SURROGATE MODELLING WITH DEEP LEARNING FOR OPTIMIZING MANUFACTURING ASSEMBLY LINES

Maryam SAADI[a b], Vincent BERNIER[a] , Gregory ZACHAREWICZ[b], and Nicolas DACLIN[b]

[a]Airbus Helicopters, Marignane, FRANCE
{*maryam.saadi,vincent.bernier*}@*airbus.com*
[b]Laboratory for Science of Risks, IMT-Mines Ales, FRANCE
{*gregory.zacharewicz,nicolas.daclin*}@*mines-ales.fr*

ABSTRACT

Airbus Helicopters needs to modify its manufacturing lines and workshops to meet diverse client requests and growing demands for customization. The challenge is to develop adaptive, dynamic production systems and to optimize key performance indicators. The main goal is to maximize customer satisfaction and minimize delivery times, investments, costs, and work in progress. Airbus Helicopters has long used a classical simulation-based technique to define the best settings for its production lines. Nonetheless, the model needs 48 hours to complete each run and test a single set of parameters for the workshop. This paper presents an artificial intelligence based surrogate model designed to outperform traditional simulations by potentially delivering similar results much faster, in seconds rather than hours. It has been trained with synthetic data generated by a genetic algorithm and the simulation.

Keywords: artificial intelligence, surrogate model, genetic algorithm, simulation

1 INTRODUCTION

Due to the increasing market demand for customization, Airbus Helicopters must quickly modify its production techniques to satisfy a wide range of customer needs. It is difficult to balance the need for flexibility with the importance of optimizing performance indicators, like work-in-progress, investment, and delivery times. The company has always used simulation to optimize manufacturing parameters. This methodology's enormous number of characteristics and complexity make it difficult to quickly identify the optimized organizational strategies.

Numerous studies have noted that selecting the best settings in simulation models is difficult due to the vast number of configurations [1]. To overcome this issue, some works have looked into connecting machine learning (ML) with simulation models. Simulation models are used to construct predictive models, which are subsequently trained on synthetic data [2]. This method helps reduce calculation time and total expenses, which makes it useful in complex simulations.

The method described in [3] is a major step in this direction, building on a study of machine learning's potential for simplifying complex simulation models. It presents an approach that integrates machine learning meta-models with active learning within extensive simulations. This approach has been used in industrial settings, especially sawmilling, where it controls model training across a wide range of simulation parameters. By applying this innovative approach, the complexities of parameter combinations in simulation models are more effectively managed, leading to enhanced precision in forecasting outcomes.

Proc. of the 2024 Annual Simulation Conference (ANNSIM'24), May 20-23, 2024, American University, DC, USA
C. Ruiz-Martin, B. Oakes and R. Cárdenas, eds.

A lot of progress has been made in the field of aeronautical engineering. As explained in [4], machine learning techniques have been applied to improve the design and optimization of electric aircraft motor drive systems. Aeronautical science has advanced with this research, which could result in more effective and efficient electric aircraft propulsion systems.

The key element of artificial intelligence (AI) is data. The context and application determine the type and source of data. In order to guarantee that AI models are precise and dependable in real-world applications, it is crucial to train and improve them. On the other hand, there are situations in which acquiring real-world data is difficult or impossible. Data that has been artificially created to mimic real-world occurrences is known as synthetic data. Its purpose is to closely emulate the attributes of real data, enabling the training and evaluation of AI models in environments or circumstances where access to real data is limited or non-existent [5]. This method works well when there's limited real data for training models. It ensures the machine learning models are accurate and flexible, ready to deal with various future situations and challenges.

This paper focuses on presenting a deep learning model designed as an alternative to conventional discrete event simulation models. The model will be integrated with a genetic algorithm—a method inspired by natural selection processes in biology used to solve optimization problems by evolving solutions over generations [6]—to optimize the parameters of production lines. To address these challenges, the initial step involves creating a comprehensive dataset. This will be accomplished by coupling a genetic algorithm with the Anylogic[7] simulation model—a versatile platform for modeling and simulation of complex systems, supporting methodologies like discrete event and agents -to generate the necessary data. Subsequently, this data will be utilized for training the neural network. Once the training is complete, the neural network will serve as a surrogate for the simulation model. The goal of this integration is to accelerate and enhance the optimization process of production line parameters. This integration aims to improve the efficiency and effectiveness of determining the optimal settings and configurations for production lines, which can include factors like the number of operators at each workstation, scheduling, resource allocation, and workflow management.

2 BACKGROUND

2.1 Industry 4.0: Modernizing for the Future

Airbus Helicopters is in the process of modernizing its industrial operations to align with the advanced concepts of Industry 4.0. As the European Factories of the Future Research Association (2012) points out, this shift toward an industrial model that is future-focused makes use of digital simulation and prediction technologies, which are essential for the integrated management and design of production systems. Cutting-edge technologies, such as artificial intelligence (AI), digital twins, and the Internet of Things (IoT), are at the core of Industry 4.0 [8]. Predictive metamodels, augmented by historical data, are particularly advantageous in the field of AI [9]. These models are fundamental to the development of ML technologies. Adapting multilayer perceptrons for simulation model optimization -like in sawmill workshops—is one of these developments. The critical role of digital twins in virtualization and IoT, particularly in improving information sharing, is highlighted in [10]. Even if Airbus Helicopters hasn't reached digital maturity yet, the company has all the tools required for efficient workshop modeling. Even though these models don't presently communicate with their real-world counterparts directly, they are nonetheless very useful for developing, scaling, and testing operational modes in workshops. This results in enormous datasets that are ready for AI research and use.

