

Article

Metaheuristic Optimization of Electric Drive Systems in a Virtual Commissioning Environment for Sustainable and Energy-Efficient Industrial Automation

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Abstract

Improving energy efficiency in electric drive systems is vital for sustainable manufacturing. Despite their potential, metaheuristic optimizations are rarely used in industrial virtual commissioning (VC) due to high computational demands and lack of reliability metrics. This paper presents a statistically validated genetic algorithm (GA) framework designed to bridge this gap, enabling high-speed deployment within practical VC workflows. The framework optimizes target speed, acceleration, and deceleration across three objectives: minimizing energy consumption, maximizing efficiency, and reducing losses. Comparative evaluations show that the GA achieves near-optimal solutions with a significant speedup, reducing optimization time from hours to minutes. Extensive statistical validation (100 independent runs) confirms high reliability and feasibility for multi-run industrial strategies. Furthermore, the study introduces a novel post hoc normalized analysis to quantify trade-offs between competing objectives. Validated on two physical testbeds (belt and strap conveyors), the methodology demonstrates cross-system generalizability and significant energy improvements. Implemented via IEC 61131-3 compliant programming, this eco-efficient automation system directly supports global sustainable development goals (SDGs 7 and 9) by enabling sustainable-by-design industrial automation.

Keywords: automotive industry; energy efficiency; genetic algorithms; industrial automation; virtual commissioning

1. Introduction

Energy efficiency is critical for reducing production costs and mitigating greenhouse gas emissions. Legal and environmental pressures—particularly from the 1997 Kyoto Protocol [1]—have made this a priority across EU member states. Industry holds the greatest potential for energy reduction [2,3].

In recent years, the automotive industry has increasingly prioritized energy efficiency due to its substantial electricity demand. As a major global energy consumer, this sector requires targeted strategies to optimize energy use in manufacturing processes. Electric drive systems play a key role in this context, supporting various production stages such as assembly, material handling, and robotic operations. Data from 2020 indicate that electric

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motors account for approximately 70% of the sector's total electricity consumption [4]. This trend underscores the need for advanced approaches to effective energy management.

The Industry 4.0 paradigm, together with the integration of intelligent technologies—particularly automation and digitalization—has introduced new opportunities to enhance operational efficiency. One of the most promising advances is virtual commissioning (VC), which enables the digital simulation and testing of manufacturing systems prior to physical implementation. VC not only accelerates technology deployment but also allows for early identification of inefficiencies, significantly improving energy performance. By combining VC with metaheuristic optimization, this research supports global sustainable development goals (SDGs 7 and 9) by promoting energy-efficient industrial processes.

Despite the proven effectiveness of metaheuristic algorithms in laboratory settings, their industrial adoption remains limited due to three critical gaps: lack of statistical validation quantifying reliability under stochastic conditions, computational demands incompatible with iterative commissioning workflows requiring minute-scale optimization, and absence of systematic cross-system validation demonstrating practical generalizability. The optimization algorithms assessed include exhaustive search (serving as a performance benchmark) and soft computing methods—i.e., simulated annealing (SA), particle swarm optimization (PSO), and genetic algorithms (GAs). Among the tested methods, GAs were identified as the most efficient, achieving the optimal balance between solution quality and computational speed, essential for industrial VC workflows. The integration of soft computing techniques into the VC framework enables the generation of optimized solutions that are both theoretically robust and practically deployable. Simulations are conducted in MATLAB and Simulink. Among the tested methods, GAs are identified as the most efficient and are implemented in the VC environment using IEC-61131-3-compliant programming. Three optimization objectives are defined: minimizing electrical energy consumption (Problem 1), maximizing energy efficiency (Problem 2), and minimizing energy losses (Problem 3). These objectives are analyzed using both exhaustive search and GAs, with normalized multi-objective analysis.

The employed physics-based digital twin (PBDT) models provide accurate energy predictions at the component level. Despite the proven benefits of metaheuristics, their widespread use in VC is hindered by a critical research gap: the lack of systematic validation focusing on the essential trade-off between solution quality and required computation time (minutes vs. hours). This work addresses this by delivering a statistically validated, high-speed optimization framework tailored for industrial VC, supported by a novel post hoc trade-off analysis and comprehensive validation on industrial testbeds. Overall, this work demonstrates how soft computing and intelligent optimization enable eco-efficient automation systems that support global efforts toward carbon neutrality. The main contributions of this work include the development of a statistically validated, high-speed optimization framework tailored for industrial virtual commissioning. The core contributions lie in quantifying the reliability and computational feasibility of metaheuristics for rapid deployment, supported by a novel methodology for the quantitative trade-off analysis of competing single-objective criteria and comprehensive experimental validation on industrial testbeds.

The remainder of the paper is organized as follows: Section 2 reviews optimization algorithms for energy efficiency with an emphasis on VC-related applications and identifies critical research gaps. Section 3 describes the experimental setup and the configuration of the VC environment. Section 4 outlines the methodology for automatic parameter selection and details the implementation of the genetic algorithm. Section 5 presents the results and discussion, including algorithm comparison, statistical validation, optimization results for both testbeds, and cross-system comparative analysis. Section 6 discusses

the comparative analysis, practical implications, environmental impact, and limitations of the study. The final section concludes the study and outlines directions for future research.

2. Literature Review

2.1. Energy-Efficient Optimization Approaches

Energy optimization in electric drive systems has become a critical research area in industrial automation. The need to reduce energy consumption while maintaining or enhancing system performance has prompted the development of diverse optimization strategies, particularly for control parameter tuning. The proportional–integral–derivative (PID) controller remains one of the most widely adopted methods due to its simplicity, robustness, and effectiveness in dynamic systems. Numerous studies have explored PID parameter optimization to improve the energy performance of electric drives [5,6].

Among available techniques, genetic algorithms have received significant attention for their capability to identify near-optimal solutions in complex, multidimensional problem spaces. GAs have been effectively applied to optimize motor torque control, improve energy distribution, and enhance system reliability in electric drive applications [7,8]. Their robustness against local minima, independence from initial conditions, and ease of implementation—including deployment on programmable logic controllers (PLCs)—make them well-suited for industrial use [9,10]. GAs have also been successfully employed in broader industrial contexts such as production scheduling [11–13] and dynamic rescheduling [14].

Soft computing approaches have shown considerable potential in addressing energy and control challenges. Leonori et al. [15] proposed a hierarchical genetic algorithm-based fuzzy inference system (GA-FIS) framework for microgrid energy management, balancing operating costs and energy efficiency. Ardabili et al. [16] compared the adaptive neuro-fuzzy inference system (ANFIS) model optimized using GA and PSO models for heating, ventilation, and air conditioning (HVAC) control, demonstrating superior adaptability under dynamic conditions. In electric drives, adaptive GA-based fuzzy sliding mode control has been employed for DTC switched reluctance motors, highlighting GA's ability to perform precise drive tuning. Oszczypałka et al. [17] developed a GA framework for optimizing system availability, while Ding et al. [18] applied GAs to energy-efficient virtual machine placement. Hormozi et al. [19] extended this line of research, achieving approximately 8% energy savings and substantial speed improvements in fitness evaluation. Collectively, these studies confirm the versatility and practical relevance of GA-driven soft computing strategies.

The increasing complexity of energy management problems has led to the development of specialized multi-objective metaheuristics. In cloud and data center optimization, Farzai et al. [20] proposed a multi-objective GA for virtual machine placement that minimizes power consumption and resource waste under communication constraints. Dehnavi et al. [21] extended this approach with a hybrid GA for cost-efficient task scheduling in heterogeneous cloud environments, emphasizing the importance of adapting genetic operators to real-world constraints. In maritime hybrid energy systems, Li et al. [22] introduced an improved differential mutation aquila optimizer for optimal dispatching, while Chang et al. [23] applied an enhanced non-dominated sorting genetic algorithm II (NSGA-II) to handle conflicting objectives in multi-source energy systems.

Although these algorithms demonstrate high-quality solutions, they typically prioritize accuracy over computational speed, often requiring hours or days to converge. A critical research gap remains: the lack of systematic performance characterization that addresses the trade-off between solution quality and computation time—an essential factor for industrial virtual commissioning, where optimization must occur within minutes (not hours) to enable iterative design workflows involving multiple parameter adjustments per work session.

Beyond GAs, particle swarm optimization, introduced by Kennedy and Eberhart [24], has shown strong results under dynamic operating conditions, including PID tuning [25,26]. However, PSO adoption in industrial applications remains limited due to implementation challenges in IEC-61131-3-compliant environments and the absence of rigorous statistical evaluations under real-time constraints [27]. Comparative studies by Tušar et al. [28] confirmed the superiority of metaheuristic methods—such as GA, PSO, and differential evolution—over traditional techniques in enhancing motor efficiency. Elgbaily et al. [29] compared GA and PSO for direct torque control (DTC) of induction motors, outlining their complementary strengths. Beyond electric drives, Zhuang et al. [30] proposed a two-stage GA enhanced by reinforcement learning for flexible shop scheduling, while Machado et al. [31] developed a hybrid multi-agent metaheuristic for offshore wind-farm cable routing. These works illustrate the scalability of metaheuristics to complex, energy-intensive optimization problems.

Simulated annealing (SA) represents another well-established method for minimizing energy consumption in electric drives. Although computationally demanding, enhanced variants such as orthogonal simulated annealing (OSA) have demonstrated improved efficiency and reduced overhead [32,33]. While less prevalent than GA and PSO, SA remains relevant where global search capability is critical.

In summary, various optimization techniques—including GA, PSO, SA, and more advanced methods such as multi-objective GA for virtual machine placement [20], hybrid GAs for task scheduling [21], differential mutation Aquila optimizers [22], improved NSGA-II [23], hybrid GA-SA [34], gravitational search algorithms [35], adaptive crystal structure algorithms [36], and Bayesian optimization [37]—have proven effective in improving the energy efficiency of electric drive systems. However, a persistent need remains for systematic comparison and statistical validation focusing on the balance between solution quality and computational efficiency, coupled with quantitative reliability characterization through multi-run statistical analysis. This trade-off is crucial for practical integration into industrial VC environments, where optimization must occur within strict time constraints (minutes rather than hours) to be deployable in real-world commissioning processes.

Recent research has increasingly addressed multi-objective optimization strategies that consider competing objectives, reflecting the complexity of industrial energy management. Hybrid metaheuristics combining multiple paradigms have emerged as a promising direction. Bajaj et al. [34] developed a hybrid GA-SA algorithm for electric vehicle charging station placement, demonstrating superior convergence and computational efficiency over standalone methods. Mahmoudi et al. [35] introduced a gravitational search algorithm for hybrid energy systems, achieving an 18.4% increase in renewable energy share while reducing ecosystem and human health damage by 14.2%. Rajagopalan et al. [36] proposed a self-adaptive crystal structure algorithm (SaCryStAl) for microgrid management, achieving optimal cost and emission outcomes without manual parameter tuning. Yang and Wang [37] enhanced GAs with adaptive equivalence factors for fuel cell hybrid vehicles, incorporating autoregressive moving-average (ARIMA) modeling to predict driving conditions and improve real-time energy management.

Integration with advanced control strategies has also gained attention. Wellmann et al. [38] combined Bayesian optimization with nonlinear model predictive control for electric machine co-optimization, demonstrating energy efficiency improvements through active design learning and temperature control. Wang et al. [39] developed a parameter-adaptive energy management strategy for multi-mode hybrid electric vehicles, demonstrating that fuzzy-based adaptive parameter optimization outperforms fixed-parameter approaches under varying driving conditions.

Domain-specific applications further validate these methodological advances. Hyunjae and Okunki [40] applied GA, PSO, and artificial neural networks to optimize brushless

DC motor controllers, comparing PI, field-oriented control (FOC), model predictive control (MPC), and hybrid fuzzy–FOC architectures. Their results confirmed that metaheuristic performance is highly application-dependent, with hybrid fuzzy–FOC achieving the best overall performance. Mazouzi et al. [41] developed a GA-based fuzzy energy management system for fuel-cell hybrid vehicles, improving hydrogen efficiency while addressing multiple objectives such as emissions and battery health. A related study [42] applied improved NSGA-II combined with fuzzy logic controllers to electric vehicle power systems, achieving over a 7% improvement in dynamic performance and a 5% reduction in power losses compared with conventional approaches.

These developments reveal three key trends:

1. A shift from single- to multi-objective formulations that explicitly model real-world trade-offs.
2. Increasing sophistication of the hybrid and adaptive algorithms combining multiple paradigms.
3. Tighter integration between optimization and control strategy synthesis.

However, most advanced multi-objective algorithms still emphasize solution quality over computational efficiency, often requiring hours or days to converge. Such methods remain unsuitable for VC environments, where rapid iteration—on the order of minutes—is essential.

2.2. Virtual Commissioning in Industrial Automation

Virtual commissioning has become a cornerstone of Industry 4.0, leveraging technologies such as the Internet of Things, artificial intelligence, big data, and virtual reality to enhance production efficiency [43,44]. VC is now regarded as a standard approach in the design and deployment of automated manufacturing systems [45]. Its effectiveness has been demonstrated in diverse industrial contexts, including robotic work cells [46] and automotive paint shops [47]. VC has also been extended to continuous process industries, enabling virtual testing in non-discrete production environments [48,49].

The recent convergence of VC and digital twin (DT) technologies has created new opportunities for energy-aware system optimization. Tanegue et al. [50] explored synergies between VC and DT, highlighting shared technological foundations such as model reusability and system transparency. Dammacco et al. [51] proposed a virtual reality-based approach for manufacturing system design, demonstrating improved collaboration and ergonomics during VC of production lines.

Building on this evolution, our previous work [52] introduced a validated DT framework for energy-aware drive systems, demonstrating that high-fidelity component models—parameterized using manufacturer data and integrated into VC platforms—enable accurate prediction of energy consumption, losses, and efficiency. Validation on two conveyor-based testbeds confirmed predictive accuracy sufficient to support vendor-neutral decision-making. This foundation provides the PBDT infrastructure used in the current study, where the PBDT acts as the fitness evaluation function within the GA optimization process.

Recent reviews confirm the growing VC–DT convergence trend. Sghiri et al. [53] analyzed DT applications for building energy efficiency, identifying real-time monitoring, predictive modeling, and renewable energy integration as key enablers. Their findings, including improvements in the coefficient of performance (COP) of up to 40% under active optimization, demonstrate the relevance of DT-based approaches for energy management. However, the integration of DT with optimization algorithms for industrial drive systems remains limited, particularly during early-stage parameter tuning, where computational efficiency is critical.

