

DIGITAL TWINS FOR REAL-TIME BOTTLENECK ANALYSER USING PLANT SIMULATION

Rafael Gomes Paes de Lira

Instituição: UFPE - Universidade Federal de Pernambuco

Endereço: Av. Prof. Moraes Rego, 1235 - Cidade Universitária, Recife - PE, 50670-901

Email: rafael.gplira@ufpe.br

Lucas Matheus Nascimento

Instituição: UFPE - Universidade Federal de Pernambuco

Endereço: Av. Prof. Moraes Rego, 1235 - Cidade Universitária, Recife - PE, 50670-901

Email: lucas.matheusn@ufpe.br

Leandro Henrique Gomes da Silva

Instituição: UFPE - Universidade Federal de Pernambuco

Endereço: Av. Prof. Moraes Rego, 1235 - Cidade Universitária, Recife - PE, 50670-901

Email: leandro.hgsilva@ufpe.br

William da Silva Macedo Formágio

Instituição: UPE - Universidade de Pernambuco

Endereço: Av. Gov. Agamenon Magalhães - Santo Amaro, Recife - PE, 50100-010

Email: formagio.william@gmail.com

Dênis Leite

Instituição: UPE - Universidade de Pernambuco

Endereço: Av. Gov. Agamenon Magalhães - Santo Amaro, Recife - PE, 50100-010

Email: denisleite@poli.br

Márcio José das Chagas Moura

Instituição: UFPE - Universidade Federal de Pernambuco

Endereço: Av. Prof. Moraes Rego, 1235 - Cidade Universitária, Recife - PE, 50670-901

Email: marcio.cmoura@ufpe.br

ABSTRACT

This paper introduces a tool integrated with Plant Simulation for automatic bottleneck detection in industrial production lines. Initially developed as a custom library, it simulated stochastic scenarios using real factory data and employed virtual sensors to identify constraints. The solution evolved into a Digital Twin, where bottleneck logic was embedded in PLCs, enabling real-time detection within the control system. This hybrid approach — combining simulation and physical control — offers fast diagnostics and supports better decision-making, such as precise resource allocation to resolve critical issues. The tool is currently deployed at the Recife (PE) and Águas Claras (RS) sites, leading to notable gains in agility, productivity, and digital maturity. The paper details the development methodology, showcases the results, and highlights how this system contributes to a more intelligent and autonomous production environment.

KEYWORDS. Bottleneck Analyser, Discrete Event Simulation, Digital Twin.

Paper topics: Introduction, Methodology, Evolution Perspective, Conclusion and Acknowledgements.

1. Introduction

The increasing competitiveness of modern industry has driven the search for innovative solutions that promote the optimization of production processes. Bottleneck identification — the detection of constraint points that limit the efficiency of the production system — plays a central role in this effort, as it directly impacts throughput and the utilization of manufacturing resources [Tang et al., 2024]. Traditionally, this identification has been carried out based on historical data and operational experience, through manual approaches. This was the case in a multinational aluminum can manufacturer, where bottlenecks were identified using Excel spreadsheets based on reactive analysis of past data and operators' perceptions.

Although this model meets occasional needs, it proves limited in the face of increasing variability and complexity of industrial systems, where intermittent failures, changes in machine speeds, and fluctuations in buffer levels pose challenges to traditional analysis methods [Lai, 2022; Su et al., 2022]. Such limitations have motivated the development of more dynamic and data-driven methods for bottleneck identification, as demonstrated by several authors. For example, [Li et al., 2023] proposed a dynamic detection approach coupled with the evaluation of production losses in assembly lines, while [Subramaniyan et al., 2018] developed a predictive algorithm based on machine active periods. Similar approaches can be found in [Viehhauser, 2023], who applied simulation in job-shop environments, and [Lemessi et al., 2012], who presented a semi-automated solution to detect operational constraints influenced by stochastic events.