2.2 Integrating Machine Learning with Simulations

AI, especially machine learning, is frequently integrated with simulations. A study [2] categorizes this integration into two approaches: simulations enhancing machine learning and vice versa. Simulations can be embedded into machine learning algorithms for direct integration [11] or to expand training data [12]. Conversely, machine learning models can replace standard simulations [13] or analyze data within them [14]. However, [2] points out a gap in research: the full integration of simulation and machine learning. The study suggests future research should focus on optimizing the use of simulation outputs, embedding machine learning into simulation engines for interactive processes, and developing surrogate models within simulations to enhance efficiency and adaptability.

2.3 Machine Learning in Industrial Optimization

Optimization challenges and their solutions are common in the industrial sector, spanning diverse areas such as supply chain management, production scheduling, and energy efficiency. However, due to the complexity and multitude of parameters involved, finding the best solution is often a time-consuming and computationally expensive task. Machine learning, particularly neural networks, offers a promising approach to these challenges by adeptly handling high-dimensional data and complex variable relationships. [15] goes into more detail about a new way to speed up optimization in industrial settings by combining neural networks with multi-fidelity models. This integration enables the neural network to mimic the operational procedures of the less complex model, reducing the need for expensive data in the learning process. Such a method not only enhances computational efficiency but also provides high-quality solutions with limited data, marking a significant improvement over traditional optimization methods. Looking ahead, further research and development in this area could focus on scaling and adapting these techniques to a wider range of industrial applications, potentially revolutionizing the way industries approach optimization.

2.4 Optimization Based on Surrogate Models

A surrogate model is an alternative to complex simulations or computational programs, designed to reduce computational effort in engineering and optimization tasks. This method uses techniques like Kriging, quadratic interpolation, or least squares regression, which are used after a first simulation that uses a lot of resources [16]. Surrogate-based optimization, as suggested in [17], is particularly effective in fine-tuning the operating parameters of workshop machines. This technique uses a range of optimization methods, quickly converging to an optimal solution—local or global— by substituting the original, computationally demanding model with a more cost-effective surrogate. A machine learning model, once trained to interpret simulation inputs and predict outcomes, can serve effectively as a proxy.

3 METHODS

Manufacturers face challenges in making complex helicopter parts like the Main Gear Box (MGB) and Main Rotor Hub (MRH) due to growing customer demands. They aim to make helicopters safer, more reliable, and readily available. Adopting digital technologies helps in design and testing. Working with industry partners is key to enhancing processes and ensuring quality. This situation underscores the continuous need for innovation in helicopter production.

3.1 Context and Industrial Problems

Figure 1 shows the collaborative efforts of Airbus's Industrial Architect System Team. This team is divided into two main groups: the Product Design Team, which focuses on helicopter design, and the Production

System Design Team, tasked with developing the production framework. They work together to ensure the design is practical and the production system is ready for manufacturing. The Simulation Analysis Group plays a crucial role in this integrated approach. They validate the design and manufacturing plan by developing and fine-tuning complex simulation models. These models are key for assessing design viability and enhancing manufacturing setups. Lastly, the Production Operations Team oversees the execution of the production process. They rely on key production metrics to efficiently start production and plan for future production needs.

