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SIMULATION META-MODEL OF ASSEMBLY LINE WITH CONWIP CONTROL

Milan Gregor[1], Patrik Grznár[1], Michal Gregor[2], Lucia Mozolová[1], and Štefan Mozol[1, *]

[1]Department of Industrial Engineering
University of Žilina
Slovakia
[*]Corresponding author's e-mail: stefan.mozol@fstroj.uniza.sk

[2]Institute of Competitiveness and Innovations
University of Žilina
Slovakia

This research navigates the application of simulation meta-modeling in understanding and controlling assembly line dynamics. Aimed at unveiling the relationship between input factors and output parameters in a production system, a precise meta-model was devised based on real system data and simulation statistics. The meta-model predicts parameteR-values within a verified validity range, simplifying complex variable relationships for enhanced decision-making in intricate systems. The accuracy of the model was notable within the tested range of CONWIP cards from 1 to 25, showcasing reliable output approximation. This study highlights the classical approach to simulation meta-modeling as cumbersome, propelling the quest for further simplification in analyzing complex production systems. The utilization of simulation meta-modeling emerged as a pivotal tool for validating complex simulation models and swiftly testing system sensitivity to input factor alterations. Noteworthy findings include the identification of an optimal number of CONWIP cards for maximizing throughput without excessive increases in Work-In-Progress or throughput time. The research also underscores the potential of 5th-degree polynomial models in approximating production performance and throughput time accurately, offering robust tools for informed decision-making. This venture marks a significant stride towards a more streamlined, accurate, and efficient analysis of complex production systems, showcasing the promising applicability of simulation meta-modeling in industrial engineering and production management.

Keywords: Simulation Meta-Modeling, Simulation of Production Systems, CONWIP.

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1. INTRODUCTION

Changes in customer behavior necessitate a quick response from the manufacturer, which can be ensured by selecting an appropriate production management system and an effective management strategy. Traditionally, the MRP management system was utilized in production, capable of scheduling both production and ordering activities within the relevant planning horizon. A drawback of MRP management was that any change in or around the production system required re-planning after the plan was created. MRP operates with high inventories of work-in-progress (WIP), and its planning method is referred to as push. Several production management concepts have addressed the issues of the MRP system. Among the most well-known are Load Oriented Control (LOC), bottleneck control (Drum Buffer Rope DBR), Kanban control and CONWIP control (Constant Work in Progress Inventory CONWIP). In contrast to MRP control, Kanban and CONWIP systems operate in a pull manner, and the DBR system is a mixed pull-push control system. Each of the above control concepts has its own advantages and disadvantages and is particularly suited for a certain type of production environment.

Given the array of production management systems discussed, it becomes imperative to delve into methods that aid in understanding, evaluating, and comparing these systems to guide manufacturers in making informed decisions tailored to their specific operational context. Among the methodologies employed for this purpose, simulation stands out as a powerful tool, offering a visual and computational platform to replicate and study the dynamics of production environments under varying conditions (Romero *et al*., 2021).

The evolution of production systems has witnessed significant acceleration due to the emergence and maturation of numerous advanced technologies. Among these, computer simulation has undergone a transformation facilitated by personal computing technologies, transitioning from large computing centers to designers' desks, thus becoming accessible to a broader

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audience. Modern simulation systems employ rapid computing algorithms and professional graphic animation systems with virtual reality (Krajcovic *et al*., 2021; Krajcovic *et al*., 2022) alongside a variety of complex and demanding statistical methods (Pekarcikova *et al*., 2023). These features are further enhanced with robust support for statistical data processing and evaluation, with some advanced simulation systems enabling the simulation of complex systems behavior through multi-agent approaches.

The trajectory of production systems development was initially influenced by information and communication technologies, enabling swift automation of production processes and, later, the automation of product design processes. The early '90s saw the initial attempts to integrate the entire value creation chain, known as computer-integrated manufacturing systems (CIM) (Cechura *et al*., 2012).

The digital twin technology emerged as a significant player, referred to as the symbiotic simulation system (S3) by certain authors (Raska *et al*., 2021), (Staczek *et al*., 2021). This technology, pivotal in the design and testing of production systems, entails a symbiotic system comprising a physical system and its analogous simulation system. The operational S3 generates output data, facilitating advanced analysis and decision-making by comparing data between the S3 and the physical system, followed by the application of machine learning methods and optimization algorithms.

Germany's announcement of its Industry 4.0 program in 2011 marked a new era in the industrial revolution (Basl *et al*., 2017). The driving force behind this revolution is cyber-physical systems (Malaga *et al*., 2020). The decisive technologies of this new industrial era include the Internet of Things connected with massive sensory systems utilization, artificial intelligence, and cloud computing solutions. The advent of sensors, instant data collection, and intelligent data processing enabled by high-speed internet has facilitated "virtualization" in manufacturing (Broum *et al*., 2020; Hnilica *et al*., 2013). This technological transition has allowed machines, devices, and even products to attain a higher level of autonomy in the production process (Kliment *et al*., 2021).

The advancements in the production environment necessitated novel approaches for the dynamic analysis of production systems. The demand for efficient, cost-effective methods led to the rising utilization of simulation meta-modeling, a method aimed at simplifying the input-output behavior of complex simulation models by approximating it with a more straightforward mathematical model or a meta-model (Soares de Amaral *et al*., 2022). This method offers a deterministic output and is computationally less demanding, thus serving as a powerful tool for analyzing dynamic systems.

Analyzing real systems can be demanding and often expensive. In certain cases, such analysis is not feasible either because the system in question does not yet exist (conceptual system) or it could result in the destruction of the system being analyzed (Pekarcikova *et al*., 2021). Simulation simplifies the analysis process, making it significantly more cost-effective, albeit it remains a complex and not-so-cheap method when a highly accurate and valid model is required, especially if the system being modeled is complex (computational complexity) (Buckova *et al*., 2019).

Simulation does not directly explain the behavior of the observed system. When interpreting simulation outputs, analysts require not only a strong theoretical foundation but also practical experience with simulation experimentation (Pekarcikova *et al*., 2014). Despite the detailed theory of planning experiments, most analysts resort to the trial-and-error method in practice.

The outputs generated by the simulation are valid for the given input conditions. To verify other factor values, analysts must simulate again, thereby necessitating simpler solutions for analyses that can approximate the simulation model outputs. Simulation meta-modeling emerges as such a solution, approximating the input-output behavior of the simulation model and, by extension, the real (conceptual) system. Utilizing meta-models presents three primary advantages: they have a clearly explicit form, provide a deterministic output, and are computationally undemanding (Cen *et al*., 2022).

Previously, it was believed that to analyze the dynamics of a mobile robot's operation in a production system at speed "v" and predict the alterations in production conditions when the speed of the mobile robot is marginally increased to "v + Δv", a new simulation was essential. However, current techniques allow for the estimation of the system's future development based on the ongoing experiment (Ojstersek *et al*., 2021).

Computer simulation, as a method for dynamic systems analysis, offers analysts a broad scope for creating complex models capable of representing the desired properties of the simulated system. During the simulation, analysts gather extensive statistical data and estimate the values of the system's output parameters based on this data (Lazreg *et al*., 2023) and Oh (2023). Should data providing more detailed insights into system behavior be available, it's apparent that analysts would leverage methods allowing further analysis of the obtained data. Simulation meta-modeling serves as such a method, enabling the interpolation of system behavior within defined boundaries from simulation outputs and, conversely, the extrapolation of possible future development trajectories using suitable methods (Barton, 2020).

The simulation's objective is to answer the question of what the model system outputs will be if the combination of influential input factors and their levels is known. Therefore, the simulation operates like a black box, representing the dependencies existing between the input factors and the output parameters of the modeled system (Wozniak *et al*., 2017).

Complex processes are often depicted through extensive models providing a good approximation of reality. Nonetheless, decision support, exploratory analysis, and fast adaptive computing frequently necessitate a simpler description of facts.

Despite being a demanding method, simulation requires an extended duration and high qualification. Consequently, for quick decision-making needs, meta-models and simulation meta-modeling are employed, representing approximations of outputs by suitable mathematical models. In this context, modeling refers to the identification of regression dependencies (models) in the simulation output data and testing the resulting mathematical model's tightness with the simulation data using the correlation coefficient or the coefficient of determination. As the obtained regression model approximates another model (our simulation model), we are dealing with a model of another model, commonly known as a meta-model.

The primary aim of this research was to unravel the relationship between input factors and output parameters within a production system and encapsulate this relationship through an apt meta-model. This venture was geared towards devising and validating a suitable meta-model based on real system data, considering the resulting simulation statistics of the modeled system along with the values of its input factors. The envisioned meta-model is intended for predicting the observed parameteR-values within the verified validity interval of the proposed meta-model. This methodology aids in representing complex variable relationships in an understandable format, thereby bolstering the decision-making process in intricate systems. Additionally, it's vital to note that a relatively straightforward and low-complexity simulation model was employed in this research. This model might not necessarily extend the results to more complex models containing more elements, resources, entities, varied and complex probability distributions, transfers, special causes of variation, and so on. Nonetheless, despite these generalization hurdles, the research unearthed insightful results and showcased a promising approach to navigating complex system dynamics. This is indicative of the potential efficacy and applicability of the proposed meta-model, even within a limited scope. The study unveiled a range of utilization rates across different stations, hinting at room for optimization to balance the workload across the assembly line. A significant finding was the identification of an optimal number of CONWIP cards, around 7, for maximizing throughput without unnecessary increases in Work-In-Progress (WIP) or throughput time. Furthermore, the research validated the use of 5th-degree polynomial models, which exhibited high fidelity in approximating both the production performance and the throughput time, serving as robust tools for decision-making within their valid range.

