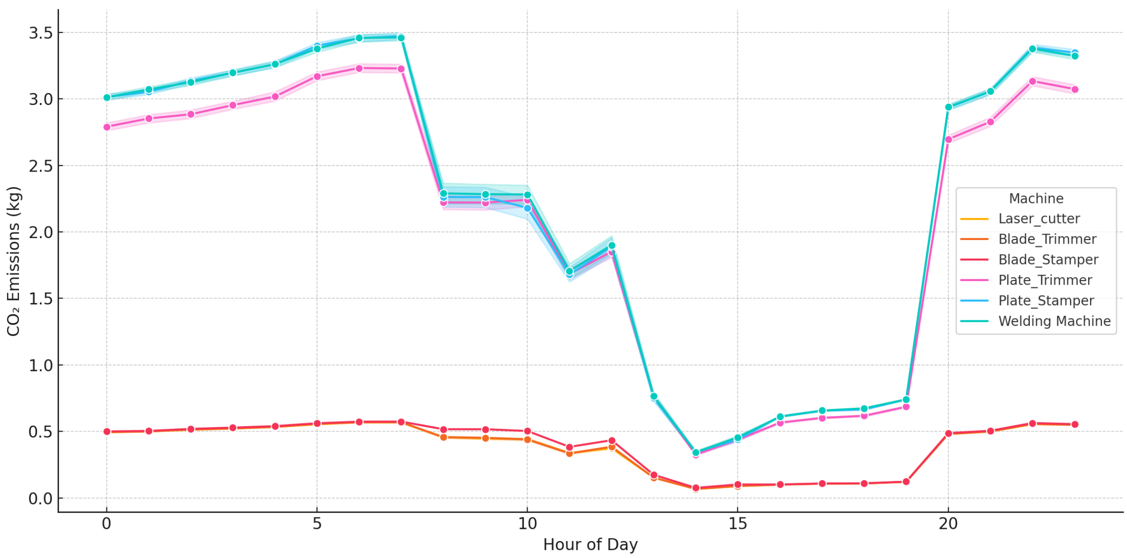

Figure 5.6: Average Hourly CO_2 Emissions Per Machine for Scenario 2 of the experimentation

5.4.3 Scenario 3: Process Re-organisation

Scenario 3 explored the possibility of reducing the idle times of machines by optimising the workflow. This came with inter-arrival tweaking and batch production. Idle times had a sizeable contribution to emissions (standby energy draw).

1. Reduction in idle time added more production time, leading to higher production throughput.
2. Idle time was reduced by introducing batching and a stable arrival time sequence of 235 seconds for selected machines.
3. The overall idle time was reduced by 11.72 % and throughput by 2.85%.

Table 5.4: Effects of Scenario 3 implementation on idle time reduction

Machine	I_{base} %	I_{bat} %	I_{d} %	TP_{base}	TP_{scn}
Laser cutter	86.82	91.13	4.31	635	653
Blade trimmer	94.39	85.68	-8.71	212	218
Blade stamper	92.19	85.47	-6.72	212	218
Plate trimmer	85.66	36.85	-48.81	424	436
Plate stamper	87.12	36.89	-50.23	424	436
Welding machine	45.48	85.31	39.83	218	218

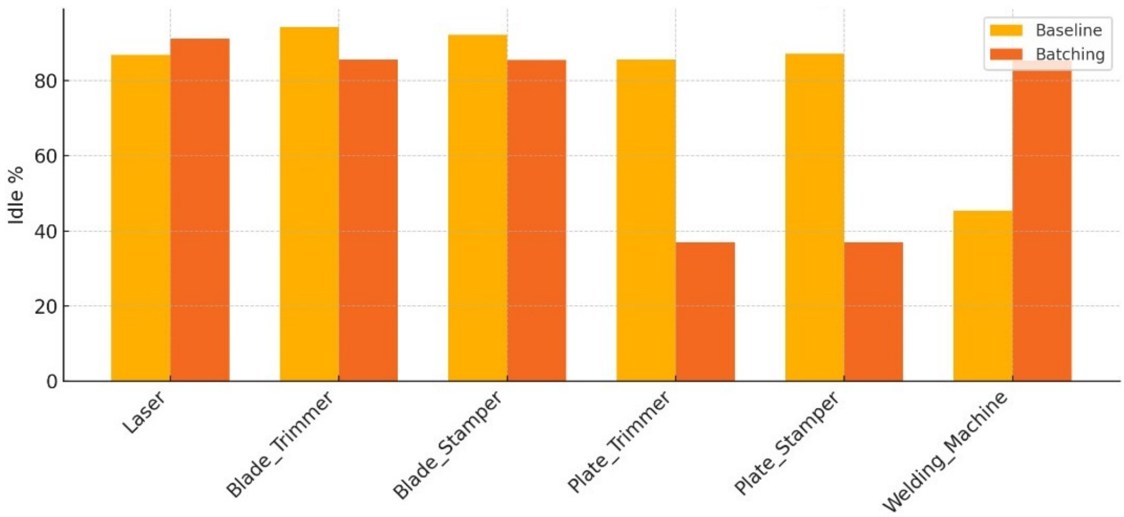

Figure 5.7: Idle time comparison with batching

5.5 Summary of Results

The summary of results presents the results obtained from each scenario in a concise format, facilitating better comprehension.