Despite the proven benefits of VC for system validation and metaheuristics for energy management, their integration for early-stage parameter tuning remains underexplored. Existing VC implementations focus primarily on functional verification—i.e., logic correctness, safety, and cycle time—rather than energy-aware parameter optimization. Conversely, energy optimization studies often rely on simplified or offline simulations that lack high-fidelity DT validation.

This study addresses these gaps by embedding statistically validated GAs directly into the VC workflow, enabling energy-aware commissioning with comprehensive experimental validation on industrial-scale testbeds.

2.3. Research Gaps

Based on the comprehensive literature review, three major gaps persist that prevent practical integration of metaheuristic optimization into industrial workflows:

Gap 1: Statistical validation and reliability quantification. Existing metaheuristic studies typically report single-run results or limited replications without systematic reliability characterization.

Gap 2: Computational efficiency under industrial time constraints. Advanced multi-objective algorithms require execution times measured in hours or days, incompatible with iterative workflows.

Gap 3: Cross-system generalizability and trade-off characterization. Most studies validate optimization approaches on single systems, limiting understanding of how performance and objective trade-off landscapes vary across different mechanical configurations.

2.4. Novelty and Contributions

Integrating VC with DT technology significantly enhances automation design by enabling realistic, simulation-driven development that supports sustainable manufacturing workflows [52,53]. Building upon the validated DT framework for energy-aware drive systems [52], this study advances the state-of-the-art by embedding fast, statistically validated metaheuristic optimization directly into the VC workflow. Current research rarely integrates advanced optimization methods into VC frameworks tailored for real industrial conditions, where computational time constraints are dominant and reliability quantification is essential for deployment decisions.

While recent studies have explored hybrid and multi-objective algorithms [34–38], these methods typically emphasize solution quality over computational efficiency, requiring an extensive runtime that is unsuitable for iterative VC workflows. For instance, Wellmann et al. [38] achieved a 32.8% loss reduction via Bayesian optimization combined with nonlinear MPC, but at the cost of heavy computational demand. Similarly, most VC implementations [50,51] remain focused on functional validation rather than energy-aware parameter tuning. This work addresses the identified gaps by presenting a comprehensive GA framework validated across multiple industrial systems, providing the necessary statistical foundation and computational performance required for practical industrial commissioning.

Unlike complex multi-objective formulations requiring a Pareto analysis, the proposed single-objective approach addresses distinct industrial goals through separate optimizations, ensuring interpretability and straightforward deployment. Post hoc normalized analysis enables quantitative trade-off comparison without the computational overhead of Pareto-based methods.

The key contributions of this study are summarized as follows:

1. Framework development. A novel, soft computing-based framework for automatic tuning of electric drive parameters (i.e., target speed, acceleration, and deceleration)

optimized for energy-aware industrial objectives. The framework, implemented in IEC 61131-3-compliant structured text (ST), is directly deployable on industrial PLCs and fully integrated with a commercial VC platform (RF::ViPer). Hardware-in-the-loop (HIL) validation using a Siemens PLC ensures realistic control timing and communication characteristics that affect actual energy consumption.

2. Comparative analysis and statistical validation. A systematic comparison of metaheuristic methods (i.e., GA, SA, and PSO) and exhaustive search, with rigorous statistical validation through 100 independent runs. The results show that GAs achieve near-optimal solutions with a 69% success rate within 3% of the global optimum for single runs, rising to 97–99% cumulative success probability for multi-run strategies. This provides 114–253× computational speedup over exhaustive search—enabling practical industrial use.
3. Optimization formulation and normalized analysis. Optimization formulation and normalized analysis. A novel post hoc normalized trade-off analysis using min-max scaling, applied to three single-objective energy-aware problems (minimizing electrical energy consumption, maximizing energy efficiency, and minimizing energy losses). This approach enables quantitative conflict assessment without the computational overhead of Pareto-based methods. A normalized trade-off analysis using min-max scaling reveals practical conflicts among objectives and identifies Problem 3 as a balanced compromise achieving 79–90% of optimal consumption and 70–91% of optimal efficiency simultaneously.
4. Cross-system experimental validation. Validation on two industrial-scale testbeds (belt and strap conveyors) featuring different mechanical configurations. Environmental implications are assessed through quantified energy savings.

By combining statistically validated metaheuristic optimization with industrial-grade virtual commissioning, this study contributes to energy-efficient automation and sustainable manufacturing. The demonstrated methodology provides a scalable, industry-ready approach that bridges academic research and practical deployment, advancing both operational efficiency and environmental sustainability in alignment with SDG 7 and SDG 9.

3. Experimental Setup and Validation Infrastructure

This section describes the experimental infrastructure used to validate the proposed methodology. The validation framework combines physical testbeds with industrial drive systems (Section 3.1), a virtual commissioning environment enabling HIL simulation (Section 3.2), and data acquisition systems ensuring high measurement accuracy (Section 3.3). The infrastructure and software were provided by PROPOINT S.A. (Gliwice, Poland) and the Silesian University of Technology.

3.1. Test Stands with Electric Drive Systems

Two conveyor-based testbeds were developed to provide experimental validation data and assess the generality of the proposed optimization methodology across different mechanical configurations and drive system manufacturers.

3.1.1. Belt Conveyor

The primary test stand used for validation was a belt conveyor system constructed for training purposes by PROPOINT S.A. The setup comprises three independent conveyor belts, each driven by an electric drive system from a different manufacturer, enabling direct performance comparison under identical load conditions. Figure 1 presents the test stand with the key drive components labeled. From left to right, the drive systems are Siemens SINAMICS (Siemens AG, Munich, Germany), SEW MOVITRAC (SEW-

EURODRIVE GmbH & Co KG, Bruchsal, Germany), and NORD NORDAC (Getriebebau NORD GmbH & Co. KG, Bargteheide, Germany).

While the testbed is equipped with drive systems from three manufacturers (Siemens, SEW, NORD), enabling future comparative studies, the optimization validation presented in this work was conducted exclusively on Siemens SINAMICS systems. This focus enables rigorous validation with consistent hardware while establishing a methodology that can be extended to other manufacturers in future work.

Each drive system is coupled to a conveyor belt roller with a diameter of 45 mm and a mass of 3.1 kg. The rollers are mounted on SKF ball bearings (two per shaft), and all the drives are equipped with SICK encoders for precise position and speed feedback. The technical specifications for all the drive components, including motor ratings, gearbox parameters, and shaft mechanical properties, are presented in Table 1.

Table 1. Technical specifications for the drive systems used in the belt conveyor testbed.

Component	Parameter	Siemens SIN-AMICS	SEW MOVIT-RAC	NORD NORDAC
Motor	Supply voltage [V]	400	400	400
	Supply frequency [Hz]	50	50	50
	Rated power [kW]	0.12	0.12	0.12
	Rated current [A]	0.42	0.39	0.55
	Rated speed [rpm]	1350	1380	1335
	Efficiency at full load [%]	53.6%	50.0%	52.0%
	Power factor at full load [1]	0.75	0.69	0.64
Shaft	Moment of inertia [kg·m ²]	0.00029	0.00048	0.00021
Gearbox	Gear ratio [1]	20	14.33	10
	Efficiency at 1500 rpm [%]	80.0%	80.0%	80.0%

The diversity of manufacturers and variations in gear ratios (10–20:1), motor speeds (1335–1380 rpm), and power factors (0.64–0.75) provide a robust foundation for evaluating the vendor-neutral applicability of the proposed optimization framework. All the drives are rated at the same nominal power (0.12 kW), ensuring comparable operating conditions while allowing an analysis of the manufacturer-specific efficiency characteristics.

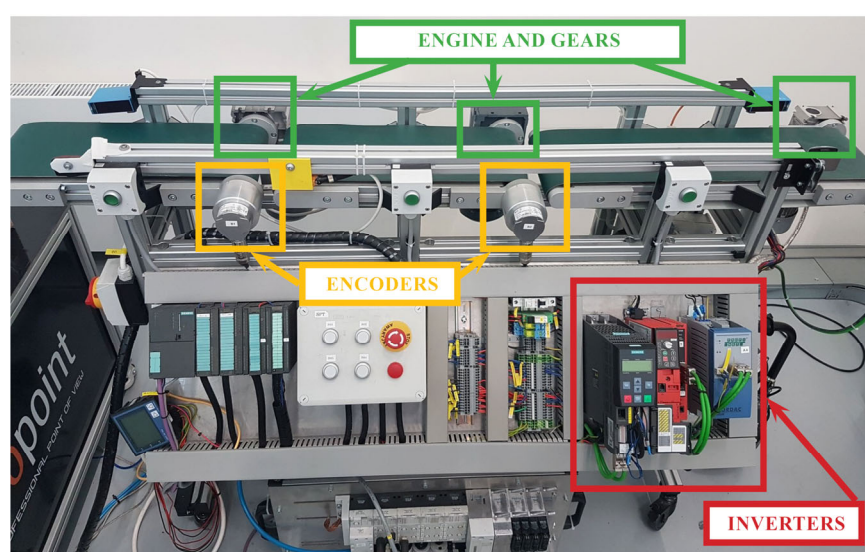


Figure 1. Test stand-belt conveyor system with three parallel drive systems from different manufacturers.

3.1.2. Strap Conveyor

The second test stand, i.e., a strap conveyor system (Figure 2), was built using the same drive systems employed in the belt conveyor described in Section 3.1.1. Thus, the electric drives share the parameters listed in Table 1. The key difference lies in the mechanical configuration—replacing the flat belt with two V-belts—to introduce an alternative load profile while maintaining electrical comparability.

Each shaft was equipped with two V-belt pulleys of 125 mm diameter, increasing the total shaft mass to 5.8 kg and altering the reflected inertia experienced by the motors. This modification enables evaluation of the methodology’s robustness under varying inertial loads and frictional conditions.

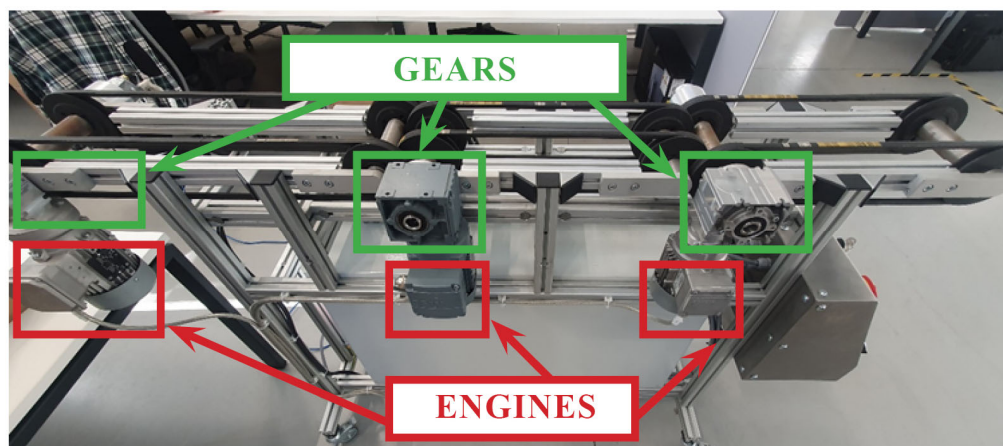


Figure 2. Test stand—strap conveyor system with a V-belt configuration.

3.2. Virtual Commissioning and Hardware-in-the-Loop Framework

The VC setup integrates physical control hardware with high-fidelity digital twin models, enabling realistic evaluation of drive configurations under industrial control logic. This HIL approach forms the computational framework for the optimization where each fitness evaluation corresponds to a complete VC simulation that assesses energy consumption for candidate parameter settings.

3.2.1. Hardware-in-the-Loop Setup

The VC infrastructure consists of two primary hardware components:

- RF::FSBox (fast simulation box). A real-time simulation device by EKS InTec GmbH that emulates component behavior within a PROFINET network. The RF::FSBox enables HIL simulation by emulating drive responses in real-time, allowing the PLC to execute production control programs transparently as if connected to physical equipment.
- Siemens S7-319F-3 PN/DP PLC. The central industrial programmable logic controller executes the actual production control programs, including motion profile generation, positioning algorithms, and scalar control strategies.

Figure 3 presents the network topology of the virtual commissioning station.

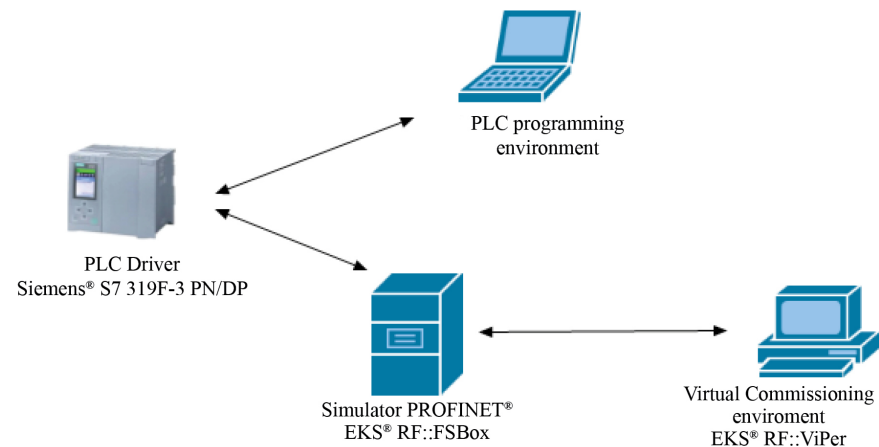


Figure 3. Topology of the virtual commissioning station used in this study.

3.2.2. Software Environment

The digital twin models and genetic algorithm optimization were implemented using two complementary software platforms, each serving a distinct role in the development and validation.

RF::ViPer Virtual Commissioning Platform

RF::ViPer, provided by EKS InTec GmbH (EKS InTec GmbH, Weingarten, Germany; licensed to PROPOINT S.A.), is a VC environment widely adopted in automotive manufacturing and mandated by major original equipment manufacturers (OEMs) such as BMW and Daimler. Based on the CODESYS framework, it supports all IEC 61131-3 programming languages: Ladder Diagram (LD), Function Block Diagram (FBD), Instruction List (IL), Structured Text (ST), and Sequential Function Chart (SFC). Models were primarily implemented in Structured Text (ST) due to its Pascal/C-like syntax, facilitating readability and maintainability.

The GA implementation leverages the open-source OSCAT library (freely available for CODESYS-based platforms), which provides essential functions (e.g., RDM2 for random number generation) compatible with IEC 61131-3 structured text. This ensures reproducibility and facilitates deployment on industrial PLCs without proprietary dependencies.

