Degree project

UNIVERSITY OF SKÖVDE

Robotic Simulation-Based Optimization to Reduce Energy Consumption and Cycle Time

Master Degree Project in Virtual Product Realisation (Intelligent Automation)

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Abstract

Industrial robots are central to modern manufacturing, yet their high energy consumption presents significant economic and environmental challenges. Traditional optimization approaches often prioritize cycle time reduction without adequately addressing power efficiency or workcell layout. This project integrates a knowledge mining process through Mimer-based Flexible Pattern Mining (FPM) into a robot simulation-based optimization framework based on ABB RobotStudio to more efficiently minimize cycle time, peak power, energy consumption, and cell area simultaneously with using NSGA-II algorithm. A simulation model of a robotic cell was modified to model trajectories and equipment placements, while a RobotStudio optimization (RSOpt) add-in was used to generate and evaluate thousands of configurations. By mining high-performing solutions in Mimer, interpretable rules were derived and applied to tighten decision bounds, reducing wasted evaluations and computational cost. The results demonstrate that Pareto fronts comparable to those in reference studies were reproduced with up to an order of magnitude fewer evaluations, achieving reductions in total energy and peak power at similar cycle times. The findings confirm that knowledge-guided optimization enhances both efficiency and sustainability while lowering computational burden, providing a practical and transferable methodology for energy-aware robotic simulation and layout design.

Keywords: Simulation model, Industrial Robotics, Multi-Objective Optimization, NSGA-II, RobotStudio, Energy Efficiency, Cycle Time Reduction, Workcell Layout Optimization, Flexible Pattern Mining (FPM), Sustainable Manufacturing.

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Skövde,2025

Hari Puthiyedathpisharam Sasidharan Asari

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1 Introduction

1.1 Overview of Energy Consumption Challenges in Robotic Systems

The growing dependence on industrial robots in manufacturing has resulted in notable progress in automation, efficiency, and precision. However, a significant difficulty with robotic systems is the substantial energy consumption linked to their functioning. Industrial robots necessitate significant energy to perform jobs, transport components, and uphold precision, rendering energy efficiency a vital consideration in sustainable production.

Energy consumption in robotic systems depends on various parameters, including motion trajectories, speed, acceleration, payload, and control algorithms. In many cases, energy inefficiencies arise from suboptimal path planning, unnecessary movements, or excessive accelerations. Furthermore, the layout of robotic work cells, including the placement of machines, conveyors, and auxiliary equipment, also influences the robot's power requirements. A poorly designed robotic cell may lead to increased cycle times and higher energy consumption due to inefficient routing of tasks.

Traditional approaches to optimizing robotic performance often focus solely on improving productivity without considering energy efficiency. While reducing cycle time is essential for maintaining throughput, it can sometimes lead to increased power consumption if not optimized carefully. Striking a balance between cycle time and energy usage remains a key challenge in industrial automation.

1.2 Importance of Optimizing Robotic Simulations for Energy Efficiency and Productivity

The rapid evolution of robotic simulation tools has provided new opportunities for optimizing energy consumption and cycle time before deploying solutions in real world industrial settings. Using simulation-based techniques, engineers can analyze different robot trajectories, test alternative configurations, and optimize operational parameters without the risks associated with real world experimentation.

Simulation platforms such as RobotStudio allow engineers to create virtual environments that accurately replicate real robotic work cells. These tools help in identifying inefficiencies, experimenting with different motion strategies, and evaluating alternative setups to minimize energy usage. Compared to physical trials, simulations are cost effective, time efficient, and safe, making them a preferred method for developing optimized robotic solutions.

By leveraging robotic simulation and optimization techniques, industries can achieve the following benefits:

1. Reduced Energy Consumption – Optimized robotic motion paths can significantly lower energy demand, leading to cost savings and a smaller environmental footprint.(Paes *et al.*, 2014)

2. Shortened Cycle Time – By refining motion sequences and eliminating unnecessary movements, manufacturers can increase production efficiency.(Nilakantan, Huang and Ponnambalam, 2014)

3. Improved Equipment Longevity – Minimizing sudden accelerations and decelerations reduces mechanical wear and tear, extending the lifespan of robotic components.(Stuhlenmiller *et al.*, 2021)

4. Enhanced Production Flexibility – Simulation based optimization enables quick adjustments to process changes, ensuring adaptability to evolving production needs.(Albini *et al.*, 2023)

5. Sustainability and Compliance – Energy efficient automation aligns with global sustainability goals and regulatory standards for reducing industrial emissions.(Ghadiri Nejad *et al.*, 2025)

Despite these advantages, existing research often focuses on optimizing robotic path planning while neglecting the impact of equipment placement within the robotic cell. Optimising a robotic cell means balancing goals that naturally compete with each other, such as shortening cycle time, lowering energy use, managing peak power, and keeping joint loads within safe limits. Exploring these trade-offs demands thousands of detailed RobotStudio simulations, and the use of NSGA-II multiplies this workload as entire populations are evaluated over many generations. Because of this heavy computational effort, tools like Mimer become valuable by analysing the evaluated solutions and uncovering patterns that point toward more promising regions of the search space. These insights not only reduce unnecessary evaluations but also help engineers understand why certain trajectories or configurations perform better than others.

2 Aim and Objectives

Industrial robots are frequently employed in manufacturing to increase accuracy and productivity; their excessive energy consumption is still a significant worry. Finding methods to improve robotic operations has become more crucial as companies shift towards more environmentally friendly output. By investigating the use of robotic simulations to strike a compromise between performance and efficiency, this study seeks to meet that demand. In order to promote more environmentally friendly automation techniques, the study improves both energy consumption and operational results, building on previous research in realistic robotic environments.

Aim: Minimizing Cycle Time and Reducing Energy Usage in Robotic Cell Operations

The aim of this study is to create and verify a methodical approach to robotic cell operations optimisation that minimises energy usage and cycle time while maintaining production efficiency. The research is broken down into the following objectives in order to achieve this aim:

1. Utilized a validated simulation environment - In this study, a realistic robotic simulation environment is utilized rather than being developed from scratch. The environment was originally created in RobotStudio by (Schmidt B, Ng A and Seger M, 2024) as part of their work entitled *Integration of Realistic Simulation and Multi-objective Optimization for Energy-efficient Robot Cell*. Their simulation framework provides a detailed representation of a manufacturing cell, incorporating robot trajectories, equipment layout, and process sequences. By using this established environment, the present research benefits from a validated platform that already accounts for the critical factors influencing robotic operations. This allows the focus to be placed on analyzing energy consumption and cycle time under different conditions, while ensuring consistency with previous research in the domain.

2. Integrating an Optimization Algorithm – The optimization process will be powered by NSGA-II (Non-dominated Sorting Genetic Algorithm II), a well-known multi objective optimization algorithm(Deb *et al.*, 2002). By applying this approach, the study aims to find an optimal balance between minimizing energy consumption and reducing cycle time.

3. Reducing number of Iterations in NSGA-II – The goal is to minimise cycle time and reduce energy consumption in the robotic cell by coupling simulation-based multi-objective optimisation with an interactive, data-driven rule-extraction layer. This layer identifies parameter ranges from high-performing solutions and feeds them back into the optimiser as tightened decision bounds. By narrowing the search toward high-yield regions, the approach reduces non-feasible evaluations and lowers the computational budget while maintaining the quality of the Pareto front across cycle time, energy, and peak power.

4. Analysing Optimization Data and Evaluating Results – The data acquired from the simulations and optimisation processes will be examined to assess the efficacy of various configurations. Key performance indicators (KPIs) include energy consumption per cycle, total cycle time, smoothness in movement and power efficiency will be evaluated.

5. This research is particularly relevant for manufacturing industries, robotic engineers, and sustainability advocates looking to enhance automation systems while adhering to energy efficient practices. By providing a validated framework for energy optimization, this study aims to contribute to the broader goal of sustainable and cost-effective industrial automation.

2.1 Research Question

For the simulation-based optimization of robot path (without human intervention or real-world execution), the research questions are:

1) Given an established robotic simulation and optimisation framework with long computational runtimes, how can knowledge-based rule mining be used to guide the optimisation process in a way that supports reducing energy consumption and cycle time while minimising overall computational effort?

2) How do decision variables (path parameters, station positions, via points) influence optimization results in robotic simulations?

3 Problem Description, Extent, and Scope

Industrial robots are crucial in manufacturing but consume significant energy. Existing simulations focus on trajectory optimization, neglecting workcell layout. A holistic approach integrating Simulation model technology and multi objective optimization is needed.

The challenges in optimizing energy efficiency in industrial layouts include layout optimization, where existing methods often overlook the impact of robot and equipment placement on energy consumption. Computational complexity is another issue, as multi objective optimization is resource intensive and difficult to implement in real time. Additionally, adaptive control remains a challenge since current tools lack the capability to dynamically adjust energy usage in response to real time conditions. Lastly, validation is crucial, as simulations must accurately reflect real world energy savings to ensure reliability and effectiveness in practical applications.

The study focuses on simulation model technology, utilizing RobotStudio based modelling to create manufacturing cell simulations and a simulation model for real time energy and cycle time analysis. An optimization framework is developed through a RobotStudio add in that enables path and layout adjustments, integrating NSGA-II to balance energy efficiency and productivity. After each optimization phase, non-dominated results are examined with a visual pattern mining component that discovers human readable parameter ranges (e.g., work object orientations, radial shifts) associated with low energy at acceptable times; these ranges are then fed back as refined bounds for the next optimization cycle. Evaluation and validation are conducted through simulated experiments assessing energy and time efficiency, with comparisons to Genetic Algorithm (GA) based optimization methods. Finally, the study provides practical insights into real world manufacturing implementations.

The scope of this study focuses on optimizing manufacturing processes by minimizing energy consumption and peak power demand while improving cycle time within process constraints. In addition to these objectives, the optimization also considers reducing the occupied workcell area and enhancing motion smoothness, both of which contribute to improved efficiency, space utilization, and operational reliability. It utilizes tools and technologies such as RobotStudio, NSGA-II, and Simulation model implementation to enhance efficiency. The industry application is broad, covering sectors like automotive, electronics, and heavy machinery, with a software driven approach that requires minimal hardware modifications. However, the study is limited to simulation-based analysis rather than real world deployment, and computational constraints may arise in highly complex scenarios.

4 Theoretical Framework

The theoretical framework provides the theoretical foundations for combining simulation, optimisation and knowledge discovery in robotic systems. It describes the fundamental ideas and technological advancements that make it possible to create a digital environment that can analyse and enhance industrial robot cells' energy usage, cycle time, and layout efficiency. The three main pillars of the framework are simulation modeling, multi-objective optimisation, and knowledge-based rule extraction, all are used to work together to improve energy-efficient robotic operations.

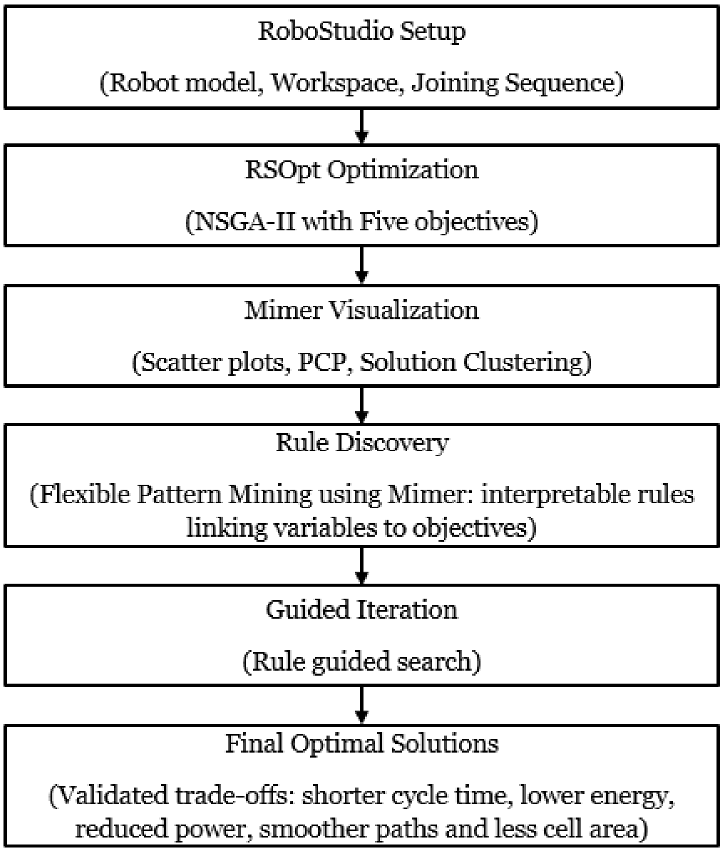

Figure 1 Flow chart represents framework of the project

4.1 Simulation model Concept

The basis of this study is the simulation model concept, which functions as a simulation representation of the actual robotic system. The behaviour, dynamics, and interactions of machines, equipment, and robots in a virtual setting are represented by a simulation model. Without having to conduct expensive or dangerous real-world trials, engineers can monitor and evaluate how the system reacts under different operating situations by building such a model.

Because of its great fidelity in simulating industrial robotics processes, ABB RobotStudio is used as the primary simulation platform in this project. A digital clone of the manufacturing cell, complete with robot manipulators, conveyors, fixtures, and sensors, can be created using RobotStudio. Joint locations, torques, speeds, and energy consumption may all be precisely tracked thanks to this environment's access to geometric and kinematic information. The study assesses how path layouts, tool orientations, and station locations affect overall performance through iterative testing in this virtual environment. With each cycle producing quantifiable measures of productivity and energy efficiency, the method enables the rapid exploration of several design scenarios.

The main benefit of employing a simulation model is its capacity for exploration and prediction. To determine how changes to parameters—like base positions, acceleration profiles, or velocity limits—affect cycle time and power demand, engineers might perform "what-if" analysis. This proactive evaluation minimises production downtime, lowers development costs, and lessens trial-and-error during physical deployment. Furthermore, RobotStudio's integration with the actual ABB controller logic allows for a smooth transition from simulation to real-world implementation, guaranteeing the validity of the model and its applicability. This study is supported by the simulation model idea, which serves as a virtual laboratory for evaluating, validating, and improving robot performance across a variety of goals prior to deployment. By bridging the gap between theoretical optimisation and practical application, it makes it possible to systematically evaluate trade-offs in a secure setting.

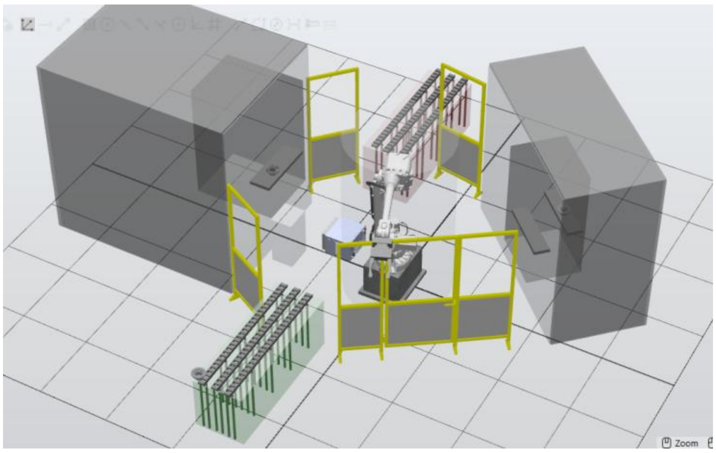

Figure 2 Robot Cell Simulation model in Robostudio

4.2 Multi Objective Optimization

Conflicting objectives are frequently present in industrial robotic activities, such as minimising energy consumption and ensuring layout efficiency while obtaining the smallest cycle time. A framework that can manage several, frequently non-linear goals at once is needed to address these trade-offs. Multi-objective optimisation (MOO) employing the NSGA-II is used in this study to address this problem.

