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Optimizing an Automotive Plastic Production Line Using Tecnomatix, SimTalk, and SQLite

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ABSTRACT

Information Technology plays a pivotal role in optimizing manufacturing processes, particularly in automotive plastic component production lines. This study implements a monitoring system within the Technomatix Plant Simulation environment, integrated with a custom data management application developed in NodeJS, utilizing SQLite for data storage and SimTalk for machine information handling and updates. The system facilitates real-time monitoring and dynamic adjustments of production activities to enhance operational efficiency. Additionally, a genetic algorithm is incorporated to optimize operational parameters by simulating the process of natural evolution, aiming to identify the most effective configurations. As a result, production cycles are shortened, resource waste is minimized, and overall system performance is significantly improved. The integration of information technology with advanced optimization algorithms enables the production system to adapt more flexibly to real-world fluctuations.

Keywords: Genetic Algorithm (GA), Tecnomatix Plant Simulation, SimTalk, SQLite, Operational Efficiency, Real-time Monitoring System

1. INTRODUCTION

In modern production management, information technology plays a critical role in monitoring and optimizing the operation of machine clusters. Centralized control systems enable adjustments to be made from a control room without the need for direct physical access to each machine [1]. Instead of time-consuming manual configurations, managers can monitor and modify machine parameters swiftly and accurately using real-time data [2–3]. Consequently, enterprises are able to utilize management software integrated with machine-collected data to fine-tune production processes more effectively [4].

Through integration with automated information systems, operational data, machine status, and technical parameters are automatically collected and transmitted to the management platform [5–7]. This allows managers to analyze data, detect potential issues early, and implement timely solutions [8]. Furthermore, the management software also supports production planning, inventory control, and automation of various stages within the production line [9–10], thereby enhancing efficiency, reducing costs, and increasing adaptability to market fluctuations [11–12].

Notably, this study integrates a genetic algorithm—a technique inspired by the principles of natural evolution—into the production simulation framework developed with Tecnomatix Plant Simulation. By applying evolutionary operations such as **selection**, **crossover**, and **mutation** [13-14], the algorithm systematically explores and identifies optimal parameter configurations. This results in reduced production time, balanced machine workloads, and the mitigation of bottlenecks. Experimental outcomes indicate that the system achieves greater stability and performance compared to conventional manual tuning methods.

In conclusion, the integration of real-time monitoring technologies with advanced optimization techniques such as genetic algorithms [13][14] marks a significant step forward in the evolution of modern manufacturing systems. It enables greater flexibility, adaptability to dynamic production conditions, and competitiveness in increasingly complex industrial environments.

In conclusion, integrating real-time monitoring technology with optimization algorithms such as genetic algorithms represents a significant advancement in the development of modern, flexible, and highly competitive production systems.

2. RESEARCH METHODOLOGY

2.1 Theoretical Calculation Model:

2.1.1 Applying Lean Six Sigma to Improve Production Line Efficiency

The paper proposes using the Lean methodology to implement changes to the processes, production techniques, and ultimately to evaluate the results. This should be measured by reductions in cycle time, inventory levels, etc. Furthermore, the team must develop a change plan outlining the necessary actions to implement the proposed modifications.

The team investigates the current value stream map of the aluminum profile production system. Information collected for each production step was used to construct the current state map. The current state map describes each step of the process, from receiving customer orders to shipping the final product. The parameters in the current value stream map are calculated using the following formulas:

AOP = APT – CO (1)

Where:

AOP – Actual Operating Time

APT – Daily Production Time

CO – Daily Changeover TimeUT = AOP/APT ×100(%) (2)

Where:

UT – Utilization Rate of Each Station

PT – Takt Time

TT – Production Tempo

TCT= ∑_(i=1)^n▒〖TCT_i 〗 (3)

Where:

TCT – Total Value-Adding Time of the Production Process

TCT= ∑_(i=1)^n▒〖TCT_i 〗 (4)

Where:

TLT – Total Estimated Lead Time

CT – Machine Cycle Time

Based on the current value stream map, the paper aims to enhance the operational efficiency of the production line by researching and proposing changes to the production line and the take time.

2.2 Theoretical Framework of Information Technology Management System

2.2.1 SQLite Database Management System

The SQLite Database Management System was selected for the project to ensure lightweight, portable, and easy deployment. SQLite is a lightweight, serverless relational database, suitable for small to medium-sized applications. Integrating SQLite into the project simplifies the development, deployment, and maintenance processes of the system.