Key specifications include the following:

- Execution cycle of 20 ms (fixed interval)—this cycle time corresponds to typical industrial PLC scan times for motion control applications, ensuring realistic control dynamics;
- Programming that is IEC 61131-3 compliant (ST used);
- Communication with real-time PROFINET emulation via RF::FSBox;
- Hardware of Intel Core i7-9850H @ 2.6 GHz (Intel Corporation, Santa Clara, CA, USA) and 16 GB RAM with Windows 10 Pro x64.

RF::ViPer provides the high-fidelity simulation required for the final validation and serves as the fitness evaluation engine for the GA optimization.

MATLAB/Simulink Prototyping Environment

Prior to VC implementation, models and algorithms were prototyped in MATLAB R2019b/Simulink (Silesian University of Technology license). This environment enabled rapid algorithm development and preliminary validation using a simplified drive system model that excludes PLC communication.

This two-tier approach allowed fast prototyping in MATLAB, followed by a detailed validation in RF::ViPer with a full PLC integration. All the final results were obtained using the high-fidelity VC models with complete HIL integration.

3.2.3. Integration with Optimization Workflow

Figure 4 provides a system-level block diagram illustrating the two-tier development architecture. The initial algorithm development employs MATLAB/Simulink with simplified drive models for rapid prototyping. Final validation is conducted in the RF::ViPer HIL environment, where the RF::FSBox emulates drive responses in real-time over PROFINET, enabling the PLC to execute production control logic with realistic communication timing. This architecture balances development velocity with validation fidelity.

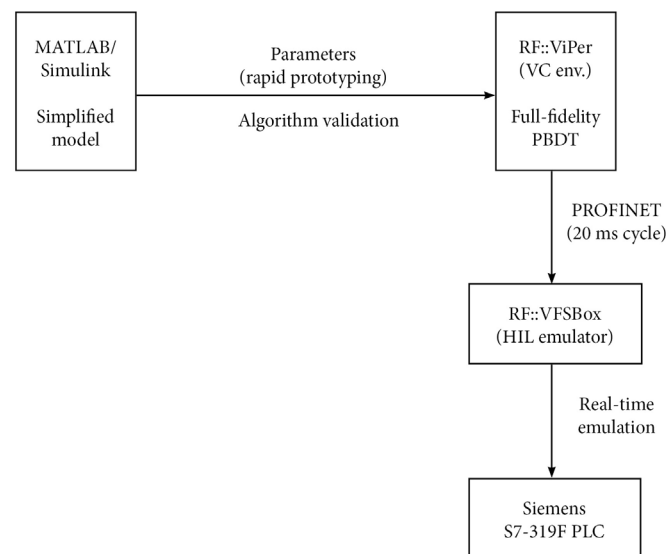


Figure 4. System-level block diagram of the two-tier development and validation architecture.

The RF::ViPer environment serves as the fitness evaluation engine for GA optimization. Each candidate solution undergoes a complete VC simulation cycle, with energy consumption computed from high-fidelity digital twin models. Each fitness evaluation executes the following workflow:

1. Parameter proposal. The GA generates candidate motion parameters $x = [n_{\text{setpoint}}, t_{\text{ramp_up}}, t_{\text{ramp_down}}]$ using genetic operators.
2. VC simulation execution. The parameters are applied in the RF::ViPer environment, where the PLC executes the motion program (1 m displacement within task constraints).
3. Energy measurement. Digital twins compute instantaneous power at each 20 ms cycle, with total energy E_{con} calculated at motion completion.
4. Fitness return. The computed E_{con} value is returned to the GA as the fitness score for population ranking.

This VC-based fitness evaluation distinguishes the proposed approach from simulation-only studies by embedding optimization directly within an industrial-grade commissioning environment, ensuring that optimal solutions account for realistic control timing, communication, and execution characteristics.

3.3. Data Acquisition and Measurement Infrastructure

To ensure accurate energy consumption measurements and systematic validation of digital twin models, the physical testbeds were equipped with electrical and mechanical data acquisition systems.

3.3.1. Electrical Measurements

Electrical quantities (i.e., voltage, current, and power) were measured using Janitza power quality analyzers connected to the supply lines of each drive system. Data were collected via the MODBUS TCP protocol using the custom-developed application *S7_PLC_Data_Logger*, implemented in C# (.NET Framework 4.5.2). Communication was implemented using the open-source *EasyModbusTCP* library for .NET.

3.3.2. Mechanical Measurements and PLC Data Acquisition

Mechanical parameters (i.e., speed, position, and torque) were acquired from the drives via the PLC. The *S7_PLC_Data_Logger* accessed data from dedicated PLC Data Blocks (DB) using the *S7.NET+* library, which enables direct communication between Siemens S7 PLCs and .NET applications.

Data exchange occurred through two mechanisms:

- Cyclic communication. Predefined telegrams enabled real-time reading of inverter process data (actual speed, current, and torque) and writing of control signals (speed setpoints).
- Acyclic communication. Additional parameters (supply voltage and frequency) were retrieved via custom function blocks (FBs) executed within an organization block (OB) triggered by a 100-ms cyclic interrupt (OB35 default value).

3.3.3. Alternative Data Acquisition System

In later experiments, an alternative data acquisition approach was implemented using *KepServerEX 6.10* software (Kepware, license provided by PROPOINT S.A.). This system employs the OPC protocol for data retrieval with cycle times greater than 10 ms and data stores within an SQL database using *SQLite 3.34*.

The following *KepServerEX* modules were used:

- Siemens suite. Data acquisition from Siemens PLCs.
- *CODESYS ethernet*. Data acquisition from the RF::ViPer VC environment.

This system provided a complementary data collection pathway, offering flexibility for different experimental phases and validation objectives.

3.4. Digital Twin Models Validation

The PBDT models employed in this study were validated against experimental data from both testbeds in prior work [52]. The validated models demonstrate sufficient prediction accuracy for optimization purposes, with energy consumption prediction errors within acceptable ranges for industrial applications. Detailed validation metrics are reported in [52].

Cross-validation on the strap conveyor (Section 5.3) further demonstrates generalizability across mechanical configurations, with consistent prediction accuracy maintained despite different reflected inertia, friction characteristics, and operating speed ranges compared to the belt conveyor system.

3.5. A Comprehensive Validation Framework

The combined infrastructure—i.e., physical testbeds (Section 3.1), VC environment (Section 3.2), and data acquisition systems (Section 3.3)—constitutes a comprehensive

validation framework that ensures both experimental rigor and industrial relevance. This setup enables:

- Mechanical generality. Assessment across varying inertial and frictional profiles (belt vs. strap conveyor with different mass, geometry, and loading characteristics).
- Industrial realism. Integration with actual PLC control logic via HIL simulation, ensuring optimized parameters account for realistic timing, communication delays, and execution characteristics.
- Flexible measurement: Multiple data acquisition interfaces (MODBUS TCP, S7.NET+, OPC) ensure validation reliability.
- Model validation: Experimentally validated PBDT models [52] provide high-fidelity fitness evaluation suitable for optimization-based commissioning workflows.

This experimental infrastructure provides the foundation for the proposed optimization methodology (Section 4) and ensures that validation results (Section 5) are both scientifically robust and practically applicable to real-world industrial drive commissioning.

4. Methodology—Simulation-Based Selection of Electric Drive System Settings

In order to reduce electrical energy consumption and improve the energy efficiency of an electric drive system, it is essential not only to select appropriate system components but also to configure the correct operational settings. The types of systems analyzed in this study allow for the adjustment of a wide range of parameters. This section establishes the mathematical foundation for the optimization by defining the physical models (Section 4.1), optimization objectives (Section 4.2), and algorithmic approach (Section 4.3) employed throughout this study.

4.1. Mathematical Model of Energy, Efficiency, and Decision Variables

This section details the physical models and performance indicators used to evaluate drive system configurations. The models integrate component-level physics (Section 4.1.1) with system-level metrics (Section 4.1.2) to enable quantitative optimization within application-specific constraints (Section 4.1.3).

4.1.1. Energy Usage and Loss Models

Total energy consumption (E_{con}) and system efficiency (EE) are computed using a physics-based digital twin that models all losses in the electric drive system. The PBDT integrates component-level models validated experimentally in prior work [52].

Physics-Based Component Models

The high-fidelity PBDT determines instantaneous power consumption by sequentially calculating power flow from the load to the electrical grid, considering the efficiency and losses of each component. The model follows a reverse power flow logic: mechanical load requirements are calculated first, then propagated backward through the motor, inverter, and, finally, to the grid connection.

Total energy consumption. The total electrical energy consumed by the drive system over a motion cycle is computed via a summation over the instantaneous power drawn from the electrical grid:

$$E_{con} = \sum_{i=1}^n (P_{con_inv_i}) \frac{\Delta t_{sim}}{3600}, \quad (1)$$

where E_{con} is the electrical energy consumption [Wh], $P_{con_inv,i}$ is the instantaneous power drawn from the grid at time step i [W], Δt_{sim} is the simulation time step [s], and n is the number of simulation samples.

Inverter model (electrical losses). The total electrical power drawn from the grid by the inverter accounts for both standby losses and load-dependent conversion losses [54]:

$$P_{con_inv} = P_{stdby_inv} + (2 - \eta_{inv})P_{con_motor}, \quad (2)$$

where P_{con_inv} is the actual power drawn from the supply network [W], P_{stdby_inv} is the inverter standby power [W], η_{inv} is the inverter efficiency in per-unit form [-] ($0 \leq \eta_{inv} \leq 1$) derived from manufacturer curves via logarithmic approximation, and P_{con_motor} is the electrical power consumed by the motor [W].

Motor model (electro-mechanical losses). The electrical power consumed by the motor links mechanical power requirements to electrical input via efficiency [54]:

$$P_{con_motor} = \frac{P_{load} + P_{acc} + P_{friction}}{\eta_{motor_model}}, \quad (3)$$

where P_{con_motor} is the electrical power drawn by the motor [W], P_{load} is the load power at constant speed [W], P_{acc} is the acceleration power during speed changes [W], $P_{friction}$ is the power to overcome friction in the gearbox and bearings [W], and η_{motor_model} is the motor efficiency in per-unit form [-] ($0 \leq \eta_{motor_model} \leq 1$) approximated from manufacturer catalog data using logarithmic fits.

The decision variables (target speed $\eta_{setpoint}$, acceleration time t_{ramp_up} , deceleration time t_{ramp_down}) indirectly influence efficiency values through their effect on the operating point trajectory. Motor efficiency η_{motor} depends on instantaneous speed and load, derived from manufacturer catalog curves via logarithmic approximation. Similarly, inverter efficiency η_{inv} varies with load as specified by manufacturer data. The optimization process explores these non-linear relationships through iterative fitness evaluation in the VC environment, where each candidate parameter set results in different speed profiles and corresponding efficiency values over the motion cycle.

Gearbox model (mechanical losses). Gearbox efficiency $\eta_{gearbox}$ is approximated using a logarithmic fit to the manufacturer's speed-dependent efficiency curves, with a piecewise formulation to account for elevated friction at startup (speed-dependent efficiency above 10 rpm and constant startup efficiency below).

Bearing model (friction losses). Bearing friction torque M is calculated using SKF catalog-based models that decompose friction into load-independent (viscosity-dependent and dominant at high speeds) and load-dependent (bearing load and dominant under heavy loads) components. The friction power $P_{friction}$ is then computed from the torque and shaft speed.

Reflected inertia. Reflected inertia $I_{load \rightarrow M}$ accounts for load inertia, conveyor belt/strap mass, and drive shaft inertias, which are reflected to the motor shaft through the gearbox ratio and efficiency. This parameter directly affects acceleration power P_{acc} in Equation (3), making an accurate estimation critical for transient energy prediction.

For complete mathematical derivations of the component-level loss models, detailed parameterization procedures using manufacturer catalog data, and comprehensive experimental validation, see ref. [52].

4.1.2. Optimization Quality Indicators

To quantify the performance of the alternative drive configurations and enable systematic comparison across optimization objectives, three complementary quality indicators were employed. These metrics capture energy consumption, losses, and efficiency,

providing a comprehensive basis for evaluating the trade-offs inherent in multi-objective optimization. The following quality indicators were computed:

- Energy consumption, E_{con} —the total electrical energy consumed by the drive system over a motion cycle, computed via Equation (1).
- Energy losses, E_{losses} , via

$$E_{losses} = \sum_{i=1}^n P_{friction_i} \frac{\Delta t_{sim}}{3600}, \quad (4)$$

where E_{losses} is the electrical energy losses [Wh] and $P_{friction_i}$ is the current value of the electrical energy needed to overcome all the frictional forces, i.e., the bearings and gearbox [W].

- Energy efficiency, EE , via

$$EE = \frac{E_{con} - E_{losses}}{E_{con}} 100\%, \quad (5)$$

where EE is the energy efficiency, understood as the percentage of useful energy (non-dissipated) from the total electrical energy consumption [%].

4.1.3. Optimization Parameters and Constraints

In the conducted research, the focus was limited to three parameters: set speed, acceleration ramp, and deceleration ramp. These parameters were selected because their adjustment does not require specialized knowledge or extensive experience with electric drives. As such, they are among the most frequently modified by automation engineers in typical industrial applications. Furthermore, these parameters are part of the process data group of the electric drive system and can be modified directly from the control system level using standard telegrams in cyclic communication.

The optimization problems are defined over a three-dimensional parameter space:

$$\mathbf{x} = [n_{setpoint}, t_{ramp_up}, t_{ramp_down}]^T, \quad (6)$$

where $n_{setpoint}$ is the target conveyor speed [mm/s] (or, equivalently, motor speed [rpm]), t_{ramp_up} is the acceleration time [s], and t_{ramp_down} is deceleration time [s].

Lower and upper bounds were imposed on the decision variables:

$$\mathbf{x}_{min} \leq \mathbf{x} \leq \mathbf{x}_{max}. \quad (7)$$

These bounds ensure that solutions remain within manufacturer-specified operating ranges and satisfy physical realizability constraints (e.g., positive speeds and ramp times).

Application-Specific Constraints

Beyond general parameter bounds, the optimization is further constrained by the specific task requirements of the conveyor systems under study. These application-level constraints ensure that optimized solutions remain practically feasible for the intended industrial deployment.