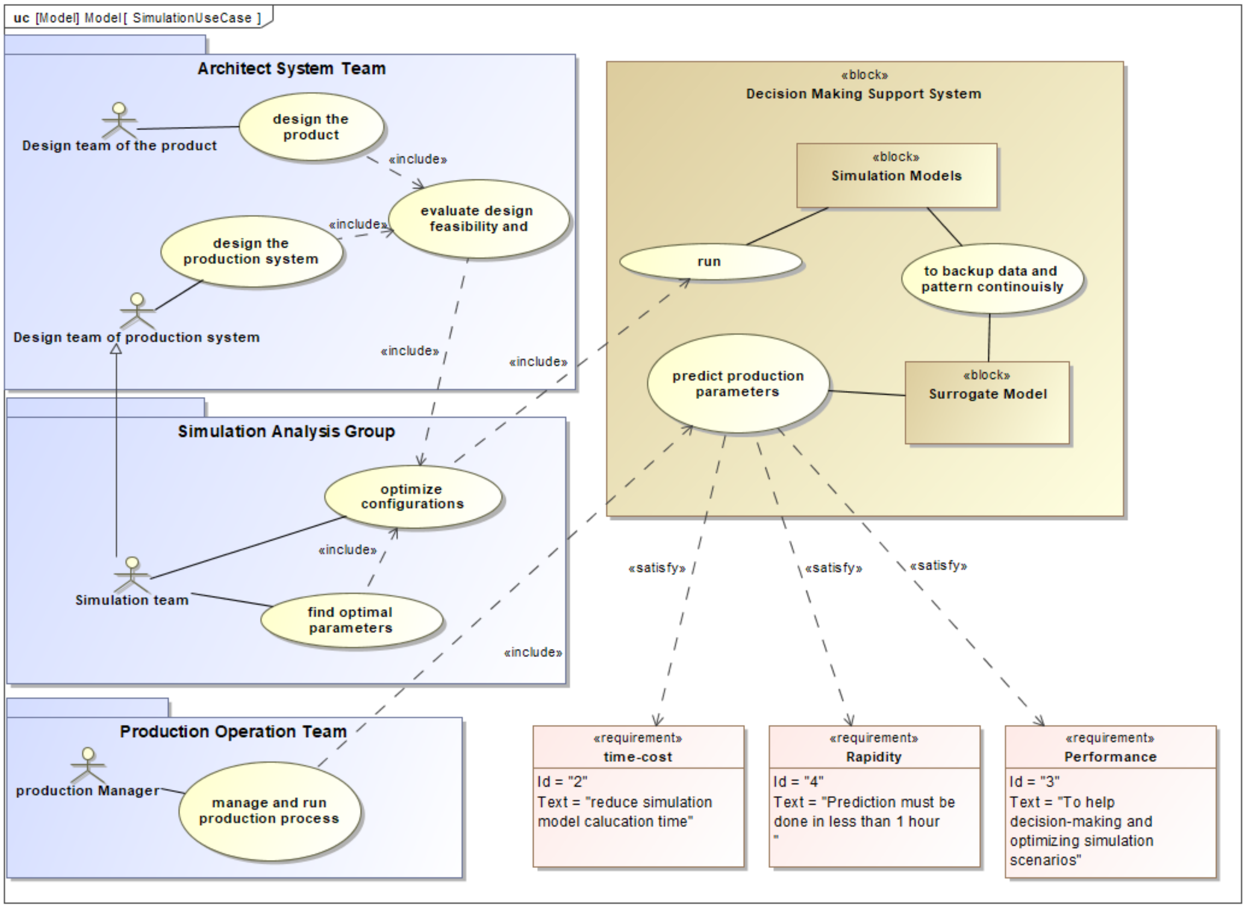

Figure 1: Use case for simulation and surogate model.

An initial collaboration between Airbus Helicopters and Aix-Marseille University, focusing on ML and simulation, has highlighted the challenges associated with simulation models in real-world production environments. Therefore, although these models are effective in predicting and confirming design choices, they often struggle to provide the quick turnaround required in actual production settings. This collaboration underscores the need to overcome these limitations to enhance the efficiency and responsiveness of production processes.

To bridge this gap, the research proposes the development of surrogate models. These models offer faster, more practical feedback for real-time production scenarios, which is essential for the dynamic environment of helicopter manufacturing. By enhancing simulation methods and improving algorithms, as explored in the Airbus-University collaboration, these surrogate models can provide the agility needed in production processes.

The surrogate models developed from this collaboration serve as a decision-making tool, offering a quicker and more streamlined alternative to traditional simulation models. This advancement helps to achieve a fluid, responsive production flow, enabling manufacturers to rapidly adapt to both planned strategies and unforeseen changes in the workshop. This development contributes to the creation of a responsive, fluid production flow that makes it possible for manufacturers to quickly adjust to both anticipated and unanticipated changes in the workshop. As a result, the project marks a substantial advancement in the practical, real-world integration of cutting-edge technologies like machine learning and simulation in the aircraft manufacturing industry.

3.2 Case study: advancing manufacturing efficiency with discrete events and agent-based simulation

The 'MECA 4.0' workshop at Airbus Helicopters, specialized in manufacturing transmission boxes, rotors, and rotor assemblies, plays a pivotal role in producing new components for final assembly lines (serving internal customers) as well as maintaining and producing spare parts (for in-service helicopters). Each customer has specific requirements for components based on the helicopter's intended use. The workshop is organized into various stations for assembling sub-components and additional 'backup' stations for storing parts during production delays. The production pace is set based on assembly demand projected over three years, with workshop policies potentially changing annually.

Anylogic is used at the MECA 4.0 workshop as a simulation tool to test various scenarios. Its hybrid approach combines discrete event and agent-based modeling to deliver an in-depth analysis of operational workflows. Discrete event modeling efficiently tracks distinct processes and the circulation of materials, while agent-based modeling provides insights into the behaviors and interactions of individual elements, such as workers and workstations. This integration of methods enhances the simulation, offering a more sophisticated understanding of the dynamics within the workshop.

3.3 Data

To conduct precise simulations with Anylogic, two types of data are essential: customer demand and workshop parameters. The customer orders set out the assembly sequence for the next three years, including specifics on each part, its production method, and the deadline. While the quantity of parts and deadlines are constant in this study, the nature of the demand changes based on the type of part and applied production policies. Thus, each order consists of 754 demands, with each demand defined by seven attributes as shown in Table 1.

Table 1: Description of customer demand characteristics.