1. Scenario 1 explored the implications of lowering machine energy requirement levels as an upgrade for machines with high energy requirements on the emission levels. The result was a 10% reduction in focus area on average in terms of energy usage and CO_2 emissions for the machines described above, and overall 8.84% reduction the emission. Also, the idle energy was greatly reduced.
2. Scenario 2 focused on scheduling optimisation by shifting the work hours to a time with a lower CO_2 intensity(avoiding dirty hours of the day), resulting in a drop in CO_2 emissions. This change resulted in 7.32% CO_2 emission drop across the focus area. This change also lowered the energy demand in the peak hours due to the shift.
3. Scenario 3 is process reorganisation. This improvement sought a reduction in idle times for machines by introducing batched production. The results show 50% drop in the idle times for the plate trimmer and stamper, whereas 40% for the welding machine. Also, the overall idle time reduction was 11.72% and throughput increased by 2.85%.

5.6 Multi-Criteria Decision Analysis (MCDA)

An MCDA matrix was made to compare the results obtained by applying various scenarios. The comparison was made across aspects like CO_2 emission reduction in %, feasibility, flexibility, and cost. This comparison was used for the justification of recommendations given to the company.

Table 5.5: MCDA Matrix for Scenario Comparison

Scenario	CO_2 change	Feasibility	Flexibility	Cost
Scenario 1	- 8.84%	Medium	High	Medium
Scenario 2	- 7.35%	High	Low	Low
Scenario 3	-7.00%	High	Medium	Medium

6

Discussions

Here, we interpret the relevance of the results towards selecting an adequate solution for the problems discussed earlier.

6.1 Interpretation of Results

In this section, the interview, base model, scenarios and sensitivity analysis results were discussed and interpreted to support the net zero emission projects of Grundfos.

6.1.1 Detailed Interpretation of Base model Findings

The project model was modelled using the series of data collected through the discussed methods in the Section 4.2 of the methodological part of this report.

The modelling started with the exploration of different methods of Python-Flexsim integration that best suit the aims of the project. Recall in Chapter 2, the project aim to dynamically evaluate carbon emission using FlexSim software integrated with python, so that the important emission evaluation parameters could be manipulated from the python, even by non-expert of simulation engineering. Several of this method were exploited, like calling the batch script from inside Flexsim software, Python- Flexsim integration using the socket method (Leon et al., 2022). Even though the integration were successful, the real-time communication between the model and the python for dynamic evaluation was not fulfilled. The final method of integration that ticked all the boxes is FlexSimPy API, developed by FlexSim to control parameters and extract performance measures from models. Section 4.5.3 explicitly explain interactions between Python and FlexSim model using FlexSimPy.

The project progressed to the collection of production data from production monitoring systems, direct observation during the production line visit and grid data from Electricity maps. Table 4.1 shows how the data were grouped and a brief description of all the data used for the modelling.

The next step of DES modelling after data collection was the conceptual modelling, which was presented in the Figure 4.2 For every stage of the modelling, the industrial supervisor and a simulation expert validated the results, and signal a go ahead to move to the next stage. The validation method employed in the project as presented by Robert G. Sargent (2010) in his paper was face validity by a domain expert and model users and historical production data. This saved time, effort and also increased the confidence of the model.

The base model includes Python script, integrated API for the grid data, FlexSimPy and FlexSim software. Data collected was used in the model development and a python script for the model control, extraction of output data, calculation of carbon emission and visualisation was also created in conjunction. Energy consumption, process time, setup time, shift schedules, CO_2 intensity from the grid and equipment stay time are the most significant data needed to dynamically evaluate carbon emission using a DES model.

The base model was configured to 16 hrs double shift from (07:00-23:00), with the mean inter-arrival of 235s that matches the lead time, and no batching. The model was run for 84600 seconds(one day) to confirm that the throughput matches the available production data and power log by the model reflect real-life power logs of the machines. The model includes the following tables: a time-stamp table that records emissions per 40-second interval, energy used per machine, and emissions per machine.

For the Python script, the hourly energy consumption for each processor was coded into the script using a triangular energy distribution. The solution have both the script and the model doing the calculations and logging the result in a CSV file.