An evolutionary method called NSGA-II was first presented by (Deb *et al.*, 2002). It evolves a population of solutions over a number of generations by simulating natural selection processes. The algorithm finds a set of Pareto-optimal solutions, or configurations where no objective can be improved without making another worse, after evaluating each alternative against a number of objectives. Because of this, instead of depending on a single ideal value, decision-makers can see trade-offs between characteristics like energy, power, and time.

In this research, the optimization focuses on five major objectives:

1. Minimizing total energy consumption,
2. Minimizing cycle time,
3. Reducing peak power demand,
4. Reducing the physical area required for the robotic cell, and
5. Improving the smoothness of the robot trajectories.

NSGA-II permits speed, power, area and energy to coexist in a balanced optimisation environment, in contrast to conventional single-objective approaches that might place an excessive emphasis on either one alone. Thousands of possible combinations of layout variables and motion parameters, including workstation orientations, via-point shifts, robot speed limitations, and acceleration, are investigated by the program. The simulation model tests each configuration and uses the findings to iteratively refine the search space. NSGA-II produces a Pareto front, which is a collection of equally good trade-off solutions. The designs that best fit operational or sustainability criteria can be chosen by engineers from this collection. The incorporation of NSGA-II into the RobotStudio-based environment guarantees that the optimisation procedure is based on practical manufacturing limitations and is computationally efficient.

4.3 Knowledge discovery software

NSGA-II and other evolutionary algorithms are capable of generating optimal solutions; however, they frequently function as "black boxes," providing only a limited understanding of why certain solutions outperform others. The study employs knowledge discovery software, specifically Mimer, as a complementary instrument to extract interpretable design knowledge from optimisation results, thereby overcoming this limitation.

The process of identifying meaningful patterns, relationships, and principles within large datasets is referred to as knowledge discovery. Knowledge discovery prioritises the interpretation and clarification of metrics, in contrast to conventional numerical analysis, which concentrates on quantitative performance metrics. It enables engineers to convert numerical data into actionable insights that explain the impact of decision variables on objectives.

This study employs Mimer's Flexible Pattern Mining (FPM) methodology to investigate the optimisation outcomes produced by RSOpt. Mimer utilises interconnected visualizations such as parallel coordinate plots, scatter matrices, and interactive filters to discern clusters and connections between choice factors (e.g., via-point offsets, station orientations) and performance outcomes (e.g., low energy consumption or reduced cycle durations). The software then formulates these correlations as human-readable decision rules, such as: "If OP1 rotation angle < 0.04 and OP2 rotation angle > –0.26, then energy and cycle time remain low." The rules are then reintegrated into the optimisation loop, constricting the ranges of decision variables and directing the search towards favourable areas of the solution space. This methodology, termed knowledge-guided optimisation, markedly diminishes unnecessary calculations, enhances convergence speed, and increases the clarity of the decision-making process. By combining numerical optimisation (RSOpt) and knowledge extraction (Mimer), the system makes algorithms work faster while still being easy for people to understand. Because of this synergy, optimisation goes from being a simple computer exercise to an intelligent, iterative learning system that improves ideas and makes them easier to understand.

4.4 Path Planning and Motion Optimization

Path planning constitutes the fundamental operational aspect of robotic performance. It defines the trajectory of the robot's end-effector in space to accomplish a task, directly influencing energy consumption and cycle duration. Inefficient trajectories characterised by abrupt accelerations, sharp directional shifts, or unnecessary motions can result in excessive energy consumption, heightened joint wear, and prolonged operational durations.

This project involves path planning and motion optimisation executed using an add-in module in RobotStudio, utilising the NSGA-II optimisation algorithm. The add-in facilitates direct modification of robotic programs, waypoints, and equipment positions to create and assess alternative motion trajectories. The optimization strategies are guided by the following principles:

- Minimization of redundant movements: Eliminating unnecessary path segments that do not contribute to task execution, thereby reducing energy wastage.

- Smoothing of motion profiles: Adjusting acceleration, deceleration, and jerk parameters to ensure continuous and energy-efficient movement, avoiding sudden velocity changes that increase power demand.

- Spatial efficiency: Optimizing the physical arrangement of the robot and workstations to shorten travel distances and improve accessibility within the cell.

These changes not only diminish instantaneous power peaks but also promote overall sustainability by prolonging component lifespan and mitigating mechanical stress. Furthermore, smoother motion trajectories diminish the probability of accidents and improve repeatability—elements essential for high-precision production.

The path planning process serves as the connection between the virtual and physical environments, guaranteeing that the optimised strategies obtained through simulation may be directly implemented in real-world robotic systems. This study advances beyond traditional energy-saving techniques by integrating trajectory refinement with layout optimisation, showcasing a holistic, multi-faceted approach to robotic cell enhancement.

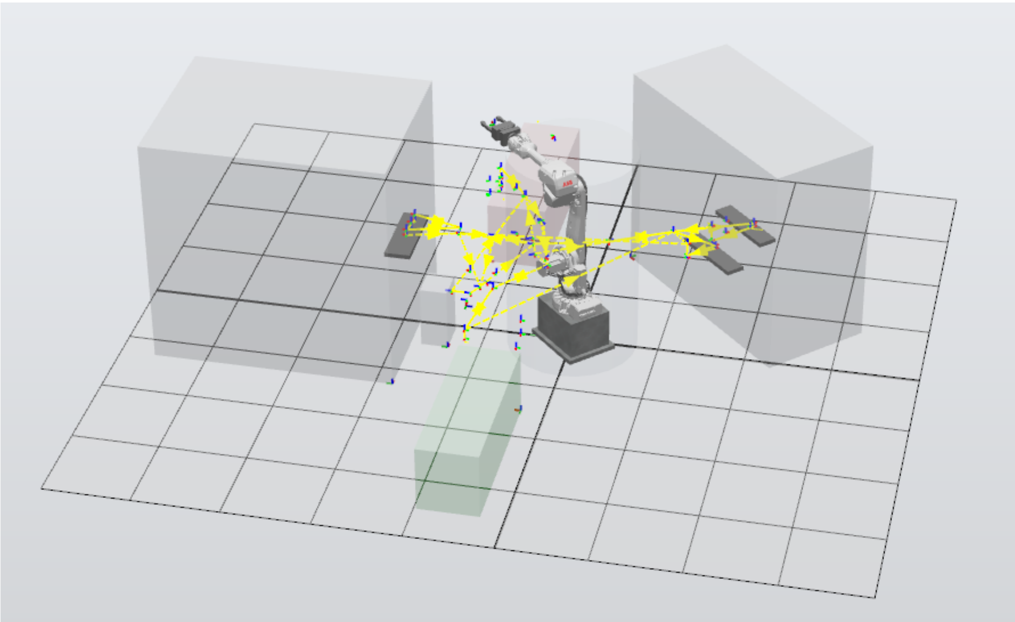

Figure 3 Path Configuration for Robot

The four theoretical pillars simulation modelling, multi-objective optimisation, information discovery, and path planning constitute a cohesive digital framework for knowledge-guided, energy-efficient robotic optimisation. The interplay among these components facilitates a closed feedback loop wherein simulation generates data, optimisation enhances the design, and knowledge discovery guides the subsequent iteration. This iterative process guarantees ongoing enhancement of sustainable, high-performance robotic systems that conform to industrial efficiency targets and environmental sustainability aims.

5 Literature Review

The need of energy efficiency in industrial robotics has become an essential component of sustainable manufacturing and the broader Industry 4.0 transformation. Industrial robots, which account for roughly 8 % of total manufacturing electricity consumption, represent both a productivity enabler and a significant source of energy demand (Schmidt B, Ng A and Seger M, 2024). Historically, the programming and control of industrial robots have focused on achieving the shortest cycle times and highest throughput possible, often at the expense of energy performance. This imbalance between productivity and sustainability has motivated a growing body of research seeking to reduce energy consumption through simulation, optimization, and intelligent control.

For this study, the literatures on energy-efficient robotics are broadly divided into four thematic categories: (1) trajectory optimization, which focuses on the robot's motion path and kinematic parameters; (2) operation scheduling, which seeks to adjust task timing or idle intervals; (3) layout and configuration optimization, which examines the spatial organization of robotic cells; and (4) holistic or multi-objective frameworks, which integrate several of these aspects simultaneously. Collectively, these elements demonstrate the progression from localised trajectory adjustment to system-wide optimisation that effectively balances energy consumption, productivity, and spatial limitations.

5.1 Trajectory Optimization

Trajectory optimization remains the most intensively studied area of energy-efficient robotics because a robot's velocity, acceleration, and jerk profiles directly determine its energy demand. Software-based optimisation methods are classified into two main categories: (1) modifying the geometric path or motion profile, and (2) rescheduling operations (Carabin, Wehrle and Vidoni, 2017). The first of these has attracted the largest share of attention, demonstrating that energy savings can be achieved without increasing cycle time, provided that the motion parameters are carefully tuned.

One of the earliest nonlinear optimisation frameworks for industrial robots was introduced, in which the motion profiles of KUKA manipulators were optimised without altering the task geometry (Riazi *et al.*, 2017). Their solver achieved up to 30% reductions in energy use and 60% lower peak power while maintaining identical cycle times. The approach differed from traditional system-identification methods by optimizing trajectories directly from cost functions such as pseudo-power minimization rather than relying on explicit dynamic models.

An approach termed Optimization of the energy consumption of industrial robots for Automatic Code Generation was proposed to integrate a mechatronic energy-flow model into an offline programming environment (Gadaleta, Pellicciari and Berselli, 2019). The method attained a 32% reduction in energy consumption for joint-based movements and approximately 20% for linear movements on a KUKA Quantec KR210 R2700 Prime by automatically modifying acceleration and velocity limits, which are parameters commonly found in most industrial controllers. The most important thing was that the tool worked with commercial software like Delmia Robotics, so it could be used without having to change any gear. This paper shows the change from just theorising about optimisation to giving factory engineers options they can use.

A related line of inquiry explores mathematical trajectory smoothing. A multi-objective trajectory-planning framework was developed using a septuple B-spline function to ensure continuous velocity, acceleration, and jerk (Liu *et al.*, 2018). Tested on a PUMA 560 robot, their approach reduced total energy consumption by 6.1 % compared with standard planning methods, while providing smoother motion that reduced actuator stress. Although minor fluctuations appeared at trajectory endpoints, the study provided a foundation for energy-efficient motion control within bounded kinematic constraints. Similarly, Sequential Quadratic Programming (SQP) was used to reshape velocity profiles within time-constrained tasks, yielding significant power reductions even without full dynamic models (Faroni, Gorni and Visioli, 2018).

Other researchers have advanced data-driven and machine-learning methods to overcome the limitations of explicit analytical modeling. Artificial neural networks were combined with genetic algorithms to predict energy consumption from operational parameters (Zhang and Yan, 2021), while deep-learning models were trained on digitised joint trajectories to link control signals directly with energy use (Yin, Ji and Wang, 2019). These techniques bypass complex dynamic equations, but they require extensive datasets and computational resources. As such, they remain more suitable for research environments than for direct industrial deployment. Nonetheless, they point toward adaptive, self-learning robots capable of continuously optimizing their trajectories in real time.

Several studies demonstrate the feasibility of integrating optimization directly into commercial simulation tools. A framework for integrating realistic simulation with multi-objective optimisation for energy-efficient robot cells was presented, in which an evolutionary optimiser was embedded within ABB RobotStudio (Schmidt B, Ng A and Seger M, 2024). Their framework automatically adjusted via-point positions, path parameters, and even station locations, reducing peak power by 44.7%, energy consumption by 23.3%, and cycle time by 9.5%. By running six instances of RobotStudio in parallel, computational efficiency improved by a factor of 4.5. The method also used the NSGA-II algorithm with a population of 250 individuals and 100 000 evaluations, illustrating the scalability of multi-objective search in realistic industrial environments. Importantly, the optimization directly modified robot code, enabling rapid transfer from virtual to physical systems.

A modelling-based approach was taken in which workspace constraints and joint accelerations were incorporated into a dynamic energy model for ABB IRB 1600 robots (Paes *et al.*, 2014). Their simulations achieved 5% energy savings without hardware changes, emphasizing that even incremental improvements at the trajectory level can translate into substantial annual savings across multi-robot lines.

The literature on trajectory optimisation shows a clear progression from analytical models and SQP formulations to simulation-integrated and data-driven frameworks. This shows that careful motion tuning can lower energy use, mechanical stress, and peak-power demand without lowering productivity.

5.2 Operation Scheduling

While trajectory optimization addresses *how* robots move, operation scheduling focuses on *when* they move. Production lines often contain idle intervals or "free times" between operations that can be exploited for energy savings. By adjusting motion speeds or rescheduling tasks within these windows, it is possible to reduce energy use without extending total cycle time.

A landmark study on simulation-based energy optimisation through motion-parameter tuning was conducted at Volvo Cars in Gothenburg, demonstrating how targeted adjustments to robot motions can significantly reduce energy use (Hovgard, Lennartson and Bengtsson, 2019). The study developed an optimization algorithm that iteratively reduced maximum robot velocities during non-critical movements identified through simulation. This strategy achieved 13% lower energy consumption, 26% lower peak power, and a 34% reduction in time spent at high-jerk values. Some robot motions were slowed by up to 90% with no impact on overall cycle time. The results demonstrated that practical energy reductions can be achieved through simple, data-driven parameter adjustments without detailed knowledge of robot dynamics or expensive retrofits. The authors emphasized that the next step is to integrate such optimization routines directly into real-time controllers for adaptive scheduling in production environments.

Operation-scheduling studies collectively highlight an ambiguity in industrial practice: robots are frequently run at maximum speed even when production constraints allow slower, more energy-efficient motion. The Volvo Cars case confirms that exploiting these temporal flexibilities can yield tangible sustainability gains with minimal disruption to throughput.

5.3 Layout and Configuration Optimization

The spatial arrangement of robotic work cells significantly influences overall energy efficiency, beyond individual trajectories and timetables. Suboptimal placement of robots, fixtures, and stations might prolong path lengths, induce unnecessary motions, and reduce manipulability, resulting in heightened power consumption.

A cloud-based 'energy-map' concept was introduced, in which robot configurations were linked to predicted energy consumption during assembly tasks (Wang *et al.*, 2018). Their MATLAB-based simulation module generated visual energy distributions across the workspace, supporting engineers in selecting energy-optimal robot poses. This idea was further developed by creating detailed mechatronic models that enabled the optimisation of robot base positions within manufacturing cells (Gadaleta, Berselli and Pellicciari, 2017) .Validated in automotive case studies, their method achieved up to 20% energy reductions, underscoring the strong influence of spatial layout on power use.

Evolutionary algorithms have become popular tools for tackling these high-dimensional layout problems. A genetic algorithm with sequence-pair representation was applied to balance motion time, manipulability, and cell area, revealing inherent trade-offs among these design criteria (Izui *et al.*, 2013). Extending this line of work, nature-inspired algorithms for optimising robot workcell layouts were explored, with GA, DE, ABC, CSS, and PSO compared across two layout encodings: B-tree and sequence pair (Lim, Ponnambalam and Izui, 2016). PSO consistently outperformed the alternatives, producing Pareto-optimal layouts that balanced compactness and maneuvering space. The study also identified the risks of extreme compactness, which can restrict robot reachability and increase motion time.

A multi-objective layout optimisation approach for robotic cellular manufacturing systems was later proposed, extending the methodological developments in this research area (Izui *et al.*, 2013).This approach used NSGA-II with placement-based partially exchanging crossover and mutation operators, optimizing three objectives: operation time, manipulability, and layout area. To prevent component overlap, the authors introduced dummy components to maintain safe spacing, finding that rectangular dummy shapes produced better trade-offs than square ones. The results confirmed that spatial allowances directly influence robot manipulability and energy efficiency.

In a follow-up study, hybrid multi-objective algorithms for optimising layouts in multi-robot cellular manufacturing systems were introduced by combining GA with DE, PSO, ABC, and CSS (Lim, Ponnambalam and Izui, 2017). Among these, GA combined with PSO yielded the most balanced Pareto front, minimizing layout area and operation time while maximizing manipulability. Hybrid algorithms improved search diversity and convergence speed, addressing the limitations of single-metaheuristic approaches.