Characteristics	Type	Interval	Description
Client request	Categorical	MGB, MRH , Poste	Type of product
Needed Date	Date	Delivery date	Date to deliver the product to the customer
MRH Model	Categorical	M1.1, M1.2, M1.3, M1.4	Variants of Main Rotor Hub (MRH)
MGB Model	Categorical	M2.1, M2.2, M2.3, M2.4	Variants of Main Gearbox (MGB)
Poste Model	Categorical	M3.1, M3.2, M3.3, M3.4	Variants of poste
Customer	Binary	[0, 1]	0 : Internal, 1: External
Assembly line	Binary	[0, 1]	0 : Line 1, 1: Line 2

Table 2 details vital parameters for the MECA 4.0 workshop, identifying their type (mainly integers), range of values, and specific definitions. These parameters, established in collaboration with the operational team, are key to adapting the workshop to meet client requirements. They encompass elements such as pre-stock for MGB and MRH components, numbers of production and backup stations for different components, and the availability of trolleys and kits. This framework helps understand the impact of each parameter on manufacturing efficiency.

The CONWIP system [18], used by Airbus for managing production inventory, CONWIP MGB and CONWIP MRH specifies the stock levels for these components, while CONWIP PSE determines the reserve for assembled MRH and MGB components. The workshop features two main production lines, line 1 and line 2, each with several stations denoted by number of stations dedicated to production for line 1 and number of stations dedicated to production for line 2. Components are moved to backup stations in case of assembly delays. These parameters control both daily operations and the workshop's performance over three years, ensuring a consistent production rate in line with dynamic customer demands. The goal is to enhance and support manual management of these processes for efficient, market-responsive manufacturing.

Table 2: Parameter characteristics description.

Characteristics	Type	Interval	Description
PSE CONWIP	Integer	[10, 40]	Elementary pre-stock for assembly of MRH and MGB
MGB CONWIP	Integer	[10, 40]	Advance MGB stock
MRH CONWIP	Integer	[5, 40]	Advance MRH stock
Poste CONWIP	Integer	[4, 30]	Pre-stock assembly of MGB and MRH components
Number Stations line 1	Integer	[2, 6]	Number of stations dedicated to production for line 1
Number Stations line 2	Integer	[1, 5]	Number of stations dedicated to production for line 2
Backup pse	Integer	[1, 5]	Number of backup stations pse
Backup MRH	Integer	[1, 5]	Number of backup stations MRH
Backup MGB	Integer	[2, 5]	Number of backup stations MGB
backup poste	Integer	[2, 5]	Number of backup stations poste
Trolley 1	Integer	[1, 5]	MGB trolley number
Trolley 2	Integer	[2, 5]	MRH trolley number
Trolley 3	Integer	[1, 3]	Poste trolley number
Number of kits for pse	Integer	[1, 5]	Maximum number of pse kits
Number of kits for MGB	Integer	[1, 5]	Maximum number of MGB kits
Number of kits for MRH	Integer	[2, 5]	Maximum number of MRH kits
Number of kits for poste	Integer	[2, 5]	Maximum number of poste kits

3.4 Analysis and Simulation Objectives with the Anylogic Model.

'Parameters' and 'Customer Request' are the two Excel files required in order to run the Anylogic model. As shown in Figure 2, these files are used to create the intended outcome file. Analyzing and simulating the workshop's daily work in progress (WIP) and precisely estimating the dates of each product's production completion are the main goals of the Anylogic model. This data is used to calculate the two key performance indicators (KPI), which are the average WIP of three years and customer satisfaction, which is defined as an average of the delay in delivery time. These two KPIs, as well as the production stations' financial investment, are the fundamental prediction goals of our improved model. As such, the present study centers on a regression analysis designed to accurately assess these variables. This is done to improve delivery time and the workshop's operational efficiency while effectively controlling financial expenses.

3.5 Coupling Simulation with Genetic Algorithm.

In the following section, we go over the optimization strategy that was utilized to fine-tune the workshop settings in order to improve operations, increase delivery time, and reduce Work in Progress (WIP) and investments. To accomplish this, a set of fictitious client requests was constructed in order to calibrate a production simulation model built using AnyLogic. A genetic algorithm was selected for this challenge since it is inspired by natural evolution concepts such as selection, mutation, and genetic crossover as depicted in Figure 2.