For a gate-to-gate evaluation and simulation of a day, the total energy consumption for all 6 processors was 23.91 kWh per day. Out of the 6 equipment on the line being investigated, the plate operation, that operate in parallel with blade operation and welding process, dominates the energy consumption. The Plate Trimmer and Stamper together account for 56.83% of the total energy consumption of the investigated production line. The welding process alone consumes 27.58% of the energy, while Blade Trimming, Stamping and Laser cutting processes represent less than 15.59% of the daily use.

Using the Swedish grid CO_2 intensity factor, the daily carbon emission stands at 23.52 kg for the production line and 0.029 and 0.080 CO_2 emission per product for Blade and Plate, respectively. Despite the production volume, the per unit carbon footprint remains significantly above zero, indicating that the process pacing, CO_2 intensity factor and timing have a first-order effect on emissions.

The daily throughput stands at 75000 and 212 per day(365 no break). This meets nominal demand but leaves little space for variability, maintenance, or future volume increase without further optimisation.

The extracted Performance Measures of the stay time for all the 6 machines show the Laser, Blade Trimmer and Stamper, Plate Trimmer and Stamper, and Welding machine with idle percentage of (92.09, 94.85, 92.82, 88.96, 91.82 and 64.13)% respectively. This is an average 87.45% idle percentage across stations. Even though the line have parallel operation and is sized for 16 hours of operation, the machines spend the vast majority of operating hours waiting, incurring a "standby" energy draw that adds directly to CO_2 without producing parts. Though welding was the least idle, downstream processes and starvation still make it idle for almost half of the working time.

The emission profile for average hourly CO_2(for all machines) revealed the peak hours to be during midday with an average of 2.42 kg CO_2 per hour, and the trough(overnight) to be an average CO_2 emission of 1.65 kg CO_2 per hour. With the shift of (07:00-23:00), the production falls in the dirty hours of the day when emissions are at the peak, thereby increasing the per-unit carbon footprint.

With this revelation of the base model, high idle rates across all the machines drive standby energy, leading to under-utilisation. Smoothing the production flow could dramatically raise busy time and lower per-unit energy consumption. Shifting production into cleaner grid hours could offer a lever for immediate CO_2 cuts without capital investment. Welding and Plate stations consume disproportionate energy; balancing arrivals with downstream capacity could reduce both queue starvation and blocking.

6.1.2 Significance of each Scenario Tested and their Implications

6.1.2.1 Machine Upgrade

From the evaluation of the base model, a few of the machines were identified to cause high emissions on the line, due to their high volume of energy consumption from setups, processing time, idling and size. To verify their direct impact on the total emission from the production line, a machine upgrade was carried out on the three identified machines(Welding Machine, Plate Trimmer and Stamper), the upgrade reduces the energy draw by each of the machines by 10%. Seow et al. (2013) categorised machine-level profile into Theoretical and Auxiliary Energy that covers the non-productive states of machines like start-up, standby, waiting and how they affect the total energy consumption. The simulation model captures all these and concrete upgrades like inverter motors, variable-speed drives were carried out to trim down auxiliary energy.

The scenario result shows 8.84% overall reduction in both energy and emissions while maintaining base model throughput, see Figure 5.5 and 5.4. The utilisation rate for all the machines remains the same, the savings was only on the energy draw and carbon emission.

The result from the scenario was linear as the investment in machine upgrade directly reduced the total energy consumption and carbon emission, but needed to be paired with flow optimisation to solve the standby energy draw by other equipment as a result of under utilisation.

6.1.2.2 Shift Schedule Optimisation

Since the project is aimed at dynamically evaluating the carbon emission of the selected production line, a careful study and analysis of a day CO_2 intensity factor from grid (Electricity Maps (2025), 2025), shown in the Figure 5.3. The data shows a clear trend of when the emissions are the lowest every 24 hours. This lead to the idea of exploring production scheduling when emissions are at their lowest and varying how much impact it would have on the total emissions from the production line in a day, without considering seasonal variation. So, the scenario explored "when" to run, by aligning production with cleaner grid windows.

In the study by Zhang (2015), a DES modeling evaluation was carried out to show relationships between activity timing and intensity during earthwork projects, the outcome shows non-trivial changes in total CO_2 and NOx, that proves that "when" and "how intensive" tasks run matters for emissions. In another study by Hong and Lü (2022), DES integrated On-site PEMS measurement was used in achieving a 8.1% reduction in GHG. This solution allowed scheduling-optimisation to be ran, that later led to remarkable reduction in both GHG and fuel by 8.1% and 6.6% respectively.

Two separate shift other than the base model were explored, the (09:00-01:00) window shows 2.8% of CO_2 reduction, while shift (17:00-09:00) resorted in a significant 7.35% of CO_2 reduction, the largest less capita-intensive emission reduction technique identified.