Bottleneck identification in complex production systems cannot be treated as a trivial task or one based on simplified static methods. In highly automated industrial environments subject to stochastic variability — as is the case with the studied multinational — multiple factors interact dynamically, making it difficult to precisely identify constraint points. The analyzed system possesses characteristics that intensify this complexity: the existence of intermediate buffers with specific control policies, speed variations between equipment, intermittent operational failures, setup cycles, and product changeovers that continuously alter the behavior of the production line throughout the shift.

In this scenario, traditional approaches such as simple per-machine production analysis in spreadsheets become insufficient to adequately capture the real bottlenecks of the process. In addition to not accounting for the dynamic effects of resource interactions, these methods are incapable of addressing the mobility of bottlenecks, which may shift over time due to different operational conditions. This calls for a more robust approach, one that is sensitive to system dynamics — capable of representing uncertainties and providing automated diagnostics based on realistic simulations. In this context, the use of Discrete Event Simulation (DES) [Banks et al., 2014] is justified as a fundamental tool for the efficient and contextualized identification of production bottlenecks.

In the company studied, to overcome these limitations, DES was adopted through the use of Siemens' Plant Simulation software, with the aim of generating stochastic scenarios that incorporated the realistic dynamic behavior of the production process. The models simulate different operational configurations, considering variations in equipment performance and the effects of buffer occupancy. From the generated data, a specific calculation method was developed for the automatic identification of bottlenecks, using empirical rules based on signals from virtual sensors strategically placed along the production line. This calculation will be detailed throughout the article, with an explanation of its logic, parameters, and practical application.

This proposal aligns with recent efforts to forecast and manage bottlenecks using data-oriented models and digital integration, such as those by [Li et al., 2011], who applied time series analysis, and [Lai et al., 2021], who emphasized the importance of real-time analysis in complex systems. Even sectors such as mining have benefited from this approach, as demonstrated by [Mousavi et al., 2025], reinforcing its versatility and robustness in highly variable operational environments.

By replacing manual methods with an automated tool integrated into simulation, it became possible to significantly improve the accuracy of bottleneck detection and, most importantly, to

anticipate future constraints based on predictive data. This anticipation capability enables faster operational response, establishing a proactive stance toward production dynamics. This article presents the theoretical foundation of the developed model, the methodology used for implementing the tool, its application in a real industrial environment, and the results obtained, with special emphasis on productivity gains and informed decision-making.

2. Methodology

2.1 Manual Bottleneck Identification Process

Before the development of the automated tool presented in this work, bottleneck identification was performed manually by production line operators, using spreadsheets developed in Excel. Although this procedure was structured, it required frequent human intervention and relied heavily on the operator's experience to collect and interpret the data. Furthermore, it was based exclusively on historical data, which limited its ability to respond to real-time variations during the operation of the production process. This traditional approach, lacking access to dynamic system information, introduced delays in decision-making and hindered agile responses to unexpected events or changes in production conditions.

For each analysis, the operator accessed the factory database — continuously updated by sensors distributed along the line and by supervisory systems monitoring machine conditions. The extracted information included the minimum and maximum speeds (in CPM — cans per minute) of each machine, as well as data on operational availability over a defined time interval, usually the previous day or the most recent shift.

These data were then manually entered into the spreadsheet, which contained predefined equations to calculate the theoretical daily output of each machine. The formula used was:

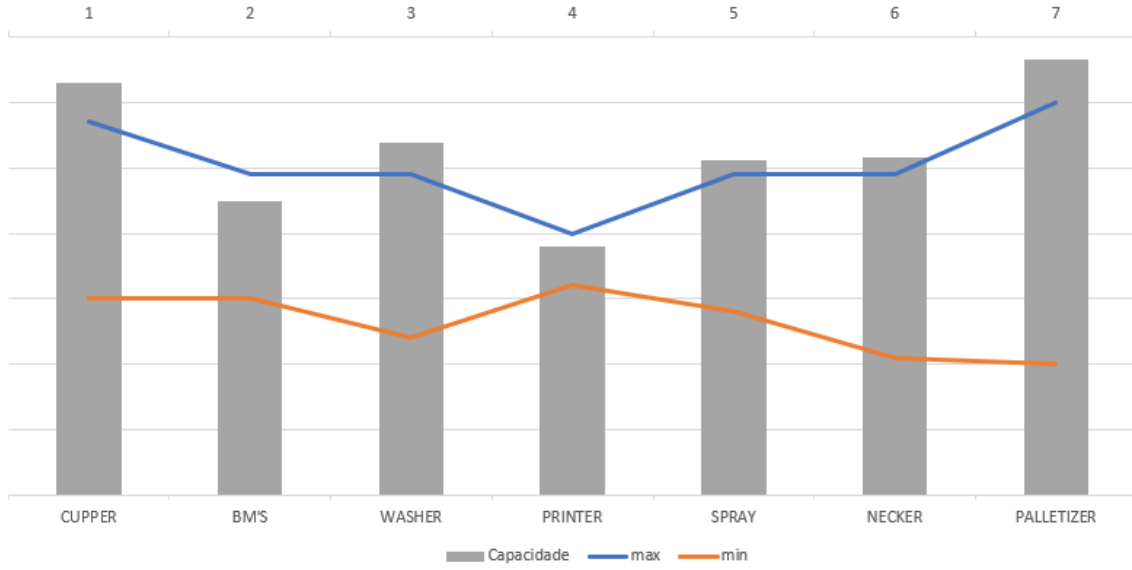
$$Production = Speed_{max} * Availability * 1440 \quad (1)$$

Where:

- $Speed_{max}$ represents the machine's maximum speed in CPM;
- $Availability$ is the machine's availability (a percentage value between 0 and 1);
- 1440 corresponds to the number of minutes in a day, converting the per-minute production rate into daily production.

The spreadsheet would automatically generate a bar chart with the estimated daily output of each machine. On this chart, two horizontal lines indicated the minimum and maximum speeds, allowing a quick visual assessment of each machine's production capacity and its proximity to operational limits. This visual analysis enabled the operator to reasonably identify which machine was acting as the bottleneck at that moment, as illustrated in Figure 1 with fictitious data.

Figure 1: Bottleneck Identification Chart



Source: Author

It is important to note that the production capacity shown in the chart does not correspond directly to the machines' nominal maximum speed. This is because effective capacity considers the machine's operational availability over the analyzed period, reflecting the actual operating conditions of the line. The equation used is:

$$Capacity = Speed_{max} \times Availability \times Operating Time \quad (2)$$

In this context, the time is typically considered as the total duration of the day (e.g., 1,440 minutes). Availability — a fundamental component of OEE (Overall Equipment Effectiveness) — includes losses caused by stoppages, failures, setups, and other unplanned interruptions. Therefore, the estimated capacity provides a more realistic view of the machine's productive potential, offering a more reliable basis for bottleneck analysis than simply using nominal speed.

In addition to identifying the bottleneck, it was also possible to project the expected production for the next day, considering the impact of potential multiple bottlenecks. For this, the operator would select the machines believed to be acting as bottlenecks and, based on them, use the lowest of the maximum speeds ($\text{Min}[Speed_{max}]$) and the average availability of those machines ($Availability_{avg}$). A 5% correction factor was applied for each bottleneck considered, representing spoilage. The formula used was:

$$Prod_{proj} = Speed_{max} * Availability_{avg} * 1440 * 0.95^n \quad (3)$$

Where:

- $Prod_{proj}$ represents the projected production;
- $Speed_{max}$ is the machine's maximum speed;
- $Availability_{avg}$ is the average availability of the machines;
- n represents the number of bottlenecks considered simultaneously.

This simple and empirical model was effective for point-in-time analyses but presented significant limitations, such as reliance on the subjective interpretation of operators, the high amount of time spent extracting and organizing data, and the lack of sensitivity to the dynamic

fluctuations of the process. These factors motivated the development of the automated tool described in the next section.