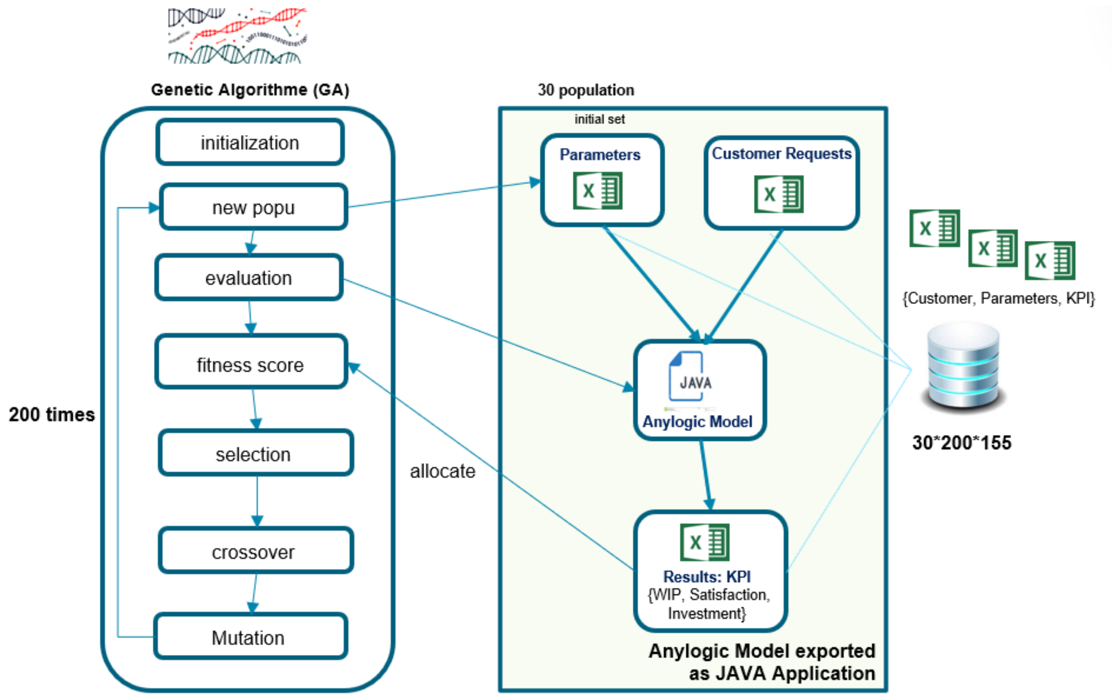

Figure 2: Integrating Genetic Algorithms in Simulation Processes for Synthetic Data.

The evolutionary algorithm's fundamental goal is to discover the optimal combination of production parameters to dramatically improve the workshop's performance based on key performance indicators (KPIs). Iterative optimization occurs over 200 cycles to progressively adjust the parameters towards the most optimal solution. The procedure begins with the first populating of parameter files in conjunction with client request files. These are sent into the Anylogic model, which then computes the KPIs, such as work in progress, investments, and customer satisfaction. Each set of parameters is examined, and a fitness score is given. The best configurations are chosen for crossings and mutations, resulting in a new parameter population. This fresh population is reintroduced into the Anylogic model for another round of KPI assessment. This cycle is performed 200 times for each of the 30 demographics in response to the 155 customer requests. The whole procedure enables full traceability and triplet records in a database organized as triplets: customer request, workshop parameters, and achieved outcomes. Finally, the database contains 30 × 200 x 155 triplets, which provides a significant quantity of data for training a neural network model. This systematic approach provides accurate optimization and a full examination of the numerous aspects and their influence on the workshop's operating goals.

3.6 Optimizing Surrogate Models with Neural Networks in Active Learning Frameworks

Inspired by the work in [19], which integrates a principal component with a cost prediction module, this research developed a multi-layer perceptron (MLP) model. The model comprises three layers, each one having 128 neurons and using the Selu activation function. Similarly, the cost prediction module employs the Selu activation function, leveraging the MLP structure to generate precise cost estimates across various data combinations. The model was trained in batches of 8 for 300 epochs, with hyperparameter optimization carried out via the GridSearch technique. This process of evaluating different network architectures and activation functions led to the selection of the current MLP configuration and the Selu activation function, ensuring an optimal blend of computational efficiency and performance for the dataset. Following the training phase, the cost prediction module was assessed for its effectiveness in the context of active learning. The model was then combined with a collection of 155 queries and fed into a genetic algorithm for data selection as shown in Figure 3. This procedure centered on picking the top 50 triplets with the greatest cost projections, as indicated by the module, who were then evaluated using the Anylogic oracle. The correctness and reliability of the module's cost function were established in the active learning framework via a comparison with the Mean Squared Error (MSE) measure. This method, which incorporates a cost prediction module inside an MLP model, represents a substantial development in optimizing data selection for active learning, hence improving the overall efficiency and accuracy of the learning process. The model develops

