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A Digital Twin of a Galvanic Production Line in the Unity Environment as a Multi-Agent System for Modeling, Testing and Optimization of Process Flows and Intralogistics Involving Mobile Robots*

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Abstract

This article presents the development and validation of a digital twin of a galvanic production line and a multi-agent system using the Unity environment as a simulation platform. The primary objective was to create a tool that supports the analysis, testing and optimization of process flows and intralogistics involving autonomous mobile robots. The model replicates the actual structure of the technological line, taking into account the sequence of operations, energy consumption, processing times and transport logic. By applying a modular architecture, input data—such as layout configuration, energy usage and operation sequences—are imported from external configuration files, enabling rapid generation and comparison of various scenarios. A series of simulation experiments was conducted and the results were compared with an idealized mathematical model. The analysis revealed the presence of bottlenecks, shifting throughput limitations, as well as queuing and routing conflicts that cannot be captured by simplified analytical models. Furthermore, it was shown that expanding the process structure increases total energy consumption but improves energy efficiency per produced unit. The developed digital twin enables safe testing of structural and operational changes and provides a foundation for future integration with MES or SCADA systems, as well as the advancement of predictive production process management.

Keywords: Digital Twin, Galvanization, Multi-Agent Systems, Intralogistics

Introduction

The dynamic development of information technologies in recent decades has significantly influenced the functioning of modern industry, becoming a cornerstone of the Fourth Industrial Revolution, commonly referred to as Industry 4.0. This transformation is based on the integration of physical and digital systems, process automation and the intensive use of real-time data. Among the key technologies enabling the realization of this vision, the concept of the Digital Twin stands out as one of the fundamental pillars of modern production engineering.

A digital twin is a dynamic, real-time updated digital representation of a physical system, machine, or process. Originally developed in the aerospace industry, this technology is now applied across various sectors of the economy, including automotive, energy, logistics and technological processes such as electroplating. It enables not only the visualization and real-time monitoring of system operations but also the execution of diagnostic analyses, testing of optimization scenarios without interfering with the physical environment and the prediction

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of system behavior under changing operating conditions. As a result, it becomes possible to increase operational efficiency, reduce costs, make better use of resources and minimize the risk of failures and downtime.

The growing interest in implementing digital twins is therefore fully justified, however, their deployment faces a number of technological and organizational challenges. One of the key issues is the integration of data from multiple sources - often originating from heterogeneous devices operating under different communication protocols. Additionally, it is essential to ensure high data quality, including filtering and synchronization, which can be time-consuming and requires specialized analytical tools. Equally important is the validation of the model's accuracy in representing the real-world process, both in terms of its operational logic and time-related or functional parameters.

To develop a functional digital twin, it is essential to mathematically and logically model the entire production process. In practice, this requires a detailed analysis of task sequences, resource allocation, temporal dependencies and logistical constraints. Given the complexity of real-world systems, digital twin models are often simplified to maintain their practical usability while limiting the number of variables and parameters. The goal is not to fully reconstruct the physical system but rather to create an analytical tool that supports data-driven decision-making.

In this study, a digital twin of the galvanization process was developed. The model incorporates successive technological stations, operational times associated with each stage of the process, as well as mobile transport robots responsible for moving semi-finished products between stations, including logistical constraints and the synchronization of operations over time.

The objective of this study is to develop a digital twin as a tool to support the analysis and optimization of the galvanization process - particularly through the identification of bottlenecks, the optimization of the sequence and layout of technological stations and the determination of the minimum required number of machines and transport robots.

Literature Review

Digital twins represent an advanced digital technology that enables the replication of real-world objects, processes, or systems within a virtual environment. The literature distinguishes between various types of digital twins, which differ in terms of their level of representation and degree of integration with physical reality. At the most basic level are product twins, which represent individual physical objects and are used, for example, to monitor the technical condition of products. The next level includes process twins, which model and optimize complex production or operational processes, allowing for real-time simulation and analysis. The most advanced form consists of system twins, which integrate multiple components and processes within entire organizations or industrial systems. The ability to simulate, learn and respond autonomously defines the maturity levels of digital twins - ranging from simple monitoring models to intelligent systems that support real-time decision-making [1], [2].