This scenario introduced more flexibility into the operational processes by encouraging dynamic shift planning based on real-time or forecasted grid carbon intensity. Though this would require coming into mutual agreement with operators to find a common ground on dynamic shift scheduling.

6.1.2.3 Process Reorganisation and Batching

The scenario examined the impact that the optimisation of material flow and WIP control would have on the energy consumption and carbon emission. The base model shows a high rate of under utilisation of machines due to a slow materials flow, thereby increasing the standby energy consumption of the production process. Tweaking of inter-arrival time and buffering strategies (fixed-size batches) was explored.

While many studies have been carried out to address energy consumption per machine and scheduling optimisation, reorganisation and batching strategies are yet to be explored. As highlighted in the Table 3.1, this study bridges the void by testing how machine routing changes and batch logic can reduce idle energy consumption and emission

The analysis led to the following findings: inter-arrival tweaking of ±20% of the base model inter-arrival time shows -3% idle improvement, +2.85% CO_2 increase and +2.87% throughput increase. With 40-part batches, overall idle time went down by -11.7%, CO_2 by -7% and throughput by +2.8%.

This scenario implies that introducing batching increases WIP and may also affect lead time, but reduces carbon emissions and productivity gains. At that point, there may be a need for a trade-off between inventory and throughput.

The fastest means to zero-carbon emission goal is through renewable energy source; there may be a trade-off between cost efficiency and total sustainable production.

6.2 Alignment with Grundfos's Sustainability Objectives

6.2.1 Direct relevance and alignment of research outcomes with Grundfos's net-zero goals

The aim and objectives of this project to provide actionable insight that support Grundfos effort of achieving net-zero CO_2 emission target by 2030 across it operations(scope 1 and 2) has practically been met. Discussed below are the direct ways in which the study has provided insight that support the commitment of the company towards to net-zero emission(gate-to-gate):

1. **Identification of Emission Hot spot:** Through the base model output, the study was able to identify the emission culprits on the selected production line(Plate stamper, trimmer and welding machine), based on the total energy consumed and utilisation rate. This assisted in focusing the emission reduction strategies(scenarios) for effective changes and effort conservation.
2. **Quantified Emissions Reduction:** Different scenarios exploited have shown quantifiable impact they have on the daily emission on the investigated production line. Up to 6.96% cut in scope 2 emission by implementing batching and shift timing. All these were demonstrated with the developed model and presented in the result analysis of the report.
3. **Operational De-carbonisation Pathway:** The Scenario 2 and 3 of the study revealed that process changes with minimal to investment can yield a substantial CO_2 emission reduction. Using emission forecast to plan production shift and smoothing workload through batching can yield up to 22% CO_2 reduction per product when compared to the base model result. This is a quick means to significant emission reduction, while Scenario 1 could be sustained for future as it requires larger investment and implementation.
4. **Scalable Decision Framework:** With the already set framework and modularisation through the FlexSim-Python integration, the solution can be scaled into other lines and processes(supply chain) to speed up zero-carbon emission journey that include scope 3 emissions.

6.2.2 Practical Recommendations Based on Scenario Analyses

Acting on the CO_2 emission reduction scenarios experimented in this study, the following practical recommendation are suggested to the company in order of feasibility and risk spread:

1. Adopt the low emission shift window(17:00-09:00): The scenario result shows potential cut in CO_2 emission by 8.84% when compared to the base model result with negligible difference in the throughput loss. This method leveraged the historical emission data and a day forecast to determine when the peak, trough and lowest period of emission to select the shift.
2. Implementation of Fixed Batching and Inter-Arrival Rate: In scenario 3, both arrival rate and batching were combined to smoothing the workflow and reduce idle time that causes standby energy draw. The experimentation resulted in 2.8% increase in throughput and 7% drop in the CO_2 per part. This methodology smooths downstream starvation and blocking and increase utilisation of the machines on average from 18% busy to 26%. This method is actionable and less capital intensive just some buffer mechanism and update to the system.
3. Machine Upgrades: The identified emission culprits in the production line can start to be upgraded through a gradual process without causing disruption to the system. This is a very strategic move that needed to be handle with good planning and management.
4. Adopt This Solution as Decision Support Tool: The solution is designed to be scaled into other production line and processes within the organisation with minimal maintenance. It has also been modularised that non-expert can manage and perform analysis with it.

6.3 FlexSim-Python Integration Insights

This study designed and developed a FlexSim-Python integration solution that dynamically evaluate energy consumption and emission on the production line and validated against real production data. The Figure 4.3 explicitly shows the process flow and interaction path in the solution where the API (FlexSimPy) developed by FlexSim act as the bridge and controller between Python and FlexSim model.