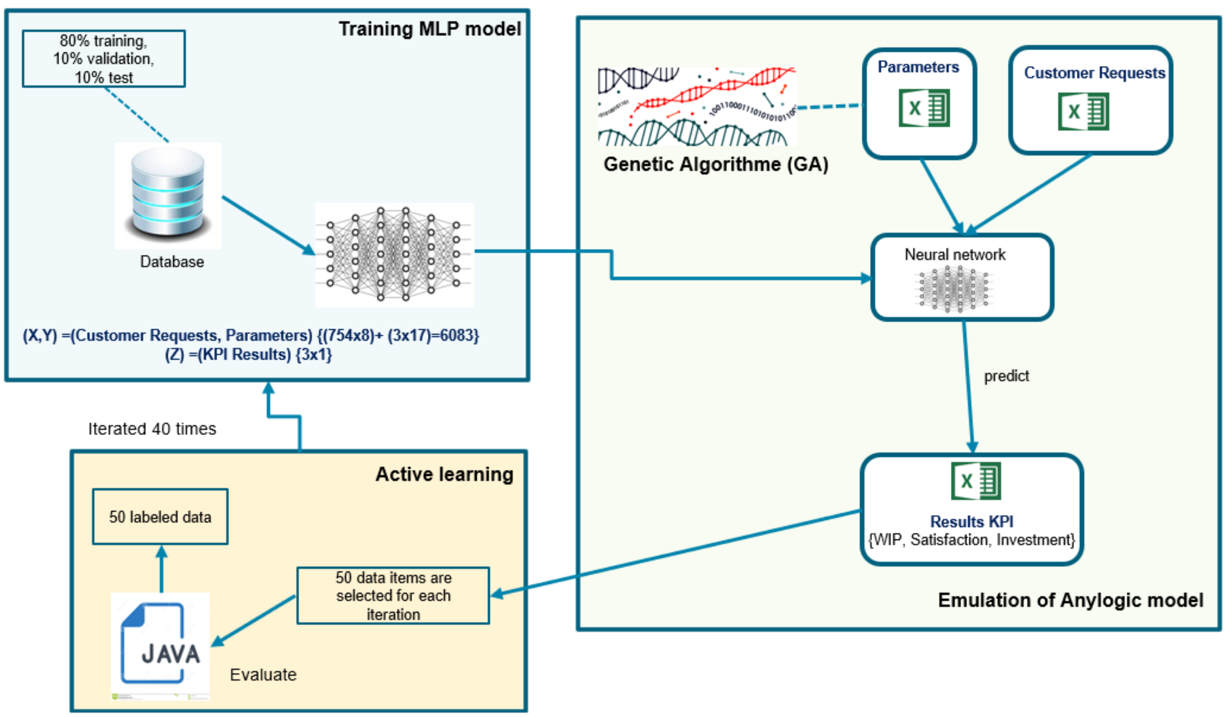

Figure 3: Integrating Genetic Algorithms and Neural Networks for Surrogate Models.

a tendency to predict certain attributes, such as high customer satisfaction, in a disproportionate manner when those attributes predominate in the training data. This phenomenon is further intensified when the dataset is constrained, thereby impeding the model's capacity to acquire knowledge of a wide range of scenarios. In order to rectify this disparity, active learning has been incorporated into our methodology. Active learning is a methodology in which the model proactively recognizes and chooses annotated data that, when incorporated into the training set, optimizes the gain of valuable insights. We looked at two active learning approaches side by side: the one suggested in [19] is specifically designed for improving models, and the one created in [13] is focused on picking the best data for classification. While the former has yet to be evaluated in the context of model substitution, it does provide an intriguing viewpoint on the matter of data selection. The efficacy of the latter has been previously showcased in more straightforward frameworks. 80%, 10%, and 10%, respectively, are the training, validation, and test sets in our database. Initial training is conducted using a dense neural network on standardized data. Our research is distinguished by the way in which we convert sequential data into a matrix structure that is appropriate for dense neural networks. Following the preliminary assessment, active learning is executed. Fifty data points are labeled using Anylogic and incorporated into the training set in accordance with the selected method. By repeating this cycle forty times, the model is progressively refined.

4 RESULTS

This portion of the paper discusses the findings of the active learning experiment, with an emphasis on data selection via cost function prediction and optimization.

4.1 Data Selection by Cost Function Prediction

The study in [19] demonstrates the strategy's effectiveness in selecting data for labeling in classification and regression tasks. This method was used to forecast variables based on many criteria, including WIP, investment, and delivery time. Significant variations in prediction error and accuracy were found when two different cost functions, Mean Squared Error (MSE) and Learning Loss Loss Function (3LF), were used for assessment. However, the model had difficulties in practical application, especially when attempting to forecast customer satisfaction, which resulted in an overestimation of the population and prevented optimum convergence.

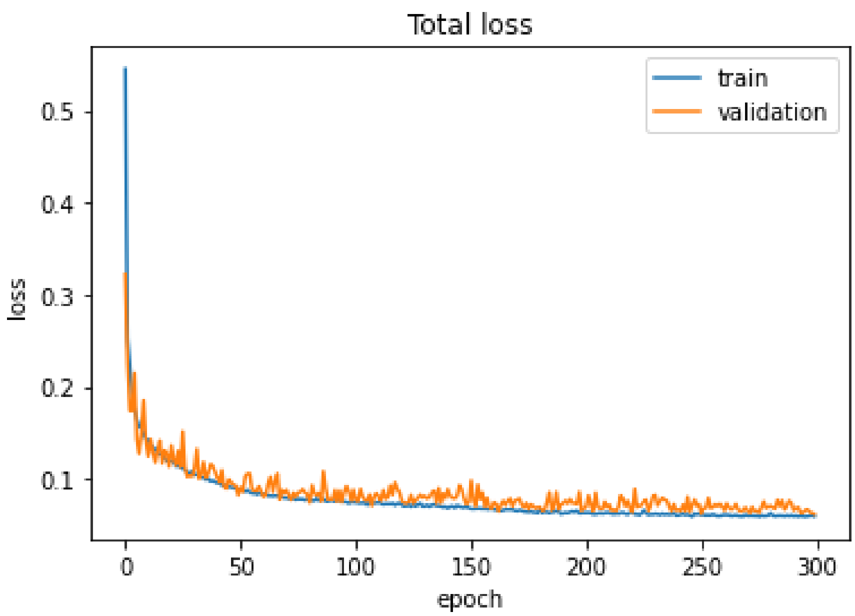

Figure 4: Training and validation cost functions.