In the literature and industrial practice, ambiguities are often observed in distinguishing concepts such as *simulation, Digital Model, Digital Shadow* and *Digital Twin*. Although all these concepts operate within the domain of digital representation of reality, they differ significantly in terms of the extent of integration with the physical object, the direction of data flow and the scope of interactive capabilities.

A Digital Model is a static, structural representation of a real object or process, typically developed in engineering environments such as CAD or as a mathematical model. It is not automatically fed with real-world data nor does it possess operational capabilities - its purpose is description, documentation, or manual analysis. In contrast, a simulation is a process - a dynamic analytical operation that utilizes such a model to predict the behavior of the object under specified conditions. Simulation can be conducted using historical or hypothetical data but does not imply a direct connection to reality [3].

A Digital Shadow is a digital model that receives data from the physical object in a one-way manner. Sensor information is automatically transmitted to the digital model, enabling monitoring, analysis and reporting. A key characteristic of the Digital Shadow is the absence of feedback - there is no possibility to influence the physical object from the model. While this model can be updated in real time, it serves solely an observational function. In this sense, it represents an intermediate stage in the development towards a fully functional Digital Twin [4], [5].

A Digital Twin is an advanced tool that integrates real-world data with simulations and decision-making algorithms. Unlike a Digital Shadow, a Digital Twin provides bidirectional synchronization: data from the physical system feeds the digital model, which in turn can influence the behavior of the physical object, for example, through parameter optimization or automated control decisions. Digital Twins are used for prediction, control and optimization of complex systems, particularly in industry, energy and smart manufacturing [6], [7].

Multi-Agent Systems (MAS) are increasingly used as an architecture for Digital Twins, especially in the context of modeling and managing complex industrial and cyber-physical systems. In this approach, the digital twin consists of multiple autonomous agents, each representing a specific physical component or system function. The agents operate independently but collaborate with one another, enabling decentralization of decision-making processes and enhancing the system's ability to respond to changing operational conditions.

The application of MAS in Digital Twins offers a range of benefits. Primarily, it enables modular system construction, where each agent can be developed, tested and evolved independently, enhancing transparency and simplifying the management of complex architectures [8]. Thanks to decentralized decision-making, agents can quickly respond to local changes, reducing communication delays and improving the operational efficiency of the Digital Twin [9]. This architecture is also highly scalable and resilient, allowing new components to be easily added, while the failure of a single agent does not compromise the stability of the entire system [10]. Additionally, MAS facilitate continuous integration with real-world data. Agents can dynamically update the state of the Digital Twin, supporting real-time decision-making [8]. Multi-Agent Systems are particularly effective in modeling complex and distributed environments such as production lines, logistics, smart cities and energy systems, where adaptability, collaboration and the ability to operate autonomously are required [11].

Digital Twins play a significant role in optimizing the design and operation of production lines. By providing a realistic representation of physical production systems, they enable the simulation of various machine layout scenarios and analysis of material flow, allowing for the identification of bottlenecks and inefficient points within the system. By integrating real-time operational data, Digital Twins support decision-making regarding the number and placement of machines to achieve optimal performance levels while minimizing downtime and overload. An example of such an approach is the Digital Twin model presented by Arffa et al. in [12], which facilitates the analysis of production layouts and bottleneck detection using heuristic methods and artificial intelligence. Similarly, Liu et al. in [13] applied a Digital Twin for dynamic resource allocation optimization in production lines with variable flow, demonstrating its effectiveness in identifying inefficient processes and recommending machine quantities in real time. Additionally, Kappatos in [14] demonstrated the usefulness of a Digital Twin for experimenting with layout configurations and adjusting resource allocation in sink production plants, resulting in improved efficiency and better machine utilization.

Digital Twins can be used not only to model the operation of machines and technical systems but also to represent the competencies and efficiency of individual workers in the production process. Based on this, it is possible to create models that enable optimal task allocation to employees according to their skills, availability and historical operational performance. In the work by Kochańska et al., a method is presented that combines operator efficiency assessment (considering availability, productivity and quality of work) with risk analysis and a Tabu Search optimization algorithm. This approach allows for assigning workers to production positions in a way that maximizes performance and quality while minimizing the risk of errors [15].