2. RELATED WORKS

Meta-modeling has evolved significantly since its inception in the 1970s, transitioning from simple regression and Design of Experiments (DoE) methods to more sophisticated techniques leveraging Artificial Neural Networks (ANNs). This evolution has been primarily driven by the need to reduce the time and computational resources required for simulations, as initially proposed by Blanning (1974). The popularization of meta-modeling was mainly due to the works of Kleijnen (1975) and Barton (1992). The progress in the development of production systems and the related development of simulation systems and simulation meta-modeling is illustrated in Figure 1.

In Figure 1, the x-axis represents the time frame of development, while the y-axis corresponds to sophistication, complexity, and application in the industry. The right part of the figure illustrates the type of production system, whereas the left side depicts software and marks the area where meta-modeling finds its application. The centered, bounded section of the image describes the specific applications and software that were utilized during that period. The field of meta-modeling is vast, with various approaches, notably regression methods and response surface methods. The discourse on meta-modeling in simulation has been thoroughly expounded in recent works such as those by Soares de Amaral *et al*. (2022) and Abolghasemian *et al*. (2022). An extensive review of meta-modeling methods in simulation is provided by Khatouri *et al*. (2022), while the modern methodologies are well delineated in the guide by Carvalho *et al*. (2021).

The pioneering algorithm by Persson *et al*. (2010), which leverages a meta-model to enhance performance—dubbed Meta-model Enhanced Local Search (MMELS)—marks a milestone in optimization algorithms. Despite its roots in simulation optimization, its applicability extends to any optimization variant where a computationally intensive function evaluation can be approximated by a simpler function shape estimate. The MMELS algorithm, grounded on the "steepest ascent" concept of the Hill Climbing algorithm, orchestrates a series of local evaluations to unearth a better solution.

Simultaneously, Bork *et al*. (2018) introduced a new framework for simulating multi-stage industrial processes using meta-modeling building blocks, as demonstrated via ADOxx. Villarreal-Marroquin *et al*. (2013) also introduced a method for optimization through simulation using meta-modeling and evaluated its effectiveness in a real-world automotive manufacturing scenario. Furthermore, the framework by Stavropoulos *et al*. (2023) for meta-modeling manufacturing processes and automation workflows, inclusive of human-in-the-loop process optimization, aligns with the creation and operation of digital twins.

In a significant study (Chen *et al*., 2021), a meta-model-based two-stage simulation optimization was proposed for Automated Guided Vehicle (AGV) systems to identify optimal settings at both design and operational levels, Utilizing data collected from a real production environment, showcasing the pragmatic utility of meta-modeling in real-world manufacturing scenarios (Dong *et al*., 2022). Authors (Parsonage *et al*., 2023) deal with multi-fidelity meta-modeling and model management framework designed to efficiently incorporate increased levels of simulation fidelity from multiple competing sources into early-stage multidisciplinary design optimization scenarios.

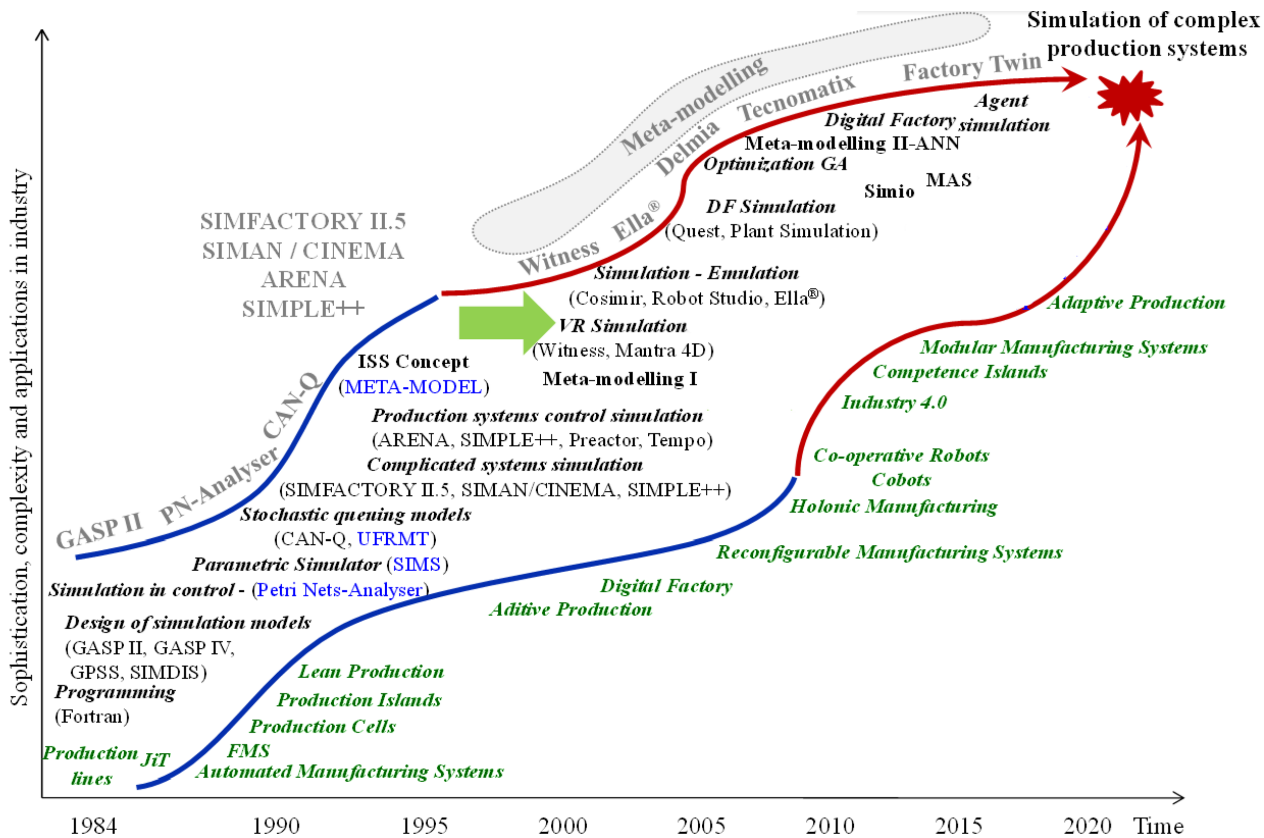


Figure 1. Development of simulation and simulation meta-modeling

Recent years have seen a surge in the adoption of Artificial Neural Networks (ANN) in meta-modeling, overtaking traditional techniques that demand fewer assumptions and precise information about the modeled system. The seminal works by Pierreval (1992a; 1992b) laid the foundation for the development of ANN meta-models, a trajectory later advanced by Chen *et al*. (2002), who combined an ANN meta-model with a stochastic local search approach based on Simulated Annealing (SA) to optimize manufacturing systems. In similar pursuits, Altiparmak *et al*. (2002) employed an ANN meta-model alongside simulated annealing to optimize bin capacity in a theoretical 15-station asynchronous assembly system.

A deep-learning-based meta-modeling workflow has also been proposed to forecast the cooling and heating loads of buildings at individual and district levels in the early design stage, highlighting the versatility and broad application spectrum of meta-modeling techniques (Zhou *et al*., 2022).

Historically, the focus has largely been on Utilizing regression and response surface methodologies for meta-modeling, as seen in the notable work by Persson *et al*. (2010) on the Meta-model Enhanced Local Search algorithm and the multi-stage industrial process simulation framework by Bork *et al*. (2018). However, traditional methodologies have often been cumbersome and intricate, necessitating consistent adjustments and verifications for the meta-models with every change in the investigated system.

Our study advances beyond these conventional methodologies by substantiating the efficacy of simulation meta-modeling in approximating system parameter values from known input factors. We discerned that the use of 3rd or 4th-degree polynomials achieves a good accuracy level in reflecting genuine relationships between input factors and output parameters. Nevertheless, the inherent intricacy and time-demanding nature of conventional simulation meta-modeling methodologies pose substantial challenges. This exploration unveils two notable advancements: the automation of simulation meta-model generation and application via numerical solutions for regression coefficient estimations. Particularly, the latter development facilitates smooth incorporation into a management system, thereby accelerating the meta-modeling process and diminishing the necessary time and effort. These progressions unveil a hopeful pathway for overcoming the constraints intrinsic to traditional simulation meta-modeling methodologies, potentially diminishing the time and effort entailed in the meta-modeling process.