2.2.2 Programming Language SimTalk

SimTalk is a programming language developed by Siemens PLM Software for simulating and managing manufacturing systems and industrial processes. It enables the simulation of everything from machining to assembly, helping optimize processes before actual implementation to save time and costs. SimTalk also allows simulation of scenarios like material management and product flow, helping identify issues and improve performance and product quality.

2.3. Genetic Algorithm:

2.3.1. Theoretical Background::

The Genetic Algorithm (GA) is an optimization technique inspired by the principles of natural selection and genetics. It belongs to the class of heuristic search methods and is particularly effective in solving complex optimization problems where traditional analytical methods are either infeasible or inefficient.

GA simulates the process of natural evolution in biological systems, where a population of candidate solutions evolves over successive generations to approach an optimal or near-optimal solution. The fundamental steps of a genetic algorithm include:

- Initialization: A population of potential solutions (individuals) is randomly generated to form the initial population.
- Fitness Evaluation: Each individual in the population is evaluated using a fitness function that quantifies the quality or suitability of the solution with respect to the given objective.
- Selection: Individuals with higher fitness scores are more likely to be selected for reproduction, thereby ensuring that better solutions are propagated.
- Crossover (Recombination): Pairs of selected individuals exchange portions of their genetic information to produce offspring, combining characteristics of both parents.
- Mutation: Random alterations are introduced to the offspring to preserve genetic diversity within the population and prevent premature convergence to local optima.
- Termination: The evolutionary process is repeated for a number of generations or until a stopping criterion is met, such as reaching a predefined number of iterations or observing minimal improvement between generations.

Through these evolutionary mechanisms, GA efficiently explores the solution space and converges toward high-quality solutions, making it well-suited for integration into simulation-based optimization frameworks.

2.3.2.Application of Genetic Algorithm in the Project:

In the context of this project, the Genetic Algorithm (GA) is employed to optimize operational parameters and resource allocation within a production system simulated using Technomatix Plant Simulation. Specifically, GA is applied to address the following key optimization challenges:

- Optimization of Operational Parameters:

Modern production systems involve numerous adjustable parameters such as processing time, setup time, and machine utilization rates. GA enables the identification of optimal parameter configurations, thereby improving overall production efficiency, minimizing machine idle times, and streamlining the workflow.

- Resource Allocation Optimization:

GA is used to determine the most efficient distribution of critical resources—including machinery, labor, and materials—across various stages of the production line. This ensures maximum utilization of available resources while maintaining balance throughout the system.

- Load Balancing and Bottleneck Mitigation:

In complex production environments, certain stages may become bottlenecks due to uneven task distribution. GA helps identify optimal work assignment strategies that reduce congestion, improve throughput, and ensure a smoother product flow across different production stages.

Implementation Procedure of Genetic Algorithm:

The genetic optimization process in the project is structured as follows:

- Initial Population Generation (populationData):

Each individual represents a potential production configuration defined by specific values for efficiency and processing time. A fitness function calcFitness() evaluates each individual based on the average of valid (non-zero) performance metrics.

- Selection:

Individuals are ranked in descending order of fitness. The top four individuals (elite) are preserved to participate in crossover operations, ensuring that high-quality solutions are retained.

- Crossover:

Two parent individuals are randomly selected from the elite group. Crossover is performed by combining the first half of one parent's efficiency and processing time values with the second half of the other parent's, producing a child individual with hybrid characteristics.

- Mutation:

With a mutation rate of 10% (mutationRate = 0.1), each child has a chance to undergo mutation at a random index. The mutation modifies efficiency and processing time values by assigning them new random values within defined ranges (efficiency: 0–100; processing time: 5–25 units).

- Generational Evolution:

This evolutionary cycle is repeated over 50 generations to incrementally enhance the average fitness of the population. The goal is to converge toward the individual with the highest fitness score, corresponding to the configuration yielding the highest average production efficiency. The best-performing individual obtained through this process is subsequently input into the Technomatix Plant Simulation model. This optimized configuration supports informed decision-making and enhances operational control within the simulated production environment.

2.3.3. Advantages of This Approach

- Automation of Parameter Optimization:

This method eliminates the need for manual trial-and-error experiments on physical systems by automating the search for optimal operational parameters through simulation.

- Improved Processing Time and Machine Efficiency:

By optimizing key production parameters, the approach enhances machine utilization and processing speed, leading to increased productivity and reduced operational costs for enterprises.