Application of Digital Twins in Electrochemical Processes

Due to the complex nature of physicochemical phenomena occurring during electrodeposition processes, the implementation of Digital Twins in this area requires the use of advanced predictive models capable of capturing the relationships between operational parameters and the properties of the resulting coatings [16].

In the context of galvanic processes, Digital Twins enable monitoring and simulation of key technological parameters such as current density, chemical composition of the electrolyte bath, process temperature, pH value and electrolysis duration. These parameters determine the functional properties of metal coatings, including their thickness, uniformity, crystalline structure, morphology, corrosion resistance, hardness, adhesion to the substrate and the current efficiency of the process [16], [17].

One application of Digital Twins in this area was the development of a model supporting the hard chrome plating process of aircraft engine components. This model enabled not only the simulation of the chromium electrodeposition process but also the prediction of coating behavior under operational conditions, taking into account the effects of variable mechanical and thermal loads. As a result, it was possible to optimize technological parameters to enhance component durability [18].

Another example is the monitoring and optimization system for the nickel plating process developed by Siemens, which integrates sensor data collected from the galvanic line (including measurements of temperature, pH, metal ion concentrations and electrical parameters) with a digital model capable of predicting coating quality. This system also allows automatic adjustment of parameters when deviations from reference values are detected [6].

Another system designed for monitoring and predicting the outcomes of aluminum anodizing in the aerospace industry was described by Afzal. This solution integrates Internet of Things (IoT) technology, artificial intelligence (AI) and cloud computing (CC), enabling the prediction of oxide coating properties such as thickness, porosity and corrosion resistance based on historical data and real-time process parameters. Additionally, the system allows dynamic real-time optimization of the process while considering variable quality requirements [19].

A distinct category includes Digital Twin implementations in galvanic processes utilizing pulsed current. In such technologies, the ability to precisely modulate pulse parameters (including amplitude, duration and frequency) allows the production of coatings with characteristics unattainable using direct current.

Modeling these phenomena in a digital model, however, requires the use of advanced mathematical modeling tools and high computational power, enabling the analysis of nucleation processes and crystal growth under variable power supply conditions. Additionally, in studies on single crystal growth processes, Digital Twins utilizing deep learning techniques combined with physicochemical modeling have enabled real-time monitoring of parameters such as pH, temperature and reagent concentration, demonstrating the potential of Digital Twins to capture phenomena characterized by high variability and complex dynamics [20].

Contemporary implementations of Digital Twins in the galvanic industry represent stages of advanced technological deployment. However, the effective implementation of such systems requires access to measurement data with high temporal and qualitative resolution, as well as the use of advanced analytical methods, including machine learning algorithms. These algorithms enable the identification of cause-and-effect relationships between process variables and the final properties of coatings [21].

In the context of practical implementations, a key stage in building Digital Twins of technological processes - such as those occurring in electrochemical systems - is the selection of appropriate modeling methods and tools. A Digital Twin is not a single, monolithic model but a complex structure that represents the behavior of the real system using diverse mathematical, logical and computational representations. Depending on the nature of the process and the modeling objective, both discrete-event approaches (e.g., for describing material flow, transport between stations, task queuing) and continuous models (e.g., to replicate the kinetics of electrochemical reactions or changes in physicochemical parameters over time) are applied. Contemporary frameworks for Digital Twin development increasingly rely on hybrid simulation concepts that combine elements of both approaches within a unified computational architecture.

The logical structure and operational process flows within the twin can be defined using tools such as BPMN (Business Process Model and Notation), which enables clear representation of dependencies between tasks and object states, or Petri nets, which are particularly useful for modeling concurrent processes and systems composed of multiple shared resources [22]. Such models can be enriched with real-time data acquired through Manufacturing Execution Systems (MES), allowing not only the representation of the system's current state but also the performance of predictive analyses and "what-if" scenario simulations, which are valuable for assessing the impacts of failures, changes in input parameters, or production resource reorganization.