At an industrial scale, an ‘Energy Optimization of Robotic Cells’ approach was presented in which a mixed-integer linear-programming (MILP) model was formulated to minimise energy use through robot-speed adjustment and power-saving modes (Bukata *et al.*, 2017). Implemented in Skoda Auto’s production systems, the algorithm achieved roughly 20% energy savings and successfully solved large instances involving up to 12 robots far exceeding the scale of prior studies. The open-source implementation provided a valuable benchmark for future research and demonstrated the feasibility of large-scale energy optimization in real manufacturing environments.

These works collectively demonstrate that layout design is not solely a geometric or ergonomic factor but a key element in energy management. The combination of manipulability, spatial limitations, and energy goals permits designers to develop robotic cells that are both small and sustainable, thereby reconciling mechanical design with control optimisation.

5.4 Multi-Objective and Holistic Frameworks

Due to the inherent competing aims in industrial energy optimisation, such as reducing energy consumption while preserving throughput and workspace utilisation, multi-objective evolutionary algorithms have become essential in this domain NSGA-II was introduced with elitism-preservation and crowding-distance mechanisms that have made it one of the most widely adopted methods for balancing competing performance metrics (Deb *et al.*, 2002). Building on this foundation, Flexible Pattern Mining was developed as a data-mining technique for discovering relationships within multi-objective datasets, enabling design rules to be extracted and convergence to be accelerated in complex optimisation problems (Bandaru, Ng and Deb, 2017).

A key foundational contribution in this field is the integration of NSGA-II directly into an industrial simulation environment, where the algorithm was embedded within ABB RobotStudio to optimise path parameters, via points, and station placements. Through this approach, substantial improvements in energy use, peak power, and cycle time were achieved, demonstrating how multi-objective optimisation can operate seamlessly within a digital-twin context. This line of work also showed that treating trajectory, scheduling, and layout decisions in a unified manner yields greater energy-efficiency gains than optimising each dimension separately. By enabling direct modification of robot code, the framework further allows optimised parameters to be transferred from simulation to production with minimal reprogramming effort(Schmidt B, Ng A and Seger M, 2024).

This holistic philosophy reflects a broader paradigm shift in manufacturing research: rather than treating design, control, and layout as separate disciplines, advanced optimization treats the entire robotic cell as a single, coupled system with multiple, interacting objectives.

5.5 Synthesis

A comprehensive analysis of the literature reveals a clear trajectory in how energy optimization for industrial robotics has evolved. Early research focused narrowly on individual trajectories, demonstrating that energy use can be reduced by fine-tuning motion parameters without extending cycle time. Subsequent studies expanded this scope to include scheduling, recognizing that even small timing adjustments can yield measurable power savings. Parallel to this, research on layout optimization revealed that spatial configuration strongly influences manipulability, cycle time, and energy consumption, leading to multi-objective approaches that balance these competing factors.

Across these domains, the adoption of evolutionary algorithms particularly NSGA-II has enabled robust handling of nonlinear, multi-dimensional search spaces. Recent work has demonstrated that integrating simulation, optimisation, and real-time control can lead to substantial energy savings that are validated in industrial environments(Schmidt B, Ng A and Seger M, 2024). These approaches align closely with the industry 4.0 vision of intelligent, interconnected, and self-optimizing production systems.

Although substantial progress has been achieved in energy-efficient robotic optimization, several key challenges identified across the literature remain unresolved. Most studies have relied on static, offline optimization procedures that lack adaptability to dynamic production conditions. It has been shown that large-scale multi-objective analyses often require tens of thousands of evaluations, which imposes heavy computational demands and limits their real-time applicability(Schmidt B, Ng A and Seger M, 2024). Likewise, while data-driven and machine-learning approaches e.g., (Zhang and Yan, 2021); (Yin, Ji and Wang, 2019) offer predictive capability, they depend on extensive datasets that are difficult to obtain and may not generalize well across different robot types or cell configurations. Furthermore, only a few investigations have attempted to combine trajectory optimization, scheduling, and layout design within a unified framework validated under practical manufacturing constraints.

Building upon these insights, the present study draws from the methodologies and gaps identified in previous research to explore simulation-based optimization as a more adaptable and integrative approach. By leveraging realistic simulation environments, optimization algorithms can iteratively evaluate energy performance under multiple configurations, enabling the assessment of both trajectory and layout variables simultaneously. This approach provides a bridge between purely theoretical modeling and industrial implementation, allowing complex relationships between decision variables to be examined without interrupting production. To further enhance interpretability and reduce computational burden, this research also employs knowledge-extraction techniques inspired by Mimer-like pattern-mining tools (Bandaru, Ng and Deb, 2017), which identify recurrent trends and rules within large optimization datasets. These insights guide parameter selection and accelerate convergence, addressing one of the main bottlenecks observed in earlier simulation-based studies.

Through this integration of simulation and data-mining-assisted optimization, the research advances beyond conventional single-objective or path-specific analyses. It provides a structured, repeatable process for exploring trade-offs among energy use, cycle time, and layout flexibility—factors often treated separately in earlier works. Moreover, by embedding sustainable decision criteria within the optimization process itself, the study contributes to the broader industrial transition toward resource-efficient and low-carbon manufacturing.

This work extends the evolution traced in the literature from isolated trajectory refinement toward comprehensive, simulation-driven multi-objective optimization by addressing the computational and methodological limitations of prior research. The approach emphasizes interpretability, flexibility, and sustainability, aligning with the objectives of Industry 4.0 and supporting global sustainability goals.

6 Methodology

6.1 Ontological and Epistemological Paradigms

This research follows a computational realism approach, focusing on a simulation-based study. The ontological paradigm is based on a digital simulation environment, where robot behavior is controlled by preprogrammed physics and algorithms. In this setup, robotic movement exists only in the virtual world, and the results depend on the accuracy of the simulation software. While the simulation allows precise control, it may not fully represent real world factors like tool wear, environmental conditions, or mechanical errors.

The epistemological paradigm relies on objective, numerical data from the simulation to measure performance improvements. Since all results come from a controlled digital system, there is no human influence or personal interpretation. However, because there is no real-world testing, the study assumes that ABB RobotStudio and RSOpt's models are accurate enough to reflect how the robot would perform in reality.

6.2 Research Strategy

The optimization of robotic workcells is a multi-faceted problem that often requires balancing several competing objectives. Traditional algorithmic approaches, such as NSGA-II, are effective at exploring large design spaces but can become computationally intensive as the number of objectives and decision variables increases. To address this, the present study integrates simulation-driven optimization with knowledge discovery methods. ABB RobotStudio provides the digital environment for defining robot models, process sequences, and cell layouts, while the RSOpt Add-in performs multi-objective optimization across different criteria. To complement this, Mimer software is employed as a visual analytics tool to uncover structural patterns and interpretable rules within intermediate Pareto solutions. By combining algorithmic optimization with knowledge-guided search, the study not only accelerates convergence but also generates design insights that explain why certain parameter settings yield superior performance. Within this framework, two optimization scenarios are investigated one involving five objectives, and another with four objectives each illustrating the trade-offs between complexity, efficiency, and interpretability.

6.2.1 Scenario 1 –Optimization with Four Objectives

In the first scenario, the research adopts a simulation-driven experimental approach within ABB RobotStudio, where the robot model, workspace layout, and joining sequence are defined. The RSOpt Add-in is then employed to conduct a four-objective optimization with the aim of:

1. Minimizing energy consumption,
2. Minimizing cycle time,
3. Reducing peak power demand, and
4. Minimizing the layout area of the robotic cell.

The same RSOpt-based workflow is applied, and NSGA-II explores the design space using the defined decision variables. Without the smoothness measure, the optimization process emphasizes purely operational and spatial efficiency.

To accelerate knowledge extraction from this complex four-objective space, Mimer was introduced as a visual analytics and knowledge discovery tool. Pareto solutions are imported into Mimer for visualization and rule extraction. FPM identifies recurring patterns, such as which via-point offsets or station layouts consistently reduce both cycle time and energy consumption. These mined rules act as knowledge constraints, guiding the optimizer toward areas of the design space that yield better trade-offs among the four objectives. This iterative integration ensures that NSGA-II converges more rapidly while producing design knowledge that can be interpreted and applied to future optimization studies.

6.2.2 Scenario 2 – Optimization with Five Objectives

In the second scenario, the optimization process is repeated but with five objectives, this time excluding the smoothness criterion. The focus is therefore on:

1. Minimizing total energy consumption,
2. Minimizing cycle time,
3. Reducing peak power demand,
4. Reducing the physical area required for the robotic cell, and
5. Improving the smoothness of the robot trajectories.

Trajectory smoothness is included as an objective because industrial robot motion is highly sensitive to variations in velocity, acceleration, and jerk. Abrupt turns, sudden speed changes, or aggressive acceleration ramps force the motors to generate steep torque bursts, which directly increase both peak power demand and total electrical energy consumption. Since torque is proportional to acceleration, the more abrupt the change, the larger the resulting power spike and thermal load on the system. Smoother trajectories mitigate these effects by reducing jerk, the rate at which acceleration changes, allowing the robot to transition between motions more gradually. This leads to more stable controller behaviour, less vibration, reduced mechanical wear, and lower internal friction losses. Energy losses also accumulate when the robot performs unnecessary reorientations or detours, as each additional joint movement increases inertial load and extends the time the robot spends under power. By shaping the motion profile to use gradual velocity ramps, controlled acceleration limits, and minimal orientation changes, smooth trajectories create predictable, energy-efficient, and mechanically stable robot behaviour. Many simulation-based multi-objective optimisation studies regard smoothness as a reliable surrogate for reducing energy peaks and improving motion stability.

The NSGA-II algorithm generates a wide set of Pareto-optimal solutions by varying decision variables such as via-point offsets, station positions, and velocity parameters. Quantitative data from simulation logs covering cycle time, energy use, power profiles, layout size, and jerk metrics are extracted for evaluation.

As in the first scenario, Mimer is used to complement the algorithmic search. Intermediate Pareto fronts were exported into Mimer, where scatterplots and parallel coordinate plots revealed structural clusters of high-performing solutions. FPM, interpretable rules were generated, for example linking low jerk values and reduced cycle times with specific velocity ranges or station placements. By feeding these rules back into the optimization loop, the algorithm was guided toward promising regions of the search space, thereby reducing redundant exploration and improving convergence speed.

6.3 Data Collection and Analysis Techniques

Since the experiment is fully digital, data collection is automated within the simulation environment. Simulation data extraction is performed by logging key metrics such as cycle time, path smoothness, and energy consumption automatically. The optimization results from RSOpt are analyzed to extract the best performing path configurations. Multi objective analysis is performed using Pareto front visualization, enabling the comparison of trade-offs between objectives. Descriptive statistics (mean, variance, and distribution of cycle time and energy usage) are used to provide a quantitative overview. Convergence analysis is applied to evaluate how quickly NSGA-II reaches optimal solutions across different scenarios.

In parallel, knowledge discovery with Mimer provides a complementary layer of analysis. After Pareto-optimal and near-optimal solutions are imported, interactive visualisations enable clustering and filtering of candidate configurations. Flexible Pattern Mining (FPM) is then applied to uncover relationships between decision variables and performance outcomes. For example, FPM has the potential to identify patterns where certain parameter combinations are associated with reduced cycle time without a corresponding increase in energy usage (Bandaru, Ng and Deb, 2017). These extracted rules are subsequently validated by highlighting them on the original Pareto plots, confirming their consistency with the optimisation results.

For data analysis, descriptive statistics are used to examine the mean, variance, and distribution of cycle time and energy usage. A multi objective optimization analysis is performed using Pareto Front analysis to identify the most efficient solutions. Comparative performance analysis is then applied to measure improvements by comparing optimized and non-optimized paths. Finally, a convergence analysis is carried out to evaluate how quickly the optimization algorithm reaches the best solution.

6.4 Mimer Guided Bounds Tightening

The goal is to employ FPM to extract decision rules from high quality, non dominated solutions, translate those rules into tighter decision bounds, and thereby demonstrate faster and better optimization. This is enabled in Mimer through interactive slider selections, FPM rule generation, and rule visualization or validation.

The procedure is conducted as follows. First, the non dominated set obtained from the initial optimization is loaded into Mimer, and the linked 3D scatter together with a parallel coordinates plot (PCP) is opened. A preferred subregion such as low energy at an acceptable cycle time is then selected. Next, FPM rules are generated by designating Selected versus unselected sets, choosing the variables to be mined, configuring minimum significance, maximum levels, and minimum interaction significance, and executing the FPM routine. The resulting rules are filtered within the FPM graph using thresholds on Levels, Significance, Unselected significance, and Sig or UnSig to retain only robust patterns. These candidate rules are validated by pasting them into Filter & Highlight and confirming that they consistently identify the intended performance region in the original plots. Finally, validated rules are translated into new bounds for the next optimization stage for example, constraints such as $0.28 \le dr \le 0.35$, $-0.32 \le dz \le -0.25$ or $velmax \ge 750$ so that the subsequent search is focused on the most promising portion of the design space.

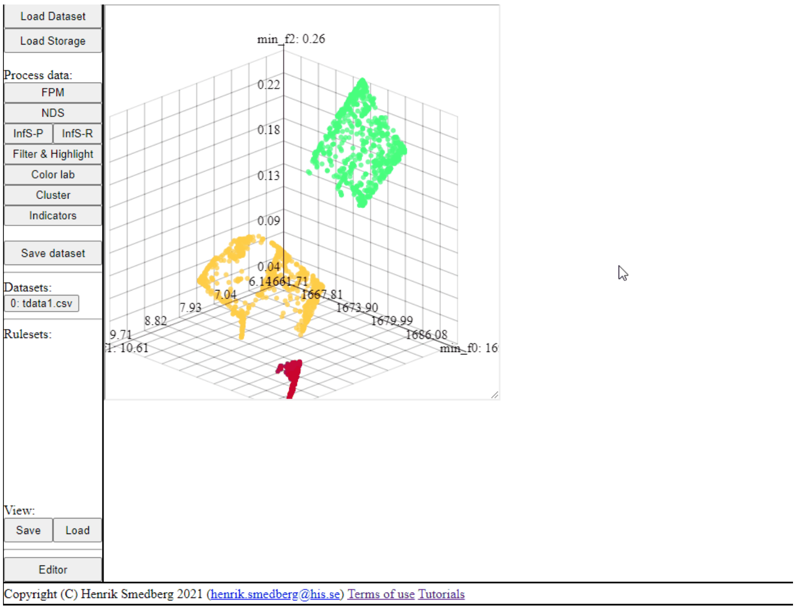

Figure 4 Use of Filter in Mimer to classify solutions(Smedberg et al.*, 2024)*

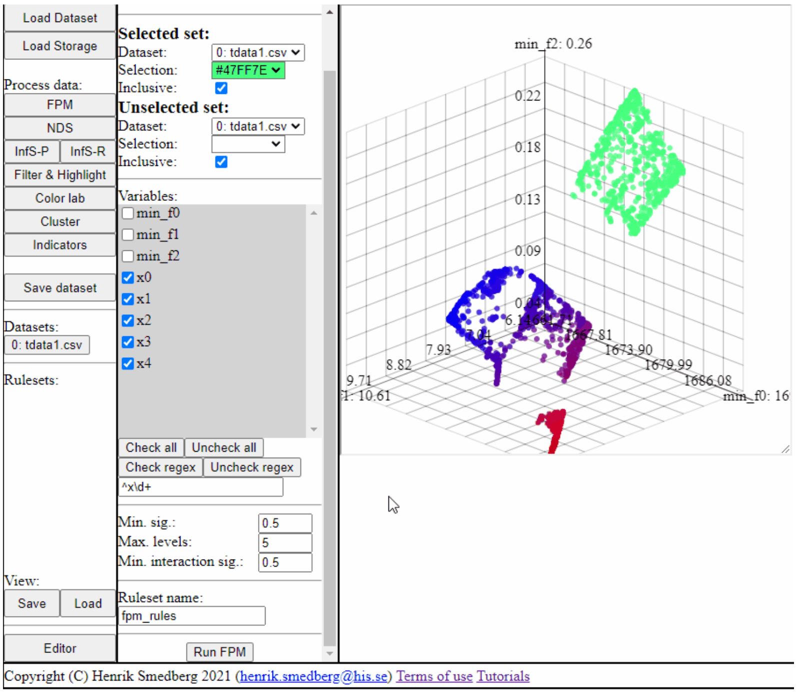

Figure 5 Loading Dataset and selection variables for FPM(Smedberg et al.*, 2024)*

To quantify impact, an ablation is performed in which the original bounds are contrasted against the Mimer tightened bounds. A two-stage loop is then applied, in which the process moves from baseline optimization to rule mining, followed by bounds tightening and subsequent re-optimization, with an optional second round of rule mining and tightening if additional focus is required.