3. THE PROPOSED FRAMEWORK

Meta-models are frequently employed to probe the behavior of systems, with the foundational data for meta-model creation supplied by computer simulation responses. (Box *et al.*, 1987) delineate the distinction between a meta-model and a simulation model: a simulation model embodies a causal (or mechanistic) framework, while a meta-model represents an empirical paradigm. The ambition of meta-modeling is to unearth simplistic correlations between the output data of the simulation model (model parameters) and its input variables. Hence, simulation meta-models elucidate the fundamental input-output correlations of the system via straightforward mathematical functions, primarily regression models, enabling the prediction of output Y for a given vector of inputs X. Figure 2 illustrates the basic tenet of simulation meta-modeling.

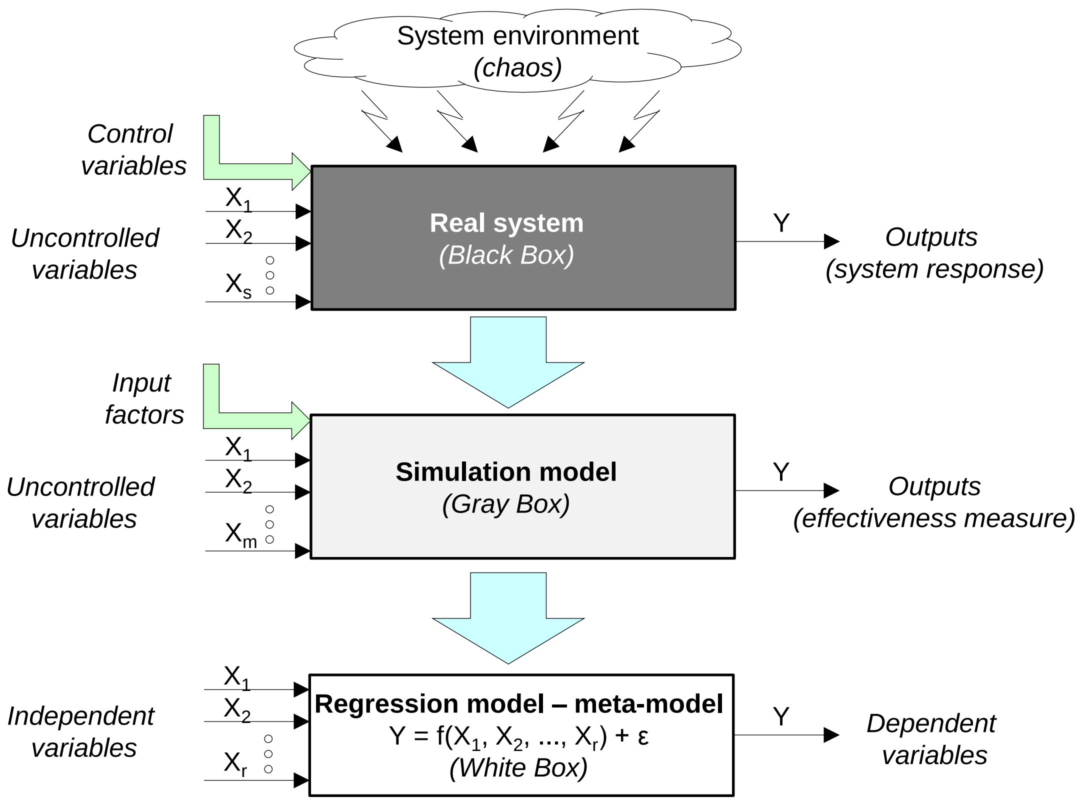


Figure 2. Principle of simulation meta-modeling

Figure 2 showcases how meta-modeling substitutes a complex production system with a simplified simulation model, retaining only the crucial attributes of the real system. If further simplification proves beneficial, a new model, a meta-model, emerges from the simulation model. A simulation meta-model is a mathematical (regression) model derived from analyzing the simulation model data. This meta-model unveils the essential nature of the system's input-output relationships via simple mathematical functions (1):

$$Y = f(X) \tag{1}$$

3.1 Types of Meta-models

Predominantly, meta-modeling techniques anchor on the parametric polynomial approximation of the outputs. A spectrum of techniques has been proposed for meta-model construction:

- Linear polynomial approximations (Kleijnen *et al*., 2000); Cheng (1999); (Cheng *et al*., 1999) are straightforward to implement, earning favor among simulation researchers. However, the efficacy of linear regression using polynomials is hampered by the inadequacy of low-degree polynomials to adequately approximate simulation data values and the tendency of high-degree polynomials to "fluctuate" the curve of approximated values amid given data, particularly in the boundary region. In cases where polynomials deliver a subpar fit, typically when the output exhibits a flat region, alternative meta-model varieties are warranted.

- Nonlinear techniques offer a more versatile and intuitive avenue but entail greater complexity. These methodologies encompass non-linear regression – (Santos *et al*., 2007); Kriging models – (Kleijnen *et al*.,2005); (Allen *et al*., 2003); and neural networks – (Juzon *et al*., 2023). Regression of nonlinear functions demands a comprehensive and adaptable repertoire of possible curves alongside meticulous selection of well-suited approximating starting values.

Other mechanisms include:

- Rational meta-models (Hendrickx *et al*., 2005),
- Radial bases of functions (Jin *et al*., 2000),
- Bayesian approaches Chick (2004).

Alternative modeling approaches (various models) discussed in recent literature include Taguchi models, generalized linear models, spline-based methods (tensor product, reciprocal splines, MARS, etc.), kernel smoothing, spatial correlation models, approximations from the realm of periodic waveforms (Fourier and sinusoid), and neural networks.

In addressing the subsequent case study, linear regression models of the following type were employed:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{in} + \varepsilon_i, \tag{2}$$

With a linear regression function:

$$\eta_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_n x_{in}, \tag{3}$$

Here:

$\beta_0, \beta_1, \ldots, \beta_n$ are the model parameters (regression coefficients),

x_{ij} -- the ith value (i = 1, 2, ... n) of the explanatory variable X_j (j = 1, 2, ... n),

ε_i – vector of random numbers (the summary result of the action of not specifically specified and accidental influences; the corresponding error which has zero expected value).

The pertinent types of regression models utilized in meta-model creation were thoroughly examined by the authors (Gregor *et al*., 2021). This manuscript encapsulates the basic forms of all meta-model types, with a primary focus on polynomial models and the application of ANN meta-models.

3.2 Procedure for Creating Simulation Meta-models

The meta-modeling venture mandates an initial definition of fundamental properties, followed by an articulation of the questions to be addressed during the creation of a specific meta-model. Post identification of basic properties and critical questions, the creation of the meta-model commences. Figure 3 delineates the generic process of simulation meta-model creation.

To elaborate on the generic process depicted in Figure 3, we provide an in-depth explanation of each step involved in the creation of a meta-model:

1. Defining the Research Problem and Objectives - The cornerstone of any research endeavor is a well-defined problem statement and research objectives. At this juncture, the focus is on providing a rigorous formulation of the research question, outlining the scope of the study, and setting specific, measurable, achievable, relevant, and time-bound (SMART) objectives. This step sets the direction and context for the entire research project.
2. Selection of Influential Factors and Determination of Their Levels - In this stage, critical variables or factors that significantly influence the system under study are identified through literature reviews, expert consultations, and preliminary analyses. Subsequently, the levels at which these factors will be studied are determined, either based on existing research or through experimental pilot runs.
3. Design of Experiments - The experimental design phase involves constructing a detailed plan for how the simulation experiments will be conducted. This includes specifying the combination of levels for each influential factor, the number of runs, randomization methods, and the criteria for data collection and analysis. Experimental design techniques like factorial design, response surface methodology, or Taguchi methods may be employed.
4. Design, Verification, and Validation of Simulation Model - A simulation model that mimics the real-world system is constructed. Verification is conducted to ensure that the model's internal logic and algorithms are error-free and aligned with the conceptual model. Validation is performed using real-world data to ensure that the model faithfully represents the actual system dynamics.

5. Pilot Simulation Runs - Before full-scale experiments are launched, pilot simulation runs are conducted. These preliminary runs serve multiple purposes: they test the functionality of the simulation model, offer an opportunity to calibrate model parameters and help researchers become familiar with the model's behavior and output metrics.
6. Conduction of Simulation Experiments - The full-scale simulation experiments are conducted as per the experimental design. During this phase, meticulous data collection is essential, and any anomalies or unexpected outcomes are carefully noted for later investigation.
7. Processing of Simulation Statistics - Post-experiment, the raw data are subjected to statistical analyses to draw meaningful inferences. Statistical methods, including but not limited to descriptive statistics, inferential tests, and confidence interval calculations, are used to interpret the data.
8. Choosing the Type of Dependencies for Creation of Meta-models - Based on the processed statistics, researchers decide on the mathematical forms or dependencies that best represent the system's behavior. This could range from simple linear relationships to complex non-linear models or machine learning algorithms.
9. Visualization of Selected Dependencies - Graphical methods, such as scatter plots, line graphs, or heat maps, are employed to visually represent the selected dependencies. This aids in providing an intuitive understanding of the system dynamics and validates the appropriateness of the selected meta-models.
10. Finding Appropriate Fitting Models - A range of candidate models is fitted to the data, and their goodness-of-fit is evaluated using criteria like the coefficient of determination (R-squared), Akaike Information Criterion (AIC), or Bayesian Information Criterion (BIC). The model that offers the best fit is selected as the meta-model.
11. Validation of Meta-models - The robustness and generalizability of the chosen meta-models are rigorously tested by applying them to a reserved or new dataset. The accuracy of the model's predictions is assessed, and any limitations are duly noted.
12. Use of Meta-models for Predictions - Finally, the validated meta-models are employed for making predictions or simulations under different scenarios. This could range from real-time decision-making to long-term strategic planning, thereby demonstrating the practical utility of the research.