2.2 Automated Bottleneck Identification Tool

With the objective of assisting plant operators and overcoming the limitations of the manual process described above, a customized library was developed within the discrete event simulation software Plant Simulation, by Siemens Software — already widely used by the company's engineering team. This library not only automates the functionalities previously performed in Excel spreadsheets but also incorporates additional features such as the use of random variables, execution of multiple simulated scenarios, and predictive analysis based on real data, replacing historical averages with probabilistic distributions that more accurately represent the production system's behavior.

In other words, the developed solution represents a paradigmatic shift: moving from a deterministic model based on historical time series — subject to the limitations of fixed averages and incapable of capturing inherent system variability — to a stochastic model. This new model incorporates probability distributions for cycle times, empirical failure distributions (e.g., Weibull for MTBF), and dynamic line control methods (such as adaptive prioritization policies). Such an approach not only reflects the actual behavior of the production system more faithfully, but also enables scenario evaluation under uncertainty.

The Plant Simulation software, which has been used for years by the company, already includes a validated digital model of the plant, ensuring that the simulated scenarios fall within an acceptable margin of error for environments with stochastic variability. This validated foundation enabled the construction of a solution that integrates seamlessly with the existing simulation environment, using the same operational and structural parameters as the real production line.

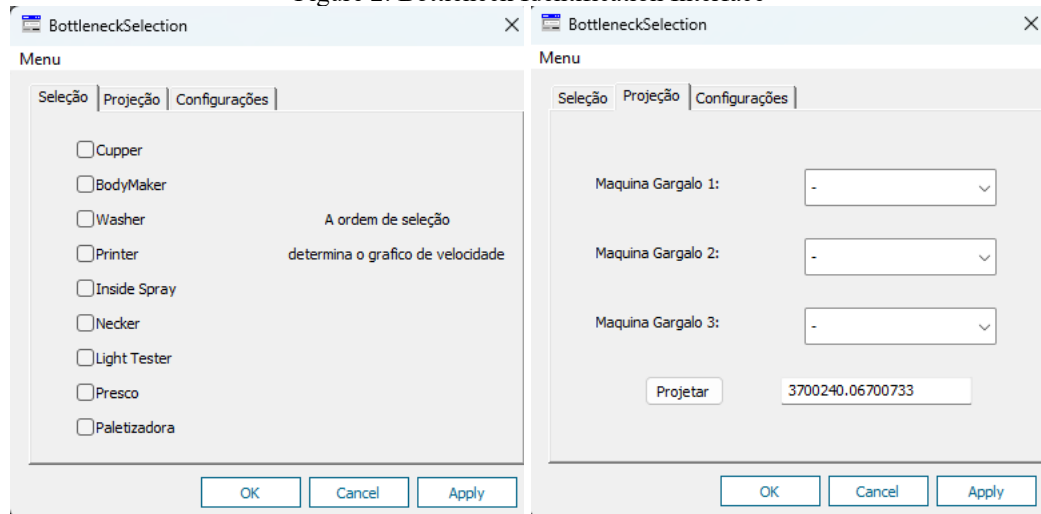
The developed library provides an interactive interface directly accessible within the Plant Simulation environment, with functionalities that simplify usage for operators. The interface allows users to:

- Define the order of machine visualization in the production chart;
- Select the machines considered potential bottlenecks for projected output calculations.

These settings are configured via checkboxes and intuitive menus, as shown in Figure 2. The formula for projected production maintains the same mathematical structure as the previous method, but has been reformulated under a stochastic approach that incorporates random variables to represent operational failures, process errors, and is validated through multiple simulation replications.

The major innovation lies in replacing static, average-based analysis with a dynamic set of simulated scenarios. The most recent real-world data are extracted directly from the factory's database and fed into the model before each simulation run. This enables operators to generate forecasts multiple times during a single shift, without manually downloading data or filling out spreadsheets — significantly reducing both time and operational effort, while increasing the fidelity of the diagnosis to the actual current state of the plant.