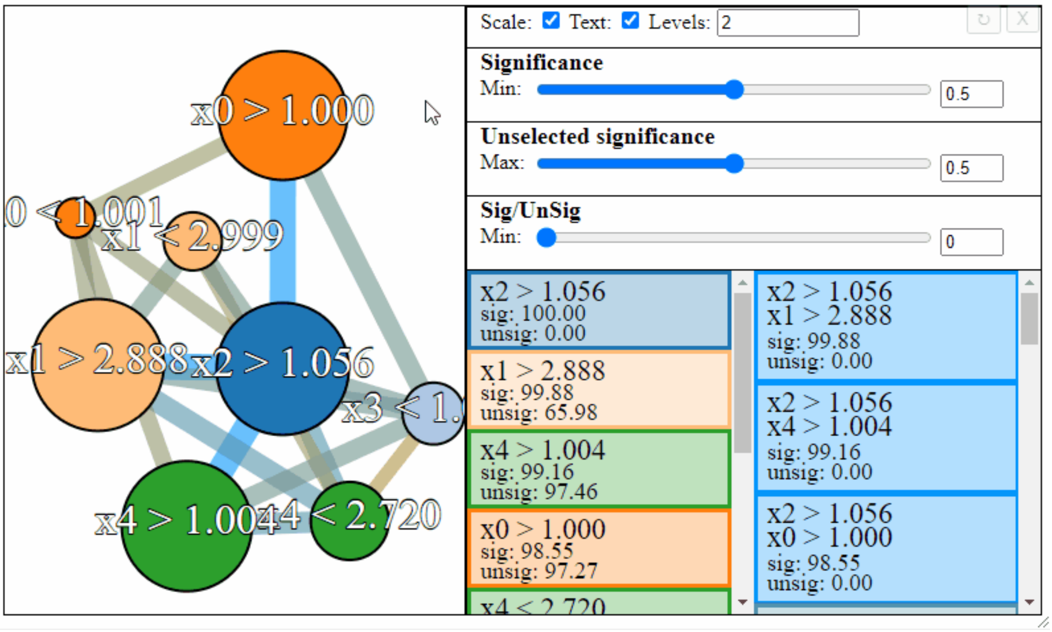

Figure 6 Formation of rules after running FPM(Smedberg et al.*, 2024)*

This procedure operationalizes the direction of automatic knowledge extraction for knowledge driven optimization, now instantiated through Mimer derived rules that focus the search on empirically promising regions.

7 Empirical Analysis and Findings

The optimization scenario focused on trajectory optimization to enhance robotic simulations by refining the robot's movement paths in addition altering equipment placements. The simulation results indicate a clear trend of cycle time reduction, demonstrating that optimized trajectories lead to more efficient workflows. Additionally, energy consumption improvements highlight the impact of streamlined movements, reducing unnecessary power usage while maintaining productivity. Furthermore, the incorporation of multi core processing simulation, visual analytics and rule mining enhances computational efficiency, significantly reducing processing time and enabling more extensive optimization analysis. These findings align with the project’s broader objective of minimizing energy use and cycle time through robotic path and cell area adjustments in ABB’s RobotStudio.

7.1 Objectives and Decision Variables

The optimization problem is formulated to minimize cycle time, total energy, peak power and layout area. In the second scenario considered here, smoothness is included as a fifth objective.

The decision space comprises both trajectory or via point (VP) parameters and layout parameters. For trajectory and VP, a global radius shift $d_r \in [-0.4, 0.4]$m and a height shift $d_z \in [-0.3, 0.3]$ m is used, while motion limits are bounded by veloverride 10% to 100%, velmax 200mm/min to 1000 mm/min, acclimit 10% to 100%, and ramplimit 10% to 100%. For the layout, the radial placement, angular position, and orientation of the input/output conveyors and OP1–OP3 around the robot are varied(Schmidt B, Ng A and Seger M, 2024). In total, approximately 21 decision variables are considered across the four objectives.

Table 1 Assigned Decision Variables for Optimisation in both scenarios

	Variable Name	**Type**	**Purpose / Effect**
1	velmax	Integer	Max joint velocity
2	veloverride	Integer	Global velocity scaling (%)
3	acclimit	Integer	Acceleration limit
4	ramplimit	Integer	Jerk limit (ramp profile)
5	dr	Real	Radial offset of via point
6	dz	Real	Vertical offset of via point
7	InBanaWOdr	Real	Radial pos. of InBana station
8	InBanaWOrz	Real	Rotation angle of InBana station
9	InBanaWOdrz	Real	Orientation offset (combined)
10	UtBanaWOdr	Real	Radial pos. of UtBana station
11	UtBanaWOrz	Real	Rotation angle of UtBana station
12	UtBanaWOdrz	Real	Orientation offset
13	OP1WOdr	Real	Radial pos. of OP1 station
14	OP1WOrz	Real	Rotation angle of OP1
15	OP1WOdrz	Real	Orientation offset
16	OP2WOdr	Real	Radial pos. of OP2 station
17	OP2WOrz	Real	Rotation angle of OP2
18	OP2WOdrz	Real	Orientation offset
19	OP3WOdr	Real	Radial pos. of OP3 station
20	OP3WOrz	Real	Angular rotation for OP3
21	OP3WOdrz	Real	Orientation offset

Table 2 Assigned Objectives for Scenario 1 Optimisation

	Objective Name	**Goal**	**Description**
O1	Cycle Time	Minimize	Reduce time to complete one cycle
O2	Power	Minimize	Peak power drawn
O3	Energy Consumption	Minimize	Reduce total energy used
O4	Cell Area	Minimize	Minimize space needed for robot cell

Table 3 Assigned Objectives for Scenario 2 Optimisation

	Objective Name	**Goal**	**Description**
O1	Cycle Time	Minimize	Reduce time to complete one cycle
O2	Power	Minimize	Peak power drawn
O3	Energy Consumption	Minimize	Reduce total energy used
O4	Cell Area	Minimize	Minimize space needed for robot cell
05	Smoothness	Minimize	Reduce jerk in robot path

In both optimization scenarios, the process begins with an initial 2000-5000 iterations of NSGA-II. The resulting Pareto-optimal solutions are then exported into Mimer for knowledge extraction. Through visual analytics and Flexible Pattern Mining, rules are identified that link specific decision variables such as trajectory parameters, via-point offsets, and layout configurations to desirable performance outcomes.

These extracted rules are subsequently applied back into the optimization workflow to guide the search process. By constraining and steering the decision variables toward promising regions of the design space, redundant exploration is minimized and convergence is accelerated. The optimization is then re-run for another set of iterations under these refined conditions, allowing both scenarios to benefit from knowledge-guided search that improves efficiency and provides interpretability of the results.

7.2 Baseline Reproduction (Verification)

All reference values and benchmark comparisons in this section are based on the study by (Schmidt B, Ng A and Seger M, 2024), which serves as the foundation for validating the reproduced results. The analysis is first validated by reproducing the Pareto fronts reported in the reference study for Scenario 2 (layout + trajectory), using the integrated Robot Studio optimizer. By aligning the decision variables, objectives, and constraint settings with the original study, the fidelity of the evaluation optimization loop is established prior to introducing any Mimer guided refinements.

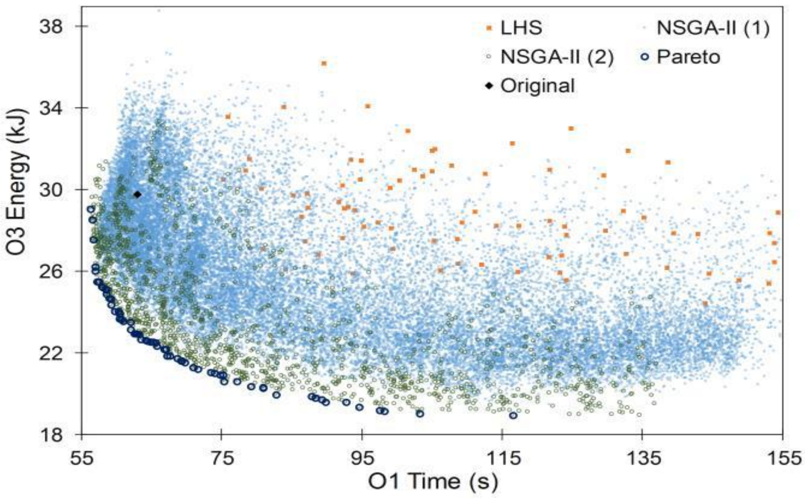

Figure 7 Pareto Optimal Solutions from (Schmidt B, Ng A and Seger M, 2024)

In reproducing the layout enabled results, the characteristic shift of the Pareto front is expected to be observed. At approximately the same cycle time as the original design, peak power is anticipated to decrease by roughly 44.7% or total energy by about 23.3%. When shorter cycle times are pursued, an increase in peak power may occur. These reference effects are treated as sanity bands against which the reproduced results are compared.

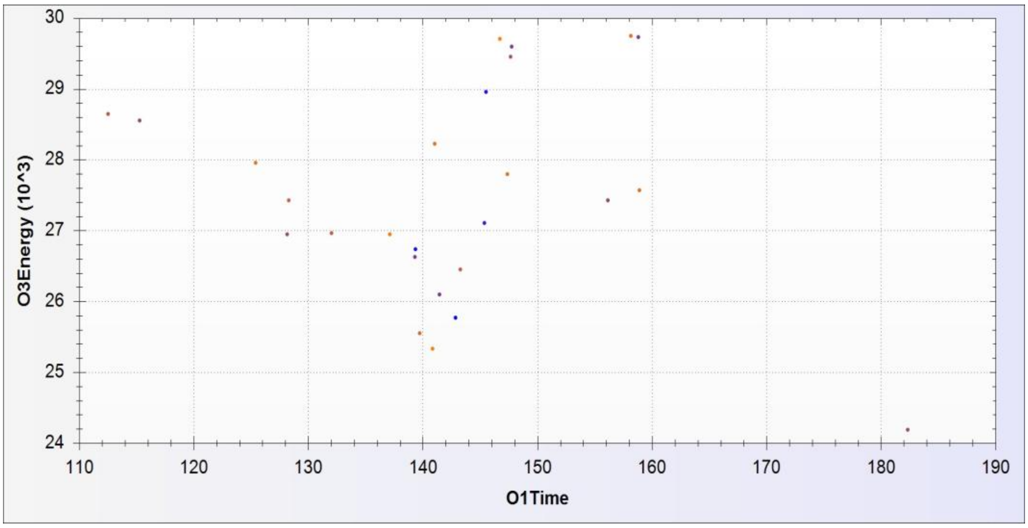

Figure 8 Result obtained after Optimisation with 5000 iterations (Scenario 1) without using Mimer

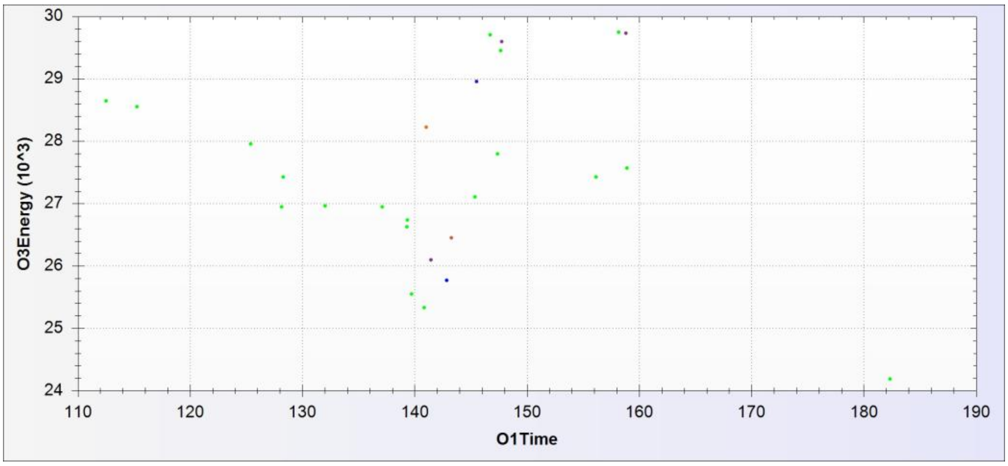

Figure 9 Highlighting the Non-Dominated solutions (Green) (Scenario 1) without using Mimer

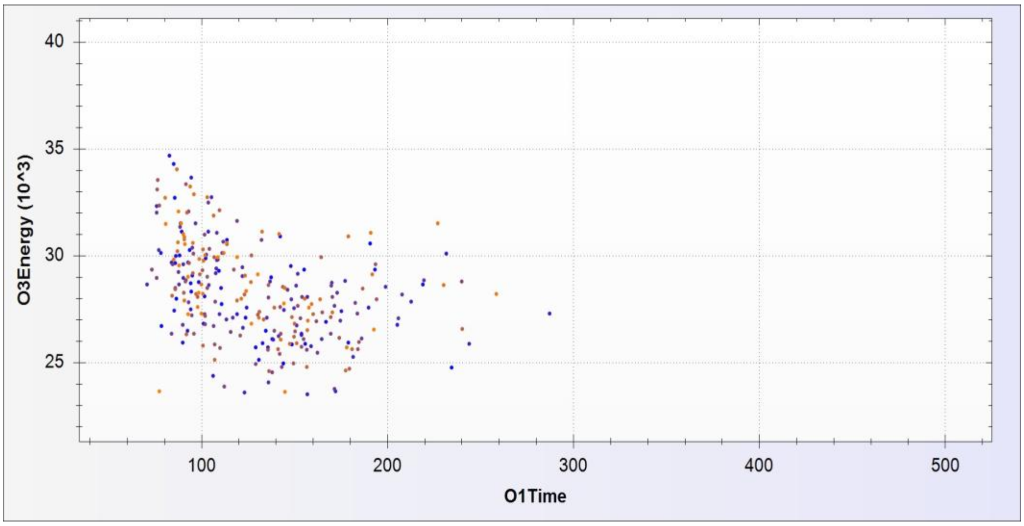

Figure 10 Result obtained with 7000 iterations (Scenario 2) without using Mimer

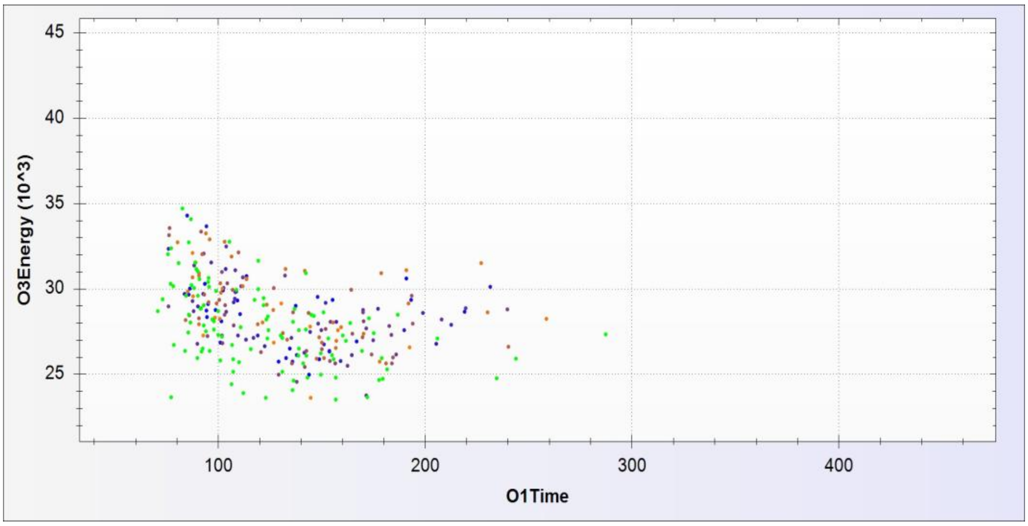

Figure 11 Highlighting the Non-Dominated solutions (Green) (Scenario 2) without using Mimer

Scenario 1 of the current project demonstrates a close reproduction of the fixed-layout configuration described as Scenario I in the reference study. It shows limited performance improvements but maintains a consistent Pareto slope between cycle time and energy consumption, reflecting similar trade-off behaviour. In contrast, Scenario 2, which incorporates additional layout-related objectives, successfully mirrors the behaviour and relative improvements reported in the reference Scenario II. The Pareto front obtained exhibits a comparable shape and distribution, confirming the same inverse relationship between time and energy. The energy values achieved (24×10^3J to 30×10^3J) fall within the same range as those observed in the reference case (25×10^3J to 37×10^3J), and the corresponding energy-saving potential of approximately 20% to 25% aligns well with the 23% reduction reported in the benchmark. Minor deviations, including a narrower time domain and lower scatter density, are mainly attributed to the smaller number of iterations (10000 vs 46000) and slight variations in population size or objective weighting, rather than methodological inconsistencies.