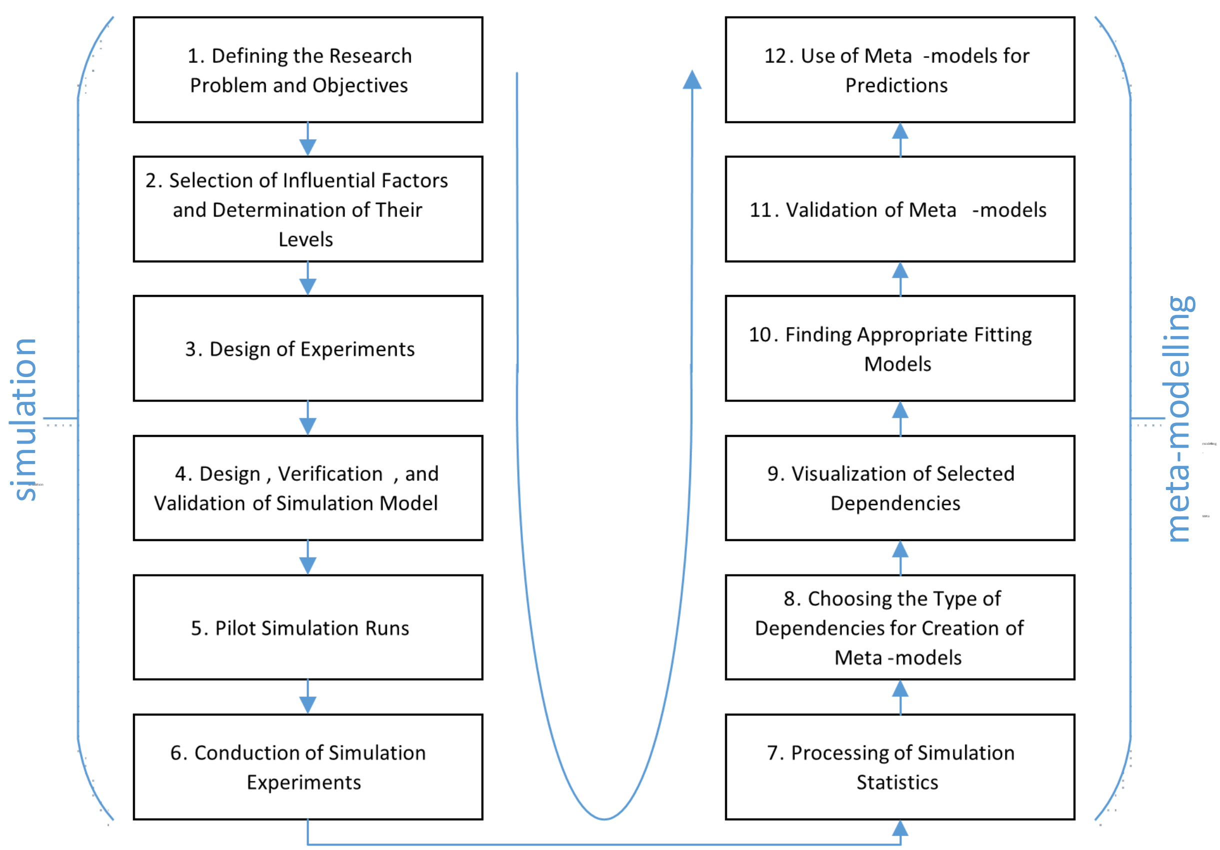


Figure 3. General process of creating a meta-model

4. A CASE STUDY FOCUSED ON PRODUCTION MANAGEMENT

The following section presents research results derived from real data. Each step described above is indicated with the chapter number and the number to which it corresponds.

4.1 - The subject of the investigation was the influence of the utilized production control system on selected output parameters of the assembly system, focusing on a line producing automotive products. The goal of the research was to develop suitable meta-models usable for production management with the support of simulation meta-modeling.
4.2 - Figure 4 shows the investigated assembly system with six assembly workplaces.

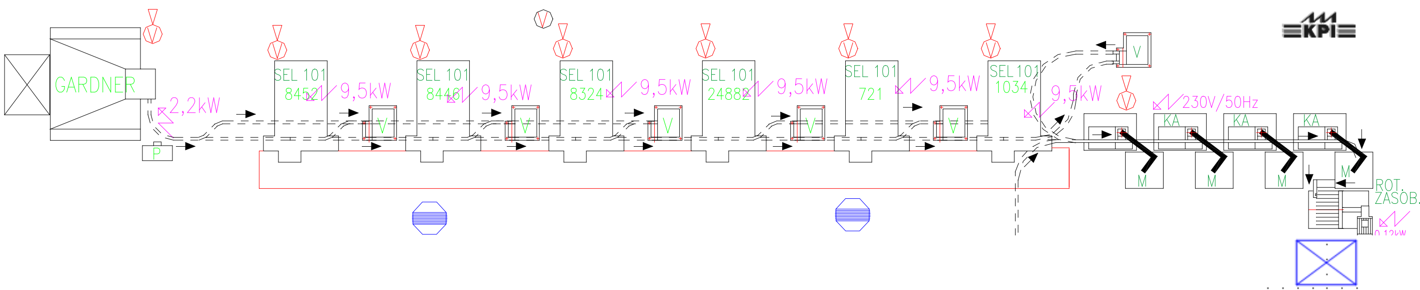
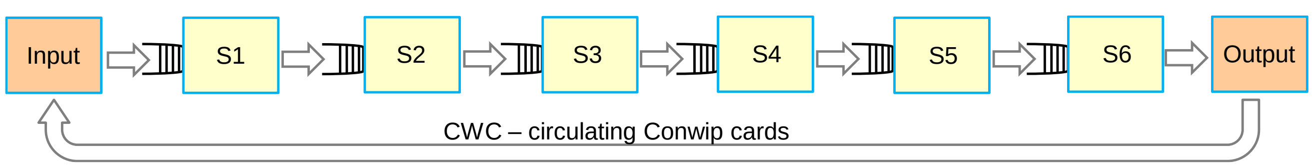
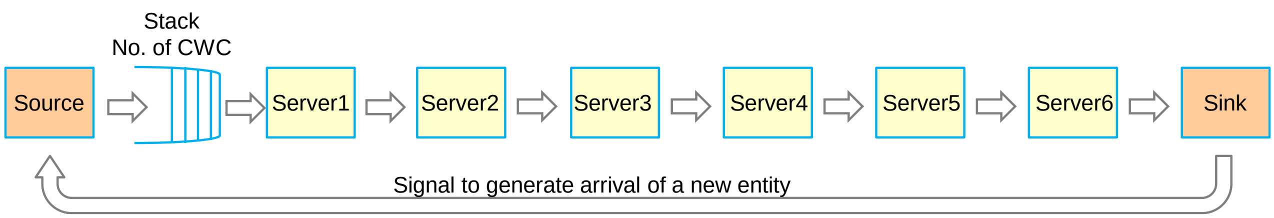


Figure 4. Assembly line layout with CONWIP control

Figure 5 illustrates an intermediate storage buffer in front of each workplace, along with a schematic representation of the assembly line demonstrating the principle of circulation of CONWIP cards and the implementation of CONWIP management in the simulation model. The simulation experiments were carried out in the advanced Simio simulation system. During the creation of the simulation model, special constructions of the Simio simulation system were utilized, enabling the generation of the required number of CONWIP cards (CWC) at the start of the simulation, placing them in front of the first assembly station, and then allowing the generation of a new entity at the entrance to the line only if the finished product exits the line. This solution ensures that only a pre-defined number of CONWIP cards will circulate in the circuit, through which it is possible to regulate the progress of production. During initialization, there is a stock of entities in front of Server1 equal to the number of CONWIP cards in the circuit. Whenever one entity leaves the system, a signal is sent from the Sink output module to generate the arrival of another entity in the Source.



(a)



(b)

Figure 5. Schematic representation of the assembly line (a) principle of circulation of CONWIP cards; (b) principle of implementation of CONWIP management in the simulation model

Incorporating the CONWIP system in the assembly line has already laid a foundation for controlled production flow. However, precise determination of the number of CONWIP cards through meta-modeling further refines the production management process. This determination, empowered by simulation meta-modeling, aids in tailoring the CONWIP system to the unique operational dynamics of the assembly line, thereby promoting a more synchronized and efficient production flow. The utilization of meta-models, as developed in the case study, provides a structured approach to analyzing the interplay between the production control system and the assembly system's output parameters. This structured analysis is pivotal in making informed decisions regarding the optimal number of CONWIP cards to be deployed, which in turn significantly impacts the pace and smoothness of the production process. By employing simulation meta-modeling, the study enables a thorough examination of how varying the number of CONWIP cards affects the assembly line's performance. This examination is not only grounded in real data but also allows for a more nuanced understanding of the system's behavior under different configurations of CONWIP cards. The insights derived from this examination are instrumental in fine-tuning the CONWIP system to better match the production line's operational characteristics, leading to improved throughput, reduced wait times, and overall enhanced operational efficiency. Moreover, the simulation meta-modeling facilitates a data-driven approach to managing the intermediate storage buffer efficiently, ensuring that the assembly stations are consistently supplied with work items while averting overproduction. This data-driven approach is crucial in achieving a balanced and well-regulated production flow, which is a central objective of the case study focused on production management.