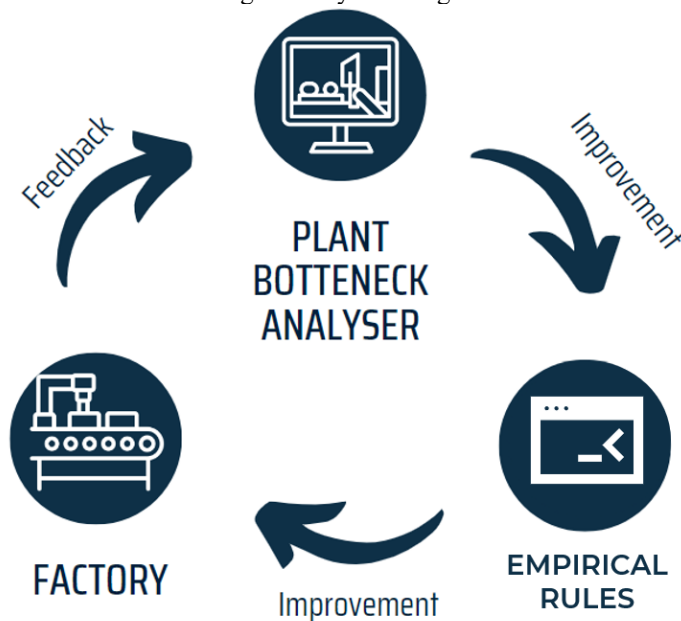
Figure 2: Bottleneck Identification Interface



Source: Author

The library was also designed to allow simulation repetition with different bottleneck configurations and input parameters, providing a more robust quantitative basis for real-time decision-making. The complete logic of the system is shown in Figure 3.

Figure 3: System Logic



Source: Author

The flow begins with real production line data being sent to the simulation model, which feeds the bottleneck identifier based on empirical rules related to the behavior of buffers and machines. From these data, the system can accurately identify process constraints, allowing managers to act more strategically. Accurate bottleneck identification prevents misguided decisions, such as allocating resources to a secondary machine when the true limitation lies in another part of the process.

Although the system allows for speed adjustment suggestions in the programmable logic controllers (PLCs), such actions are not yet fully automatic or detached from human judgment. The main benefit lies in delivering updated diagnostics that support fast, data-driven decision-making.

Thus, the analysis cycle restarts continuously, promoting an adaptive control environment based on simulation, directly supporting the prioritization of corrective and preventive interventions.

This process enables frequent updates to production planning, based on accurate and current bottleneck diagnoses, reducing response time to system changes and supporting more informed operational and strategic decisions.

3. Digital Twins

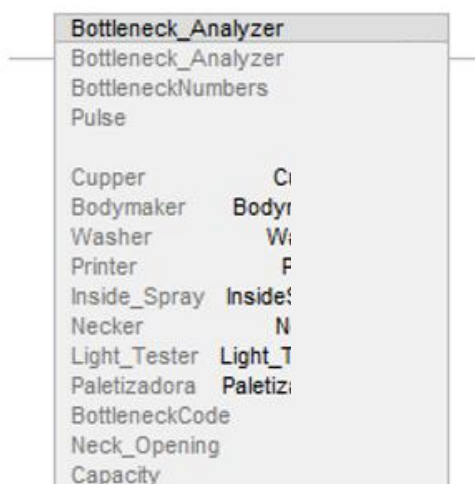
The concept of a Digital Twin has gained significant traction in academia and industry, representing a key component of Industry 4.0 [Hermann et al., 2016]. A Digital Twin is a virtual representation of a physical asset or system, which is dynamically updated with real-time data from its physical counterpart. This synchronized connection between the physical and virtual worlds is a defining characteristic, enabling advanced analysis, simulation, and prediction of the system's behavior [Singh et al., 2021]. The value of a Digital Twin lies not only in its ability to mirror the physical world but also in its capacity to provide feedback, allowing for optimized decision-making and control.