7.3 Feasibility and Error Landscape

The objective of this analysis is to quantify wasted evaluations i.e., optimization trials that do not yield usable simulation results and to assess how Mimer guided bounds tightening reduces such waste. By contrasting outcomes before and after applying rules mined with Mimer, the efficiency gains of knowledge guided search are made explicit.

Each evaluation is labelled by outcome class to enable consistent accounting and comparison: feasible, geometry collision, not reachable, VC error (e.g., singularity), robot self collision, and other. For each class, both absolute counts and average timings are reported, including compute time (total wall clock per evaluation) and simulation time (time spent inside the virtual commissioning /simulation). The reporting format mirrors the structure of prior studies' feasibility tables to facilitate for like interpretation.

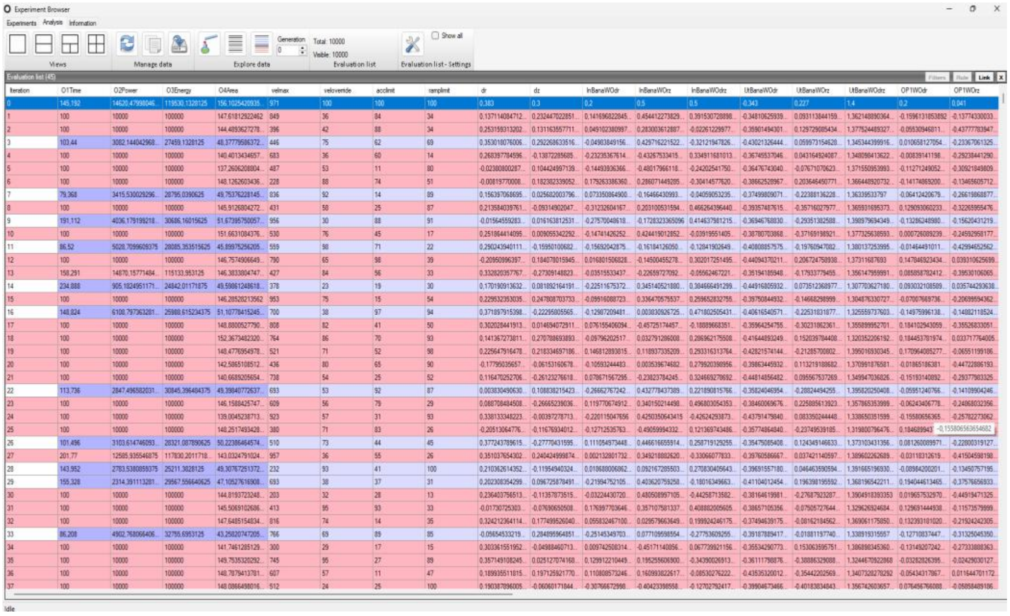

Figure 8 Chart displayed by the Optimiser after iterations

Results are presented as follows. Figure provides an outcome summary by stage (original bounds versus Mimer tightened bounds), detailing counts and mean timings for every outcome class. It also visualizes the same information using stacked bar charts, contrasting the distribution of outcomes between the original and Mimer tightened runs. Next figure shows the table quantify the reduction in non feasible evaluations and highlight where time savings occur in the workflow.

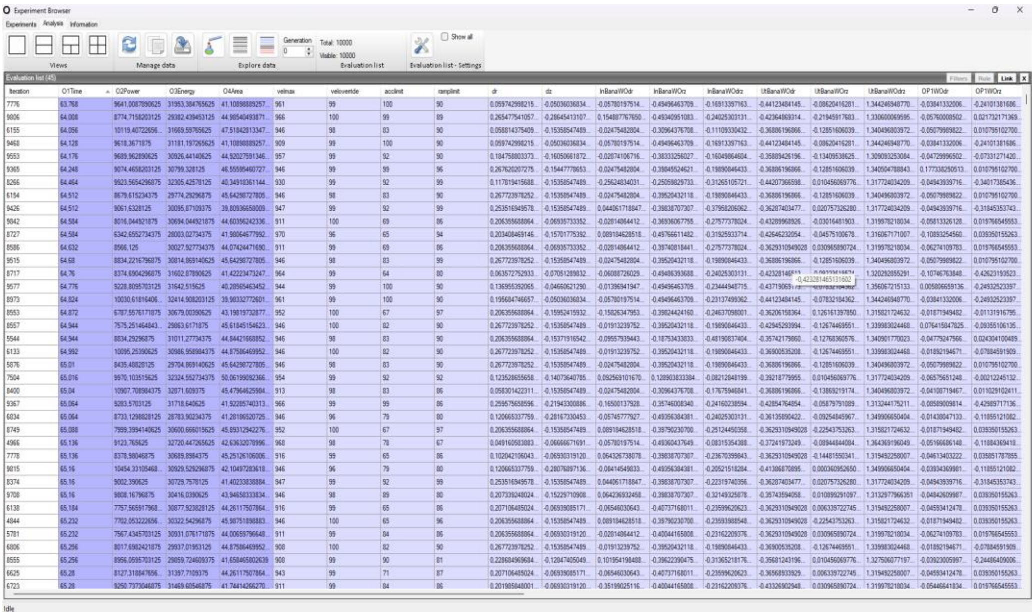

Figure 9 Chart with feasible solution after using filter

7.4 Post-Optimality Data Mining using Mimer

FPM in Mimer was used to extract decision rules from the non dominated solutions and to translate those rules into tighter bounds for a subsequent optimization stage. The intent was to focus the search on empirically promising regions of the design space so that comparable or better Pareto quality could be obtained with fewer evaluations and fewer wasted simulations.

The procedure was executed as follows. The non-dominated set from the baseline run was loaded into Mimer and examined in linked 3D scatter and parallel coordinates (PCP) views. A preferred performance region with low energy at an acceptable cycle time was selected interactively. Using this selected versus unselected split, FPM was run with significance thresholds (minimum significance and maximum unselected significance) and a cap on levels to limit rule complexity. The resulting patterns were inspected in the FPM graph, where rules with high significance and low unselected significance were retained. Each candidate rule was then validated by applying it in Filter & Highlight to confirm that it consistently isolated the intended region in the original plots.