4.3-4.7 - By analyzing the assembly line, operating times at individual assembly stations were determined. A triangular distribution was chosen as the most suitable for their generation in the simulation. Operating times at the assembly stations and selected assembly line simulation results using the current production management system are listed in Table 1. A period of 12.000 min was simulated (5 weeks of operation). The start-up period of the simulation was 50 min. Ten independent replications were simulated in each experiment.

Table 1. Operation times at individual assembly stations and selected simulation results

Station	Minimum (min.)	Mode (min.)	Maximum (min.)	Average queue length (pcs)	Waiting time in magazine (min.)	Utilization (%)
S1	1.80	1.96	2.11	11.26	22.28	95.64
S2	1.88	2.15	2.27	78.77	161.22	99.94
S3	1.90	2.13	2.24	0.25	0.53	99.48
S4	1.87	2.19	2.28	17.75	37.22	99.89
S5	1.92	2.11	2.25	0.11	0.24	98.89
S6	1.94	2.13	2.34	29.10	61.60	99.87

During the simulation of the assembly line with the current management system, the value of the mean time between the arrivals of entities was Time Between Arrivals (TBA) = EXPO(2.01) and the following results were obtained: production output = 5612 pcs., average throughput time = 288.72 min., work-in-progress after the end of the simulation = 143.36 pcs. The responses of the production system to a change in the number of CONWIP cards were investigated. Table 3 shows the number of CONWIP cards with which the simulation experiments were carried out. The number of CONWIP cards used in simulation experiments are as follows: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 20, and 25.

Upon completion of the initialization and configuration of the simulation model, steps were taken to verify and validate it. Verification of the model was carried out by comparing the results of the simulation with theoretical assumptions and ensuring that the model was correctly implemented without any errors in the code or logic of the model. This process included checking the distributions of operation times and comparing statistical results, such as average queue lengths, waiting times, and station utilization, with assumptions. Validation of the model was carried out by comparing the simulation results with real data obtained from the operation of the assembly line. Historical data on operation times, queue lengths, waiting times, and station utilization were collected and compared with simulation results. A statistical analysis was also performed to determine whether the differences between the simulated and real data were statistically significant. The results showed that the simulation model is accurate enough to be used for evaluating various production management scenarios and optimizing the operation of the assembly line.

The response of the system to the change in the number of CONWIP cards was the output parameters of the production system, is summarized in Table 2.

Table 2. Simulation results

No. of CWC		1	2	3	4	5	6	7
Throughput (pcs)		951	1901	2849	3791	4716	5490	5537
WIP (pcs)		1	2	3	4	5	6	7
	Average	12.62	12.62	12.63	12.66	12.72	13.11	15.16

Throughput time (min.)	Maximum	13.29	14.54	16.73	19.11	21.03	23.52	25.51
	Minimum	11.91	11.78	11.85	11.8	11.88	12.31	12.45
No. of CWC		8	9	10	12	15	20	25
Throughput (pcs)		5537	5537	5537	5537	5537	5537	5537
WIP (pcs)		8	9	10	12	15	20	25
Throughput time (min.)	Average	17.32	19.49	21.65	25.98	32.46	43.27	54.06
	Maximum	27.79	29.88	32.24	36.7	43	54.21	65.02
	Minimum	12.45	12.45	12.45	12.45	12.45	12.45	12.45

4.8 - Based on the results obtained from the simulation experiments, different types of regression models were designed and tested. The same set of mathematical models was considered for all investigated input-output dependencies. The considered shapes are shown in Table 3.

Table 3. Design of mathematical function shapes

Model type	Model equation
Logarithmic	$y = a + b\,ln(x)$
Powerful	$y = ax^b$
Exponential	$y = ae^{b \cdot x}$
Linear	$y = a + bx$
Polynomial 2. degree	$y = a + bx + cx^2$
Polynomial 3. degree	$y = a + bx + cx^2 + dx^3$
Polynomial 4. degree	$y = a + bx + cx^2 + dx^3 + ex^4$
Polynomial 5. degree	$y = a + bx + cx^2 + dx^3 + ex^4 + fx^5$

Where: x is the number of CONWIP cards

4.9 - Figure 6 shows the dependence of production performance on the number of CONWIP cards. The dependence curve of the number of CONWIP cards and production performance actually represents the course of the well-known WIPAC curve (Work In Progress Again Capacity).

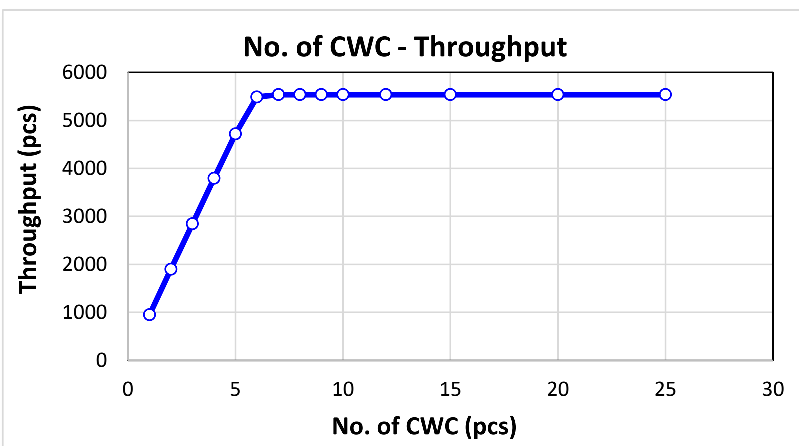


Figure 6. Dependence of production performance on the number of CONWIP cards

Table 4 shows the results of the regression analysis (meta-models) of the dependence of the number of CONWIP cards and production performance. In addition to simple types of linear models, more complex polynomial models were also verified, which more accurately approximated the simulation data.

Table 4. Results of regression analysis - number of CONWIP cards and production performance

Model	Regression function	R
Linear	$y = 145.77x + 3248.6$	0.4145
Powerful	$y = 1539\ x^{0.5236}$	0.7644
Logarithmic	$y = 1585.5\ ln(x) + 1568.6$	0.8047
Polynomial II.	$y = -20.137x^2 + 647.33x + 1257.6$	0.8226
Polynomial III.	$y = 1.9455x^3 - 93.011x^2 + 1347.5x\ - 246.33$	0.9656
Polynomial IV.	$y = -0.1187x^4 + 7.9621x^3 - 190.06x^2 + 1893x - 1018.4$	0.9846
Polynomial V.	$y = -0.0072x^5 + 0.3314x^4 - 1.949x^3 - 97.706x^2 + 1551.8x - 669.68$	0.9864

Table 5. shows the results of the regression analysis of the correlation of the number of CONWIP cards and the throughput time.

Table 5. Results of regression analysis - number of CONWIP cards and throughput time

Model	Regression function	R
Logarithmic	$y = 11.608\ ln(x) - 0.1427$	0.6311
Powerful	$y = 7.8006\ x^{0.4757}$	0.7285
Linear	$y = 1.8299x\ + 5.2396$	0.9558
Polynomial II.	$y = 0.0457x^2 + 0.6909x + 9.7607$	0.9866
Polynomial III.	$y = -0.0044x^3 + 0.2116x^2 - 0.9031x + 13.185$	0.9974
Polynomial IV.	$y = 0.0003x^4 - 0.018x^3 + 0.4312x^2 - 2.1372x + 14.932$	0.9988
Polynomial V.	$y = 2E - 05x^5 - 0.0008x^4 + 0.0047x^3 + 0.2189x^2 - 1.3529x + 14.13$	0.999

Figure 7 shows the dependence of the number of CONWIP cards and the throughput time.

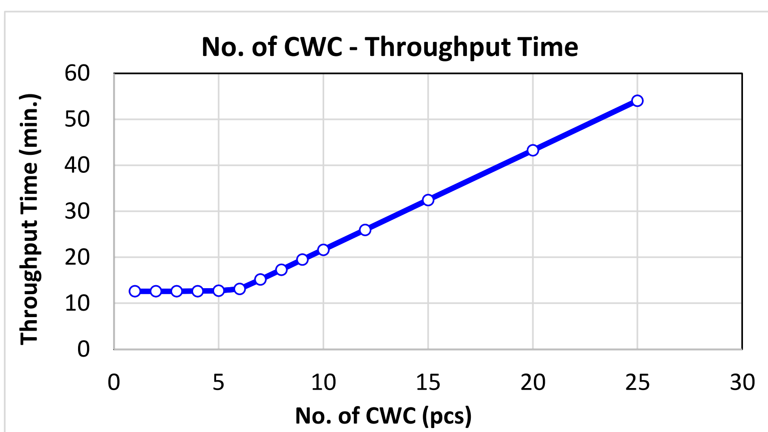


Figure 7. Dependence of throughput times on the number of used CONWIP cards

The development of continuous throughput times depending on the number of used CONWIP cards is interesting. Figure 8 shows the development of the throughput time (average, maximum, minimum) depending on the number of CONWIP cards. Figure 9 shows the dependence of the number of CONWIP cards and the level of work in progress (WIP).