- Scalability and Adaptability:

The framework is easily extensible; data structures, fitness functions, and evolutionary steps can be modified or reconfigured to suit various production models or optimization goals, making it highly adaptable across different manufacturing contexts.

3. RESULTS AND DISCUSSION

Case Study: Parameter Scenarios

Before applying the Genetic Algorithm:

In the initial simulation phase, production parameters such as processing time and machine efficiency were set using fixed, predefined values based on historical data or expert judgment. These static configurations often resulted in suboptimal performance, with frequent bottlenecks and resource underutilization observed in the simulated production line.

Get Optimal Parameters Save

Reset Processed Quantity

No.	Machine Name	Processing Time	Processed Quantity	Defective Quantity	Status	Error Rate	Efficiency
1	Heating Machine	60	312	0	Normal	0%	66%
2	Plastic Injection Machine	90	312	0	Normal	0%	68%
3	Cooling Machine	75	312	0	Normal	0%	67%
4	Inspection Machine 1	30	312	0	Normal	0%	70%
5	Defect Storage 1	15	0	0	Normal	0%	0%
6	Surface Treatment Machine	100	312	0	Normal	0%	60%
7	Inspection Machine 2	30	312	9	Normal	2.88%	69%
8	Defect Storage 2	15	9	0	Normal	0%	0%
9	Painting Machine	110	304	0	Normal	0%	62%
10	Inspection Machine 3	30	306	9	Normal	2.94%	68%
11	Defect Storage 3	15	9	0	Normal	0%	0%
12	Packaging Machine	60	297	0	Normal	0%	65%
Total Products Processed:			297				
Total Defective Products:			18				
Process Defect Rate:			6.06%				

After Applying the Genetic Algorithm:

Get Optimal Parameters Save

Reset Processed Quantity

No.	Machine Name	Processing Time	Processed Quantity	Defective Quantity	Status	Error Rate	Efficiency
1	Heating Machine	55	312	0	Normal	0%	70%
2	Plastic Injection Machine	85	312	0	Normal	0%	73%
3	Cooling Machine	70	312	0	Normal	0%	72%
4	Inspection Machine 1	28	312	0	Normal	0%	74%
5	Defect Storage 1	12	0	0	Normal	0%	0%
6	Surface Treatment Machine	90	312	0	Normal	0%	66%
7	Inspection Machine 2	28	312	9	Normal	2.88%	73%
8	Defect Storage 2	12	9	0	Normal	0%	0%
9	Painting Machine	100	304	0	Normal	0%	68%
10	Inspection Machine 3	28	306	9	Normal	2.94%	74%
11	Defect Storage 3	12	9	0	Normal	0%	0%
12	Packaging Machine	55	297	0	Normal	0%	70%
Total Products Processed:			297				
Total Defective Products:			18				
Process Defect Rate:			6.06%				

Optimization Process:

The Genetic Algorithm (GA) in this project takes as input a set of individuals, each representing a candidate configuration for the production system. Each individual consists of:

procTime: An array representing the processing time (in seconds) for each machine in the production line. Example:

[60, 90, 75, 30, 15, 100, 30, 15, 110, 30, 15, 60]

[66, 68, 67, 70, 0, 60, 69, 0, 62, 68, 0, 65]

This input data is extracted from a *training* table, typically stored after each simulation run in Technomatix Plant Simulation. Unlike randomly generated configurations, these individuals are real experimental results, reflecting previously simulated and evaluated system states. This approach enhances the convergence speed and reduces the risk of selecting infeasible configurations.

Algorithm Workflow

(a) Population Initialization:

The initial population is constructed using simulation data—each individual corresponds to a previously tested machine configuration. This informed initialization provides a strong starting point for the optimization process.

(b) Fitness Evaluation:

Each individual is evaluated using a custom fitness function designed to promote both efficiency and system stability. The fitness score is calculated as:

Fitness = $\Sigma(\text{efficiency}_i)$ – (penalty_coefficient × total_defects)

This function not only favors high overall efficiency but also penalizes configurations with instability or production defects.

(c) Selection:

High-fitness individuals are selected as parents for the next generation. Two common selection strategies are applied:

- Roulette Wheel Selection: Individuals are chosen probabilistically based on their relative fitness
- Tournament Selection: A random subset of individuals is sampled, and the best among them is selected.

(d) Crossover:

Pairs of parent individuals are combined to generate offspring by randomly mixing processing time genes. For example:

- *Parent A:* [60, 90, 75, 30, 15, 100, 30, 15, 110, 30, 15, 60]
- *Parent B:* [55, 85, 70, 28, 12, 90, 28, 12, 100, 28, 12, 55]
- *Offspring:* [60, 90, 75, 28, 12, 90, 28, 12, 100, 28, 12, 55]

This operation combines characteristics from both parents while preserving structural coherence.