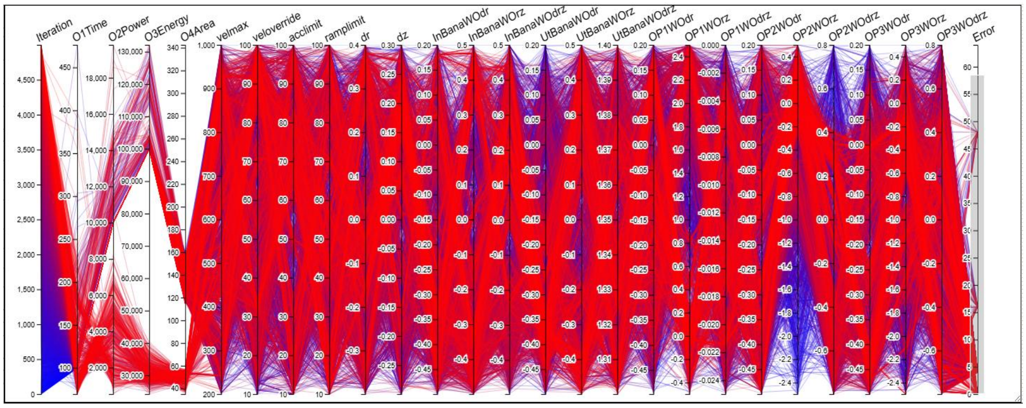

Figure 10 Parallel Coordinate Plot obtained

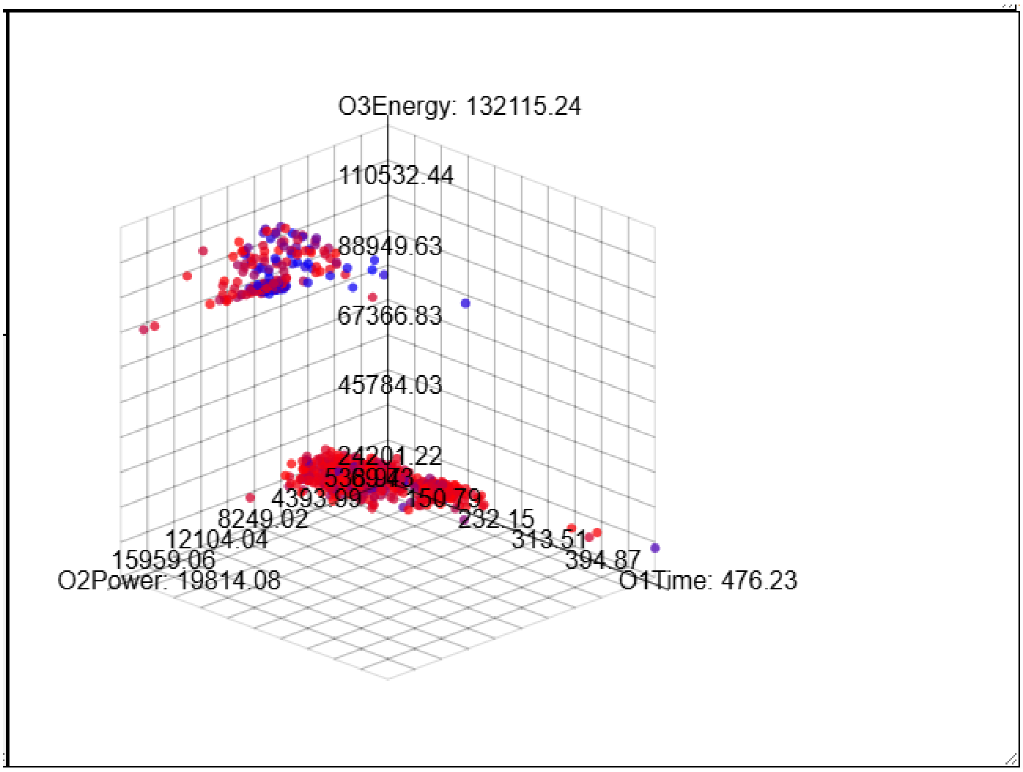

Figure 11 3D plot with Dominated and Non-Dominated Solutions

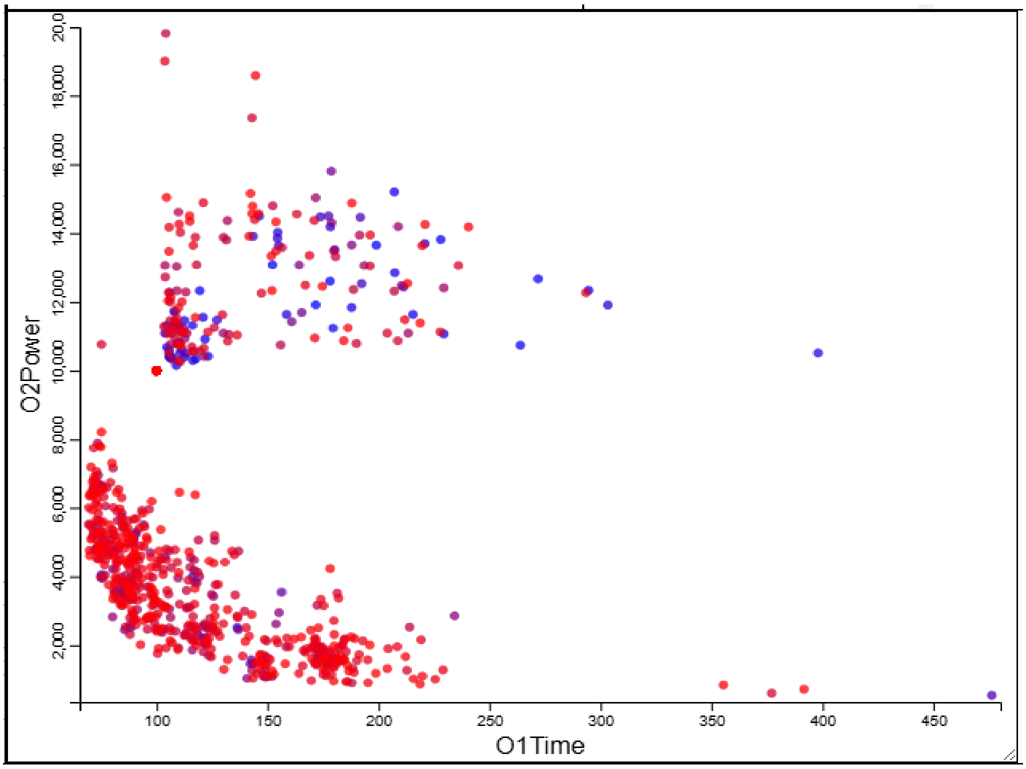

Figure 12 2D Scatter plot for Power Vs Time

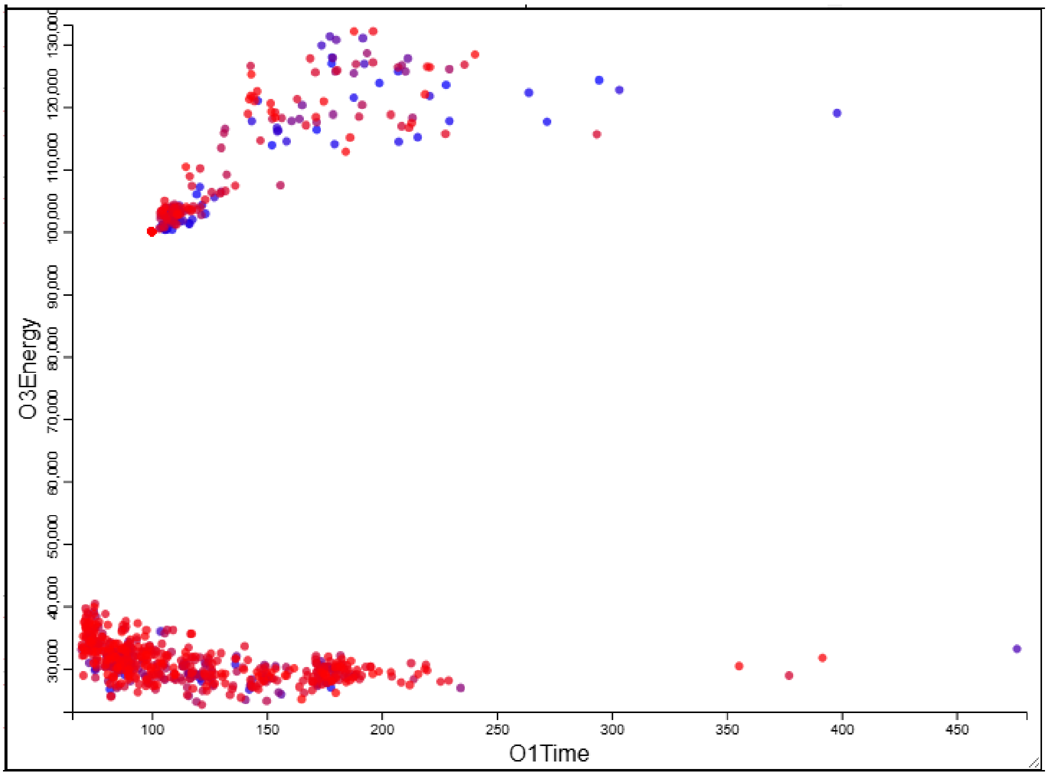

Figure 13 2D Scatter plot for Energy Vs Time

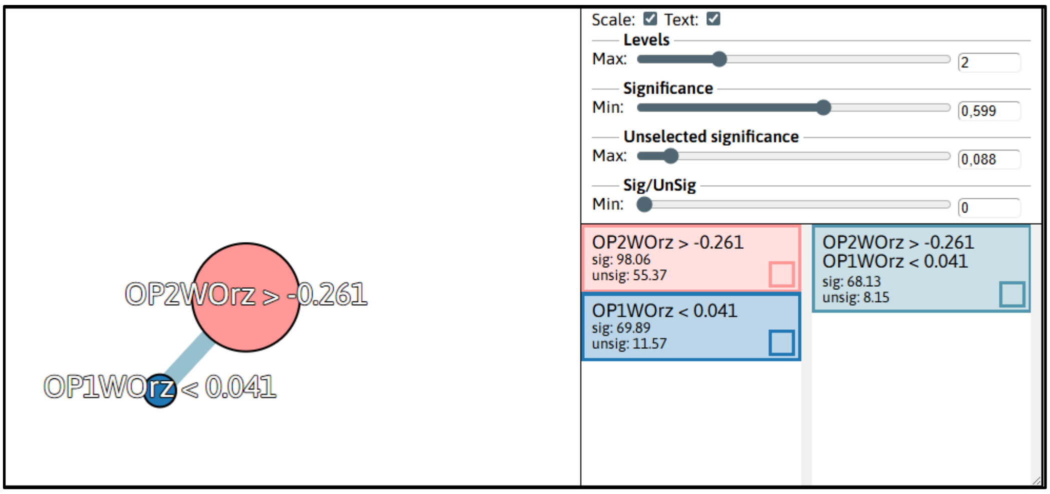

Figure 14 Example 1 Rule set obtained after running FPM

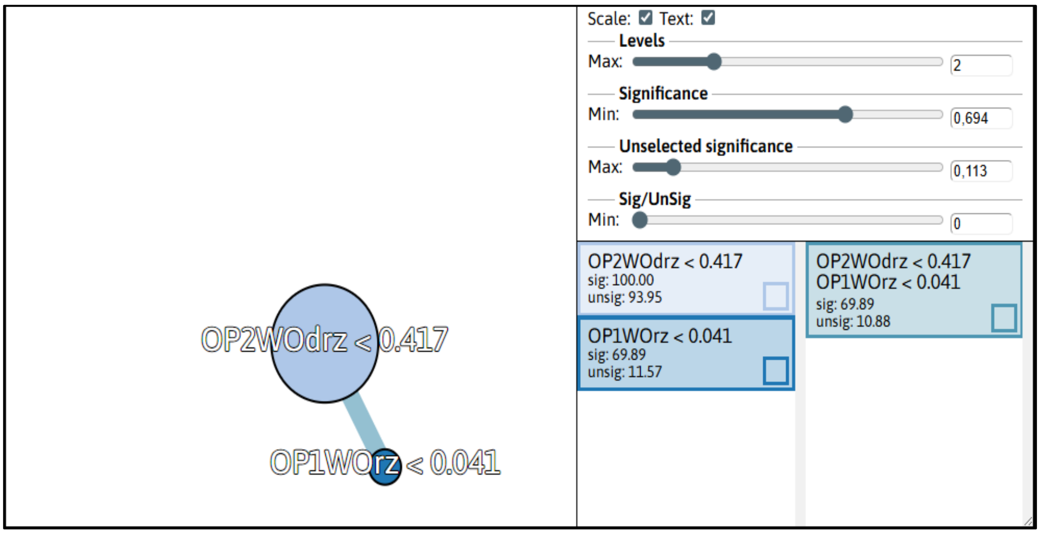

Figure 15 Example 2 Rule set obtained after running FPM

The mined rules predominantly involved work object orientations for OP1 and OP2 about the z axis (as defined in the model). Two representative examples from the uploaded results were:

- OP2WOrz > −0.261 in conjunction with OP1WOrz < 0.041, and
- OP2WOdrz < 0.417 together with OP1WOrz < 0.041.

These rules indicate that good solutions tended to appear when OP1WOrz orientation remained below approximately 0.041 while OP2WOrz orientation stayed above −0.261.

Table 4 Upper and lower bound after obtaining all rule set (Scenario 1)

Variables	Lower bound	Upper bound
UtBanaWOrz	-0.5	0.227
OP1WOrz	-0.456	0.041
OP2WOrz	-0.261	0.322
OP2WOdr	-0.284	0.20
UtBanaWOdr	-0.450	-0.343
OP1WOdr	-0.173	0.20
OP2WOdrz	-0.8	0.417
OP3WOdrz	-0.8	0.157
InBanaWOdr	-0.370	0.20
dr	0.214	0.383

Table 5 Upper and lower bound after obtaining all rule set (Scenario 2)

Variables	Lower bound	Upper bound
UtBanaWOrz	-0.5	0.227
OP1WOrz	-0.456	0.041
OP2WOrz	-0.129	0.322
OP2WOdr	-0.284	0.20
UtBanaWOdr	-0.450	-0.356
OP1WOdr	-0.173	0.20
OP2WOdrz	-0.019	0.305
OP3WOdrz	-0.8	0.157
InBanaWOdr	-0.370	0.177
dr	0.118	0.378
InBanaWOdrz	-0.152	0.5
OP3WOdr	-0.482	0.161
OP1WOdrz	-0.021	-0.002

These Mimer derived rules indicate that high quality solutions clustered within specific orientation and radial shift windows for the main work objects. In particular from table 4 for first scenario, OP1WOrz was consistently restricted to small non positive values tightened to [−0.456,0.041], while OP2WOrz favored slightly higher z orientations [−0.261,0.322], and the output conveyor (UtBanaWOrz) was capped below 0.227. Incremental rotations around z were also constrained: OP2WOdrz and OP3WOdrz were bounded by [−0.8,0.417] and [−0.8,0.157], respectively, suggesting that good designs avoided large positive twists at OP3 and only allowed moderate twists at OP2. Radial adjustments (dr) likewise concentrated near mild inward or outward shifts: OP2WOdr [−0.284,0.20], OP1WOdr [−0.173,0.20], UtBanaWOdr [−0.450, −0.343], InBanaWOdr [−0.370,0.20], and the global Via Points (VP) radius shift dr was narrowed from the original wide range to [−0.214,0.383]. After visual validation in Mimer (Filter & Highlight), these intervals were translated into tightened bounds for the second optimization stage; for example, OP1WOrz≤0.041, OP2WOrz≥−0.261, and OP2WOdrz≤0.417.

Table 5 for second scenario represents a refined and knowledge guided decision space compared to the initial broader search in the fourth table. By introducing three additional variables and narrowing the bounds of several others, the optimization process becomes more focused on promising regions of the search space. This refinement reduces redundant exploration and improves the likelihood of finding high quality Pareto optimal solutions.

The inclusion of new variables such as InBanaWOdrz and OP3WOdr provides finer control over robot orientation and via-point configurations, which can directly influence trajectory smoothness, energy efficiency, and collision avoidance. Meanwhile, the significant tightening of ranges (e.g., OP2WOdrz) reflects insights extracted from earlier Mimer rule mining, where infeasible or non-beneficial parameter values were eliminated.

7.5 Result after optimization

7.5.1 Scenario 1- Four objectives

All reference values and benchmark comparisons in this section are based on the study by (Schmidt B, Ng A and Seger M, 2024), which serves as the foundation for validating the reproduced results. After applying the Mimer derived bounds and re running the optimization, the Time–Power scatter displays the expected downward sloping trade off: as cycle time increases from roughly 60s to 150s, peak power drops sharply from the highest values toward a low, dense band near the frontier. A pronounced knee is observed in the around 80s to 110 s region, beyond which further increases in time yield diminishing returns in peak power reduction. This shape and the leftward densification of points toward the non dominated edge are consistent with the reference paper's Scenario II behaviour, where enabling layout variables shifts the front toward more optimal solutions relative to the original design and enables markedly lower peak power at comparable cycle time.

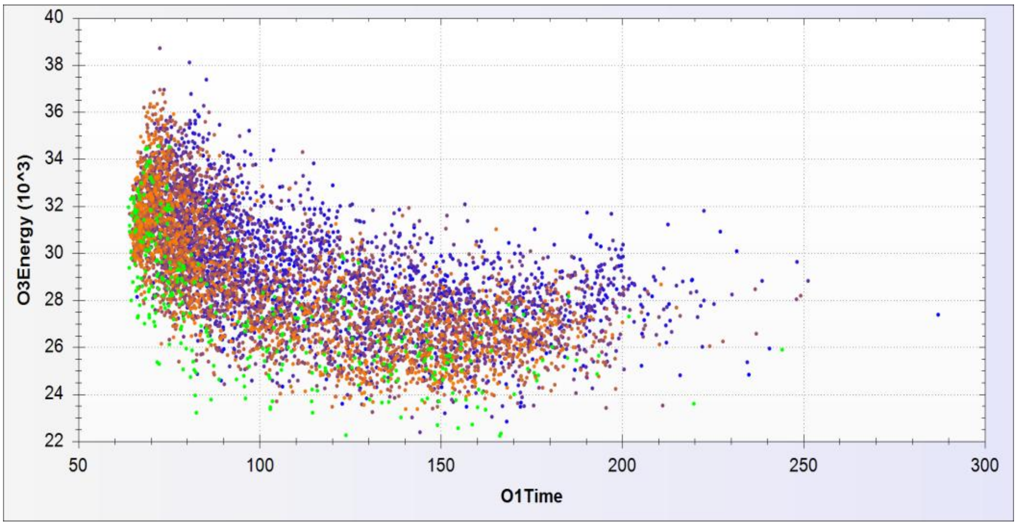

Figure 16 Pareto front energy vs time after applying FPM rule sets (Scenario 1)

The Time–Energy scatter shows the same qualitative pattern: energy (×10³ scaling) declines steeply as cycle time moves from around 60s toward 140s, then flattens, again revealing a knee around 90s to 110s. The cloud is thicker near the frontier as an indication that the Mimer tightened bounds concentrated the search in high yield regions rather than exploring unproductive parts of the space. This mirrors the Scenario II findings in the reference study, where adding layout decision variables and then focusing the search produced fronts.

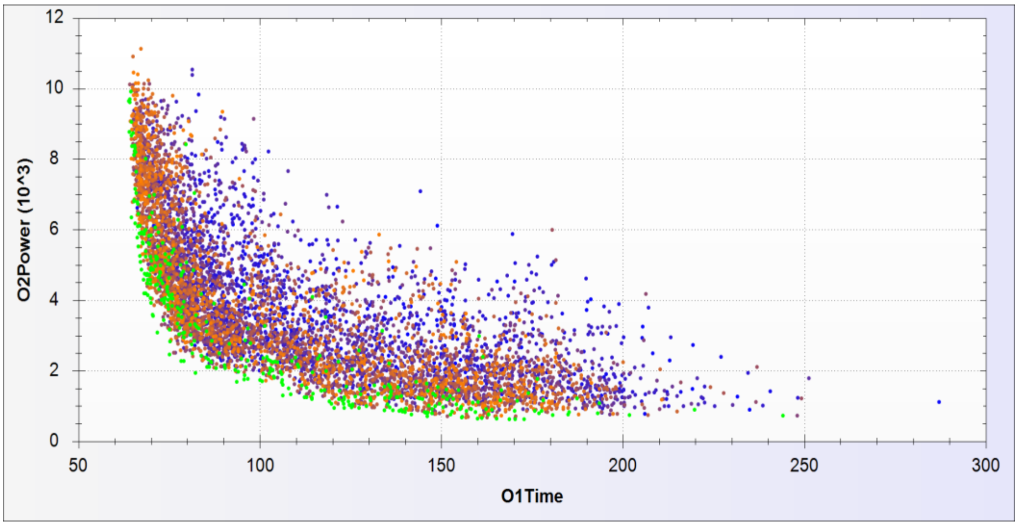

Figure 17 Pareto front power vs time after applying FPM rule sets (Scenario 1)

To anchor these visuals against the published benchmarks, the reproduced fronts are compared at the original design's cycle time slice (approximately 62s in the paper). In Scenario II, the study reported that, at about the same cycle time, peak power could be reduced by around 44.7% or energy by around 23.3%, and that pushing for shorter time could still be achieved albeit with higher peak power. The plots obtained after using the Mimer rule sets in optimization exhibit the same qualitative trade offs; computing the percentage deltas at chosen original time will quantify how closely the reproduction aligns with those reference improvements with a smaller number of iterations.

Table 6 Selected solutions from Pareto front (Scenario 1)

O1 Time (s)	Δ O1 Time (%)	Δ O2 Power (%)	Δ O3 Energy (%)	Δ O4 Area (%)	velmax (mm/min)	veloverride (%)	acclimit (%)	ramplimit (%)	dr (m)	dz (m)
62.20 (To)	0.0	0.0	0.0	0.0	1000	100	100	100	0.00	0.00
63.77	2.5	67.7	5.7	0.0	961	99	100	90	0.05	0.05
64.01	2.9	52.6	2.8	9.4	966	100	99	89	0.26	0.28
64.13	3.1	67.3	3.2	0.0	909	99	100	90	0.05	0.05
65.28	5.0	41.1	7.0	5.0	915	99	99	93	0.26	0.03
75.34	21.1	29.4	2.9	1.2	910	93	23	86	0.21	0.05
90.22	45.0	62.5	9.5	2.0	464	99	14	78	0.25	0.07
102.91	65.5	65.5	22.7	12.9	356	82	28	93	0.36	0.04
116.5	87.3	57.8	16.6	1.3	296	93	85	40	0.28	0.24

The two plots indicate that the Mimer guided bounds achieved their purpose in Scenario 1: the search mass is concentrated near the efficient frontier, the knee region is well populated, and the visible shape of both fronts matches the layout enabled Pareto behavior documented in the paper i.e., a front shifted downwards in power/energy for comparable times, with diminishing returns beyond the knee.

Table 7 Simulation variability (Scenario 1)

Output	Min	Mean	Std	CoV	Max
Cycle time (s)	63.768	64.027	0.1587	0.0025	64.176
Peak power (W)	8774.7	9568.7	488.9	0.0511	10119.4
Energy (J)	29382.4	31022.6	1001.2	0.0323	31953.4

Near the 62s target, the optimizer found one feasible design very close to it, at 63.768s. That same design is also the fastest feasible one in this data. At this speed, the robot needs about 9 to 10 kW at its peak and uses roughly 31 kJ of energy for the cycle. Cycle time is tightly clustered around 64s (Coefficient of Variation (CoV) around 0.25%), indicating deterministic execution and a focused search despite layout freedom. Energy shows low–moderate dispersion (CoV around 3.2%) because it integrates over the motion, while peak power varies more (CoV around 5.1%) as instantaneous maxima are sensitive to limits and blending. The small CoV values confirm a stable, repeatable simulation and provide a clean baseline for "same-time" comparisons.