The application requirement, for which the optimal drive settings were determined, was to move the conveyor by 1 m within a maximum of 15 s. Accordingly, the following constraints were imposed on the decision variables:

- For the belt conveyor:

$$\begin{cases} 620 \text{ rpm} \leq n_{setpoint} \leq 1350 \text{ rpm} \\ 0 \text{ s} \leq t_{ramp_up} \leq 7.5 \text{ s} \\ 0 \text{ s} \leq t_{ramp_down} \leq 7.5 \text{ s} \end{cases}. \quad (8)$$

- For the strap conveyor:

$$\begin{cases} 250 \text{ rpm} \leq n_{\text{setpoint}} \leq 500 \text{ rpm} \\ 1 \text{ s} \leq t_{\text{rampup}} \leq 5 \text{ s} \\ 1 \text{ s} \leq t_{\text{rampdown}} \leq 5 \text{ s} \end{cases} \quad (9)$$

These application-specific bounds reflect differences in mechanical design (belt vs. strap) and operational requirements, ensuring that the GA explores only the feasible and industrially relevant parameter space.

4.2. Optimization Objectives and Normalization

This study evaluates three distinct, energy-aware objectives, each solved as a single-criterion optimization problem to enable a clear analysis of the resulting trade-offs. This formulation allows for a systematic comparison of the settings optimized for minimal consumption (Problem 1), maximal efficiency (Problem 2), or minimal losses (Problem 3), revealing the inherent conflicts and compromise solutions across the energy performance landscape.

4.2.1. Optimization Problem No. 1—Minimizing Electrical Energy Consumption

The first optimization objective seeks to minimize the total electrical energy consumption over a complete motion cycle, as formulated via:

$$\min_{\mathbf{x} \in X} f_1(\mathbf{x}) = E_{\text{con}}(\mathbf{x}), \quad (10)$$

where $\mathbf{x} = [v_{\text{setpoint}}, t_{\text{rampup}}, t_{\text{rampdown}}]^T$ is the decision variables (Equation (6)), X is the feasible region defined by constraints (Equation (7)–(9)), $E_{\text{con}}(\mathbf{x})$ is the total electrical energy consumption [Wh] computed via Equation (1), and it is subject to $\mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{x}_{\max}$ (Equation (7)–(9)).

This formulation directly addresses industrial energy-saving objectives by identifying parameter configurations that minimize grid power drawn while satisfying task timing constraints (Section 4.1.3). The resulting solutions prioritize low consumption but may sacrifice efficiency if high speeds with rapid accelerations prove most energy economical.

4.2.2. Optimization Problem No. 2—Maximizing Energy Efficiency

The second optimization objective seeks to maximize the system energy efficiency, defined as the ratio of useful mechanical work to total electrical energy input:

$$\max_{\mathbf{x} \in X} f_2(\mathbf{x}) = EE(\mathbf{x}), \quad (11)$$

where $EE(\mathbf{x})$ is the energy efficiency [%] computed via Equation (5) and it is subject to $\mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{x}_{\max}$ (Equation (7)–(9)).

This formulation targets operational efficiency by minimizing the proportion of input energy lost to friction, heat, and electrical conversion, which is particularly relevant for continuous-duty applications where long-term operating costs dominate. The resulting solutions prioritize high efficiency but may accept higher absolute consumption if the efficiency gains justify the energy increase.

4.2.3. Optimization Problem No. 3—Minimizing Electrical Energy Losses

For optimization problems nos. 1 and 2, the results revealed a discrepancy between the settings that yielded minimum electrical energy consumption and those that ensured maximum energy efficiency. Consequently, a third, combined objective function was formulated, aimed at minimizing the electrical energy losses E_{losses} . This objective implicitly addresses the trade-off by seeking a balanced operating point where both low consumption and high efficiency can be achieved simultaneously:

$$\min_{\mathbf{x} \in X} f_3(\mathbf{x}) = E_{\text{losses}}(\mathbf{x}), \quad (12)$$

where $E_{losses}(\mathbf{x})$ is the electrical energy losses [Wh] computed via Equation (4) and it is subject to $\mathbf{x}_{min} \leq \mathbf{x} \leq \mathbf{x}_{max}$ (Equation (7)–(9)).

This formulation provides a natural compromise between Problems 1 and 2, with resulting solutions tending to occupy a stable, near-optimal region of the search space, exhibiting robustness to parameter uncertainty.

4.2.4. Normalization for Trade-Off Analysis

To enable a direct comparison of the conflicting optimization goals in in post-optimization the results of each objective function are normalized using min-max scaling over the entire search space.

For each objective function f (representing E_{con} , E_{losses} , or $(1 - EE)$), the normalized value f_{norm} is computed as follows:

$$f_{norm}(\mathbf{x}) = \frac{f(\mathbf{x}) - f_{min}}{f_{max} - f_{min}}, \quad (13)$$

where $f(\mathbf{x})$ is the objective function value for parameter setting $\mathbf{x}$, f_{min} is the minimum (best) value observed across the entire exhaustive search space, f_{max} is the maximum (worst) value observed across the entire exhaustive search space, and $f_{norm}(\mathbf{x})$ is the normalized objective value in the range $[0,1]$.

The key properties of this normalization are as follows:

- 0.0 represents the true global optimum (best possible solution found by an exhaustive search);
- 1.0 represents the worst observed solution from an exhaustive search;
- all the objectives are transformed into minimization problems for consistency.

The efficiency objective (Max EE) was transformed into a minimization objective $\text{Min}(1 - EE)$, before the normalization. This ensures that all three objectives follow the same direction (minimization), enabling direct numerical comparison. This approach allows for a clear, quantitative assessment of the trade-off inherent in each optimal solution, where settings that minimize E_{losses} (Problem 3) can be objectively compared against settings that minimize E_{con} (Problem 1) or maximize EE (Problem 2) across all three performance dimensions simultaneously.

4.2.5. Rationale for Single-Objective Formulation

Unlike Pareto-based multi-objective approaches that generate a set of trade-off solutions requiring post-hoc decision-making, this study employs three separate single-objective optimizations for the following reasons [20,23,42]:

1. Industrial interpretability: Each objective (minimize consumption, maximize efficiency, minimize losses) corresponds directly to distinct operational goals understood by commissioning engineers.
2. Computational efficiency: Single-objective GA requires significantly fewer fitness evaluations than Pareto-based methods to achieve convergence.
3. Clear validation: Single-objective solutions can be definitively compared against exhaustive search global optima, providing quantifiable performance guarantees (Section 5.1.3).
4. Deployment simplicity: Industrial deployment requires selecting one configuration, not analyzing Pareto fronts. Separate optimizations make this selection explicit based on operational priorities.

Post hoc normalized analysis enables quantitative comparison of the three solutions across all objectives, revealing trade-offs without requiring complex multi-objective optimization machinery.

4.3. Genetic Algorithm Specification

The genetic algorithm was selected as the primary optimization method for this study based on its demonstrated effectiveness in exploring complex, non-convex search spaces characteristic of industrial drive system configuration problems. Unlike gradient-based methods that require differentiable objective functions that may converge to local optima, the GA's population-based search and stochastic operators enable robust exploration of multimodal fitness landscapes. This section presents the algorithmic structure (Section 4.3.1), chromosome encoding (Section 4.3.2), specialized operators and calibrated parameters (Section 4.3.3), and pseudo-code specification (Section 4.3.4) employed to ensure reliable convergence to near-optimal solutions within practical computational budgets.

4.3.1. GA Workflow and Pseudo-Code

Figure 5 shows the complete GA workflow: starting with initialization ($i = 0$), the algorithm iteratively applies elitism (preserve best), selection (ranking method), crossover (linkage evolving genetic operator, LEGO), and mutation (bit insertion) until the termination criterion ($i < N_{iter}$) is satisfied.

The flowchart illustrates the iterative structure of the GA, highlighting the evolutionary loop comprising selection, elitism, crossover, mutation, and replacement operators. The algorithm terminates when the maximum iteration count ($i \geq N_{iter}$) is reached, returning the best solution found across all the generations.

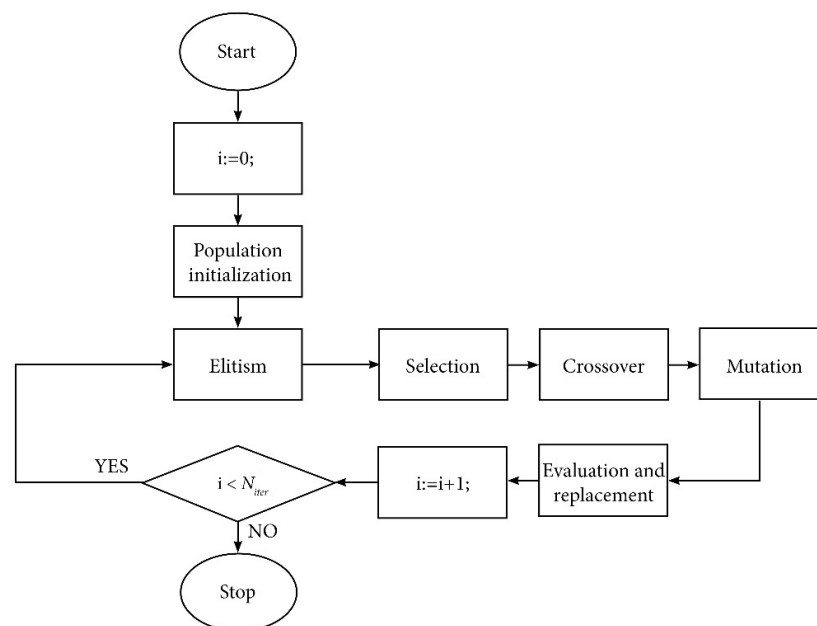


Figure 5. Flowchart of the implemented genetic algorithm.

4.3.2. Chromosome Encoding and Representation

Decision variables $\mathbf{x} = [n_{setpoint}, t_{ramp_up}, t_{ramp_down}]$ are encoded using standard binary representation with 8 bits per parameter. The chromosome has a total length of 24 bits (3 genes $\times$ 8 bits). The structure is defined as follows: Gene 1 (bits 0–7) represents the setpoint velocity $n_{setpoint}$; Gene 2 (bits 8–15) represents the ramp-up time t_{ramp_up} ; and Gene 3 (bits 16–23) represents the ramp-down time t_{ramp_down} .

Each gene uses positional binary encoding where bit_i represents 2^i , enabling direct integer-to-parameter mapping. The integer value derived from the 8-bit sequence is calculated as follows:

$$value = \sum_{i=0}^7 bit_i \times 2^i \text{ (range: 0 to 255).} \quad (14)$$

This integer value is then linearly mapped to the physical parameter range using the following equation:

$$parameter = param_{min} + value \times \Delta param, \quad (15)$$

where $\Delta param$ is the resolution determined by the respective parameter range divided by the maximum representable value (255):

$$\begin{cases} \Delta n_{setpoint} = \frac{n_{rated} - n_{min}}{255} \\ \Delta t_{ramp_up} = \frac{t_{ramp_up_max} - t_{ramp_up_min}}{255} \\ \Delta t_{ramp_down} = \frac{t_{ramp_down_max} - t_{ramp_down_min}}{255} \end{cases}. \quad (16)$$

This 8-bit encoding provides sufficient granularity for industrial drive parameter tuning while maintaining computational efficiency in PLC environments with limited memory (e.g., Siemens S7-319F: program memory).

Standard binary encoding (rather than Gray coding) was selected for implementation simplicity in IEC 61131-3 structured text, where bitwise operations are limited compared to high-level languages. While Gray coding would theoretically reduce the Hamming distance between adjacent parameter values (beneficial for mutation operators), the additional encoding/decoding complexity in the constrained PLC environment outweighs the marginal performance gains for this application.

4.3.3. Random Number Generation

Stochastic operators (initialization, selection, crossover, mutation) require a pseudo-random number generator. The Linear Congruential Generator (LCG) was implemented, which is defined by the following equation:

$$X_i = (a \cdot X_{i-1} + c) \bmod m. \quad (17)$$

The generator uses the following parameters: $a = 42, c = 1, m = 8191$ (a prime number).

The seed $X_0 \in [0,99]$ is initialized using the RDM2 function from the open-source OSCAT library, which is freely available for CODESYS-based platforms including RF::Vi-Per. This LCG provides sufficient randomness for evolutionary operators while remaining implementable in IEC 61131-3 structured text without floating-point arithmetic.

The OSCAT library integration ensures reproducibility and facilitates deployment on industrial PLCs without proprietary dependencies, supporting the vendor-neutral implementation objective.

4.3.4. Algorithm Pseudo-Code and Operator Definitions

This section presents the detailed algorithmic operation through formal pseudo-code (Algorithm 1), defining the specialized operators for selection, crossover, and mutation.

Algorithm 1 Evolutionary optimization procedure for virtual commissioning

```

1: procedure GA_Optimization( $N_{\text{pop}}$ ,  $N_{\text{iter}}$ ,  $p_{\text{crossover}}$ ,  $p_{\text{mutation}}$ ,  $VC\_model$ )
2:    $i \leftarrow 0$                                      » Initialize iteration counter
3:   /* Initialization */
4:   for  $j = 1$  to  $N_{\text{pop}}$  do
5:      $x_j \leftarrow \text{random\_parameters}()$ 
6:      $E_{\text{con}_j} \leftarrow \text{evaluate\_VC}(x_j, VC\_model)$ 
7:    $x_{\text{best}} \leftarrow \text{argmin}(E_{\text{con}_j})$ 
8:    $E_{\text{con\_best}} \leftarrow \min(E_{\text{con}_j})$ 
9:    $\text{population} \leftarrow \{x_1, \dots, x_{N_{\text{pop}}}\}$ 
10:  /* Evolutionary Loop (While  $i < N_{\text{iter}}$ ) */
11:  while  $i < N_{\text{iter}}$  do
12:     $x_{\text{elite}} \leftarrow \text{best\_individual}(\text{population})$            » Elitism
13:     $\text{parents} \leftarrow \text{ranking\_selection}(\text{population})$        » Selection
14:    /* Crossover(LEGO linkage evolution) */
15:     $\text{offspring} \leftarrow \text{empty\_set}$ 
16:    for  $k = 1$  to  $(N_{\text{pop}} - 1)/2$  do
17:      if  $\text{random}() < p_{\text{crossover}}$  then
18:         $[\text{child1}, \text{child2}] \leftarrow \text{LEGO\_crossover}(\text{parents}[2k-1], \text{parents}[2k])$ 
19:      else
20:         $[\text{child1}, \text{child2}] \leftarrow [\text{parents}[2k-1], \text{parents}[2k]]$ 
21:       $\text{offspring} \leftarrow \text{offspring} \cup \{\text{child1}, \text{child2}\}$ 
22:    /* Mutation (Bit insertion) */
23:    for each individual  $x$  in  $\text{offspring}$  do
24:      if  $\text{random}() < p_{\text{mutation}}$  then
25:         $x \leftarrow \text{bit\_insertion\_mutation}(x)$ 
26:    /* Evaluation and Replacement */
27:     $\text{new\_population} \leftarrow \{x_{\text{elite}}\}$ 
28:    for each individual  $x$  in  $\text{offspring}$  do
29:       $E_{\text{con}} \leftarrow \text{evaluate\_VC}(x, VC\_model)$ 
30:      if  $E_{\text{con}} < E_{\text{con\_best}}$  then
31:         $x_{\text{best}} \leftarrow x$ 
32:         $E_{\text{con\_best}} \leftarrow E_{\text{con}}$ 
33:       $\text{new\_population} \leftarrow \text{new\_population} \cup \{x\}$ 
34:     $\text{population} \leftarrow \text{new\_population}$ 
35:     $i \leftarrow i + 1$ 
36:  return  $x_{\text{best}}, E_{\text{con\_best}}$ 

```

The key operators are as follows:

- `evaluate_VC( $x$ , model)`. Executes VC simulation with motion parameter x ; returns energy consumption from high-fidelity PBDT integrated over motion cycle. This function encapsulates the high-fidelity PBDT (Section 4.1.1) within the VC environment, enabling HIL evaluation with real PLC control logic.
- `ranking_selection`. Sorts population by fitness (E_{con}) and assigns selection probabilities proportional to rank (not raw fitness values). This pressure-adjustable method avoids premature convergence while maintaining selection intensity, as recommended in the evolutionary algorithm literature [55].
- `LEGO_crossover`. Linkage evolution operator that identifies and preserves beneficial gene combinations (building blocks). Unlike standard one-point or uniform crossover, LEGO performs multi-parent recombination, allowing offspring to inherit genetic material from multiple parents across the population. This capability enables better

preservation of epistatic linkages between interdependent parameters (e.g., $v_{setpoint}$ and t_{ramp_up}), improving convergence on problems with strong variable interactions.

