COUPLING SIMULATION AND AI FOR ASSEMBLY LINE OPTIMIZATION

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ABSTRACT

Airbus Helicopters is adapting its production to meet increasing demands for customization, facing the challenge of optimizing dynamic systems and improving performance indicators. To address the time-consuming nature of traditional simulation techniques, this paper proposes an AI-based surrogate model. This model, built by using synthetic data from previous simulations, is supposed to give the same results as the actual simulation model but in a very shorter time. The methodology presents a promising approach to enhancing production adaptability and efficiency.

Keywords: Multi-Layer Perceptron, Genetic Algorithm, Simulation, Artificial Intelligence.

INTRODUCTION

Due to the growing need for customization, Airbus Helicopters must adapt its production techniques quickly. The 'MECA 4.0' workshop at Airbus Helicopters is crucial. It specializes in manufacturing three main components: transmission boxes, rotors, and rotor assemblies. These components are essential for new helicopters and for providing spare parts for those already in service. To address this, the workshop includes different stations for building parts and extra stations for storage during production delays. The workshop sets its production pace on the expected assembly demand over three years. Its policies might change every year. The workshop uses AnyLogic, a simulation tool, to fine-tune its operations. AnyLogic's combines two types of modeling. One is discrete event modeling, which tracks processes and material flow. The other is agent-based modeling, which looks at how individual elements, like workers and stations, interact. This combination offers a deeper understanding of the workshop's dynamics. For accurate simulations in AnyLogic, two types of data are crucial: customer demand and workshop details. Customer orders outline the assembly plan for the next three years. They include details on each part, its production method, and the deadline. Although the number of parts and deadlines are fixed in this study, the demand varies by part type and production policy. For each simulation over three years, 754 demands are introduced, each defined by seven specific attributes. Workshop parameters are equally important. These parameters outline the physical and logistical setup of the manufacturing workshop. They include the number of production and backup stations for different components, the availability of trolleys and kits for transporting parts, and stock levels. Setting these parameters involves collaboration with the operational team. Simulation has always been a tool for optimizing manufacturing at the company. However, the complexity of this method makes it hard to find the best organizational strategies quickly. It's challenging to balance flexibility with the need to optimize key performance indicators like inventory levels, investment, and delivery times. The complexity of the model and the numerous parameters needing adjustment make this process slow. This does not align well with the need for rapid adaptation. This paper suggests using an AI-based surrogate model instead.

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This model can achieve similar results much faster. It was refined using data from the simulation model runs.

METHODOLOGY

This research 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—to optimize the parameters of production lines. To address these challenges, the initial step involves creating a comprehensive dataset obtained from Anylogic simulation runs. This will be accomplished by coupling a genetic algorithm with the Anylogic simulation model—a versatile platform for modeling and simulation of complex systems, supporting methodologies like discrete events 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.

RESULTS AND DISCUSSION

In our research, we developed a surrogate model based on MLP to predict Work In Progress (WIP), investment, and the mean delivery time delays, taking into account customer demand and operational parameters in a workshop environment. We used the evaluation of the cost function prediction model which utilizes two distinct functions: the Mean Squared Error (MSE) and the Three-Layer Function (3LF). The results from the initial training reveal low prediction errors for both methods. However, the 3LF records a 20Still, when the model is used in a genetic algorithm, there are big differences between what actually happens and what is predicted. This is especially true when it comes to predicting the mean delivery time delays, which leads to overestimations and a bad copy of the Anylogic model

CONCLUSION

The results demonstrate the surrogate model's effectiveness in data selection for labeling in various classification and regression tasks. The model shows potential in streamlining the optimization process, but it faces challenges in practical applications, particularly in predicting the mean delivery time delays accurately. The study concludes that while the MLP model shows promise in certain aspects of prediction, its applicability is limited, and it exhibits data biases. To address these challenges, the paper suggests exploring more advanced neural network architectures, such as LSTM networks and CNNs. These architectures could offer more nuanced solutions to complex problems in industrial applications, potentially revolutionizing the optimization processes in manufacturing. In summary, this research contributes in integrating advanced machine learning techniques into the optimization of industrial manufacturing processes. The development of surrogate models represents a potential shift in how production lines can rapidly adapt to changing demands, leveraging the power of AI and machine learning for more efficient, responsive manufacturing.

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