Figure 9 unveils the relationship between the number of CONWIP cards used in the production system and the resulting level of Work in Progress (WIP). The relationship demonstrates a distinctly linear character where the linear regression model yielded a perfect fit with an R-value of 1.0.

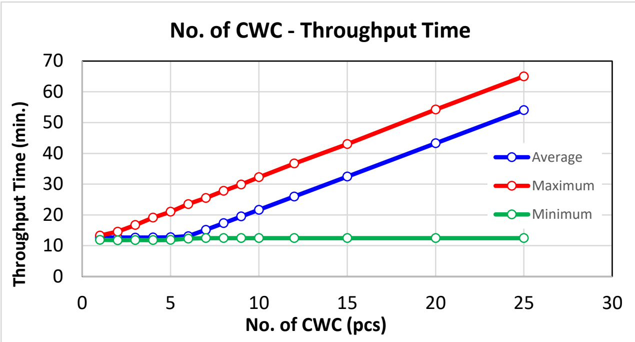


Figure 8. Dependence of continuous throughput times on the number of CONWIP cards

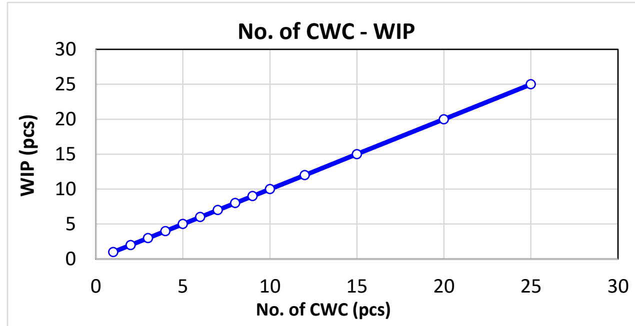


Figure 9. Dependence of WIP on the number of CONWIP cards

4.10 - In Table 4, the results of regression analysis for understanding the relationship between the number of CONWIP cards and production performance are presented. Multiple types of regression models were examined, including simple linear models and more complex polynomial models. The aim was to find the mathematical equation that best approximates the simulation data. To evaluate the accuracy of these models, the coefficient of determination, denoted as R, was used.

The linear model shows a relatively poor fit to the simulation data with an R-value of 0.4145. A powerful model offers a significantly better fit with an R-value of 0.7644. The logarithmic model slightly outperforms the power model with an R-value of 0.8047. However, polynomial models show the most promise in approximating the simulation outputs. A 2nd-degree polynomial model has an R-value of 0.8226. A 3rd-degree polynomial model shows a substantially better fit with an R-value of 0.9656. Higher-degree polynomials, specifically the 4th and 5th degrees, further improve the approximation with R-values of 0.9846 and 0.9864, respectively. Based on these results, the best-fitting model is a 5th-degree polynomial with an R-value of 0.9864. While Table 4 aimed to elucidate the relationship between the number of CONWIP cards and production performance, Table 5 shifts the focus to exploring the correlation between the number of CONWIP cards and throughput time. This pivot in the dependent variable from production performance to throughput time marks a significant difference between the two tables.

Moreover, the mathematical models used to approximate these relationships yield different coefficients and R-values, reflecting the distinct nature of the dependencies being investigated. For example, the 5th-degree polynomial in Table 4 exhibits an R-value of 0.9864, indicating a very strong fit for modeling production performance. On the other hand, the same model in Table 5 reaches an even higher R-value of 0.999, signaling an exceptionally strong fit for throughput time. These differences in R-values highlight the distinct influences that the number of CONWIP cards has on production performance and throughput time, respectively. This is further illustrated by Figure 10 for Table 4 and Figure 14 for Table 5, which visually represent these relationships.

Figure 10 shows the course of the production performance (obtained from the simulation) and the courses of the adapting polynomials.

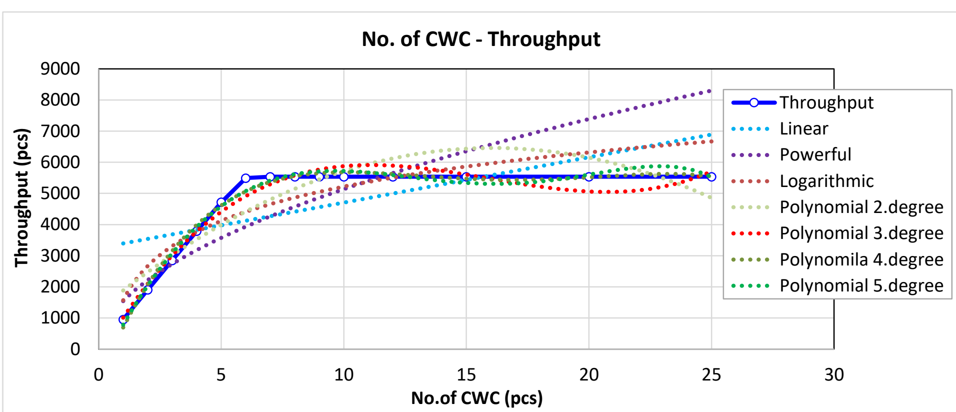


Figure 10. Production performance and substitute meta-models

The analysis showed that the best substitute for the production performance curve is a V-degree polynomial expressed by the equation:

$$y = -0.0072x^5 + 0.3314x^4 - 1.949x^3 - 97.706x^2 + 1551.8x - 669.68 \quad (4)$$

It is clear from Table 5 that already the 3rd degree polynomial sufficiently approximates the simulation outputs of production performance (see also Figure 11).

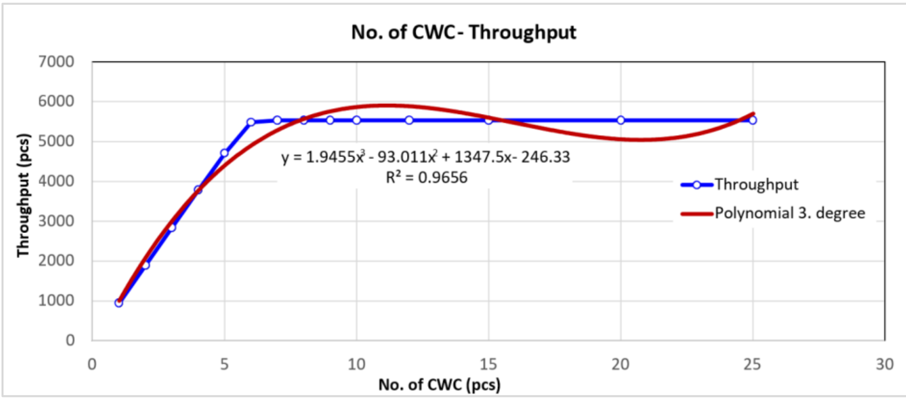


Figure 11. Substitute meta-model – 3rd degree polynomial for production performance

For illustration, the closeness of fitting the curve of the production performance by a substitute polynomial of the 4th degree (Figure 12) respectively polynomials of the 5th degree (Figure 13) are shown.

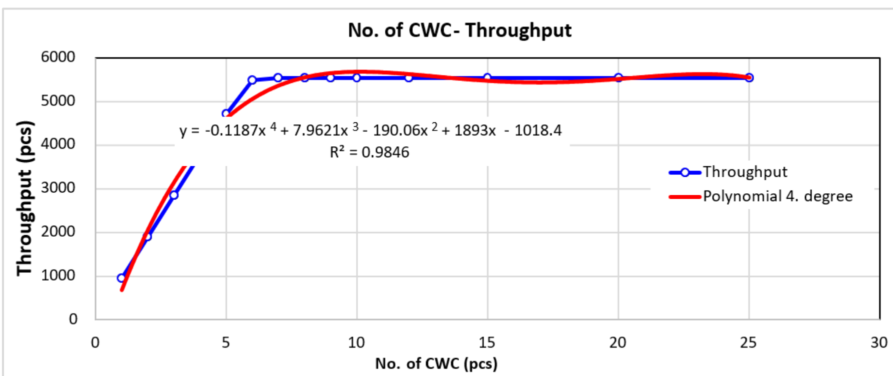


Figure 12. Substitute meta-model – 4th degree polynomial for production performance

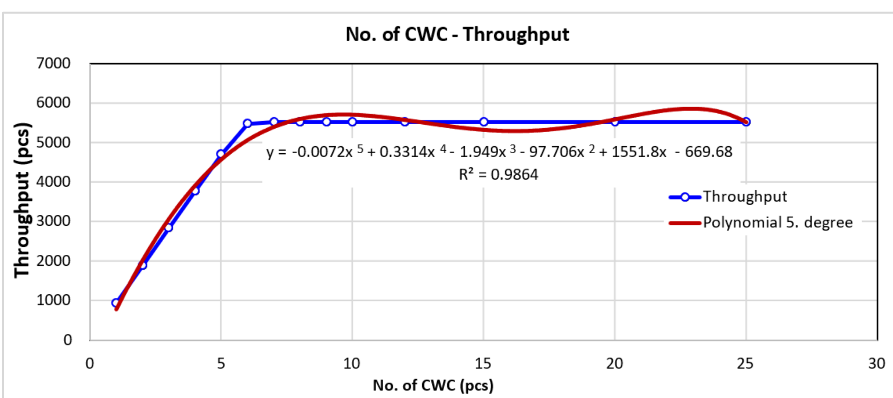


Figure 13. Substitute meta-model – 5th degree polynomial for production performance

Figure 14. shows the progress of the throughput time (obtained from the simulation) and the progress of the adapting polynomials.