6.3.1 Benefits of simulation optimisation methodology used

Briefly explained below are some benefits of this novel solution:

1. Rapid Scenario Iteration: by having the control of the FlexSim model from Python, through FlexSimPy, several "what if" scenarios could be experimented without manual model edits. This solution reduces amount of time simulation engineers or model users spend on scenario setups.
2. Reproducibility and Version Control: The python scripts have some most of the model parameters, performance measures, and logic well defined, Anyone

with knowledge of python can reproduce a given scenario or revert to base model version, reducing the risk of undocumented manual changes.

3. Data-Driven Decision Support: Logging results and exporting performance measures tables into pandas enables immediate filtering, aggregation and statistical analysis that may not be possible with simulation software alone. This speed up insight generation and support data-driven recommendations.

To sum it up, this solution of FlexSim-Python integration has revolutionised DES from largely manual process of experimentation into fully automated, reproducible and statistically robust optimisation engine. This does not only speed up research throughput and process analysis, but also created best practices of scaling, continuous testing and data-driven analysis, directly into simulation workflow, serving as a significant competitive and operational advantage.

6.4 Study Limitations and Challenges

The thesis had several limitations and challenges due to the scope of the thesis set prior and stated in Chapter 2.

6.4.1 Methodological and Practical Limitations

1. As mentioned in Chapter 3, the DES model is a replication of the real-life production setup, including all the events, cycle times, setup activities, and failures. However, there are a few limitations, like the machine performance is non-varying and exact. There are no delays between the two machines, and the material is always available on time. Also, in the model, the raw material gets transformed into the product instead of performing the actual cutting and joining operations. In reality, however, the products are cut from the same sheet multiple times.
2. The DES model obtained from such methodology is nearly exact and better performing as compared to real life, leading to better results.
3. Few entities in the real production setup could not be included in for emissions assessment, like the robot arms or the conveyor belts, since the energy consumption data was sourced only for the six machines mentioned above.

6.4.2 Implementation Challenges

1. The data used for the emission assessment, like the cycle times, setup times, and the lead times, which were measured at the time of the industrial visit using a stopwatch, might bear some degree of inaccuracy and human error, leading to a reduction in the accuracy of the overall process.
2. The scenario analysis suggested multiple different approaches to reduce the emissions caused. The enhancements made have a cost linked to their implementation. A separate cost analysis will need to be conducted to check the feasibility of the suggested improvements.
3. Due to the research scope being limited to scope 2, focusing on the purchased energy by the company, the factors like waste generation from the production

line, like coolants, oil, could not be factored in. Also, the scope being limited to CO_2 emissions did not allow for the calculation of other pollutants like Carbon Monoxide, Nitrides and Sulphur Dioxide.

4. While implementing the DES model, the lack of expertise in the software caused significant delays in the base model generation and subsequently the emission calculation.

6.5 Directions for Future Research

While this project was limited to Scope 2 emissions and to only the selected production line, the same methodology can be explored in the future for various other project in the field of sustainability or different fields like process improvement or production planning. There are several opportunities to expand this work to.

6.5.1 Expansion Opportunities

1. Scope 3 emissions: For future projects, assessment of scope 3 emissions could be incorporated. This could be valuable for the stakeholders to map the indirect emissions caused for the company operations from aspects like external logistics, outsourced services and external suppliers. The extended scope would allow for complete assessment of environmental implications of GrundFos's operations allowing for optimisation of emissions across all aspects.
2. Artificial intelligence (AI) integration: AI techniques like machine learning can enable the development of predictive maintenance and scheduling strategies for increased accuracy and adaptability of such simulation models. Emissions hot spots can be indemnified with AI by processing production logs and identifying patterns.
3. Digital Twin: Linking the DES model with the digital twin of the factory could enable real time and continuous performance monitoring in an interactive format making DES simulation a tool for sustainability management.
4. Expansive plant modelling: The DES simulation based approach for production optimisation can be applied to more production lines and factories through out the company enabling full scale assessment of production standards, capabilities and emission levels of the company.
5. Economic study integration: Along with the scenario study and improvements listed above, the economic aspect of these improvements can be integrated with the emission assessment allowing the company to comprehend the investments required for making such improvements across the desired sections of company operations.
6. Life cycle assessment (LCA): An LCA based approach would enable the complete study of the environmental effects of the products trough various life stages like production, product consumption and disposal for better understanding of emissions and material wastage.

6.5.2 Research Enhancements

1. Increased data resolution and frequency: The data used for calculating emissions based on energy consumption logs could be of higher accuracy, high volume and more frequent to allow for extensive processing of data contributing to accurate emission calculations.
2. Statistical analysis: Better statistical analysis could be carried out on the data obtained for analysis, interpretation and trend identification in the data allowing for increased accuracy.

7
Conclusion

The outcomes of thesis project has been able to demonstrate the capability of DES integrated with an external application (python) to dynamically evaluate CO_2 emission within the manufacturing sector, factoring technical, environmental and business strategies into its solution development.