Digital Twins developed for the optimization of production processes rely on the interaction of multiple mathematical models describing the operation of individual system components, including technological workstations, transport equipment and organizational units. In the present work, a Digital Twin was developed as a tool to support the analysis and optimization of the galvanizing process, with particular emphasis on identifying bottlenecks, optimizing the sequence and layout of workstations and determining the minimum number of machines and mobile robots required to carry out the process. The digital model accounted for both the duration of technological processes (including galvanizing stages) and intralogistics operations involving transport between technological and service stations.

In this context, the Digital Twin constitutes a complex structure composed of multiple partial models, ranging from physicochemical models representing electrochemical phenomena in galvanic baths (e.g., mass and charge transfer models, Nernst and Butler-Volmer equations), through models of material flow and task queuing (e.g., Petri nets, discrete event models), to models describing the behavior of mobile robots in the production environment (e.g., motion trajectory models, collision avoidance algorithms, energy consumption prediction systems). Depending on requirements and available data, individual components of the twin can be implemented in simplified forms (e.g., heuristic rules, deterministic simulations) or as advanced models (e.g., dynamic real-time simulations, prediction using machine learning models).

For modeling transport between workstations, analyzing energy consumption by mobile robots and planning transport along with charging schedules for individual robots, dedicated predictive models proposed by the authors in separate studies on energy consumption prediction by mobile robots based on mission parameters (routes) can be implemented [23], [24].

A review of the existing literature reveals significant gaps in the field of Digital Twins dedicated to galvanization processes. Despite the growing number of studies on Digital Twins in manufacturing, there is a lack of comprehensive models that integrate the specifics of electrochemical processes with intralogistics aspects, particularly involving mobile transport robotics. Current works often focus on isolated aspects, without simultaneous simulation and optimization of both technological processes and autonomous internal transport, which limits the potential for full optimization and automation of galvanic production lines.

Research Methodology

The research methodology is based on a simulation approach, with the primary objective of validating the functionality and operational effectiveness of the developed digital twin for the galvanization process. A key element involved constructing a model that accurately represents the real production system, followed by its testing under conditions closely resembling actual operation. The results were simultaneously compared with those obtained from simpler mathematical models. The entire testing process aimed to assess the digital twin's usefulness in analyzing decision-making scenarios and its potential for optimizing system performance.

The digital twin architecture was designed to be modular and scalable, enabling flexible adaptation of the model to various configurations of galvanic production lines without the need to modify the source code. The main architectural principle was the separation of the configuration layer from the simulation logic layer. Input data concerning zone layouts, transport robot parameters, technological sequences and energy consumption profiles are loaded from external CSV files, allowing rapid generation of new simulation scenarios. The core of the system is the 3D environment initialization mechanism in Unity, which automatically creates a virtual representation of the production line based on configuration data, assigning process functions and parameters accordingly. Each system element - zone, robot, or object - is represented as a separate GameObject with attached control components responsible for its behavior, interactions and communication with other objects. The architecture is further enhanced by data logging, energy management, user interface handling and process visualization systems. This clear separation of responsibilities within the system structure ensures not only code clarity and ease of expansion but also robustness against errors and future integration capabilities with external MES or SCADA systems.