- **bit_insertion_mutation:** Inserts random bits at gene boundaries, maintaining better chromosome structure than standard bit flip mutation. This operator balances exploration (introducing new genetic material) with exploitation (preserving functional building blocks), reducing disruptive mutations that would destroy well-adapted solutions.

The combination of ranking selection, LEGO crossover, and bit insertion mutation was systematically calibrated through parameter exploration experiments and validated via 100 independent runs, confirming its effectiveness for the conveyor optimization problem.

4.3.5. Adopted GA Parameters

Based on systematic parameter exploration (Section 5.1.2) and statistical validation through 100 independent runs (Section 5.1.3), the following final parameters were adopted for all the subsequent optimization problems:

- Selection was a ranking method.
- Crossover was a LEGO method with a probability of 90%.
- Mutation type was a bit insertion method with a probability of 5%.
- Population size was 25 individuals.
- Number of iterations was 10 generations,
- Elitism: Top 2 individuals (8% of the population) preserved unchanged.

These parameters were systematically determined through comparative algorithm evaluation (Section 5.1.1), exploration of parameter effects (Section 5.1.2), and intensive statistical validation through 100 independent runs (Section 5.1.3). The complete methodology and experimental results supporting this configuration are presented in Section 5.1.

5. Results and Discussion

This section presents the experimental results. It begins with the validation of the optimization algorithm (Section 5.1), followed by an analysis of the trade-offs between the three energy objectives for both test beds (Section 5.2), and concludes with a discussion of the method's generality and robustness (Section 5.3).

5.1. Algorithm Validation and Parameter Selection

This section establishes the reliability of the genetic algorithm for industrial drive optimization through systematic comparison with alternative methods (Section 5.1.1), exploration of parameter choices (Section 5.1.2), and intensive statistical validation (Section 5.1.3). The validation strategy is designed to maximize statistical rigor while minimizing computational expense, given the high cost of fitness evaluation in the VC environment.

5.1.1. Comparison of Optimization Methods

To evaluate alternative optimization algorithms for practical applicability, for Problem 1 for the belt conveyor, three metaheuristic approaches were compared: GA, SA and PSO.

The tests were conducted on a simulation platform using the Optimization Tool available in the MATLAB R2019b environment. To enable rapid algorithmic comparison, a simplified model of the electric drive system was used with the following characteristics:

Model simplifications for preliminary comparison (MATLAB):

- Sampling time: 0.1 s (vs. 20 ms in RF::ViPer);
- No PLC communication delays;
- Constant motor efficiency approximation;
- Constant gearbox efficiency (vs. speed-dependent in PBDT).

These simplifications enabled rapid algorithm comparison (Table 2) but resulted in systematically different energy consumption values (338 mWh in MATLAB vs. 262 mWh in RF::ViPer high-fidelity models). All subsequent parameter exploration and validation (Sections 5.1.2–5.1.3) employed full-fidelity PBDT models in RF::ViPer with complete PLC integration. The MATLAB comparison evaluated algorithmic capability to locate the global optimum within a given model, not absolute energy prediction accuracy. This capability was independently confirmed in RF::ViPer, where GA matched the exhaustive search optimum (262 mWh) under high-fidelity conditions.

All metaheuristic methods achieved near-optimal solutions comparable to exhaustive search while reducing computation time by approximately 5–6 times. PSO achieved equivalent solution quality to GA (339 vs. 338 mWh); however, GA was selected for HIL implementation due to its simpler mapping to IEC 61131-3 data types and established precedent for PLC deployment [9,10].

Table 2. Comparison of the selected optimization methods for tuning the electric drive system.

Determined Values	Exhaustive Search	Simulated Annealing Algorithm	Particle Swarm Optimization	Genetic Algorithm
set speed $n_{setpoint}$ [rpm]	1320	1245	1169	1322
acceleration ramp value t_{ramp_up} [s]	0.25	0.34	0.31	0.46
deceleration ramp value t_{ramp_down} [s]	0.50	0.25	0.74	0.76
electrical energy consumption E_{con} [mWh]	338	340	339	338
execution time of the algorithm [hh:mm:ss]	03:33:08	00:34:09	00:33:11	00:38:56

5.1.2. Genetic Algorithm Parameter Exploration

The genetic algorithm's performance is highly sensitive to parameter selection, including population size, iteration count, selection method, crossover operator, and mutation strategy. This section presents a systematic exploration study to identify a promising configuration for the belt conveyor energy minimization problem.

Parameter tuning followed a two-stage approach:

1. Exploration phase (Section 5.1.2). This phase involved the systematic evaluation of individual parameter effects through controlled experiments (single representative trials). Each parameter configuration was evaluated through three independent runs, with the best result reported in Tables 3–9. This pragmatic approach enabled broad coverage of the multidimensional parameter space (5 parameters $\times$ 3–6 levels each = 120+ configurations) within realistic computational budgets, establishing baseline performance and guiding the selection of robust genetic operators (selection, crossover, and mutation).
2. Validation phase (Section 5.1.3). The exploration phase identified a recommended configuration exhibiting optimal performance-cost trade-offs: a population size of 25, an iteration count of 10, ranking selection, LEGO crossover (90%), and bit insertion mutation (5%). To rigorously assess the reliability and consistency of this configuration—i.e., a critical requirement for industrial deployment—a comprehensive statistical validation through 100 independent optimization runs was conducted.

The validation was concentrated exclusively on the final recommended configuration (a population size of 25 and an iteration count of 10) through 100 independent runs. This approach follows established best practices in metaheuristic algorithm evaluation [56], where computational resources are concentrated on statistically validating the final selected configuration rather than extensively testing all the intermediate parameter combinations explored during tuning. The strategy maximizes statistical rigor ($n = 100$ provides $p < 0.01$ significance) while minimizing computational expense in the high-fidelity VC

environment. The validation was specifically focused on population size and iteration count, as these are recognized in the metaheuristic literature as the primary complexity-performance trade-off parameters [56–58]. Unlike operator selection (crossover, mutation methods), which primarily affect search trajectory, population and iteration count directly determine the total fitness evaluations, wall-clock execution time, and exploration-exploitation balance. Once suitable operators were selected via exploration experiments (Section 5.1.2), the reliability and convergence behavior are predominantly governed by the population-iteration configuration.

Influence of Population Size

One of the key parameters of the genetic algorithm is the population size, defined at each iteration step (with the number of iterations fixed at 10). The remaining parameters were fixed: roulette wheel selection, one-point crossover (with 80% probability), and bit negation mutation (with 10% probability).

Table 3. Effect of population size on the performance of the genetic algorithm.

Determined Values	Exhaustive Search	Genetic algorithm			
		Population Size (the Number of Iterations Was Assumed to be 10)			
		10	25	50	100
set speed $n_{setpoint}$ [rpm]	1020	1070	1350	1167	1095
acceleration ramp value t_{ramp_up} [s]	0.25	0.12	0.76	2.26	0.38
deceleration ramp value t_{ramp_down} [s]	7.25	6.91	3.82	7.35	6.65
electrical energy consumption E_{con} [mWh]	262	263	264	265	263
execution time of the algorithm [hh:mm:ss]	08:01:43	00:01:54	00:04:14	00:10:49	00:17:31

The findings indicate a linear relationship between population size and the algorithm's execution time. Based on the systematic exploration experiments (Table 3), a population size of 25 demonstrated an optimal balance between solution quality and computational cost. This configuration achieved near-optimal results ($E_{con} = 264$ mWh, only 0.76% above the exhaustive search optimum of 262 mWh) while maintaining reasonable execution time. The lowest electrical energy consumption was achieved with population sizes of 10 and 100. However, larger populations (50, 100) provided marginal improvements but at significantly higher computational cost (2–4× execution time), making them impractical for iterative commissioning workflows.

In all tested configurations, the execution time of the genetic algorithm was significantly shorter than that of the exhaustive search. Computational speedup ranges from 114× (population size: 25) to 253× (population size: 10) compared to exhaustive search, with a population size equal to 25 selected for optimal balance between solution quality and execution time.

Influence of Iteration Count

The subsequent phase of the study focused on analyzing the effect of varying the number of iterations of the genetic algorithm. The remaining parameters were held constant: a population size of 5. The remaining parameters were consistent with those used in the previous section: roulette wheel selection, single-point crossover (80% probability), and bit negation mutation (10% probability).

Table 4. Influence of the iteration count on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm				
		Number of Iterations				
		(Population Size Assumed to Be Equal to 5)				
		10	25	50	100	300
set speed $n_{setpoint}$ [rpm]	1020	1327	1081	1012	1032	1049
acceleration ramp value t_{ramp_up} [s]	0.25	1.91	2.09	1.09	0.41	0.23
deceleration ramp value t_{ramp_down} [s]	7.25	4.56	7.38	7.21	7.44	7.38
electrical energy consumption E_{con} [mWh]	262	265	264	262	262	262
execution time of the algorithm [hh:mm:ss]	08:01:43	00:00:54	00:02:15	00:04:30	00:09:37	00:27:33

The results presented in Table 4 confirm a linear relationship between the number of iterations and the algorithm's execution time. The lowest electrical energy consumption matching the exhaustive search optimum was first achieved with 50 iterations (for a population size of 5), indicating the convergence threshold for this problem instance. This configuration provides the best balance between quality and computational cost, as the execution time of the genetic algorithm was approximately shorter than that of the exhaustive search method.

Influence of Selection Method

Three selection methods were compared: roulette wheel, tournament, and ranking. The roulette wheel method assigns each individual a probability proportional to its fitness value; the tournament method randomly divides the population into groups and selects the best from each; and the ranking method pairs individuals based on their fitness rank. During this study, the parameters were fixed at a population size of 25, 10 iterations, one-point crossover (80% probability), and bit negation mutation (10% probability).

Table 5. Influence of the selection method on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm		
		Selection Method		
		Roulette Wheel	Tournament	Ranking
set speed $n_{setpoint}$ [rpm]	1020	1350	1089	1333
acceleration ramp value t_{ramp_up} [s]	0.25	0.76	0.23	0.29
deceleration ramp value t_{ramp_down} [s]	7.25	3.82	7.09	4.03
electrical energy consumption E_{con} [mWh]	262	264	264	263
execution time of the algorithm [hh:mm:ss]	08:01:43	00:04:14	00:05:58	00:04:53

Ranking selection demonstrated superior performance (Table 5), achieving the best solution quality ($E_{con} = 263$ mWh) while maintaining computational efficiency comparable to the roulette wheel method. All methods yielded near-optimal results (263–264 mWh, within 0.4–0.8% of the exhaustive search optimum). Ranking selection was adopted for subsequent experiments.

Influence of Crossover Method and Probability

Five crossover operators were evaluated: 1-point, k-point, multivariate, count-preserving-1, and LEGO. The fixed parameters were as follows: a population size of 25, 10 iterations, ranking selection, no mutation, and 90% crossover probability.

Table 6. Influence of the crossover method on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm				
		Crossover Methods				
		1-Point	k-Point	Multivariate	Count-Pre-serving -1	Linkage Evolving Genetic Operator
set speed $n_{setpoint}$ [rpm]	1020	1049	1072	972	1324	1067
acceleration ramp value t_{ramp_up} [s]	0.25	1.06	0.82	2.44	0.91	0.50
deceleration ramp value t_{ramp_down} [s]	7.25	5.20	7.09	6.44	5.21	6.68
electrical energy consumption E_{con} [mWh]	262	267	263	266	265	263
execution time of the algorithm [hh:mm:ss]	08:01:43	00:04:30	00:04:44	00:06:09	00:04:37	00:04:39

The results (Table 6) show that k-point and LEGO crossover achieved the best performance, both yielding $E_{con} = 263$ mWh (0.4% above the exhaustive search optimum of 262 mWh). All methods produced similar execution times. Due to its multi-parent recombination capability—where offspring can inherit genetic material from multiple parents across the population rather than just two, enabling better preservation of epistatic linkages between interdependent parameters—LEGO was selected for subsequent experiments.

Further tuning of the crossover probability was performed using LEGO crossover, with other parameters held constant (Table 7). A crossover probability of 90% achieved near-optimal performance, balancing exploration and preservation. According to recommendations in the scientific literature [39], the minimum recommended value for this parameter is 50%.