The most recent evolution of the solution presented in this work involves the direct integration of the bottleneck identification system with the plant's control system through the implementation of a Digital Twin. This approach represents a leap in digital maturity, allowing the Programmable Logic Controller (PLC) — which physically controls the production line — to execute the bottleneck identification calculations based on real-time operational data. In other words, what was previously simulated in the virtual Plant Simulation environment now occurs within the factory's control system itself, enabling continuous analysis directly linked to the shop floor.

The first Digital Twin tests were conducted at the company's Recife (PE) and Águas Claras (RS) units and continue to be used by the technical team to this day. The solution is referred to as a Digital Twin precisely because it digitally mirrors the operating plant: it not only consumes real-time data during execution but also provides direct feedback for decision-making, indicating in real time where the bottleneck is located and enabling corrective actions with greater assertiveness. This intelligent feedback transforms the simulator into a living representation of the production system, extending its functionality beyond predictive analysis.

Figure 4 shows an example of the logic block programmed directly into the PLC, responsible for executing the calculations of the Bottleneck Analyzer based on live production line data. For industrial confidentiality reasons, some information has been omitted.

Figure 4: Bottleneck Calculation Block in the PLC



Source: Author

The PLC-developed logic block contains several parameters that synthesize the real-time diagnostic of the line. Among these, the neck opening stands out — it indicates the additional number of cans that could be produced if the main constraint were removed. The capacity parameter represents the projected output of the line considering the current bottleneck, while the bottleneck code numerically identifies which machine is currently limiting the flow. Lastly, bottleneck numbers indicate the total number of constraints detected, including both the main bottleneck and secondary restrictions that affect performance. The remaining parameters serve descriptive or organizational purposes in the control system.

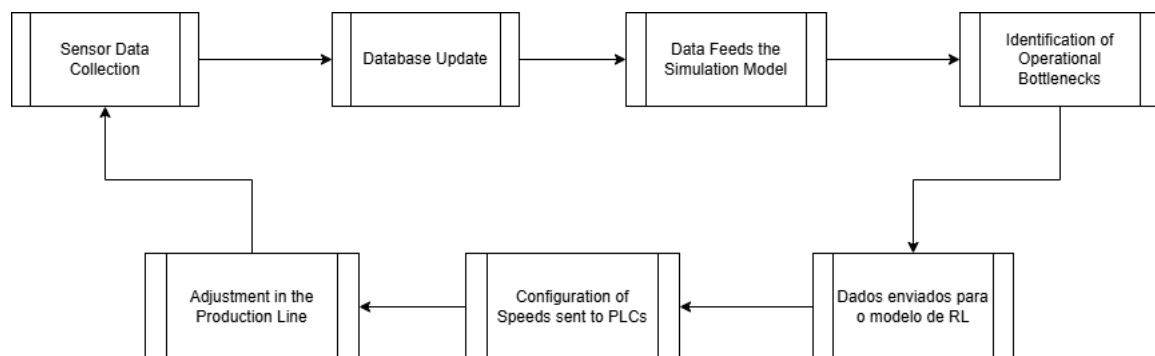
4. Future Work

With the development of the library in Plant Simulation, it became possible to support operators in bottleneck analysis and production projections, replacing spreadsheets with an automated and reliable environment. However, this advancement also paves the way for a more ambitious evolution of the methodology — the creation of a Real-Time Bottleneck Analysis System, in which operational decisions are no longer guided solely by fixed empirical rules implemented in Programmable Logic Controllers (PLCs).

In addition to the limitations of empirical rules — which are formulated based on specific conditions that do not always reflect operational variability accurately — the proposed approach also eliminates the need for manual operator interventions throughout the shift to reconfigure the analysis. With the new method, the entire process occurs in real time and autonomously, providing greater agility and accuracy in decision-making, while reducing human dependence and the potential for operational errors.