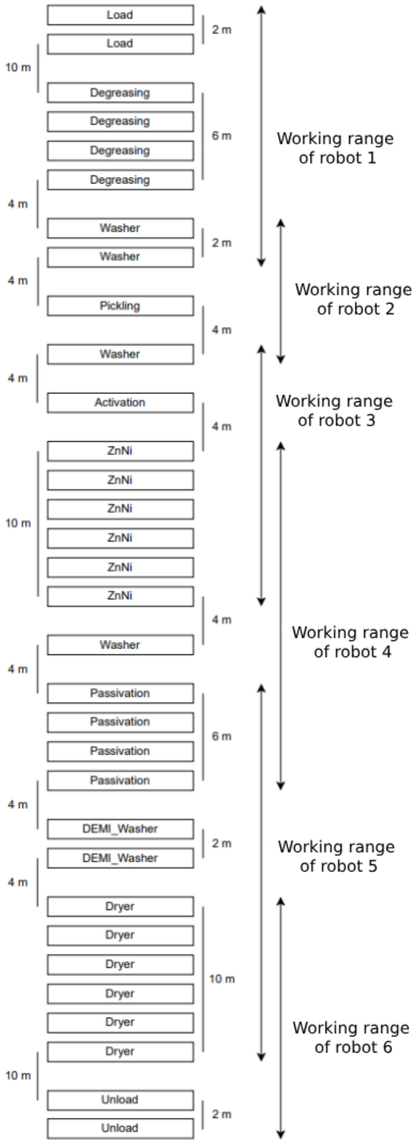


Fig 1. Imported galvanization process

The model encompasses 19 process zones corresponding to individual stages of the galvanization process. Zone parameters were based on real data, including processing times, varying energy consumption profiles depending on active or idle states and transport distances between zones. Transport robots were simulated with realistic speeds and capabilities for coordination with other units. Simulations were conducted in the Unity environment, utilizing a dedicated configuration system based on CSV files, which allowed for rapid parameter modifications. Each simulation run lasted 5 minutes, representing 5 hours of production line operation. The initial simulation configurations imported from CSV files are presented in tables 1-4.

Table 1. Initial configuration of process parameters

ID	Tag	Pos_x	Pos_y	Pos_z	Max process time [s]	Min process time [s]
1	Load	0	0	0	180	180
2	Load	10	0	0	180	180
3	Degreasing	60	0	0	600	600
4	Degreasing	70	0	0	600	600
5	Degreasing	80	0	0	600	600
6	Degreasing	90	0	0	600	600
7	Washer_1	110	0	0	150	150
8	Washer_1	120	0	0	150	150
9	Picking	140	0	0	70	70
10	Washer_Buffor	160	0	0	180	180
11	Activation	180	0	0	120	120
12	ZnNi	200	0	0	600	600
13	ZnNi	210	0	0	600	600
14	ZnNi	220	0	0	600	600
15	ZnNi	230	0	0	600	600
16	ZnNi	240	0	0	600	600
17	ZnNi	250	0	0	600	600
18	Washer_3	270	0	0	180	180
19	Passivation	290	0	0	300	300
20	Passivation	300	0	0	300	300
21	Passivation	310	0	0	300	300
22	Passivation	320	0	0	300	300
23	DEMI_Washer	340	0	0	180	180
24	DEMI_Washer	350	0	0	180	180
25	Dryer	370	0	0	480	480
26	Dryer	380	0	0	480	480
27	Dryer	390	0	0	480	480
28	Dryer	400	0	0	480	480
29	Dryer	410	0	0	480	480
30	Dryer	420	0	0	480	480
31	Unload	470	0	0	120	120
32	Unload	480	0	0	120	120

Table 2. Configuration of energy consumption of each station

ZoneTag	Energy Consumption [kWh]
Load	0.4
Degreasing	3
Washer_1	1.5
Pickling	3.2
Washer_Butfor	1.5
Activation	2.1
ZnNi	7.2
Washer_3	1.5
Passivation	1.9
DEMI_Washer	2.2
Dryer	85
Unload	4

Table 3. Configuration of the working range of robots

ID	Name	Min accesible zone id	Max accesible zone id	Speed	Idle Pos x	Idle Pos y	Idle Pos z	Additional Zone Access	Collision possible
1	Robot_1	1	8	2.5	60	0	0	false	true
2	Robot_2	7	10	2.5	140	0	0	false	true
3	Robot_3	10	17	2.5	180	0	0	false	true
4	Robot_4	12	22	2.5	270	0	0	false	true
5	Robot_5	19	30	2.5	340	0	0	false	true
6	Robot_6	25	32	2.5	470	0	0	false	true

Table 4. Configuration of operation order in the galvanization process

Sequence Name	Zone tag 1	Zone tag 2	Zone tag 3	Zone tag 4	Zone tag 5	Zone tag 6	Zone tag 7	Zone tag 8	Zone tag 9	Zone tag 10	Zone tag 11	Zone tag 12
Basic Zn	Load	Degreasing	Washer 1	Pickling	Washer Buffor	Activation	ZnNi	Washer 3	Passivation	DEMI Washer	Dryer	Unload

On the actual production line, transport robot cycle times and their energy consumption during individual operations were measured and are collectively presented in tables 5 and 6.