After the project, the study provided answers to all the research questions:

RQ1: FlexSim software was used to develop a DES model that effectively evaluated the selected production line with the gate-to-gate boundary of scope 2. Using relevant data(historical production data, CO_2 intensity factor, energy usage log and machine specific parameters), knowledge from literature on energy categorisation, the developed model replicated real-time operation of the production line and identified emission hotspots based on machines with highest energy consumption (plate line) and the bottlenecks of the system that contribute to inefficient energy utilisation.

RQ2: Three scenario-based strategies were identified and experimented with through iterative simulation, machine upgrade resulted in an 8.84% reduction in overall CO_2 emission, Scheduling optimisation lowered overall CO_2 emission by 7.35% without compromising the throughput, process reorganisation decreased the overall idle time and standby energy draw by 11.72%, reduced the CO_2 emission by 7% and also increased resource utilisation.

RQ3: The Python-FlexSim integration through FlexSimPy API enables real-time adjustment of simulation parameters, automated iteration of scenarios, dynamic logging and analysis of performance metrics, sensitivity analysis and convergence tracking, integration of real-time data from energy and emission website for calculation. This integrated solution allowed faster, flexible simulation runs and better understanding of how parameter changes affect CO_2 emission. The solution made it possible to handle multiple simulation runs, capture uncertainty effects and support decision-making under various operational configurations.

To round it up, the results obtained, the scenario analysis and the suggestions, provide momentum to ongoing industry efforts towards supporting sustainability by synchronising emissions assessment to the decision-making process behind manufacturing strategies. The performance and framework of the developed solution have proven it viability for its application to other parts of production processes as decision support, such as product development and also its extension to scope 1 and 3 for emission evaluation. It has also created an opportunity for other Industry 4.0 technologies to be integrated into the system for emission evaluation and reduction. Businesses can employ such technologies for continuous improvement, responding to upcoming compliance demands and environmental commitments.

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A

Appendix 1

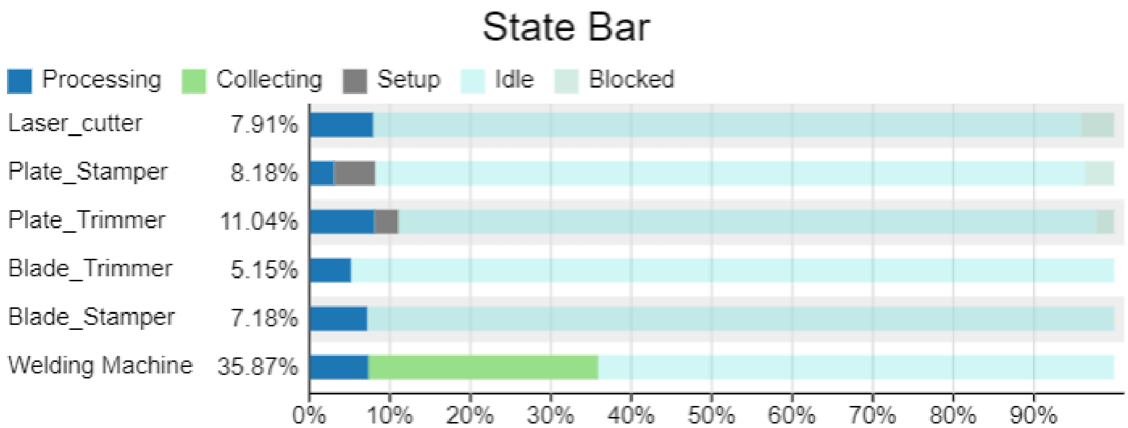

Figure A.1: Machines state percentages

B

Appendix 2

```
PRODUCT TYPE 1
{
    setlabel(item, "productType", 1);
    setlabel(item, "E_bt",   triangular(1,2,3));
    setlabel(item, "E_bs",   triangular(1,2,3));
    setlabel(item, "ct_bt",               1);
    setlabel(item, "ct_bs",               2);

    setlabel(item, "ct_laser", 1);
    setlabel(item, "ct_weld",  2);

    setlabel(item, "E_bt_used", 0);
    setlabel(item, "E_bs_used", 0);
    setlabel(item, "E_laser_used", 0);
    setlabel(item, "E_wm_used",    0);

       setlabel(item, "co2_emission", 0);
}

PRODUCT TYPE 2
{
    setlabel(item, "productType", 2;3);
    setlabel(item, "E_pt",   triangular(1,2,3));
    setlabel(item, "E_ps",   triangular(1,2,3));
    setlabel(item, "ct_pt",               1);
    setlabel(item, "ct_ps",               2);

    setlabel(item, "ct_laser", 1);
    setlabel(item, "ct_weld",  2);

    setlabel(item, "E_pt_used", 0);
    setlabel(item, "E_ps_used", 0);
    setlabel(item, "E_laser_used", 0);
    setlabel(item, "E_wm_used",    0);

    setlabel(item, "co2_emission", 0);
}
```