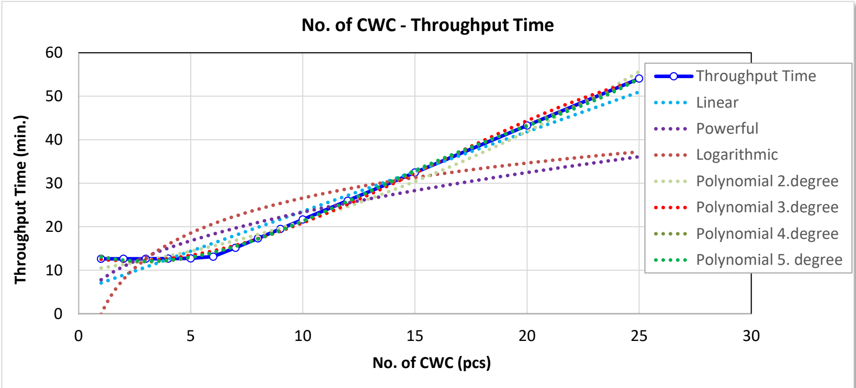


Figure 14. Substitute meta-models for the ongoing production period

As can be seen from Figure 15, the 3rd-degree polynomial sufficiently approximates the simulation outputs of the continuous throughput time.

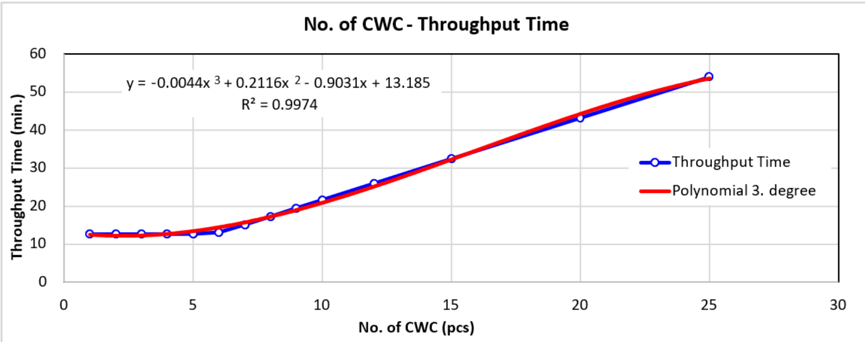


Figure 15. Substitute meta-model – 3rd degree polynomial for continuous time

Approximation of the WIP curve by a linear model is shown in Figure 16.

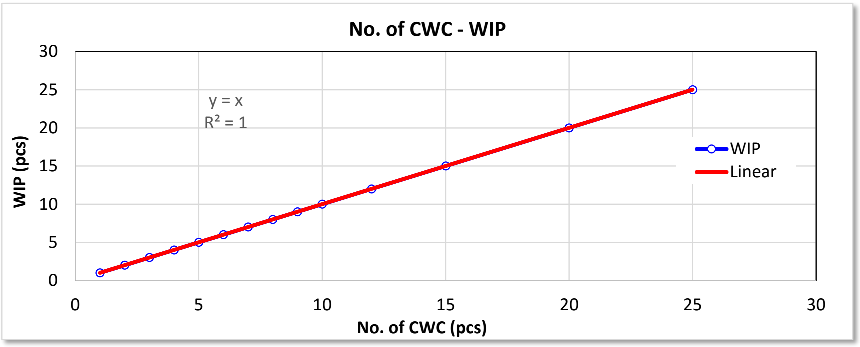


Figure 16. Substitute meta-model – linear model for WIP

4.11 - In this section, the procedure for verifying the validity of the model for the dependence of the number of CONWIP cards and the continuous throughput time is presented. As it was shown above, with the help of the defined meta-model, it is possible to determine the throughput time for a given number of CONWIP cards very quickly, even without the use of simulation. The found meta-model for the continuous throughput time has the form:

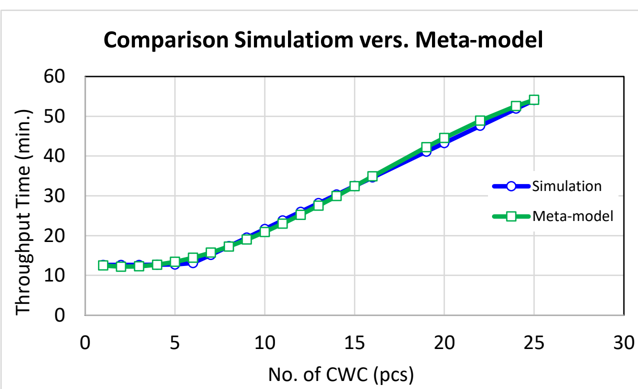
$$y = -0.0044x^3 + 0.2116x^2 - 0.9031x + 13.185 \tag{5}$$

By calculating from the meta-model, we determine the value of the ongoing throughput time, for example, for the number of CONWIP cards x = 15. By substituting into the meta-model and calculating, we obtain the value of the ongoing throughput time y = 32.40 min. Comparing this throughput time value with the value obtained from the simulation experiment (32.46 min.), the difference between these values is very small (0.06 min., which is about 0.18%). If we use different points during the recalculation than were used when creating the meta-model, we can perform a verification of the given meta-model. Table 6 shows the results of the comparison of the continuous throughput time achieved with the help of the simulation and with the help of the meta-model. From the achieved results, it is possible to see a very good reporting ability of the proposed meta-model.

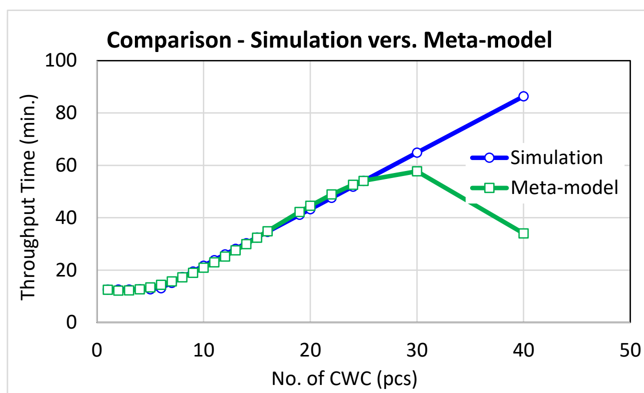
Table 6. Comparison of simulation results and mathematical model

Throughput time (min.)	No. of CWC						
	11	13	14	16	19	22	24
Simulation	23.820	28.140	30.300	34.620	41.110	47.580	51.90
Meta-model	22.998	27.538	29.942	34.883	42.234	48.880	52.567
Error	0.822	0.602	0.358	-0.263	-1.124	-1.300	-0.667
Error variance	0.113	0.060	0.021	0.011	0.211	0.282	0.074
Standard deviation	0.336	0.246	0.146	0.107	0.459	0.531	0.272

Figure 17. part (a) shows a comparison of the results for the continuous throughput time obtained from the simulation and the values obtained by calculation using the meta-model. The validity of the designed meta-model can be verified for R-values that are outside the limits for which the meta-model was created. With the help of the meta-model, we will determine the value of the continuous throughput time for the number of CONWIP cards equal to 30, which is equal to 57.73 min., while its value from the simulation is 64.84 min. Analogously, we will determine the continuous throughput time for 40 CONWIP cards, which has a value of 34.02 min, and the result from the simulation is 86.38 min. A comparison of the values of the continuous throughput time obtained by calculation from the meta-model with the results of the simulation already shows significant differences. Figure 17 part (b) shows the comparison of the throughput time values obtained from the simulation and from the meta-model.



(a)



(b)

Figure 17. Comparison of (a) the results of the simulation and the meta-model for the throughput time (b) continuous throughput times obtained from the simulation and from the meta-model

Figure 18. shows the differences of the ongoing throughput times between the simulation and the meta-model and their dispersion.