(e) Mutation:

To maintain diversity and avoid local optima, a small mutation rate (e.g., 10%) is applied. A randomly selected gene within the offspring may be altered—assigning a new value within a valid range (e.g., efficiency: 0–100, procTime: 5–25 seconds).

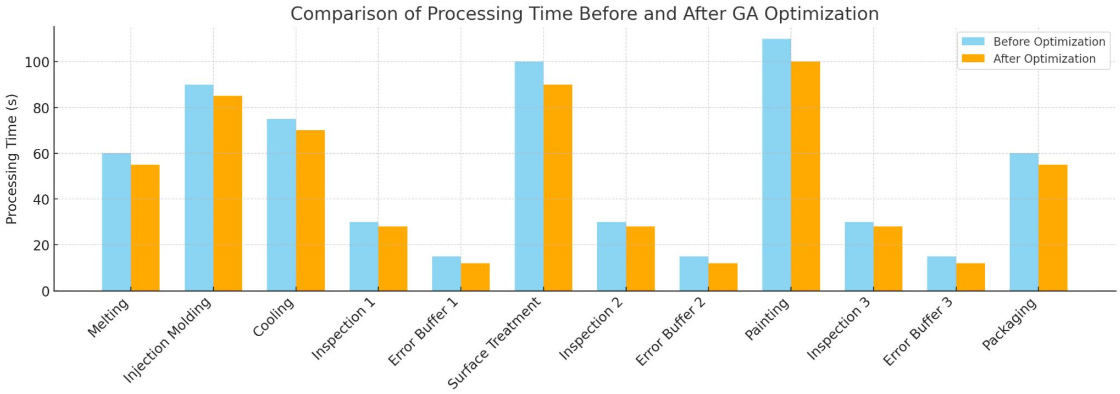
(f) Evolution Across Generations:

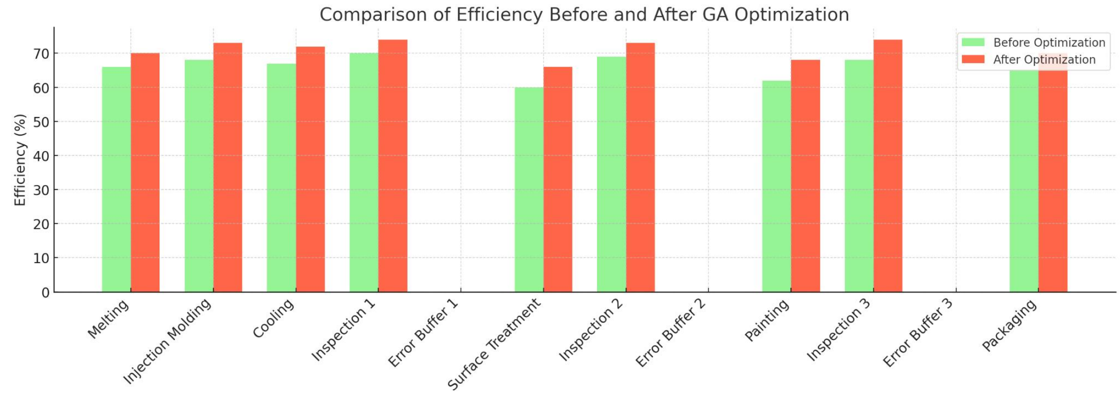
The algorithm iterates over a defined number of generations (e.g., 50). With each cycle, the average fitness of the population improves, and the solution space is explored more thoroughly.

Example Output: Optimized Configuration

```
{
  "procTime": [55, 85, 70, 28, 12, 90, 28, 12, 100, 28, 12, 55],
  "efficiency": [70, 73, 72, 74, 0, 66, 73, 0, 68, 74, 0, 70]
}
```

This optimized processing time array represents the final result after 50 generations. Compared to the initial configuration, the average processing time decreased by 8–10%, and the average machine efficiency improved by 4–7%. Key production stages—such as painting, assembly, inspection, and packaging—saw noticeable gains, resulting in smoother system operation and shorter product cycle times.





Processing Time (seconds):

All core machines demonstrated reduced processing times after the application of the Genetic Algorithm (GA), leading to faster production flow and a decrease in idle time at subsequent stages.