C

Appendix 3

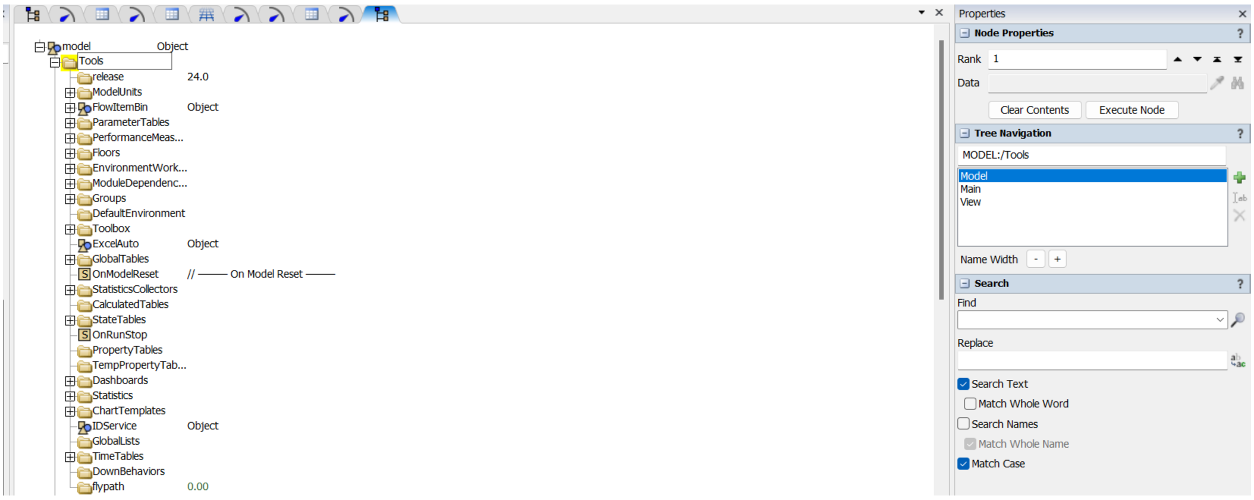

Figure C.1: Model Tree Node

D

Appendix 4

```python
import os
import time
import random
import FlexSimPy as fp
import pandas as pd

#  Configuration
MODEL_PATH  = r"<path_to_model>/Thesis_Project_Scenarios.fsm"
FLEXSIM_DIR = r"<path_to_flexsim>/FlexSim/program"
SIM_TIME    = 86400.0  # 24 hours in seconds

# Production shift window: 07:00-23:00
SHIFT_START = 7
SHIFT_END   = 23

# CO₂ emission factor based on national electricity grid
CO2_EMISSION_FACTOR = 0.041  # kg CO₂ per kWh

# Power Consumption Profiles (kW)
POWER_PROFILES = {
    "Machine_A": {"act": (1, 3, 3.), "idl": (1, 2, 2)},
    "Machine_B": {"act": (2, 2, 3), "idl": (2, 2, 2)},
    "Machine_C": {"act": (1, 7, 9), "idl": (1, 2, 6)},
    "Machine_D": {"act": (3, 8, 8), "idl": (8, 3, 8)},
    "Machine_E": {"act": (7, 9, 9), "idl": (2, 8, 9)},
}
MACHINES = list(POWER_PROFILES.keys())

def sample_triangular(params):
    low, mode, high = params
    return random.triangular(low, high, mode)
#  Model Execution
controller = fp.launch(evaluationLicense=True, showGUI=True, programDir=FLEXSIM_DIR)
time.sleep(2)
controller.open(MODEL_PATH)

controller.reset()
controller.runToTime(SIM_TIME)
controller.stop()
controller.evaluate("updateallperfmvalues();")

# Performance Measure Collection
performance_keys = [
    ("TotalCO2",             "Total CO₂ Emissions",        "kgCO2"),
    ("Energy_Machine_A",     "Machine A Energy",           "kWh"),
    ("Energy_Machine_B",     "Machine B Energy",           "kWh"),
    ("Energy_All",           "Total Energy",               "kWh"),
    ("TotalOutput",          "Total Products",             ""),
    ("Util_Machine_A",       "Machine A Utilization",      "%"),
    ("Idle_Machine_A",       "Machine A Idle Time",        "%"),
]

pm_data = []
for key, label, unit in performance_keys:
    try:
        value = controller.getPerformanceMeasure(key)
    except RuntimeError:
        value = 0.0
    if unit == "%" and value <= 1.01:
        value *= 100.0
    pm_data.append({
        "Key": key,
        "Description": label,
        "Value": round(value, 2),
        "Units": unit
    })

pm_df = pd.DataFrame(pm_data)
pm_df.to_excel("performance_measures.xlsx", index=False)
```