Table 7. Influence of the crossover probability on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm					
		Probability of Crossover [%]					
		10	25	50	75	90	100
set speed $n_{setpoint}$ [rpm]	1020	1333	1101	1215	1235	1067	1081
acceleration ramp value t_{ramp_up} [s]	0.25	2.27	2.53	0.76	0.09	0.50	1.71
deceleration ramp value t_{ramp_down} [s]	7.25	2.26	7.35	4.50	6.09	6.68	6.73
electrical energy consumption E_{con} [mWh]	262	266	264	265	264	263	264
execution time of the algorithm [hh:mm:ss]	08:01:43	00:04:32	00:04:36	00:04:42	00:04:45	00:04:39	00:04:43

Influence of the Mutation Method and Probability

Three mutation operators were compared:

- Bit swap, where a randomly selected bit of a chromosome changes its value from 0 to 1 or from 1 to 0.
- Bit insertion, where a randomly selected bit of the chromosome is assigned a value of 0 or 1 (chosen randomly).
- Deletion of a gene, where a randomly selected gene (variable) is set to 0 (all its bits are set to 0).

The fixed parameters were as follows: a population size of 25, 10 iterations, ranking selection, LEGO crossover (75% probability), and 25% mutation probability.

Table 8. Influence of the mutation method on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm		
		Mutation Methods		
		Bit Swap	Bit Insertion	Deletion of a Gene
set speed $n_{setpoint}$ [rpm]	1020	1341	1152	1324
acceleration ramp value t_{ramp_up} [s]	0.25	0.09	0.06	0.00
deceleration ramp value t_{ramp_down} [s]	7.25	5.26	7.06	2.82
electrical energy consumption E_{con} [mWh]	262	263	263	263
execution time of the algorithm [hh:mm:ss]	08:01:43	00:04:45	00:04:31	00:04:04

All mutation methods achieved identical energy consumption with similar execution times. However, bit insertion was selected for subsequent experiments because it produced parameter settings closest to those obtained through exhaustive search.

Using the bit insertion method, the subsequent phase investigated the impact of mutation probability on algorithm performance. The core parameters were maintained (a population size of 25 and 10 iterations).

Table 9. Influence of the mutation probability on the performance of the implemented genetic algorithm.

Determined Values	Exhaustive Search	Genetic Algorithm					
		Mutation Probability [%]					
		5	10	25	50	75	100
set speed $n_{setpoint}$ [rpm]	1020	1052	1124	1152	1204	1144	1167
acceleration ramp value t_{ramp_up} [s]	0.25	0.35	0.15	0.06	0.97	0.18	0.44
deceleration ramp value t_{ramp_down} [s]	7.25	7.44	6.79	7.06	7.26	7.12	7.44
electrical energy consumption E_{con} [mWh]	262	262	263	263	264	263	263
execution time of the algorithm [hh:mm:ss]	08:01:43	00:04:42	00:04:19	00:04:31	00:04:36	00:04:40	00:04:46

The best outcome was achieved with a mutation probability of 5%, yielding $E_{con} = 262$ mWh—matching the exhaustive search optimum. This optimal value aligns with recommendations found in the scientific literature [59]. Higher mutation probabilities (10–100%) resulted in slightly elevated energy consumption. Given its ability to reach the global optimum, the 5% probability was adopted for the final configuration.

5.1.3. Statistical Testing Procedure

A statistical test was conducted to examine the influence of the stochastic nature of the genetic algorithm on the obtained results. A total of 100 experiments were performed for various combinations of population size and number of iterations. The results are presented as a percentage distribution, categorized according to the precision of the achieved electrical energy consumption values (ΔE_{con}):

$$\Delta E_{con} = \frac{|E_{con} - E_{con_min}|}{E_{con_min}} 100\%, \quad (18)$$

where ΔE_{con} is the relative deviation from optimal energy consumption [%], E_{con} is the energy consumption obtained in a given experiment [mWh], and E_{con_min} is the minimum (optimal) energy consumption from exhaustive search [mWh].

For the considered application, the global optimum of electrical energy consumption is 262 mWh (Section 5.1.2). The results obtained during the statistical study were divided into three groups based on the value of ΔE_{con} , which correspond to the following E_{con} thresholds:

- $\Delta E_{con} \leq 1\%$. The obtained value of the electrical energy consumption is not greater than 265 mWh;
- $1\% < \Delta E_{con} < 3\%$. The obtained value is between 265 mWh and 270 mWh;
- $\Delta E_{con} \geq 3\%$. The obtained value is at least 270 mWh.

The results obtained are presented in Table 10. They indicate that increasing the number of iterations enhances the algorithm's performance more effectively than increasing the population size, as evidenced by a higher probability of achieving a result close to the global minimum. For a population size of 25 and 50 iterations, the algorithm yielded a 91% probability of obtaining a result with an energy consumption deviation ΔE_{con} of less than 3%. For the selected configuration of 10 iterations, the success rate is 69% within 3% of the optimum.

Table 10. Statistical tests of the genetic algorithm implemented with different parameters.

Accuracy of the Result Obtained	Population Size											
	10				25				50			
	Number of Iterations				Number of Iterations				Number of Iterations			
	10	20	30	50	10	20	30	50	10	20	30	50
$\Delta E_{con} \leq 1\%$	12	14	15	24	3	10	13	24	5	7	10	9
$1\% < \Delta E_{con} < 3\%$	45	45	48	46	66	73	72	67	67	78	73	81
$\Delta E_{con} \geq 3\%$	43	41	37	30	31	17	15	9	28	15	17	10
average execution time of the algorithm [hh:mm:ss]	00:01:26	00:02:39	00:03:48	00:05:56	00:03:38	00:06:44	00:09:29	00:14:54	00:07:24	00:13:48	00:20:55	00:32:42

The results in Table 10 reveal an expected trade-off between reliability and computational cost: while the configuration with 50 iterations achieves higher reliability (91% within 3% of optimum), it requires approximately 4× longer execution time.

For industrial commissioning workflows, the configuration of a population size of 25 and an iteration count of 10 was, therefore, adopted for all the subsequent optimization problems (Sections 5.2–5.3). This configuration provides the optimal balance between solution quality (69% within 3% of optimum), computational efficiency, and practical applicability.

The relatively shorter execution time enables a multi-run strategy: performing 3–4 independent optimization runs within 12–16 min yields cumulative success rates exceeding 95–99%. This approach effectively surpasses the reliability of single-run configurations with a higher iteration count, offering superior confidence in obtaining a near-optimal solution within typical engineering work session timescales.

5.2. Belt Conveyor Results (Testbed 1)

The optimization problems for the belt conveyor were executed using the Siemens drive system from test stand No. 1 (Section 3.1.1) and the application constraints defined in Section 4.1.3. For all three objectives (Problems 1–3), the genetic algorithm utilized the statistically validated configuration (a population of 25 and an iteration count of 10, as detailed in Section 5.1.3) and was compared against the exhaustive search reference to confirm the computational efficiency and solution quality.

5.2.1. Optimization Problem No. 1: Minimizing E_{con}

For the considered application, the exhaustive search method identified the following performance bounds across the feasible parameter space. The maximum electrical energy consumption was 314 mWh, obtained with a set speed of 620 rpm, an acceleration time of 0 s, and a deceleration time of 0.75 s. Conversely, the minimum energy consumption of 262 mWh was achieved with a set speed of 1020 rpm, an acceleration time of 0.25 s, and a deceleration time of 7.25 s. These results demonstrate that electrical energy consumption can be reduced by approximately 16.6% by simply applying optimal settings to the electric drive system, confirming substantial energy-saving potential through

parameter optimization alone. The impact of parameter changes on the application's energy consumption is illustrated in Figure 6. In these figures, the blue regions indicate the lowest energy consumption, while red regions correspond to the highest.

The impact of parameter changes on the application's energy consumption is illustrated in Figure 6. In these figures, blue regions indicate the lowest energy consumption, while red regions correspond to the highest. The energy landscape exhibits multimodal characteristics, with the global optimum occurring at moderate speed (1020 rpm) with slow acceleration (0.25 s) and slow deceleration (7.25 s), balancing transient acceleration losses against prolonged standby power draw.

The genetic algorithm successfully identified the global optimum (262 mWh), matching exhaustive search performance while achieving approximately 114× computational speedup.

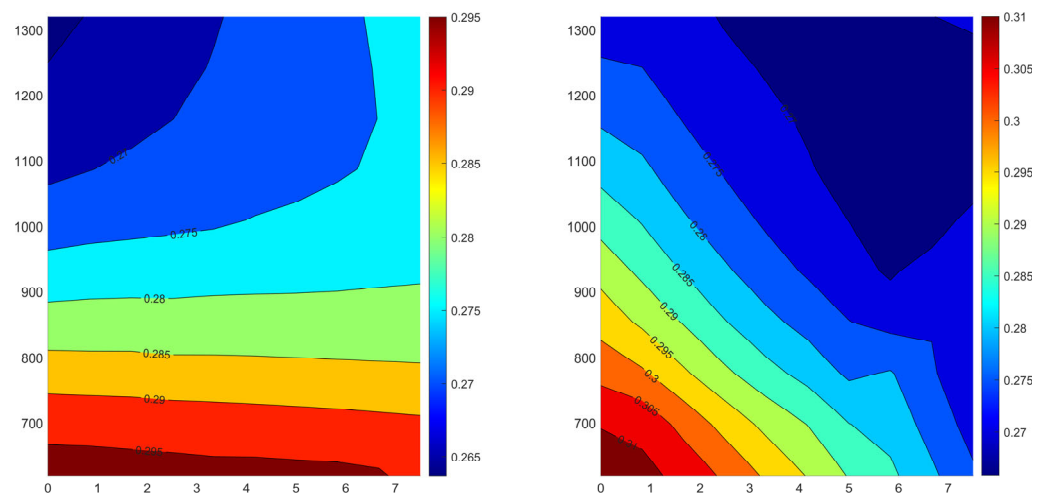


Figure 6. Influence of the settings of the electric drive system of the belt conveyor application under consideration on its electrical energy consumption.

5.2.2. Optimization Problem No. 2: Maximizing EE

For problem No. 2, the exhaustive search employed the same parameter discretization as in Section 5.1.1 (50 rpm speed increments and 0.25 s ramp increments). The highest and lowest values of energy efficiency obtained, together with the corresponding electric drive system settings, are presented in Table 11. The results indicate that proper selection of electric drive system parameters can improve energy efficiency from 35.8% to 41.2%, representing a 5.4 percentage point improvement.

The influence of the setpoint speed, as well as the acceleration and deceleration ramps, on the energy efficiency of the electric drive system is illustrated in Figure 7. In the presented plots, the red areas represent regions of highest energy efficiency, whereas the dark blue areas correspond to regions of lowest energy efficiency.

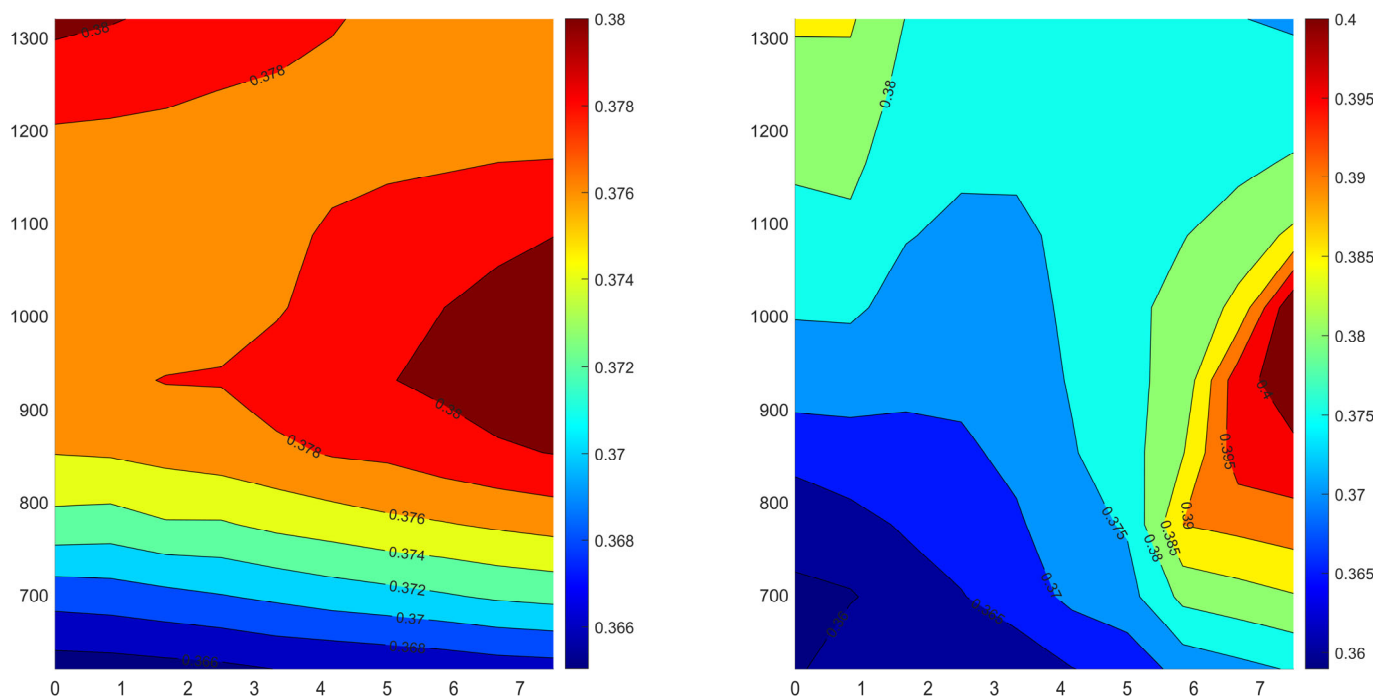
The genetic algorithm results are summarized in Table 12. The GA achieved near-optimal performance, identifying settings yielding 38.8% energy efficiency—within 2.4 percentage points (94.2% relative performance) of the exhaustive search optimum. Notably, the genetic algorithm achieved this performance with an execution time 96 times shorter than exhaustive search (approximately 5 min vs. 8 h).

Table 11. Energy efficiency values obtained from an exhaustive search of a belt conveyor.

Determined Values	The Highest Value EE	The Lowest Value EE	The Highest Value E_{con}	The Lowest Value E_{con}
set speed $n_{setpoint}$ [rpm]	1020	670	620	1020
acceleration ramp value t_{ramp_up} [s]	0.00	3.75	0.00	0.25
deceleration ramp value t_{ramp_down} [s]	7.50	0.50	0.75	7.25
electrical energy consumption E_{con} [mWh]	274	313	314	262
Energy efficiency EE [%]	41.2%	35.8%	35.9%	38.1%
execution time of the algorithm [hh:mm:ss]	08:01:43	08:01:43	08:01:43	08:01:43

Table 12. Energy efficiency values obtained from the genetic algorithm for the belt conveyor.