4.2 Active Learning through Optimization

The research looked at how active learning may be used in the optimization process and showed how it might lead to designs that are closer to the global optimum. The cost functions converged well in the early findings, and there was no sign of overfitting. Even with the use of active learning, the model's extreme confidence in its predictions persisted, especially when it came to customer satisfaction. Although the active learning strategy has shown some progress, the model as a whole is still too basic to be used in real-world industrial settings. These findings highlight the need for further developing and improving active learning techniques in order to increase their effectiveness and suitability for use in challenging situations.

5 DISCUSSION

In contrast to a stochastic strategy, the research [19] emphasizes the efficacy of a unique technique for data selection in labeling tasks across many classification and regression situations. In our research, we apply this method to predict Work In Progress (WIP), investment, and customer satisfaction, taking into account customer demand and operational parameters in a workshop environment. The evaluation of the cost function prediction model utilizes two distinct functions: Mean Squared Error (MSE) and the Three-Layer Function (3LF), as introduced in [19]. Both functions are designed to assess errors in pairwise elements within the same batch. The results from the initial training, as shown in Table 3, reveal low prediction errors for both methods. However, the 3LF records a 20% lower error rate than the MSE, indicating its potential superiority for further active learning training.

Table 3: Comparison of the accuracy and prediction errors.

	MSE	3LF
Prediction error (MSE)	9.98e-2	8.01e-2
Error in module prediction	2.45e-2	9.5e-3
Accuracy of Modules	2.82e-4	5.63e-4

Nonetheless, when applied in a genetic algorithm, the model exhibits significant discrepancies between actual and predicted distributions, notably in customer satisfaction predictions, leading to overestimations and an ineffective emulation of the Anylogic model.

6 CONCLUSION

This study highlights the potential of machine learning, particularly through the use of Multi-Layer Perceptrons (MLP), in speeding up optimization processes by simulating traditional, time-intensive models. While effective in certain aspects, especially in dynamically changing environments like workshops with varying customer demands, the complexity of tasks such as cost prediction presents notable challenges. These challenges limit the development of a fully effective active learning module with MLPs. The findings reveal that while specific cost functions show promise in the initial phases of learning with MLPs, their global applicability is limited, and there is no one-size-fits-all solution. Additionally, despite improvements in resilience, these MLP models continue to exhibit data biases, which hamper optimization results. Additionally, the study shows that MLP models can partially copy discrete event models like the Anylogic model without needing a lot of information about how the workshop works. This indicates the potential for adapting these methodologies to various types of discrete events and agent-based models. As a future perspective, it is suggested to explore the use of advanced neural network architectures such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). LSTM, with its proficiency in handling sequential and time-series data [20], and CNN [21], known for its effectiveness in spatial data interpretation, could offer more nuanced and adaptable solutions to the complex problems highlighted in the study. Their potential to provide deeper insights and more robust modeling capabilities could significantly enhance the effectiveness of machine learning models in intricate industrial applications.

REFERENCES

[1] K. Train, *Discrete Choice Methods With Simulation*. Berkeley: Cambridge University Press, 2002, version dated March 8, 2002.

[2] L. von Rueden, S. Mayer, R. Sifa, C. Bauckhage, and J. Garcke, “Combining machine learning and simulation to a hybrid modelling approach: Current and future directions,” in *International Symposium on Intelligent Data Analysis (IDA)*, 04 2020, pp. 548–560.

[3] S. Chabanet, H. Bril El-Haouzi, and P. Thomas, "Coupling digital simulation and machine learning metamodel through an active learning approach in Industry 4.0 context," *Computers in Industry*, vol. 133, p. 103529, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0166361521001366

[4] M. Lazzara, M. Chevalier, M. Colombo, J. Garay Garcia, C. Lapeyre, and O. Teste, "Surrogate modelling for an aircraft dynamic landing loads simulation using an LSTM autoencoder-based dimensionality reduction approach," *Aerospace Science and Technology*, vol. 126, p. 107629, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1270963822003030

[5] M. Duquesnoy, C. Liu, D. Z. Dominguez, V. Kumar, E. Ayerbe, and A. A. Franco, "Machine learning-assisted multi-objective optimization of battery manufacturing from synthetic data generated by physics-based simulations," *Energy Storage Materials*, vol. 56, pp. 50–61, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405829722006973

[6] X.-S. Yang, *Optimization Algorithms*, 01 1970, vol. 356, pp. 13–31.

[7] (2024) Use of simulation. Consulté le March, 2024. [Online]. Available: https://www.anylogic.com/use-of-simulation/

[8] B. A. Talkhestani, T. Jung, B. Lindemann, N. Sahlab, N. Jazdi, W. Schlögl, and M. Weyrich, "An architecture of an intelligent digital twin in a cyber-physical production system," *at - Automatisierungstechnik*, vol. 67, pp. 762 – 782, 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:203848524

[9] S. Salama and A. Eltawil, "A decision support system architecture based on simulation optimization for cyber-physical systems," *Procedia Manufacturing*, vol. 26, pp. 1147–1158, 01 2018.