In this new proposed flow, illustrated in Figure 5, operational data go through the following stages:

Figure 5: Proposed Workflow



Source: Author

1. Machine sensors collect real-time data on queue states, operation times, availability, and performance;
2. These data are automatically sent to a central database, which serves as the basis for continuous analysis;
3. The data then feed into the simulation model, which identifies operational bottlenecks based on the current state of the factory;
4. The identified bottleneck result is passed to a reinforcement learning (RL) model, previously trained on diverse scenarios generated in the simulation environment;
5. This model adaptively defines the optimal speed configuration for each machine, aiming to maximize overall system productivity;

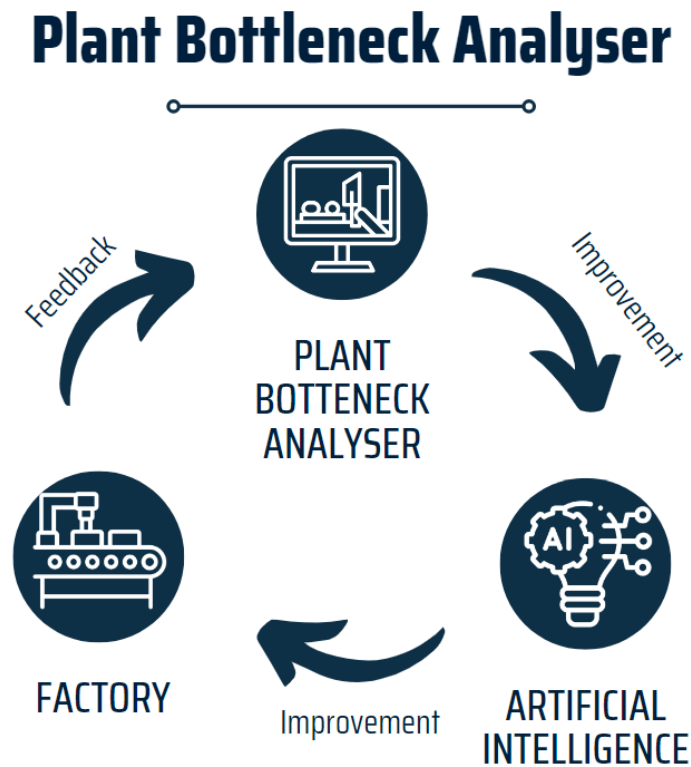
6. The new speed configurations are transmitted directly to the PLCs, which then execute the adjustments automatically on the production line.

This complete cycle, which represents the new intelligent and adaptive control model, is summarized in Figure 6, which synthesizes the overall process operation.

Unlike the current empirical rules implemented in PLCs — which are based on limited and specific operational conditions — the reinforcement learning-based model introduces a much more dynamic and adaptive approach. Trained beforehand in a simulation environment using a wide range of operational scenarios (including rare or adverse conditions), this model can respond optimally to new configurations in the production line.

Its main advantage lies in real-time adaptability: it continuously learns from previous performance, updating its decisions to maximize plant output. Additionally, the model considers multiple variables simultaneously, such as queue status, failure occurrences, demand fluctuations, and the individual efficiency of machines. This multivariate analysis capability allows the generated responses to be more robust and comprehensive, significantly reducing the losses associated with outdated or static rule-based decisions, and promoting a smarter, more resilient, and dynamically aligned industrial operation.

Figure 6: Future System Logic



Source: Author

5. Conclusion

The implementation of the library developed in Plant Simulation represents a significant advancement in the analysis and mitigation of bottlenecks in industrial production lines. By automating a process that previously depended on frequent manual interventions, the system provides greater speed, accuracy, and frequency in assessing the plant's operational efficiency.

With the use of real factory data and the ability to simulate various scenarios, operators now have a powerful decision-support tool, enabling faster interventions grounded in reliable diagnostics.