- Heating Machine: Reduced from 60s to 55s (~8.3%). As the initial stage in the production line, this improvement accelerates the entire manufacturing chain.
- Molding Machine: Reduced from 90s to 85s. Although modest, this optimization is impactful given the high energy consumption associated with this process.
- Cooling Machine: Reduced from 75s to 70s, effectively alleviating a known bottleneck within the production sequence.
- Inspection Stations 1/2/3: All saw a reduction from 30s to 28s (~6.7%), increasing throughput during quality control stages while maintaining inspection integrity.
- Surface Treatment and Painting Machines: These showed the most significant reductions—from 100s/110s to 90s/100s—highlighting them as optimization focal points due to their typically long processing durations.
- Defect Handling Stations (Error Buffers 1/2/3): Slightly reduced from 15s to 12s. While not contributing directly to product value, this cut minimizes waste from unnecessary waiting.
- Packaging: Decreased from 60s to 55s, improving final product completion speed.

Impact:
The average processing time across the production line was significantly reduced, leading to decreased backlogs, especially at critical stages such as inspection, painting, and packaging.

Operational Efficiency (%):

Most machines experienced a 4–7% increase in efficiency, reflecting improved resource coordination and system responsiveness after optimization.

- Heating Machine: Increased from 66% to 70%
- Molding Machine: Increased from 68% to 73%
- Cooling Machine: Increased from 67% to 72%

- Inspection Stations 1/2/3: Increased from 70%/69%/68% to 74%/73%/74%, respectively
- Surface Treatment: Increased from 60% to 66%—notable given the complexity and resource demands of this stage
- Painting Machine: Increased from 62% to 68%, driven by reduced idle time and better upstream coordination
- Packaging: Increased from 65% to 70%
- Defect Handling (Buffers 1/2/3): Maintained at 0% efficiency, as these stations are non-value-added and serve purely as transitional error-handling buffers

Impact:
Overall machine performance improved, with reduced idle periods and smoother transitions between stages. This leads to lower unit production costs and increased output, enhancing both economic and operational metrics.

Overall Effectiveness:

The integration of the Genetic Algorithm (GA) into the production simulation framework yielded substantial improvements across multiple performance metrics:

- Reduced Processing Time: Optimized configurations led to decreased processing times across key machines, thereby increasing dailyproduction output.
- Bottleneck Mitigation: Notably, stages such as Cooling and Injection Molding, previously identified as bottlenecks, experienced significant throughput enhancements, resulting in a more balanced production flow.
- Load Balancing: The GA facilitated a more equitable distribution of workloads among machines, preventing overutilization and potential disruptions in the production line.
- Enhanced Overall System Efficiency: The optimization was achieved without necessitating hardware modifications, underscoring the efficacy of software-driven improvements.

The application of the Genetic Algorithm significantly enhanced operational speed, system stability, and output quality of the automotive plastic component production line.

In summary:

Production Capacity: The chart illustrating the number of processed products helps determine the production capacity of the assembly line. If the chart shows stability or continuous growth, it is a positive sign for production capacity.

Process Bottlenecks: Stages with a decrease in the number of processed products may indicate bottlenecks or areas that need improvement. Focusing on these areas can increase productivity and efficiency.

Time Management: Long waiting times between stages can lead to an overall slowdown in production speed. The chart can help identify stages that need optimization to minimize waiting time.

Thus, by using the chart illustrating the number of processed products, you can identify important factors in the production process and pinpoint areas for improvement to enhance efficiency and productivity.

The chart illustrating the number of processed products before and after machine repairs shows the quantity of defective products at each stage of the production process. It can help identify bottlenecks in the assembly line or stages with high defect rates. This could be due to material quality issues, technical issues, or process errors.

Initial Stage (Heating Machine, Plastic Molding Machine): If the chart indicates a high rate of defective products at these stages, it may signal issues with the materials or machinery. Parameters such as heating temperature, molding pressure, or other machinery-related factors may need to be checked.

Intermediate Stage (Cooling Conveyor, Inspection Station 1, Surface Processing Machine): If the number of defective products increases at this stage, it could indicate problems with the cooling or quality inspection process. The inspection and cooling processes need to be re-evaluated to ensure there are no issues with machinery or operations.

Final Stage (Painting Machine, Inspection Station 3, Packaging Machine): If the chart shows a sudden increase in the number of defective products at the end of the process, it may be related to the painting or packaging process. The painting technique, paint quality, or packaging process should be examined to identify the root cause.