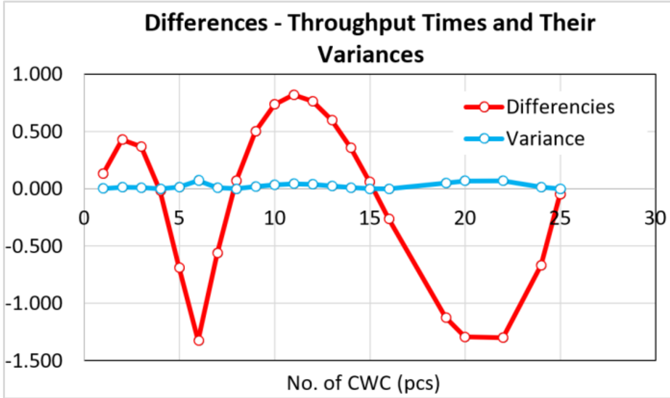
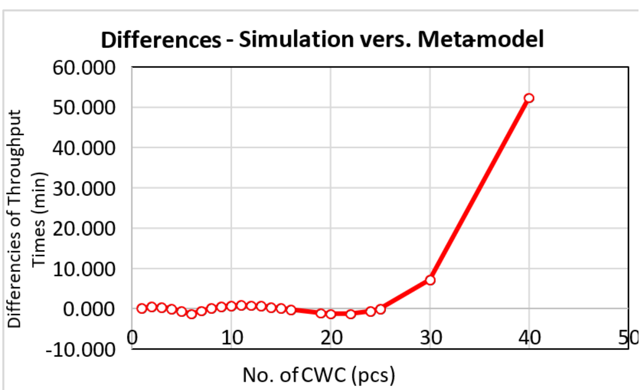


Figure 18. Differences of throughput times and their dispersion

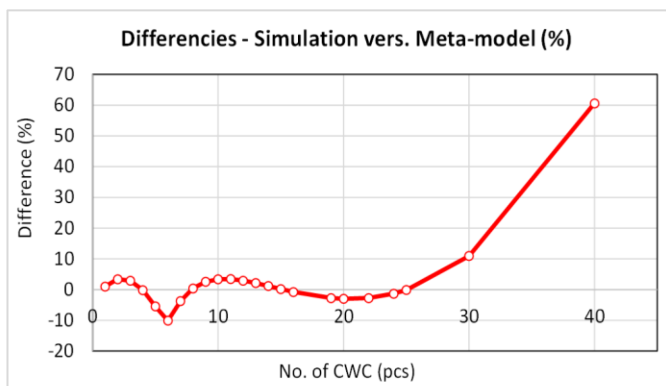
Examining the development of production lead times clearly indicates the inability of the meta-model to correctly approximate lead time values outside the validity limits. Figure 19 shows the differences in the values of the throughput times from the simulation and from the meta-model in minutes and percentages.

Figure 17 part (b) serves as a critical platform for validating the meta-model by directly comparing the throughput times obtained from both the simulation and the meta-model. The figure likely presents these throughput times against the number of CONWIP cards, with separate markers or lines representing the two methods. The closeness of these markers or lines signifies the meta-model's accuracy and its robustness as a planning tool within known parameters. On the other hand, Figure 19 part (a) shifts the focus from direct comparison to error analysis by plotting the differences in throughput times against the number of CONWIP cards. This approach magnifies the meta-model's deviations from the simulation results, offering insights into its limitations.

While Figure 17 part (b) establishes the general accuracy of the meta-model, Figure 19 part (a) identifies the boundaries of this accuracy. It shows where the model might fail to be a reliable estimator, especially when extended beyond its initial data range. Therefore, Figure 17 part (b) is instrumental for operational planning within known conditions, whereas Figure 19 part (a) serves as a cautionary guide that alerts decision-makers to the specific conditions under which the meta-model may lose its reliability. In Figure 19 part (b), the values of the differences of the continuous throughput times are expressed as a percentage of the values of the continuous throughput times obtained by simulation.



(a)



(b)

Figure 19. Differences in the throughput times of production simulation - meta-model (a) in minutes; (b) in percentages

The study reveals a range of utilization rates across different stations, with the highest being 99.94% and the lowest at 95.64%. This suggests that there may be room for optimization to balance the workload across the assembly line. In terms of throughput, the data show that it increases significantly up to the usage of 7 CONWIP cards, after which it stabilizes at 5537 pieces. This implies that there may be diminishing returns in throughput beyond this point. Interestingly, the Work-In-Progress (WIP) levels have a perfect linear relationship with the number of CONWIP cards, indicated by an R-value of 1.0, which suggests a predictable production environment under the current settings. The average throughput time starts at 12.62

minutes with one CONWIP card and increases to 54.06 minutes when 25 cards are used. This trend indicates that while throughput may increase, the lead time for production also goes up, requiring a balanced approach to optimizing both.

Moreover, the 5th-degree polynomial models offer the highest fidelity in approximating both the production performance and the throughput time, with R-values of 0.9864 and 0.999, respectively. These models can serve as robust tools for decision-making within their valid range. However, caution should be exercised when extending these models beyond their initial data range. This is evidenced by the significant deviations in throughput times for 30 and 40 CONWIP cards compared to the simulation results. Given the high fidelity of the 5th-degree polynomial model for throughput time, it is possible to quickly determine the expected throughput time for a given number of CONWIP cards without requiring a full simulation as long as the number of cards falls within the model's valid range. In conclusion, the optimal number of CONWIP cards seems to be around 7 for maximizing throughput without unnecessary increases in WIP or throughput time. However, for specific scenarios requiring finer control over lead times or utilization rates, the high-fidelity polynomial models can be invaluable tools for decision-making.

5. DISCUSSION AND CONCLUSION

Based on the research, the following conclusions can be drawn. Simulation meta-modeling is a proven method for the approximate estimation of the value of monitored system parameters when the values of its input factors are known. Within its validity limits, such as in our case, the range of tested numbers of CONWIP cards from 1 to 25, the created simulation meta-model provides a reliable approximation of the output parameters. However, beyond these limits, the differences in results become significant, rendering the model ineffective for estimating parameteR-values. The research validates the use of polynomials of the 3rd or 4th degree as adjustment curves, demonstrating their sufficiency in representing real dependencies between input factors and output parameters of the system. Employing suitable statistical software in the manual method of crafting simulation meta-models is advantageous for determining the adaptation curve.

The traditional approach to simulation meta-modeling is deemed to be relatively intricate and time-consuming. Any alteration in the system conditions necessitates the amendment and validation of the obtained meta-models. The predicament is addressable through two strategies: initially, by automating the entire process of creating and Utilizing the simulation meta-model, where regression coefficient estimates are solved numerically; more effectively, by employing artificial neural networks (ANNs) which can autonomously ascertain the suitable type of meta-model, aiding in the requisite estimations. This solution has the potential to integrate directly with the management system, epitomizing a leap toward automating and optimizing processes in industrial engineering.

Historically, analytical methods via mathematical models were the norm for modeling and scrutinizing complicated systems. These models encapsulated the system's structure, logical connections, and quantitative associations among its elements. Analysts, by varying the values of relevant factors, monitored the model's reaction to optimize the observed system. Yet, the majority of real-world systems are complex, rendering analytical models less effective for studying their dynamics. The advent of computer simulation, particularly post the fourth industrial revolution, marked a significant stride, showcasing its aptitude in examining the dynamic behavior of production systems amidst escalating system complexity.

Today, computer simulation is a conventional approach employed in complex production system analysis. Despite being resource-intensive and necessitating expert knowledge, its relevance remains undiminished. Formerly, endeavors were made to supplant experts with expert systems; contemporary advanced simulation systems often encapsulate selected expert knowledge, yet the method remains demanding. A viable avenue to mitigate the analysis complexity is the deployment of approximations or substitute models that can adequately replace intricate simulation models of production systems.

The quest for further simplification ushered in the use of simulation meta-modeling, investigating the relationships among the production system, its simulation model, and the meta-model. The essence of experimentation in meta-modeling is the validation of such models, assessing their representational accuracy of the real production system. Effective meta-model experimentation necessitates a preceding Design of Experiments (DoE) to ascertain the required output accuracy, the types of meta-models in alignment with their attributes, and other experimentation conditions.

Historically, simple meta-models were deployed for validating complex simulation models, often facilitating swift sensitivity testing of the production system's output parameters against input factor variations. Meta-models are also recognized as building blocks of complex models, where simulation models and meta-models amalgamate into hybrid solutions, propelling the efficiency of experimentation forward.

Although a well-structured theory of simulation meta-modeling exists, its substantial application in supporting production management within discrete production systems is yet to be realized, chiefly due to the manual complexity encompassing the entire process. The resolution lies in automating the entire simulation meta-modeling process.

The evolution of dynamic analysis methods for production systems is intrinsically tied to the advancement of modern computing power. This growth, bolstered by the swift progression of artificial intelligence methods, especially deep learning via ANN, has repositioned ANNs as novel tools for optimizing production systems. The maturation of ANN theory has segued into the era of practical applications of artificial intelligence, which has now permeated the production system analysis domain, becoming a part of the optimization methodology. Enhancing the efficiency of the meta-modeling process is achievable through the deployment of artificial neural networks in determining meta-model parameters. This paradigm shift towards ANNs offering a more streamlined, automated, and efficient solution for analyzing complex production systems. The uniqueness and the necessity of this method stem from its ability to simplify and accelerate the analysis process, providing a more accessible and accurate means of understanding and optimizing production systems, thus marking a significant contribution to the field.

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