It is important to highlight that the automatic bottleneck identifier is already in use at the company in question, with extremely positive feedback from operators and analysts. The ease of use, the elimination of the need to manually complete spreadsheets, and — above all — the reliability of the results contributed to a significant increase in plant productivity. Bottleneck analysis, which was previously performed a few times per shift in a reactive and isolated manner, is now carried out continuously and based on data, enabling proactive actions to maximize the efficiency of the production system.

Furthermore, the integration of this tool with existing systems lays the foundation for the transition toward a Real-Time Bottleneck Analysis System. This system under development aims to replace limited empirical rules with reinforcement learning models trained in a simulated environment, thus granting autonomy to the decision-making process and substantially increasing its adaptability to diverse operational scenarios.

By transforming the logic of machine speed control into an intelligent and responsive approach, this initiative opens the door to relevant gains in productivity, stability, and energy efficiency. The prospect of reducing the need for human intervention during shifts and ensuring continuous and autonomous bottleneck analysis highlights the transformative potential of applying artificial intelligence techniques in industrial environments. The results achieved in this work therefore point toward a promising path aligned with the principles of Industry 4.0, with a strong emphasis on digitalization, automation, and applied intelligence.

6. Acknowledgements

The authors gratefully acknowledge the financial support from the Human Resources Program of the Brazilian National Agency of Petroleum, Natural Gas and Biofuels (PRH-ANP) and the Graduate Program in Production Engineering (PPGEP), which were fundamental for the development and execution of this work.

References

- Banks, J., Carson II, J. S., Nelson, B. L., & Nicol, D. M. (2014). *Discrete-Event System Simulation* (5th ed.). Pearson.
- Hermann, M., Pentek, T., & Otto, B. (2016). Design Principles for Industrie 4.0 Scenarios. 2016 49th Hawaii International Conference on System Sciences (HICSS), 3928-3937.
- Lai, X. (2022). *Bottleneck Prediction and Resilience Improvement for Manufacturing Systems*. University of Michigan.
- Lai, X., Shui, H., Ding, D., Ni, J. (2021). Data-driven dynamic bottleneck detection in complex manufacturing systems. *Journal of Manufacturing Systems*, v. 59, p. 446–455.
- Lemessi, M., Rehbein, S., Rehn, G. (2012). Semi-automatic simulation-based bottleneck detection approach. *Winter Simulation Conference Proceedings*.
- Li, C., Yu, T., Xiao, G., Arinez, J., Chang, Q. (2023). Dynamic bottleneck identification and production loss evaluation for assembly lines. *Manufacturing Letters*, v. 37, p. 1–5.
- Li, L., Chang, Q. Xiao, G. (2011). Throughput bottleneck prediction of manufacturing systems using time series analysis. *Journal of Manufacturing Science and Engineering*, v. 133, n. 2, 021015.

Mousavi, A., Isokangas, E., Dzakpata, I. (2025). A Simulation-Based Bottleneck Identification Approach for Complex Mining Production Systems. *Mining, Metallurgy & Exploration*.

Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. (2021). Digital twin: enabling technologies, challenges and open research. *International Journal of Production Research*, 1-28.

Subramaniyan, M., Skoogh, A., Salomonsson, H. (2018). A data-driven algorithm to predict throughput bottlenecks in a production system based on active periods of the machines. *Computers & Industrial Engineering*, v. 126, p. 756–768.

Su, X., Lu, J., Chen, C., Yu, J., Ji, W. (2022). Dynamic bottleneck identification of manufacturing resources in complex manufacturing system. *Applied Sciences*, v. 12, n. 9, 4195.

Tang, J., Dai, Z., Jiang, W., Wu, X., Zhuravkov, M. A., Xue, Z. (2024). A comprehensive review of theories, methods, and techniques for bottleneck identification and management in manufacturing systems. *Applied Sciences*, v. 14, n. 17, 7712.

Viehhauser, D. (2023). Simulation-based Bottleneck Identification in a Job-shop with Changing Product Mixture and Production Volumes. *Montanuniversität Leoben*.