Figure D.1: Python code

```python
pm_data = []
for key, label, unit in performance_keys:
    try:
        value = controller.getPerformanceMeasure(key)
    except RuntimeError:
        value = 0.0
    if unit == "%" and value <= 1.01:
        value *= 100.0
    pm_data.append({
        "Key": key,
        "Description": label,
        "Value": round(value, 2),
        "Units": unit
    })

pm_df = pd.DataFrame(pm_data)
pm_df.to_excel("performance_measures.xlsx", index=False)

#  Production Count Retrieval
try:
    total_output = float(pm_df.loc[pm_df["Key"] == "TotalOutput", "Value"].values[0])
except IndexError:
    total_output = 1.0

#  Hourly Emissions Logging
hourly_log = []
for hour in range(24):
    state = "act" if SHIFT_START <= hour < SHIFT_END else "idl"
    for machine in MACHINES:
        power = sample_triangular(POWER_PROFILES[machine][state])
        energy = power * 1.0  # 1 hour duration
        co2 = energy * CO2_EMISSION_FACTOR
        hourly_log.append({
            "Hour": hour,
            "Machine": machine,
            "State": state,
            "Power_kW": round(power, 3),
            "Energy_kWh": round(energy, 3),
            "CO2_kg": round(co2, 3),
        })

hourly_df = pd.DataFrame(hourly_log)
hourly_df.to_excel("hourly_emissions_log.xlsx", index=False)

#  Daily Summary Calculation
daily_summary = (
    hourly_df.groupby("Machine")
    .agg(
        Total_Energy_kWh=("Energy_kWh", "sum"),
        Total_CO2_kg=("CO2_kg", "sum")
    )
    .reset_index()
)

def get_throughput(machine):
    if machine == "Machine_A":
        return total_output * 2
    elif machine == "Machine_B":
        return total_output * 3
    else:
        return total_output

daily_summary["Units_Processed"] = daily_summary["Machine"].apply(get_throughput)
daily_summary["Energy_per_Unit"] = daily_summary["Total_Energy_kWh"] / daily_summary["Units_Processed"]
daily_summary["CO2_per_Unit"] = daily_summary["Total_CO2_kg"] / daily_summary["Units_Processed"]
daily_summary.to_excel("daily_summary.xlsx", index=False)
```

Figure D.2: Python code

FlexSimPy /

FlexSimPy

The FlexSimPy repository includes two primary visual studio projects:

1. The PyConnector project implements the ability to bind the evaluation of nodes in FlexSim's tree to the evaluation of python functions. The project is implemented to work with python versions 3.7, 3.8, 3.9 and 3.10. The output DLLs from this project are included in the installed version of FlexSim.
2. The FlexSimPy project implements a mechanism for controlling the FlexSim application from python. It compiles to a valid python module called 'FlexSimPy', meaning that, if you have properly installed/placed the FlexSimPy .pyd dll, you can use the python command 'import FlexSimPy' and then use the resulting module to launch and control FlexSim.

Figure D.3: FlexSimPy API repository

E

Appendix 5

Question	Answer
What is the lead time for the product?	The lead time for the product is approximately 2 minutes.
What is the significance of human operators for production setup?	The machines work under human supervision, running idle when operators are on break.
What is the approximate annual throughput for this production line?	The annual throughput is approximately 75,000 products. The demand is ensured to be met by adjusting daily production.
Are there any common bottlenecks or downtime areas in the line, and what usually causes them?	According to the line manager, bottlenecks, which are always busy processing materials, were identified. Machines such as Plate trimmer, stamper and welding machines were the expected bottlenecks. This further aligned with observations made during the industrial visit to the production area.
What types of maintenance are performed regularly on the machines, and how often do unplanned breakdowns occur?	Unplanned breakdowns like machine failures or quality issues are uncommon, since sensors are used to analyse the behaviour of the machines in the line, allowing for regular checkups. Also, routine maintenance and checkups exist.
How consistent are the cycle times across different operators or shifts? Are there noticeable variations?	The cycle times are consistent since the factory is automated, and only a minor setup is needed to start production.
How is work-in-progress (WIP) managed between stations? Are there buffers or holding areas?	Yes, a few buffers are arranged between stations to cope with uncertainties. The conveyor belts also often work as buffers if needed.
What is the usual response time when a breakdown or fault occurs? How long does it take to resume operation?	If a breakdown is detected, immediate repairs are commenced to get the production back on track as soon as possible.
At each workstation, what triggers the next operation? Does it begin immediately, or is there a delay?	After completing one process, the process begins immediately if the next machine performing the process is free, since the line processes one product at a time.

Figure E.1: Question and Answers of the interviews conducted at Grundfos

AVANCEZ

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