[10] D. Wu, D. W. Rosen, L. Wang, and D. Schaefer, "Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation," *Computer-Aided Design*, vol. 59, pp. 1–14, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0010448514001560

[11] C. Zimmerling, C. Poppe, and L. Kärger, "Estimating optimum process parameters in textile draping of variable part geometries - a reinforcement learning approach," *Procedia Manufacturing*, vol. 47, pp. 847–854, 2020, 23rd International Conference on Material Forming. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2351978920313299

[12] H. S. Kim, M. Koç, and J. Ni, "A hybrid multi-fidelity approach to the optimal design of warm forming processes using a knowledge-based artificial neural network," *International Journal of Machine Tools and Manufacture*, vol. 47, pp. 211–222, 02 2007.

[13] J. Pfrommer, C. Zimmerling, J. Liu, L. Kärger, F. Henning, and J. Beyerer, "Optimisation of manufacturing process parameters using deep neural networks as surrogate models," *Procedia CIRP*, vol. 72, pp. 426–431, 2018, 51st CIRP Conference on Manufacturing Systems. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221282711830146X

[14] B. Bohn, J. Garcke, R. Iza-Teran, A. Paprotny, B. Peherstorfer, U. Schepsmeier, and C.-A. Thole, "Analysis of car crash simulation data with nonlinear machine learning methods," *Procedia Computer Science*, vol. 18, pp. 621–630, 2013, 2013 International Conference on Computational Science. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050913003694

[15] D. Kim, M. Choi, and J. Um, "Digital twin for autonomous collaborative robot by using synthetic data and reinforcement learning," *Robotics and Computer-Integrated Manufacturing*, vol. 85, p. 102632, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0736584523001072

[16] P. Saves, R. Lafage, N. Bartoli, Y. Diouane, J. Bussemaker, T. Lefebvre, J. T. Hwang, J. Morlier, and J. R. Martins, "SMT 2.0: A surrogate modeling toolbox with a focus on hierarchical and mixed variables gaussian processes," *Advances in Engineering Software*, vol. 188, p. 103571, Feb. 2024. [Online]. Available: http://dx.doi.org/10.1016/j.advengsoft.2023.103571

[17] A. Gupta, S. C. Guntuku, R. Desu, and A. Balu, "Optimisation of turning parameters by integrating genetic algorithm with support vector regression and artificial neural networks," *The International Journal of Advanced Manufacturing Technology*, vol. 77, pp. 1–9, 03 2014.

[18] Y. Jaegler, P. Burlat, and S. Lamouri, "The conwip production control system: a literature review," in *International Conference on Interaction Sciences*, 2016. [Online]. Available: https://api.semanticscholar.org/CorpusID:52216028

[19] D. Yoo and I. S. Kweon, "Learning loss for active learning," 2019.

[20] Y. Song, H. Wang, G. Frøseth, P. Nåvik, Z. Liu, and A. Rønnquist, "Surrogate modelling of railway pantograph-catenary interaction using deep long-short-term-memory neural networks," *Mechanism and Machine Theory*, p. 105386, 05 2023.

[21] M. Rahman, A. Khan, S. Anowar, M. Al-Imran, R. Verma, D. Kumar, K. Kobayashi, and S. Alam, "Leveraging Industry 4.0 – deep learning, surrogate model and transfer learning with uncertainty quantification incorporated into digital twin for nuclear system," 2022.

AUTHOR BIOGRAPHIES

MARYAM SAADI is a PHD candidate in the Department of Science of Risks at IMT Ales, France, and Airbus Helicopter, Marignane, France. She holds a Master degree in Industry 4.0 from the Mohamed 6 Polytechnic University, Morocco. Her research interests include artificial intelligence and simulation with applications in the industrial workflows of Airbus. His email address is maryam.saadi@airbus.com.

VINCENT BERNIER is an Industrial Model Based System Engineering Expert at Airbus Helicopters in Marignane, France. Previously, he worked as an Engineer and Researcher at Peugeot in Poissy, France. He received his PhD at the Graduate School of Industrial Engineering, in Grenoble, France. His thesis focused on a new flow management policy: re-sequencable scheduling. His email address is vincent.bernier@airbus.com.

GREGORY ZACHAREWICZ is a full Professor in the Department of Science of Risk at IMT, Ales, France. Previously, he was Associate Professor HDR at the University of Bordeaux, France. He received his PHD at the University Paul Cézanne Aix-Marseille III. His research includes applications to distributed modeling and the simulation of workflows. His email address is gregory.zacharewicz@mines-ales.fr.

NICOLAS DACLIN is an Assistant Professor in the Department of Science of Risk at IMT, Ales, France. Previously, he was a Research and Development Engineer at ARMINES in Nimes, France. He received his PhD at the University of Bordeaux, France. His research focuses on Enterprises Modelling, Demu Modelling, Control and Automation of Process. His email address is nicolas.daclin@mines-ales.fr.