Table 5. Transport robot cycle times between individual stations

From	To	Distance [m]	Delivery time [s]	Handling time [s]	Total time [s]
Load	Degreasing	10	25	9	44
Degreasing	Washer	6	15	9	30
Pickling	WasherBuffer	2	5	9	16
WasherBuffer	Activation	4	10	9	23
Activation	ZnNi	4	10	9	23
ZnNi	Washer	10	25	9	44
Washer	Passivation	4	10	9	23
Passivation	DEMI_Washer	6	15	9	30
DEMI_Washer	Dryer	4	10	9	23
Dryer	Unload	10	25	9	44
	Sum	64	460	99	323

Table 6. Energy consumption of robots during individual process operations

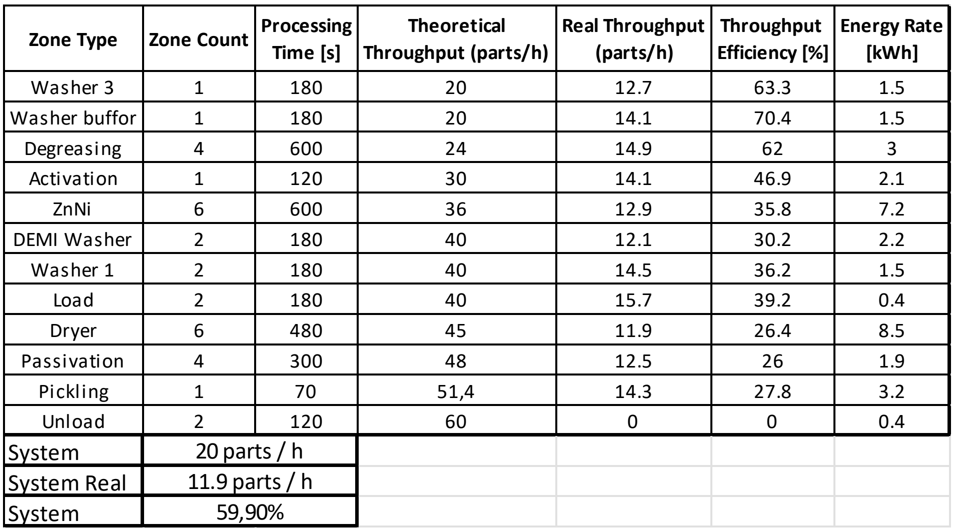
Zone type	Number of zones	Process time [s]	Energy consumption [kWh]	Assigned robot
Load	2	180	0.4	Robot 1
Degreasing	4	600	3	Robot 1
Washer 1	1	180	1.5	Robot 1 / Robot 2
Pickling	1	70	3.2	Robot 2
Washer Buffor	2	180	1.5	Robot 2 / Robot 3
Activation	2	120	2.1	Robot 3
ZnNi	6	600	7.2	Robot 3 / Robot 4
Washer 3	1	180	1.5	Robot 4
Passivaition	4	300	1.9	Robot 4 / Robot 5
DEMI Washer	2	180	2.2	Robot 5
Dryer	6	480	8.5	Robot 5 / Robot 6
Unload	2	120	0.4	Robot 6

Theoretical throughput was calculated using the formula:

$$Throughput = Number\ of\ zones * \frac{3600}{Process\ time} \left[\frac{pcs.}{h}\right] \quad (1)$$

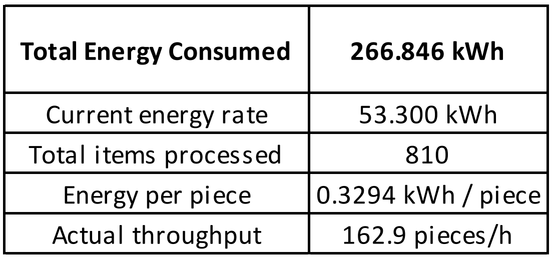
For the baseline configuration presented above, the simulation results for actual and theoretical throughput, system throughput efficiency and electrical energy consumption are shown in tables 7 and 8.