In summary:

Areas for Improvement: The chart can clearly highlight areas in the production line that need improvement. Points with high numbers of defective products indicate areas where focus is needed on quality control, machine maintenance, or employee training.

Overall Efficiency: If the chart shows a gradual increase in the number of defective products at each stage, it may indicate issues in the production process leading to error accumulation. Understanding the root cause is necessary to improve the process.

Production Costs: High numbers of defective products can increase production costs due to recycling or disposal. This can affect profitability and overall efficiency of the business. The chart illustrating the number of defective products is an important tool for evaluating and improving the production process. Through careful analysis, you can identify weaknesses in the process and implement appropriate corrective measures.

4. CONCLUSION

In this study, we presented a method of information management using information technology in manufacturing to optimize processes and enhance the efficiency of industrial machinery systems. Results from the research cases demonstrate that applying information technology to production management brings significant improvements in efficiency, cost reduction, and error reduction.

Specifically, integrating sensors and data management software allows real-time monitoring of the production process, thereby facilitating the rapid detection and resolution of technical issues. Additionally, information technology-based production management systems provide automation capabilities and efficient planning, leading to reduced waiting times and enhanced flexibility in production management.

Specific research cases have shown a significant decrease in error rates when applying information technology to production management. With the examination of three test cases, we can observe the productivity and quality of the production line's output. This demonstrates that using information technology in production management not only increases efficiency but also significantly contributes to improving product quality.

In the future, this research could be expanded by applying information technology to other manufacturing processes to evaluate the effectiveness of the proposed method in different contexts. Additionally, there is a need for further research on how to use advanced data analysis tools to predict and prevent technical issues before they occur. Therefore, it can be concluded that managing information with information technology in manufacturing is not only an effective method for optimizing processes but also a crucial strategy in improving performance and competitiveness in the industrial market.

REFERENCES

[1] R. Jardim-Goncalves, D. Romero, and A. Grilo, “Factories of the future: challenges and leading innovations in intelligent manufacturing,” International Journal of Computer Integrated Manufacturing, vol. 30, no. 1, pp. 4–14, 2017.

[2]T. Lennvall, M. Gidlund, and J. Akerberg, “Challenges when bringing iot into industrial automation,” in 2017 IEEE AFRICON, Sep. 2017, pp. 905–910.

[3] M. Indri, A. Grau, and M. Ruderman, “Guest editorial special section on recent trends and developments in industry 4.0 motivated robotic solutions,” IEEE Transactions on Industrial Informatics, vol. 14, no. 4, pp. 1677–1680, April 2018.

[4] Harvard Business Review, 2017.The Enterprise Lacks a Big Data Strategy for IoT Transformation, Harvard Business School Publishing.

[5] Joch, A., Moreno, K., 2017. Data & Advanced Analytics –High Stakes, high Rewards, Forbes Insights, Ernst&Young.

6] Groggert, S., Elser, H., Ngo, Q. H., Schmitt, R. H., 2018. Scenario-based Manufacturing DataAnalytics with the Example of Order Tracing through BLE-Beacons, in: Procedia Manufacturing 24, p. 243–249.

[7] Kampker, A, Heimes, H., Bührer, U., Lienemann, C., Krotil, S., 2018. Enabling Data Analytics in Large Scale Manufacturing, in: Procedia Manufacturing 24, p. 120–127.

[8] Shearer,C., 2000.The CRISP-DM Model: The New Blueprint for Data Mining, in: Journal of Data Warehousing 5(4), p.13-22.

[9] Marban, O., Mariscal, G., Segovia, J., 2009. A Data Mining & Knowledge Discovery ProcessModel, in: Data Mining and Knowledge Discovery in Real Life Applications, p.438 –453.

[10]Wieland, U., Fischer, M., 2013. Zur methodischen Vorbereitung von Data-Mining-Projektenunter Verwendung von CRISP-DM im Kontext diskreter Produktionsprozesse, in: Tagungsbandzum fünften Workshop der GI-Fachgruppe BusinessIntelligence, p. 1613–1673.

[11] Russom, P., 2011. Big Data Analytics, in: TDWI Best Practices Report, TDWI Research.

[12]Fayyad, U.,Piatetsky-Shapiro, G., Smyth, P., 1996. The KDD process for extracting useful knowledge from volumes of data,in: Communications of the ACM 39(11), p. 27–34.

[13]Goldberg, D. E., "Genetic Algorithms in Search, Optimization and Machine Learning" (1989).

[14]Haupt, R. L., Haupt, S. E., "Practical Genetic Algorithms" (2004).