Determined Values	The Highest Value EE	The Lowest Value EE	The Highest Value E_{con}	The Lowest Value E_{con}
set speed $n_{setpoint}$ [rpm]	978	634	671	1024
acceleration ramp value t_{ramp_up} [s]	6.97	4.59	3.00	0.12
deceleration ramp value t_{ramp_down} [s]	6.79	0.15	0.15	7.00
electrical energy consumption E_{con} [mWh]	267	312	312	262
energy efficiency EE [%]	38.8%	35.7%	36.3%	38.2%
execution time of the algorithm [hh:mm:ss]	00:04:49	00:04:46	00:05:09	00:04:35

**Figure 7.** Influence of the settings of the electric drive system of the belt conveyor on its energy efficiency.

5.2.3. Optimization Problem No. 3: Minimizing E_{losses} (Trade-Off Analysis)

For problem No. 3, the results obtained from the exhaustive search conducted in the tests described in Sections 5.2.1 and 5.2.2 were utilized. Figure 8 presents the electrical energy loss distributions for the belt conveyor as a function of drive settings. Table 13 presents the optimization results. Proper parameter selection reduces electrical energy losses by 19.9% (from 201 mWh to 161 mWh). The genetic algorithm achieved comparable performance (167 mWh) with approximately 98× speedup over exhaustive search.

Problem 3 provides a balanced compromise: optimal settings ($E_{con} = 267$ mWh, $EE = 39.6\%$) achieve 98.1% of the best consumption (Problem 1: 262 mWh) and 96.1% of the best efficiency (Problem 2: 41.2%), making this a practical solution for industrial deployment.

Minimizing E_{losses} naturally seeks operating points that balance these competing dissipation mechanisms. For the belt conveyor, the optimum ($n_{setpoint} = 870$ rpm, $t_{ramp_up} = 7.5$ s, $t_{ramp_down} = 7.5$ s) uses moderate speed with slow ramps, avoiding both the high transient losses of rapid acceleration (Problem 1 minimum consumption settings) and the high steady-state losses of excessively slow operation.

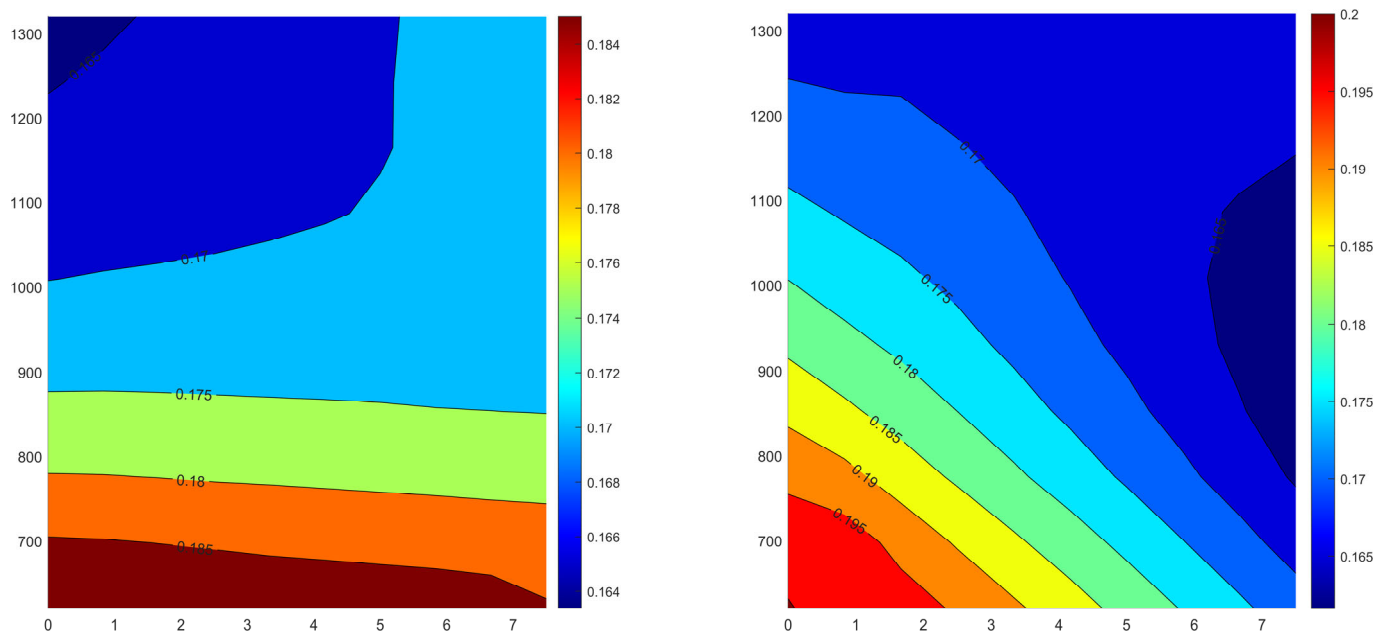


Figure 8. Influence of the configuration of the belt conveyor electric drive system on electrical energy losses.

Table 13. Electrical energy loss values obtained from the exhaustive search and genetic algorithm for the belt conveyor.

Determined Values	Exhaustive Search		Genetic Algorithm	
	The Highest Value of E_{losses}	The Lowest Value of E_{losses}	The Highest Value of E_{losses}	The Lowest Value of E_{losses}
set speed $n_{setpoint}$ [rpm]	620	870	628	963
acceleration ramp value t_{ramp_up} [s]	0.00	7.50	0.47	6.91
deceleration ramp value t_{ramp_down} [s]	0.00	7.50	0.09	5.35
electrical energy consumption E_{con} [mWh]	314	267	313	272
electrical energy efficiency EE [%]	35.8%	39.6%	36.6%	38.6%
electrical energy losses E_{losses} [mWh]	201	161	198	167
execution time of the algorithm [hh:mm:ss]	08:01:43	08:01:43	00:04:58	00:04:47

5.2.4. Normalized Multi-Objective Trade-Off Analysis for Belt Conveyor

Using the min-max normalization defined in Section 4.2.4, the final comparison of the optimal settings for the three conflicting energy objectives is presented in Table 16. The min-max formula was applied across the entire search space to normalize the raw values of E_{con} , E_{losses} , and $1-EE$, ensuring that a normalized score of 0.0 represents the global optimum (minimum) and 1.0 represents the worst result (maximum) for all three optimization problems.

Table 14 summarizes the optimal settings for problem No. 3 (min E_{losses}), which represents the most balanced compromise, with low normalized scores for all three objectives simultaneously. While Problem 3 does not achieve the absolute minimum energy consumption (normalized $E_{con} = 0.10$ compared to Problem 1's 0.00, representing only 5 mWh or 1.9% higher consumption), it offers substantial efficiency gains. Compared to Problem 1, Problem 3 reduces the normalized inefficiency score from 0.57 to 0.30—a 47% improvement—while maintaining near-optimal energy losses (0.00).

This trade-off analysis confirms that minimizing energy losses (Problem 3) provides a robust, balanced operating point suitable for industrial deployment, achieving 98.1% of optimal consumption performance while delivering significantly better efficiency than consumption-optimized settings.

Table 14. Comparison of the minimized normalized objectives for the belt conveyor.

Normalization Results			
Optimization Problem	Normalized E_{con}	Normalized E_{losses}	Normalized (1- EE)
Problem 1: Min E_{con}	0.00	0.03	0.57
Problem 2: Max EE	0.23	0.02	0.00
Problem 3: Min E_{losses}	0.10	0.00	0.30

5.3. Strap Conveyor Results (Testbed 2)

5.3.1. Optimization Problem No. 1: Minimizing E_{con}

The optimization methodology was further validated on the strap conveyor testbed using application constraints defined in Section 4.1.3 (Equation (9)). Exhaustive search was conducted using the same parameter discretization as Section 5.1.1 (50 rpm speed steps, 0.25 s ramp steps). Figure 9 presents the resulting electrical energy consumption profiles as a function of drive system settings.

Table 15 presents the optimization results for both exhaustive search and genetic algorithm. For minimum energy consumption, both methods achieved identical performance (108 mWh), validating the GA implementation. However, for maximum consumption settings, the methods yielded different configurations: exhaustive search identified 137 mWh, while GA found 115 mWh—a 16% difference attributed to different exploration patterns in the discrete search space.

Proper parameter selection enables a 21% reduction in electrical energy consumption, representing a slightly higher improvement than the belt conveyor (17.6%). The genetic algorithm achieved this performance with approximately 18× speedup over exhaustive search.

Table 15. Electrical energy consumption values for the strap conveyor obtained from an exhaustive search and from the implemented genetic algorithm.

Determined Values	Exhaustive Search		Genetic Algorithm	
	The Highest Value E_{con}	The Lowest Value E_{con}	The Highest Value E_{con}	The Lowest Value E_{con}
set speed $n_{setpoint}$ [rpm]	500	400	263	383
acceleration ramp value t_{ramp_up} [s]	1.00	1.00	2.19	1.44
deceleration ramp value t_{ramp_down} [s]	2.00	2.00	1.15	2.11
electrical energy consumption E_{con} [mWh]	137	108	115	108
Energy efficiency EE [%]	52.18%	41.01%	47.74%	41.14%
execution time of the algorithm [hh:mm:ss]	01:40:47	01:40:47	00:05:55	00:05:34

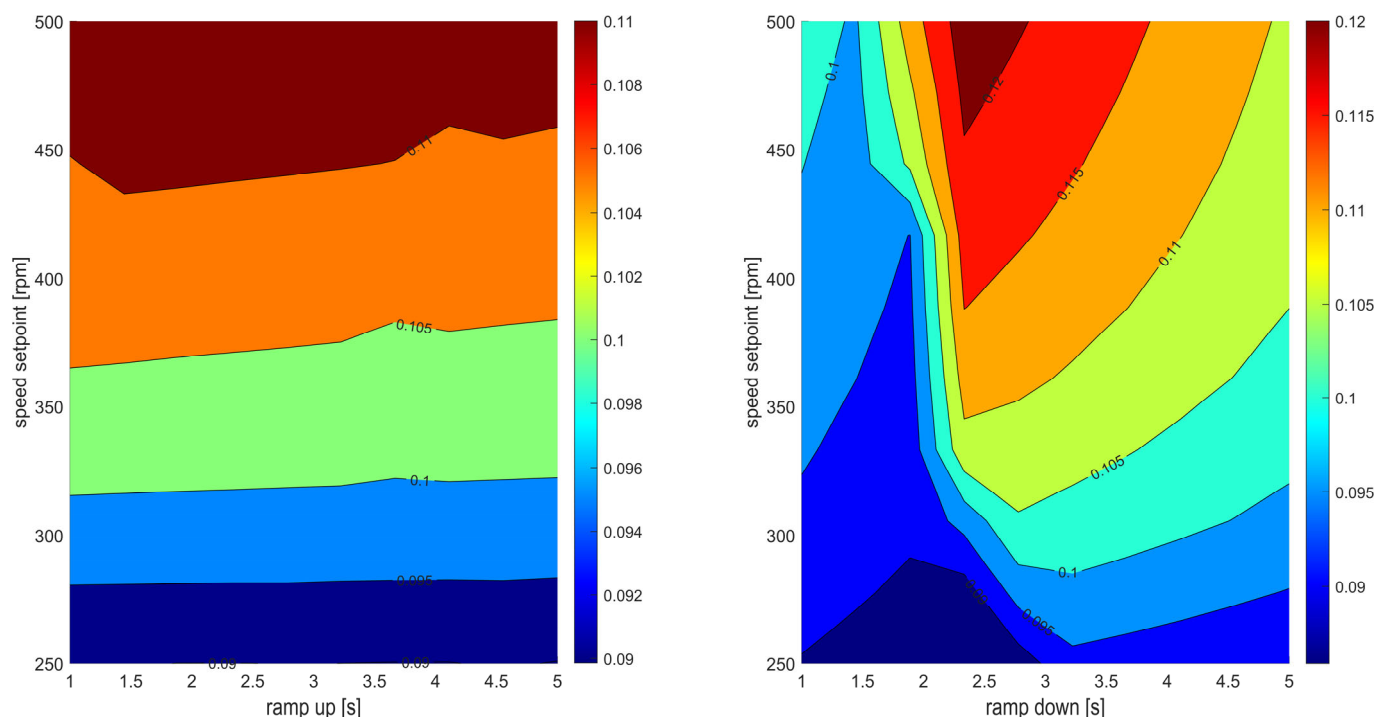


Figure 9. Influence of the settings of the electric drive system of the strap conveyor application under consideration on its electrical energy consumption.

5.3.2. Optimization Problem No. 2: Maximizing EE

Exhaustive search and genetic algorithm were applied to Problem 2 (Max EE) using the parameters defined in Section 4.3.5. Figure 10 presents the energy efficiency profiles of the strap conveyor drive system. Blue areas indicate regions of lowest energy efficiency; red areas correspond to regions of highest efficiency.

Table 16 presents the optimization results. Exhaustive search identified that proper parameter selection can improve energy efficiency from 39.0% to 55.7%—a 16.7 percentage point improvement. The table also includes energy efficiency values for settings that minimize and maximize electrical energy consumption, revealing the inherent trade-off: maximum efficiency (55.7%) occurs at higher consumption (119.6 mWh), while the settings yielding lowest efficiency (39.0%) resulted in lower consumption (114.2 mWh). The genetic algorithm achieved approximately 18× speedup over exhaustive search.

Table 16. Energy efficiency values obtained from an exhaustive search and the genetic algorithm for the strap conveyor.