Table 7. Simulation report - theoretical and actual throughput and machine utilization efficiency



Zone Type	Zone Count	Processing Time [s]	Theoretical Throughput (parts/h)	Real Throughput (parts/h)	Throughput Efficiency [%]	Energy Rate [kWh]
Washer 3	1	180	20	12.7	63.3	1.5
Washer buffor	1	180	20	14.1	70.4	1.5
Degreasing	4	600	24	14.9	62	3
Activation	1	120	30	14.1	46.9	2.1
ZnNi	6	600	36	12.9	35.8	7.2
DEMI Washer	2	180	40	12.1	30.2	2.2
Washer 1	2	180	40	14.5	36.2	1.5
Load	2	180	40	15.7	39.2	0.4
Dryer	6	480	45	11.9	26.4	8.5
Passivation	4	300	48	12.5	26	1.9
Pickling	1	70	51,4	14.3	27.8	3.2
Unload	2	120	60	0	0	0.4
System	20 parts / h					
System Real	11.9 parts / h					
System	59,90%					

Table 8. Simulation Report - Electrical Energy Consumption



Total Energy Consumed	266.846 kWh
Current energy rate	53.300 kWh
Total items processed	810
Energy per piece	0.3294 kWh / piece
Actual throughput	162.9 pieces/h

During the analysis of the results obtained using the digital twin, a significant phenomenon of bottleneck formation within the structure of the galvanic line was observed. Simulations revealed that in two specific process zones, a substantial accumulation of objects awaiting processing occurred, leading to a reduction in the overall system throughput. Although other segments of the line demonstrated high operational efficiency and short processing times, it was precisely these two low-throughput zones that determined the final performance of the entire setup. This confirmed that the maximum system efficiency does not depend solely on the average throughput of individual components, but is crucially shaped by local constraints in material flow.

The congestion observed in the simulation illustrated a classical synchronization and task queuing problem, which is typically overlooked in traditional analytical models based on uniform load distribution assumptions. In reality, as demonstrated by the digital twin, dynamic interactions between production zones and autonomous transport robots led to irregular load distribution across the system. Variable travel times to processing zones, shared transport routes and task collisions caused sharp declines in system efficiency - even under conditions of nominally high throughput. These local constraints were the key factor behind the noticeably lower actual throughput compared to the theoretical maximum. This confirms that effective system optimization requires more than just improving individual operational parameters, it demands a holistic approach to coordination and load balancing throughout the entire process.

As part of the research, a series of test scenarios were conducted, starting from the baseline configuration and progressing through the addition of new zones (WasherBuffer, Washer_3, degreasing), as well as tests involving increased robot speed and shortened item generation intervals. This approach enabled the observation of how structural and operational modifications affected both the throughput and energy consumption of the system.

Analysis of the simulation results revealed that the implementation of additional elements in the process structure, such as new technological zones, leads to an increase in the system's total energy consumption. However, a significant decrease in the unit energy consumption per final product was also observed. This phenomenon stems from the fact that expanding the production line infrastructure enables an increase in overall system throughput, resulting in more efficient use of energy resources per unit of output. In other words, although the system's total power usage rises, the growing productivity makes the process more energy-efficient on a per-unit basis, as illustrated in the graph below.