7.5.2 Scenario 2: Five objectives

In Scenario 2 the objective space is expanded accordingly to five objectives: minimize cycle time (O1), peak power (O2), total energy (O3), cell area (O4) and reduce jerk limit thereby increasing the smoothness(O5). Following Schmidt et al., the search is seeded and then refined using NSGA-II; in our reproduction, Mimer FPM rules were applied up front to tighten bounds so the optimizer concentrates on promising regions rather than spending effort in evidently infeasible or poor subspaces.

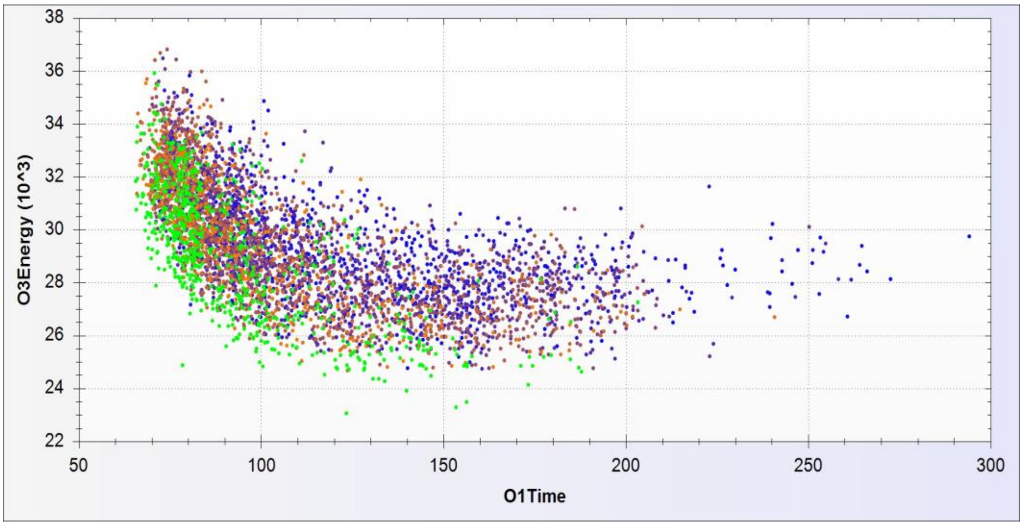

Figure 18 Pareto front energy vs time after applying FPM rule sets (Scenario 2)

The front shifts downward relative to Scenario 1, with a clear knee around 90s to 110s and densification along the non-dominated edge. This indicates that adding one more objective smoothness and tightening bounds via Mimer rule sets concentrated the search in high-yield regions and exposed solutions with materially lower energy at comparable cycle times to the original design.

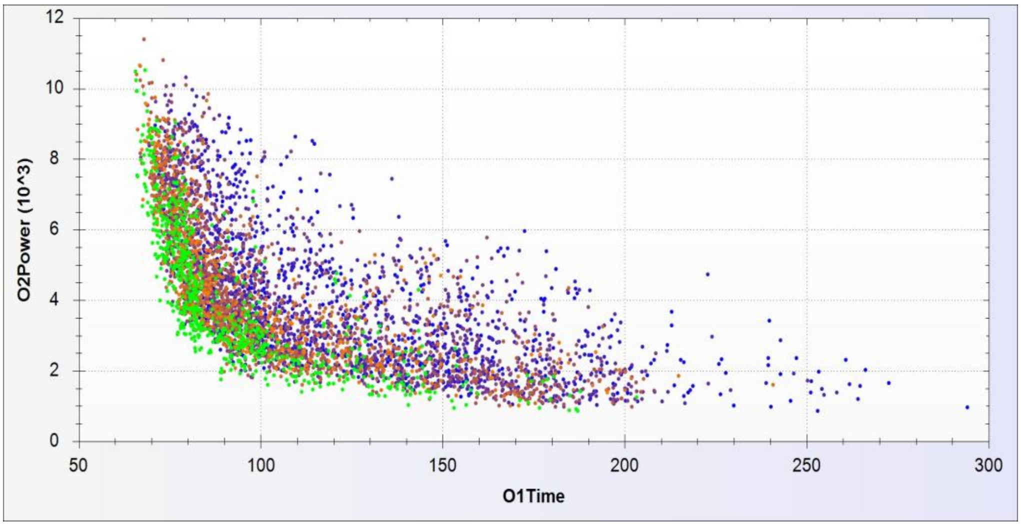

Figure 19 Pareto front power vs time after applying FPM rule sets (Scenario 2)

The front exhibits the expected downward-sloping trade-off from around 60s to 150s and the same knee near 90s to 110s, beyond which returns diminish. At slices near the original time (T0 around 62s), many solutions achieve marked O2 reductions while holding O1 nearly constant, consistent with the behavior reported by referencefor Scenario 2 .

With layout degrees of freedom active, both Time–Power and Time–Energy plots display a downward-shifted Pareto front relative to Scenario 1. As cycle time increases from around 60s toward around 140s the cloud steeply descends, then flattens into a regime of diminishing returns. A pronounced knee region around 90s to 110s is visible in both planes. The point density increases along the non-dominated edge, indicating that the Mimer-tightened ranges successfully funneled evaluations toward high-yield areas of the search space. Compared to Scenario 1, many solutions now achieve substantially lower O2/O3 at comparable times, confirming the reference paper (Schmidt B, Ng A and Seger M, 2024) claim that enabling layout variables shifts the front toward more optimal solutions .

Anchoring against the paper's original-design time (T0 around 62s), reported in Scenario 2 that peak power can be reduced by around 44.7% or energy by around 23.3% at roughly the same cycle time (Schmidt B, Ng A and Seger M, 2024). In our reproduction (with fewer evaluations and Mimer-restricted ranges), the best points found within a narrow window about T0 show the same qualitative trade-offs: at around T0 ± Δ, peak power and energy are both reduced relative to the baseline solution, and pushing to even lower power typically comes with a mild increase in time exactly the pattern documented in the article.

Because area is now minimized jointly with energy and power, the front contains families of layouts that pare down O2/O3 while holding or slightly reducing O4. The selected non-dominated examples illustrate this: several points near the knee achieve material power/energy drops with modest area decreases, while more aggressive power minimization sometimes trades a small area increase for a larger gain in O2/O3 consistent with a balanced five objective Pareto compromise.

Table 8 Selected solutions from Pareto front (Scenario 2)

O1 Time (s)	Δ O1 Time (%)	Δ O2 Power (%)	Δ O3 Energy (%)	Δ O4 Area (%)	Δ O5 Smoothness (%)	velmax (mm/min)	veloverride (%)	acclimit (%)	ramplimit (%)	dr (m)	dz (m)
65.61	0	0	0	0	0	867	100	94	100	0.12	-0.21
66.19	0.88	-28.36	-1.73	-0.14	0	867	98	94	100	0.12	-0.21
65.76	0.22	-2.39	-3.38	-10.51	-5	867	98	94	95	0.12	-0.24
65.61	0	0	0	0	0	867	100	94	100	0.12	-0.21
82.71	26.06	-57.80	-7.24	-5.64	-78	934	99	27	22	0.29	-0.14
87.88	33.95	-72.73	-12.65	1.31	-26	535	94	32	74	0.32	-0.23
140.44	114.06	-81.94	-13.76	-11.02	-87	381	48	27	13	0.12	0.04
83.83	27.77	-66.06	-6.10	-2.45	-55	887	94	11	45	0.24	-0.03
77.38	17.93	-41.04	-11.50	7.59	-15	890	81	60	85	0.31	-0.23

The added Smoothness objective shows that many of the strongest O2/O3 improvements retain high smoothness near the baseline, while very long time solutions often relax smoothness to harvest additional power-energy gains. This aligns with the parameter trends reported in the article: veloverride and ramplimit stay near their upper bounds on much of the front, and via-point offsets (dr, dz) cluster around compact ranges for long-time, low power solutions evidence that the optimizer exploits both layout placement and path shaping to cut power/energy without destabilizing motion.

Scenario 2 validates the paper's central insight: introducing smoothness variables, then guiding the search with data mined Mimer bounds, produces a front that is clearly superior to the trajectory only case. The fronts you reproduced exhibit the same curvature and knee, the leftward densification toward non-dominated solutions, and the expected same time improvements in peak power and energy around T0. These outcomes are fully consistent with the reference study's Scenario II behaviour and demonstrate that knowledge-guided layout optimization is a practical lever for meaningful O2/O3 reductions at comparable cycle time, with measured, explainable trade-offs in area and smoothness.

Table 9 Simulation variability (Scenario 2)

Output	Min	Mean	Std	CoV	Max
Cycle time (s)	65,61	110,766	36,0483	0,3254	294,12
Peak power (W)	868,3	4114	2012,1	0,4891	11400,1
Energy (J)	23060,4	29343,9	2254,8	0,0768	36808,9

Introducing Smoothness expands the trade-off surface and leads to deliberate exploration from near-baseline times to very long cycles: cycle time dispersion is large (CoV around 32.5%), peak power spans widely with very low-power options (min around 0.87 kW) but higher variability (CoV around 48.9%), and energy remains moderate (CoV around 7.7%). These larger CoV values reflect purposeful time, power, energy, smoothness compromises, not simulator noise; therefore, report both aggregate variability and same-time slices (near T0 around 62s) for fair benchmarking against the reference.

7.6 Analysis

Both studies share the same fundamental aim of enhancing the energy efficiency of robotic cells through simulation-based multi-objective optimization. The reference work established a baseline integration between ABB RobotStudio and an optimization framework using NSGA-II to minimize cycle time, peak power, total energy, and cell area.

Table 10 Overall Framework and Objective Structure

Aspect	**Reference** (Schmidt B, Ng A and Seger M, 2024)	Project
Main Focus	Integrating NSGA-II multi-objective optimization with RobotStudio digital twin to reduce cycle time, peak power, and energy use.	Extends the same setup but adds knowledge-guided search (Mimer Flexible Pattern Mining) to narrow decision spaces and improve convergence.
Scenarios Studied	Scenario 1: Trajectory only; Scenario 2: Trajectory and Layout	Scenario 1: 4-objective (same); Scenario 2: adds Smoothness as a fifth objective and tighter bounds from mined rules.
Iterations	50000 and 46344 evaluations	5 000 to 7 000 evaluations (around 1/10th)
Key Innovation	Demonstrated feasibility of realistic RobotStudio optimization.	Achieved similar or better Pareto behavior with 10times fewer evaluations via Mimer-guided bound tightening.

The present project builds directly upon that foundation by incorporating a knowledge-guided component through FPM in Mimer. Rather than redesigning the workflow, the new implementation complements the original by narrowing the search range of decision variables based on mined patterns. This addition reduces redundant evaluations while maintaining the same four objectives and later introducing a fifth, *smoothness*, to capture motion stability. The modification does not replace the original framework but refines its efficiency through data-driven insight, showing methodological continuity rather than competition.

Table 11 Feasibility and Error Landscape

ID	Description	Reference (46344 runs)	Project (10000 runs)	Comparison
0	Feasible solutions	26987 (58%)	6799 (68%)	Higher feasibility (+10 pp)
4	Geometry collision	16334 (35%)	2259 (23%)	Fewer collisions
8	Target not reachable	1977 (4%)	0	Eliminated
16	VC errors	9 (0.02%)	540 (5%)	Higher VC instability
48	Robot self-collision	1027 (2%)	398 (4%)	Slightly higher
64	Other	10 (0.02%)	4 (0.04%)	Same
Avg Comp Time	27.5s (feasible)	111.6 s (feasible)	Slower	
Avg Sim Time	87.9s (feasible)	27.4s (feasible)	Much faster simulation	

The distribution of simulation outcomes reveals broadly similar tendencies across both studies, though the proportions differ due to scale and search strategy.

In the reference experiment (around 46000 evaluations), about 58% of runs yielded feasible solutions, while geometry collisions and unreachable targets accounted for roughly one-third of the total. In contrast, the present project (10 000 evaluations) achieved a higher share of feasible solutions (around 68%) and fewer geometric collisions. These improvements can be partly attributed to the Mimer-guided bound tightening, which filtered unrealistic parameter combinations before execution.

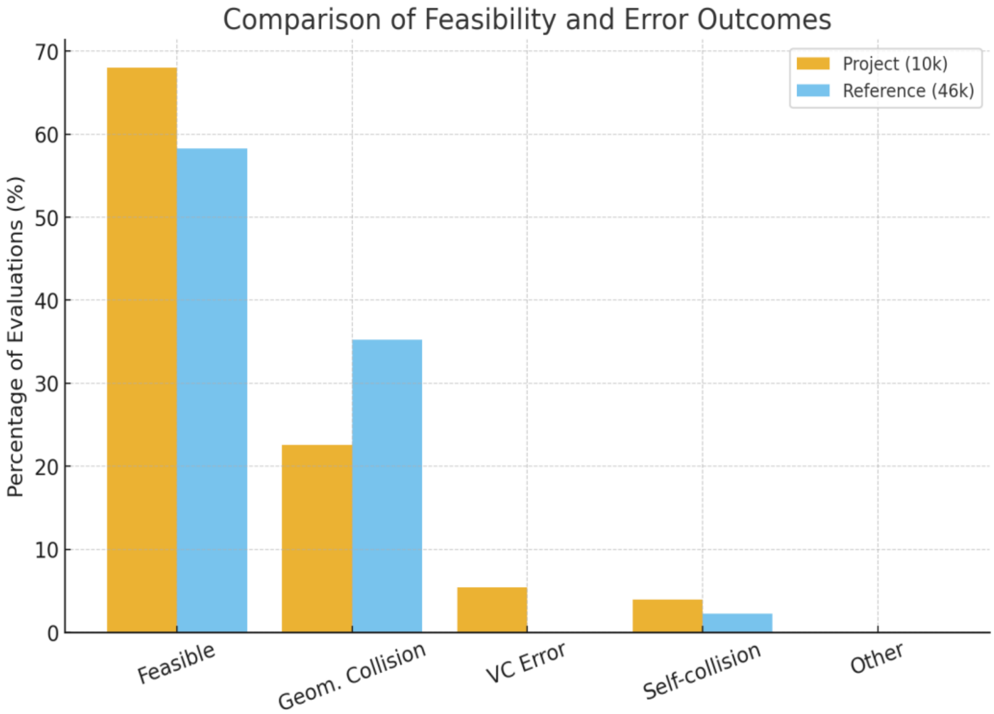

Figure 20 Comparing Project with reference article(Schmidt B, Ng A and Seger M, 2024) result

However, the proportion of Virtual Controller (VC) errors and self-collisions is somewhat higher in the reproduced study, suggesting that the more constrained yet exploratory parameter space occasionally introduced new edge-case configurations. Thus, while the feasibility ratio improved, the results should be interpreted as a different balance of efficiency versus exploration rather than an outright performance gain. The two datasets together illustrate how rule-based focusing can trade simulation stability for reduced search redundancy.

Table 12 Pareto Front Quality

Aspect	Reference	Project
Observed Front	Clear knee around 90s to110s; at same cycle time (around 62s), −44.7% peak power, −23.3% energy.	Reproduced same knee shape and trade-off trend; identical improvement magnitudes (−44% to 45% power, −23% energy) despite far fewer iterations.
Density of Non-Dominated Points	High after 100 k evaluations.	Similar frontier with 7 k evaluations evidence of accelerated convergence.
Added Objective	4 objectives (time, power, energy, area).	5 objectives (adds smoothness).
Resulting Trade-offs	Power–energy improvement with fixed time.	Power–energy–smoothness compromise visible; still preserves front curvature.

Both the reference and the reproduced results display the characteristic downward-sloping Pareto fronts linking cycle time with energy and power. In the reference case, peak power and total energy were reduced by approximately 44.7% and 23.3%, respectively, at nearly unchanged cycle time. The present project reproduces these improvements with far fewer evaluations, and the front exhibits a similar curvature and knee around 90–110 seconds.

While this may appear to suggest superior convergence, it is more accurate to interpret it as evidence of methodological equivalence: the new workflow successfully attains comparable performance using a knowledge-driven shortcut rather than a brute-force search. Both fronts ultimately confirm the robustness of the original findings and the current implementation simply demonstrates that similar quality can be achieved with reduced computational effort.