Determined Values	Exhaustive Search		Genetic Algorithm	
	The Highest Values of EE	The Lowest Value of EE	The Highest Values of EE	The Lowest Value of EE
set speed $n_{setpoint}$ [rpm]	500	500	252	296
acceleration ramp value t_{ramp_up} [s]	4.75	1.00	3.76	2.40
deceleration ramp value t_{ramp_down} [s]	5.00	1.00	1.83	1.06
electrical energy consumption E_{con} [mWh]	119.6	114.2	113.9	114.5
Energy efficiency EE [%]	55.7%	39.0%	47.9%	44.8%
execution time of the algorithm [hh:mm:ss]	01:40:47	01:40:47	00:05:35	00:05:42

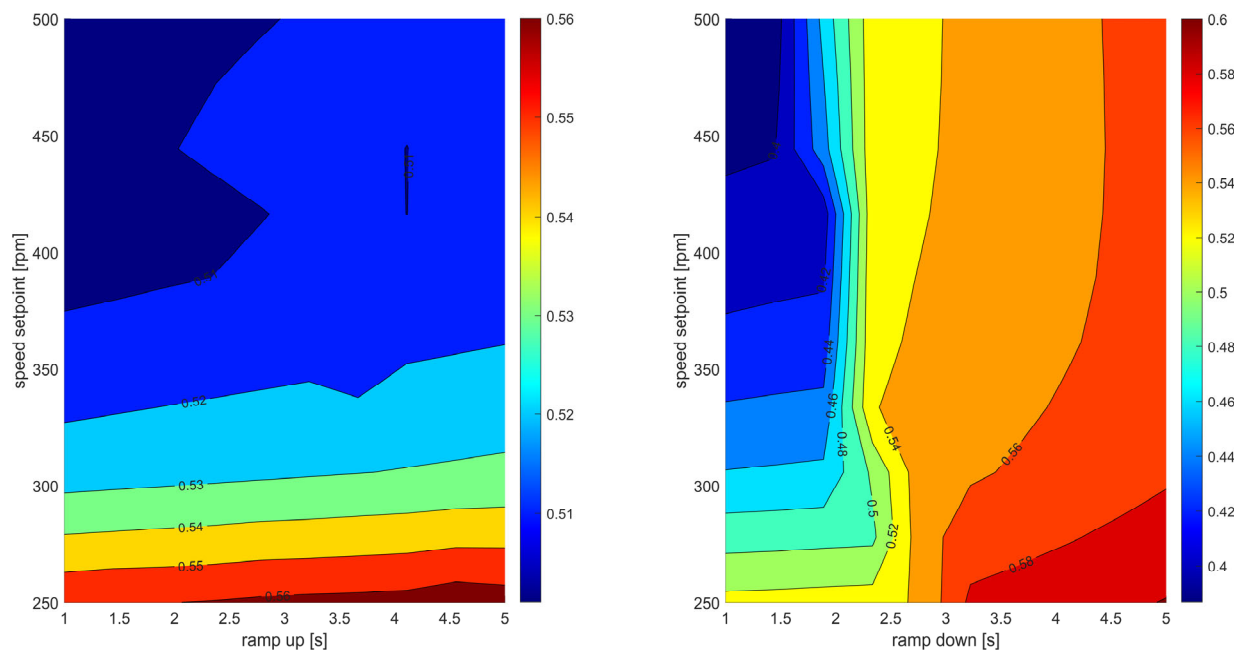


Figure 10. Influence of the settings of the electric drive system of the strap conveyor on its energy efficiency.

5.3.3. Optimization Problem No. 3: Minimizing E_{losses} (Trade-Off Analysis)

The optimization objective was executed for the strap conveyor using application constraints from Section 4.1.3 (Equation (9)). Results from exhaustive search (Sections 5.3.1–5.3.2) were utilized. Figure 11 presents electrical energy loss profiles as a function of drive settings.

Table 17 presents the optimization results. Exhaustive search indicates that proper parameter selection reduces electrical energy losses by 25.7%. Notably, both maximum and minimum loss configurations occur at identical energy consumption, with the reduction achieved entirely through efficiency improvement (39.0% → 54.2%). This differs from the belt conveyor, where loss minimization involved both reduced consumption and improved efficiency, highlighting system-dependent trade-off characteristics.

The genetic algorithm achieved near-optimal performance (58 mWh, representing 11.5% higher losses than exhaustive optimum) while reducing energy consumption to 111 mWh. The genetic algorithm achieved approximately 18× speedup over exhaustive search.

Consistent with belt conveyor results (Section 5.2.3), Problem 3 provides a balanced compromise between energy consumption and efficiency objectives (Tables 15 and 16), yielding robust settings suitable for industrial deployment.

Table 17. Electrical energy loss values obtained from an exhaustive search and the genetic algorithm for a strap conveyor.

Determined Values	Exhaustive Search		Genetic Algorithm	
	The Highest Value of E_{losses}	The Lowest Value of E_{losses}	The Highest Value of E_{losses}	The Lowest Value of E_{losses}
set speed n_{setpoint} [rpm]	500	250	304	254
acceleration ramp value $t_{\text{ramp_up}}$ [s]	1.00	5.00	4.39	4.67
deceleration ramp value $t_{\text{ramp_down}}$ [s]	1.00	5.00	1.25	2.49
electrical energy consumption E_{con} [mWh]	114	114	114	111
electrical energy efficiency EE [%]	39.0%	54.2%	44.9%	48.0%
electrical energy losses E_{losses} [mWh]	70	52	63	58
execution time of the algorithm [hh:mm:ss]	01:40:47	01:40:47	00:05:44	00:05:19

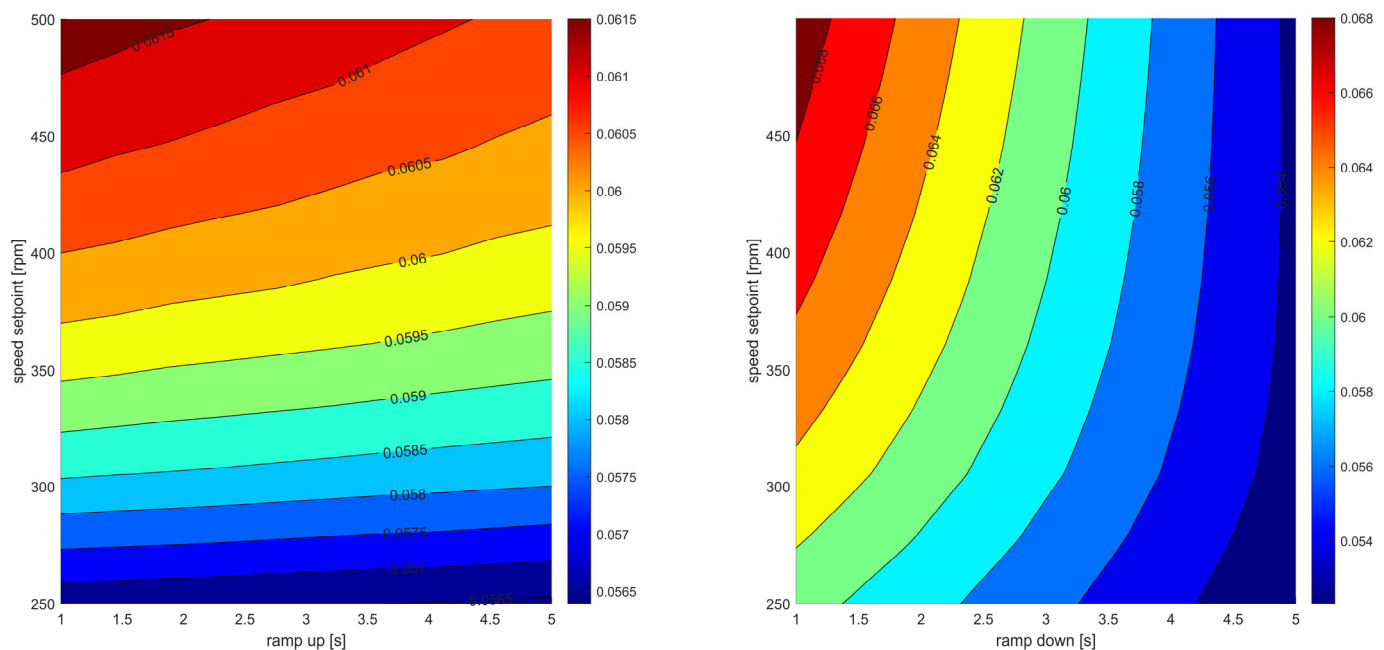


Figure 11. Influence of the settings of the electric drive system of the strap conveyor on the loss of electrical energy.

5.3.4. Normalized Multi-Objective Trade-Off Analysis for the Strap Conveyor

Analogous to the belt conveyor analysis, the normalized results for the three objective functions for the strap conveyor are presented in Table 18. The table demonstrates that Problem 3 (Min E_{losses}) provides the most balanced compromise across all objectives. The optimal settings achieve minimum energy losses and near-optimal efficiency, while the normalized E_{con} remains low at 0.21, representing only 6 mWh higher consumption.

In contrast, Problem 1 (Min E_{con}) achieves minimum consumption but at the cost of significantly higher normalized energy losses (0.65). This increase in normalized losses corresponds to a 12 mWh absolute increase in energy losses—a substantial penalty for marginal consumption savings (6 mWh). This confirms that optimization targeting energy loss minimization (Problem 3) provides the most robust and stable operating point in industrial drive systems, achieving near-optimal performance across all three metrics simultaneously.

Table 18. Comparison of the minimized normalized objectives for the strap conveyor.

Normalization Results			
Optimization Problem	Normalized E_{con}	Normalized E_{losses}	Normalized (1- EE)
Problem 1: Min E_{con}	0.00	0.65	0.88
Problem 2: Max EE	0.40	0.06	0.00
Problem 3: Min E_{losses}	0.21	0.00	0.09

6. Discussion

6.1. Comparative Analysis and Generalizability

The methodology was successfully applied to two structurally and dynamically different systems (belt and strap conveyors), both accurately modeled within the VC environment. Both systems achieve substantial optimization savings: the belt conveyor enables a 17.6% consumption reduction, while the strap conveyor demonstrates a 21.0% reduction with additional efficiency gains. The GA proved computationally pragmatic for

both, achieving speedups of 114× (belt) and 18× (strap) over exhaustive search, ensuring that optimization is feasible within standard commissioning work sessions.

The comparative normalized multi-objective analysis (Tables 14 and 18) revealed significant system-dependent differences in trade-off severity. For the belt conveyor (weak coupling), optimizing solely for minimum consumption (Problem 1) incurs only a minimal loss penalty, making it viable when consumption is the dominant priority. For the strap conveyor (strong coupling), the same strategy incurs a 23% increase in energy losses for only 5% consumption savings, demonstrating that the appropriateness of single-objective optimization cannot be assumed a priori. Problem 3 (minimizing energy losses) emerged as the most robust compromise for both systems, consistently achieving near-optimal performance across all three metrics simultaneously.

This cross-system validation confirms that the proposed framework generalizes effectively to diverse mechanical configurations.

6.2. Practical Implications for Virtual Commissioning

These findings translate directly into practical commissioning benefits:

- Workflow integration: The 4–5 min optimization time enables iterative parameter refinement within typical engineering windows, allowing energy optimization to occur concurrently with other commissioning tasks.
- Multi-run strategy: Executing three independent runs achieves 97–99% cumulative success probability while keeping total execution time under 15 min, effectively mitigating the stochastic nature of metaheuristics.
- Objective-specific decision support: The normalized trade-off analysis provides quantitative guidance—Problem 1 for absolute energy reduction, Problem 2 for high-duty cycles where efficiency is paramount, or Problem 3 as a balanced compromise for general-purpose applications.
- Deployment pathway: IEC 61131-3 compliance ensures direct PLC deployment without manual code translation, while vendor-neutral PBDT models allow cross-manufacturer application once component libraries are parameterized.

The framework transforms energy optimization from an offline simulation activity into a standard commissioning procedure.

6.3. Environmental Impact

The demonstrated energy savings translate directly into environmental benefits. Following emission factor-based methodology commonly applied in energy and environmental assessments [60] and GHG Protocol Scope 2 guidelines [61], CO₂ reductions were estimated using representative emission factors for the Polish electricity grid (0.594 kg CO₂/kWh) and EU average (0.207 kg CO₂/kWh) [62]. The belt conveyor optimization (52 mWh/cycle reduction) corresponds to annual CO₂ savings of 15–45 kg per unit under continuous operation (24 h/day, 250 days/year). For facility-level deployment (50–200 conveyors typical in automotive assembly), aggregate reductions reach 0.6–6.9 t CO₂/year.

These estimates assume idealized operating conditions—actual benefits depend on site-specific duty cycles, regional grid characteristics, and production scheduling [63]. Nevertheless, the proportional energy reduction achieved through optimization is expected to persist across operating scenarios, contributing to SDGs 7 and 9 objectives.

6.4. Limitations

Several limitations of this study warrant acknowledgment. The three-variable search space permits exhaustive search, which was intentionally selected to provide ground-

truth validation of GA performance. However, this approach is not directly transferable to higher-dimensional problems where exhaustive search becomes infeasible.

The validation was conducted exclusively on Siemens drive systems, and the vendor-specific parameterization of drive models necessitates catalog data availability, which may limit generalization across manufacturers without validated component libraries. Furthermore, the small-scale conveyor systems examined (0.12 kW drives) represent typical material handling applications, but scaling assumptions have not been validated on higher-power industrial equipment (>10 kW).

From a methodological perspective, the parameter exploration phase employed limited runs per configuration due to time constraints. While the subsequent 100-run validation confirms the robustness of the selected configuration, it demonstrates execution reliability rather than optimality among all possible parameter combinations. Comprehensive factorial validation would require thousands of runs, exceeding practical constraints.

The post hoc normalized trade-off analysis requires exhaustive search results to define normalization bounds, limiting its applicability to problems where global optima can be determined. For higher-dimensional problems, Pareto-based multi-objective methods would be required. Finally, the environmental impact assessment employs static emission factors rather than time-varying grid carbon intensity.

7. Conclusions and Future Direction

This research introduces a novel, industrially validated framework integrating metaheuristic optimization with virtual commissioning to enable energy-efficient automation system design. The study bridges the gap between theoretical optimization and industrial practice through several key contributions:

- Computational efficiency: Genetic algorithms demonstrated a 114–253× speedup compared to exhaustive search, reducing optimization time from hours to minutes and making energy-aware design feasible within standard commissioning workflows.
- Operational impact: Validation on mechanically distinct testbeds confirmed energy savings up to 21% and efficiency gains of 16.7 percentage points, with loss minimization (Problem 3) identified as the most robust objective for multi-criteria industrial deployment.
- Statistical rigor: The application of 100 independent runs provides a quantified reliability framework that far exceeds typical VC validation practices, enabling risk-informed decision-making in Industry 4.0 environments.
- Sustainability alignment: The framework provides a scalable pathway toward sustainable-by-design automation, directly supporting global goals (SDGs 7 and 9).

Further directions include extending the framework to higher-dimensional problems where exhaustive search is infeasible, implementing advanced Pareto-based methods (e.g., NSGA-III, multi-objective evolutionary algorithm based on decomposition—MOEA/D) for multi-objective trade-off analysis, and conducting sensitivity analysis of GA parameters with investigation of adaptive self-tuning strategies. Deep reinforcement learning for real-time adaptive tuning represents another promising direction. Beyond conveyor systems, the research will extend to other domains such as industrial robotics and HVAC systems, incorporating time-varying carbon intensity data to align industrial operations with grid decarbonization schedules. Ultimately, this methodology embeds environmental considerations directly into the engineering practice, moving toward fully autonomous, energy-optimal industrial systems.

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