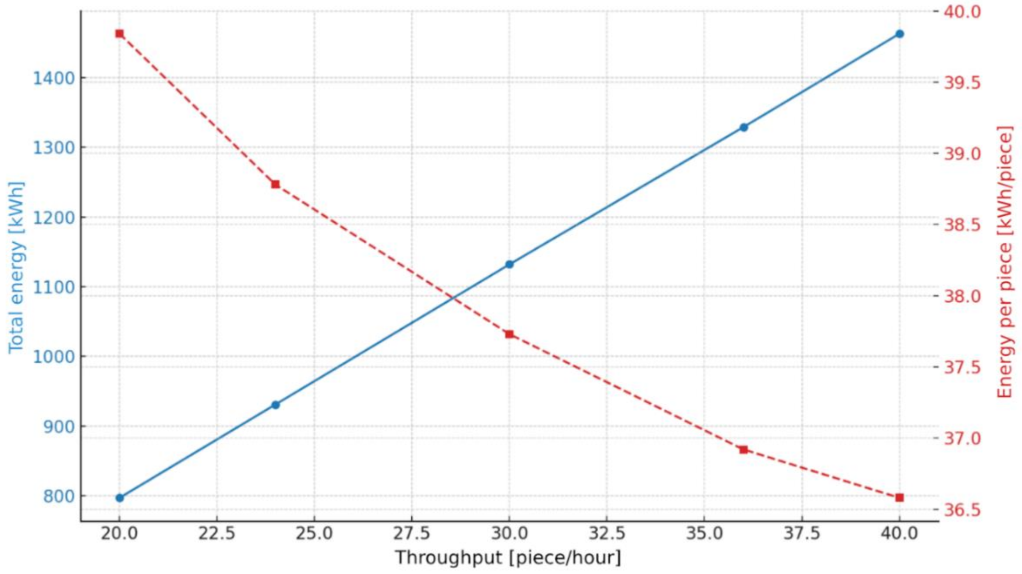


Fig 2. Electric energy consumption depending on throughput

The simulation results were compared with those obtained from a mathematical model assuming ideal operating conditions. The observed deviations stemmed from realistic phenomena such as queuing, transport blockages, variability in initial conditions and limitations in robot coordination. This approach enabled a deeper analysis of system complexity that classical analytical modeling fails to capture.

Conclusions

The analysis of the results obtained during the simulation studies confirms that the digital twin of the galvanic line is an effective tool for modeling, analyzing and optimizing complex industrial systems. Comparisons between the digital model results and analytical predictions clearly indicated the limited usefulness of classical computational methods in assessing the actual performance of the system. While the mathematical model operates under idealized conditions and does not account for system dynamics, the digital twin enables the simulation of real phenomena such as route blockages, queues of waiting robots, variability in transport times and cascading delay effects.

In particular, numerous phenomena resulting from interactions between autonomous system elements were identified, such as shifting bottlenecks and dynamic changes in capacity-limiting points. It was also observed that the actual system throughput reached values around 60 - 80% of analytical predictions, which should be taken into account when designing and planning the operation of real production lines.

From an energy perspective, simulations showed that although expanding the line with additional zones increases total energy consumption, it simultaneously allows for higher throughput, resulting in a reduction of energy consumption per single product. This effect is crucial for cost and environmental optimization. Another important conclusion is the need to reduce downtime, as process zones in standby mode still consume up to 70% of nominal power.

The evaluation of the developed solution's effectiveness and usability demonstrated that the digital twin not only allows for faithful replication of the production system's structure and parameters but, most importantly, enables safe and controlled "what-if" analyses. Simulations conducted in the Unity environment confirmed the system's capability to test alternative layouts, operational strategies and emergency scenarios, making it a valuable tool both during the design phase and throughout operation. An additional benefit is the potential use of the model as a training platform for operators as well as an environment for developing procedures to respond to atypical events.

It is important to highlight certain limitations of the adopted approach. The model does not include detailed representations of chemical and electrochemical processes, due both to computational constraints and a deliberate focus on logistical and energy-related aspects. Moreover, the lack of integration with real measurement systems (e.g., SCADA, MES) restricts the capability for real-time system monitoring and adaptive, on-the-fly decision-making.

A key direction for further development of the digital twin lies in integrating artificial intelligence (AI) algorithms, particularly machine learning methods and heuristics based on historical and simulation data. Implementing such solutions will enable dynamic real-time adjustment of process parameters, prediction of bottlenecks and automatic scheduling of tasks and routes for mobile robots based on current system conditions. The application of AI can also significantly enhance the accuracy of energy consumption and machine load forecasts, allowing not only improved operational efficiency but also cost and resource savings. Integrating these mechanisms within the existing digital twin architecture will lay the foundation for building an autonomous, data-driven production management system supported by intelligent decision-making models. As an additional point, algorithms of mapped energy consumption based on multi-parameter models for mission and environmental parameters [23, 24] could be implemented to better estimate the robots' energy usage and improve mission distribution.

In summary, the digital twin does not replace classical computational methods but effectively complements them. The synergistic combination of a mathematical model, providing a solid theoretical foundation, with digital simulation, revealing the real dynamics and complexity of the system, creates a comprehensive and effective methodology for analyzing and designing modern industrial systems. The results obtained in this research fully confirm the validity of further developing such tools within the context of Industry 4.0.

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