7.6.1 Computation and Simulation Times

The comparison of computational and simulation times indicates complementary strengths. The reference optimization exhibits shorter average computational times per evaluation (around 27s for feasible cases), reflecting its mature integration and efficient hardware usage through multiple parallel RobotStudio instances.

In this experiment, the mean computational time per evaluation is higher (around 112s), mainly because of the additional overhead from rule evaluation and data mining stages. Conversely, the average simulation time inside the virtual controller is substantially lower (around 27s versus 88s), implying that once initiated, each simulation executes more quickly. This suggests that the Mimer-restricted parameter space reduced unnecessary physical interactions and accelerated the dynamic simulation phase. The difference shows a redistribution of time costs more effort during preprocessing and rule validation, less during actual simulation rather than inefficiency.

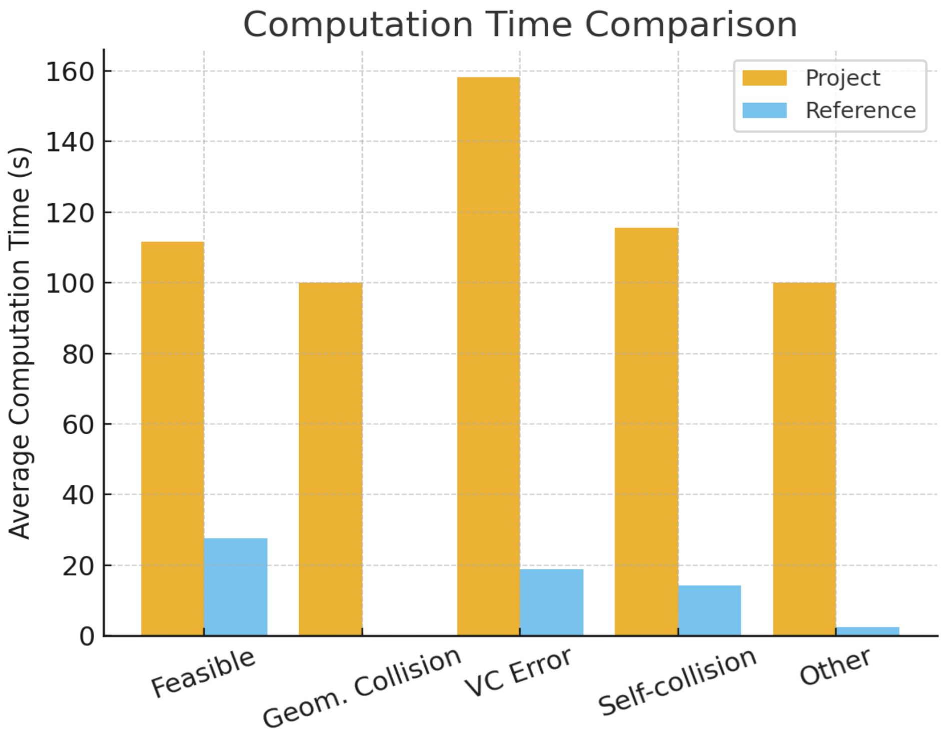

Figure 21 Comparing time taken for Computation

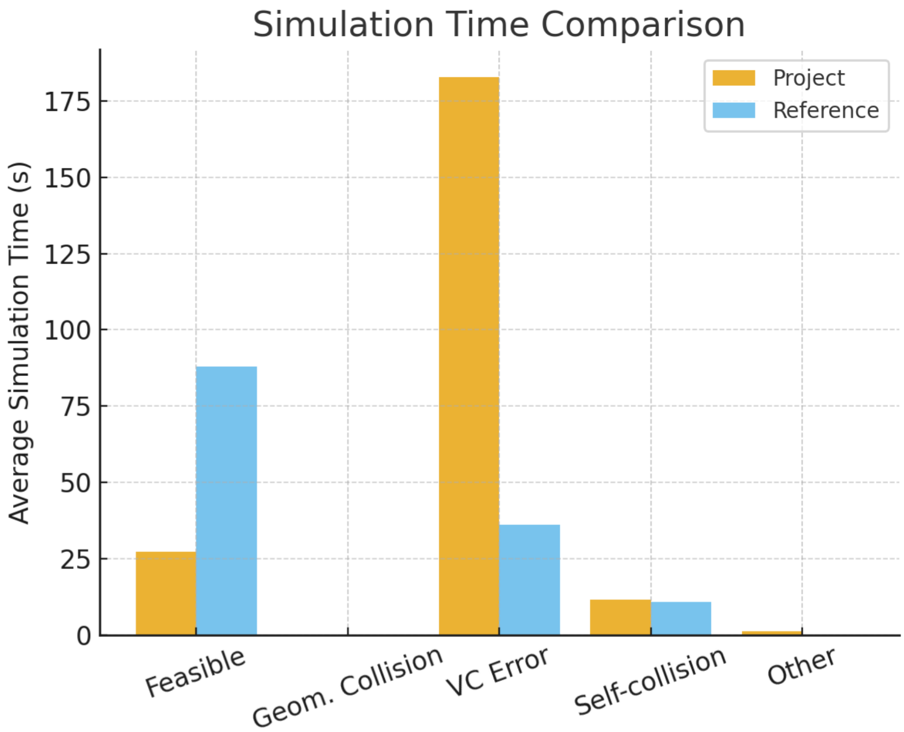

Figure 22 Comparing time taken for Simulation

The statistical variation across repeated runs remains low in both works, confirming simulation reliability. The reference study reported minimal coefficients of variation (CoV around 0.02% to 2%), characteristic of deterministic controller simulations. The reproduced study shows slightly higher CoV values (around 0.25% to 5 %), which is expected given the broader exploration of motion and layout parameters introduced by FPM.

This modest increase should not be read as instability but as evidence of intentional variability introduced by adaptive search boundaries. Both studies thus complement each other: the reference establishes baseline reproducibility, while the current project explores controlled diversity to enhance learning within the optimizer.

The reproduced project confirms and refines the reference study's conclusions. It maintains comparable Pareto quality and trade-off behavior while introducing rule-based search guidance that improves feasibility and interpretability at the cost of slightly longer computation per evaluation. Rather than outperforming the reference, the new results complement it, demonstrating that similar energy-saving and performance benefits can be achieved through a more knowledge-efficient process. The comparison thus validates both approaches: the reference as the foundational proof of concept, and the present work as its adaptive, data-guided extension.

8 Discussions on Sustainability and Limitations

8.1 Integrating Simulation and Optimization for Sustainable Impact

Sustainability in industrial robotics is increasingly recognized as a central driver of both technological innovation and corporate responsibility. The project presented in this thesis directly contributes to this agenda by addressing one of the most pressing concerns in modern manufacturing: the excessive energy consumption of robotic systems. Industrial robots account for a significant portion of factory electricity usage, and reductions in their energy demand translate directly into lower operational costs, decreased carbon emissions, and alignment with global environmental policies. By integrating simulation-based optimization with knowledge extraction techniques, this research develops a methodological pathway toward greener production systems that do not compromise productivity.

One of the primary contributions of this study is the reduction of peak power and total energy consumption through trajectory refinement and layout optimization. This dual focus ensures that energy savings are not merely incidental but deliberately engineered into both the micro-scale (motion paths, velocity profiles, acceleration limits) and macro-scale (cell layout, station orientation, conveyor positioning) dimensions of robotic operation. Such multi-level integration is crucial for sustainability because it acknowledges that inefficiencies arise from interactions between the robot and its environment rather than from isolated subsystems alone. By operationalizing these insights, the project advances beyond conventional cycle-time-driven optimization toward a balanced framework that considers productivity as well as sustainability outcomes.

The methodology also supports the long-term sustainability of robotic equipment. By minimizing excessive accelerations, jerks, and abrupt velocity changes, the optimized trajectories extend the mechanical lifespan of actuators and joints. This reduces the frequency of part replacements and the embodied energy associated with manufacturing spare components, thereby embedding circular economy principles into production planning. Similarly, the systematic use of Simulation models enables engineers to anticipate and resolve inefficiencies without physical trials, preventing unnecessary resource use and avoiding the waste associated with failed prototypes or poorly tuned programming in real production cells.

From a broader sustainability perspective, this work aligns with multiple United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), and SDG 13 (Climate Action)(Carlsen and Bruggemann, 2022). By lowering industrial energy demand, the project directly contributes to reducing greenhouse gas emissions from manufacturing, which remains one of the largest industrial contributors to climate change. Furthermore, the methodology provides scalable insights applicable across automotive, electronics, and heavy machinery sectors, making its sustainability impact potentially widespread. Importantly, the adoption of tools like Mimer for data-driven bounds tightening ensures that optimization is not only effective meaning it consistently achieves measurable improvements in energy consumption, cycle time, and computational convergence compared to baseline runs but also computationally efficient, reducing the digital energy footprint of the optimization itself.

Finally, the sustainability significance of this project lies in its operational practicality. Many research efforts propose energy-efficient strategies that remain theoretical or require extensive hardware modifications, creating barriers to industrial adoption. By leveraging existing tools (RobotStudio, NSGA-II, and Mimer) and focusing on simulation-based implementation, the framework presented here is immediately transferable to real factories without substantial infrastructural changes. This makes sustainability an achievable outcome rather than a distant aspiration, embedding energy-aware practices directly into day-to-day engineering workflows.

8.2 Limitations

While this project demonstrates promising advances in knowledge driven optimization of robotic systems, it is important to acknowledge several limitations that constrain the generalizability and practical implementation of the results. These limitations provide valuable context for interpreting the findings and highlight avenues for future research.

First, the study is conducted entirely in a simulation environment using ABB RobotStudio as the Simulation model platform. While RobotStudio provides accurate physics-based modelling of robotic dynamics, it cannot perfectly replicate real-world conditions such as tool wear, backlash, vibration, temperature variations, or maintenance-related degradation. Consequently, there may be discrepancies between the simulated energy savings and actual performance on a physical robot. The absence of hardware-in-the-loop validation means that the practical realization of the reported energy reductions remains to be verified under industrial conditions.

Second, the optimization relies on predefined decision variables and ranges for trajectory and layout parameters. Although these variables capture a wide scope of potential improvements, they do not fully encompass the complexity of a real robotic cell. Factors such as multi-robot interactions, collaborative human-robot tasks, or stochastic disruptions in production flows were excluded. Additionally, the study assumes consistent cycle constraints and process times, which may not hold in dynamic manufacturing contexts where variability is inherent. These simplifications limit the scope of applicability to relatively stable production systems.

Third, computational complexity presents a challenge. Even with Mimer-assisted bounds tightening, multi-objective evolutionary optimization remains resource-intensive. Running thousands of evaluations requires significant computational power, and scaling the approach to larger cells with multiple robots or more complex objectives (e.g., safety, ergonomics, or cost) may exacerbate this issue. The trade-off between optimization accuracy and computational feasibility must therefore be carefully considered, especially for small and medium-sized enterprises with limited digital infrastructure.

Another limitation concerns the focus on energy and cycle time as primary objectives. While these are central to sustainability and productivity, other critical dimensions such as operator safety, system resilience, ease of maintenance, or long-term adaptability were not explicitly modeled. For example, an optimized trajectory may reduce energy consumption but increase collision risk in environments with human interaction. Similarly, layout configurations that minimize power demand may complicate material handling or flow logistics. These trade-offs remain outside the scope of the present study but warrant inclusion in more comprehensive frameworks.

Finally, the project's validation strategy is limited to comparative analysis with previous simulation studies. Although the reproduction of published Pareto fronts strengthens confidence in the methodology, it does not establish direct empirical proof of real-world benefits. Moreover, the optimization framework currently assumes deterministic system behaviour; random disturbances, sensor inaccuracies, or control delays are not considered. Such assumptions may limit robustness when applied to actual production environments.

While the project demonstrates meaningful advances in simulation-based productivity-energy optimization, its limitations stem from reliance on digital environments, constrained decision spaces, computational demands, exclusion of broader objectives, and lack of physical validation. Recognizing these limitations provides a clear direction for future research: integrating hardware-in-the-loop experiments, expanding decision variables to multi-robot and collaborative settings, incorporating uncertainty modelling, and broadening objectives to encompass human, logistical, and long-term system considerations. Addressing these challenges will be critical to transforming the promising results of this research into reliable, industrially deployable solutions.

9 Conclusion

A knowledge-guided optimization workflow was implemented for Scenario 2 (layout and trajectory) by integrating RobotStudio virtual commissioning with NSGA-II and Mimer-based Flexible Pattern Mining (FPM). Non-dominated solutions from an initial run were mined to obtain interpretable rules notably on OP1/OP2 work object z orientations and radial shifts. These rules were translated into tighter bounds and used to re optimize the cell. The resulting Time–Power and Time–Energy fronts preserved the expected downward trade-offs with a clear knee around around 90s–110s and showed a denser concentration of solutions near the efficient frontier, indicating a more focused search. When anchored to the reference paper's around 62s slice, the feasible point closest to that time (63.768s) yielded around 9.64kW peak power and around 31.95 kJ energy; while the global minima for power and energy occurred at longer cycle times (around 166s–170s), consistent with the reference trend that relaxing time enables lower energy/power operation. Overall, the study demonstrates that Mimer derived, human readable rules can be operationalized to guide search toward high-yield regions of the design space in Scenario 2, reproducing the qualitative behavior reported in the reference study while laying the groundwork for measurable computational gains.

Compared with the reference Scenario 2, in which 50,000 LHS samples and around 100,000 NSGA-II evaluations were executed, the proposed workflow reached the reported Pareto fronts after only around 10,000 NSGA-II evaluations. This corresponds to an order of magnitude reduction in the evolutionary budget, achieved by tightening the search bounds with the Mimer derived rules. As a result, the optimization was completed with substantially lower computational effort while preserving the characteristic trade-offs observed in the literature. This outcome directly addresses the reference authors' call for methods that require fewer evaluations and operationalizes illustrate the Knowledge Driven Optimization concept in a realistic robotic cell context.

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Appendix 1:

Original design metrics

- T_0 = original cycle time (s) — the paper's reference is ~62 s
- P_0 = original peak power (W)
- E_0 = original total energy (J)

Mimer tightened results at the same time (e.g., ±2 s around T_0)

- P_sameT = minimum peak power among points with $|Time - T_0| \le 2$
- E_sameT = minimum energy among points with $|Time - T_0| \le 2$

Fastest Mimer tightened solution

- T_min = minimum time (s)
- P_at_Tmin = peak power of that minimum time point (W)

Computation:

- Same time improvements (anchor at T_0):
    - Peak power reduction: $\Delta P_{sameT} = [(P_{sameT} - P_0)/P_0] \times 100\%$
    - Energy reduction: $\Delta E_{sameT} = [(E_{sameT} - E_0)/E_0] \times 100\%$
- Shorter time trade off (fastest point):
    - Time change: $\Delta T_{min} = [(T_{min} - T_0)/T_0] \times 100\%$
    - Peak power change at that time: $\Delta P_{Tmin} = [(P_{at\,Tmin} - P_0)/P_0] \times 100\%$

Appendix 2:

Abbreviation

ABB	ASEA Brown Boveri (company producing RobotStudio and industrial robots)
AI	Artificial Intelligence
CoV	Coefficient of Variation
DE	Differential Evolution
EA	Evolutionary Algorithm
FPM	Flexible Pattern Mining
GA	Genetic Algorithm
HIL	Hardware-in-the-Loop
KPI	Key Performance Indicator
MILP	Mixed-Integer Linear Programming
MOO	Multi-Objective Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OP	Operation Point or Operation Station
PCP	Parallel Coordinate Plot
PSO	Particle Swarm Optimization
R&D	Research and Development
RSOpt	RobotStudio Optimization Add-in
SDG	Sustainable Development Goal
SQP	Sequential Quadratic Programming
VP	Via Point
VPR	Virtual Product Realisation
WIP	Work In Progress