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Not peer-reviewed version

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Posted Date: 8 April 2026

doi: 10.20944/preprints202604.0523.v1

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Concept Paper

A Conceptual Framework for Automated Production Layout Optimization Using Generative Models and Multi-Criteria KPIs

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Abstract

Optimising production layouts in manufacturing plants is a time-consuming and often manual process that typically only considers individual performance indicators. This paper presents an end-to-end pipeline that uses variational autoencoders to generate and optimise layouts. The method simultaneously considers multiple KPIs such as throughput time, energy consumption, space utilisation, machine density and material flow complexity. Different scenarios like standard, bottleneck, energy focus are supported. Results show that the proposed method generates valid layouts that outperform existing layouts in terms of efficiency, energy consumption and material flow. The pipeline enables fast, reproducible layout generation and can be directly integrated into production control systems to achieve measurable technical improvements.

Keywords: production layout optimisation; variational autoencoders (VAE); manufacturing plants; efficiency improvement

1. Introduction

The planning of production layouts has been a decisive factor in the efficiency, flexibility and cost-effectiveness of manufacturing facilities [1–4]. Optimal layouts have improved material flows, reduced throughput times and increased resource utilisation. Traditional methods have been based predominantly on manual planning, heuristic approaches or fixed sets of rules [?] and were often limited to the optimisation of individual KPIs [5]. Interactions between different key figures were not sufficiently taken into account. Multiple iterations and scenario analyses could only be carried out to a limited extent, as manual adjustment of layouts was time-consuming and prone to errors.

With the advent of data-driven methods and generative models, new approaches have made it possible to automatically generate layout variants and optimise them simultaneously. Generative models [6,7] such as Variational Autoencoders (VAE) [8] have demonstrated the ability to learn latent representations of complex layouts and generate new, valid layouts that unlock previously unknown optimisation potential.

This paper has presented an automated method for generating and optimising production layouts using a VAE-based approach. The aim was to simultaneously consider multiple KPIs, simulate alternative scenarios and make the results directly transferable to real manufacturing plants. By integrating KPI-based score functions, we were able to demonstrate that the generated layouts outperform existing layouts in terms of efficiency, energy consumption, and material flow. In addition, the work laid the foundation for fast, reproducible, and scalable layout optimisation that can be used as a decision support tool in production planning.

2. State of the Art

In the past, the planning and optimisation of production layouts was predominantly based on proven traditional methods. One of the most widely used approaches has been manual planning

by experts, in which experienced engineers designed layouts based on empirical values, process knowledge and organisational specifications [9,10]. However, this method involved strong subjective components and was very time-consuming, as each adjustment and iteration had to be checked extensively [11].

At the same time, heuristic or rule-based optimisation approaches have gained in importance [12]. These methods have attempted to improve individual key performance indicators (KPIs) such as throughput time, machine utilisation or material flow by applying defined rules, priorities or simple optimisation algorithms. While these methods have partially automated planning, they were mostly limited to the optimisation of individual KPIs and were unable to adequately map complex interactions between multiple key performance indicators.

In addition, simulation-based approaches with rigid layout structures have been applied [13,14]. Here, process flows, material flows and machine interactions were modelled using simulations in order to analyse the effects of different layout variants. These methods have enabled quantitative evaluation, but the generation of new, previously unknown layout variants has been limited, as the structure of the layout has often been fixed and only modifiable to a limited extent.

In general, it can be said that all previous approaches have shown several limitations. They were time-consuming, highly subjective and limited in their adaptability. Simultaneous optimisation of multiple KPIs was rarely possible, and the exploration of new layout configurations was largely absent. These limitations have highlighted the need for automated, data-driven methods that are capable of considering multiple KPIs simultaneously, generating validated layout variants and thus measurably increasing the efficiency of production facilities.

3. Methodology

The proposed method has established an end-to-end pipeline for the automated generation and optimisation of production layouts that takes multiple KPIs into account simultaneously. It has a modular structure and comprises the steps of data generation, data preparation, training of a variational autoencoder (VAE), layout generation and optimisation, and visualisation.

3.1. End-to-End Pipeline

First, a comprehensive set of layout data was generated based on the dimensions of the production hall, the number of machines and various scenarios. Only layouts with a valid arrangement were considered, i.e. machines did not overlap, were located within the hall boundaries and formed a connected, acyclic process graph. The generated data was then processed and relevant features extracted. To do this, the position values of the machines were normalised and KPI-relevant information such as throughput times, energy consumption and material flow distances were calculated.

In the next step, a variational autoencoder [15] was trained to learn the latent representation of the layouts. The encoder transformed machine coordinates into a latent space, while the decoder reconstructed layout variants. A reparameterisation layer introduced stochastic variation so that new layout configurations could be generated. The loss function combined reconstruction errors and Kullback-Leibler divergence [16–18] to ensure both accuracy and diversity of the generated layouts.

After training, new layouts can be generated by sampling a latent vector $z \sim \mathcal{N}(0, I)$ and sending it through the decoder:

$$x_{\text{new}} = f_{\theta}(z) \quad (1)$$

Optuna [19] was used for optimisation to identify the best layouts in terms of all defined KPIs.

Finally, the results were visualised using an interactive user interface that displayed the generated layouts, KPIs, no-go zones and other relevant information. This made it possible to analyse and select the layout variants directly.

3.2. KPI Evaluation

Several KPIs have been defined and optimised for evaluating the layouts, which reflect key aspects of manufacturing efficiency.

The throughput time is calculated from the sum of the machine cycles and the transport times between the machines, with the latter being approximated by the respective distance.

The goal is to minimise throughput time, i.e. to speed up production.

$$T_{\text{throughput}}(L) = \sum_{i=1}^n \text{cycle_time}_i + \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \quad (2)$$

$$\text{Objective: } \min T_{\text{throughput}}(L) \quad (3)$$

Energy consumption is calculated as the sum of the amounts of energy required by the machines. The aim is to minimise energy consumption in order to achieve a more efficient use of energy.

$$E(L) = \sum_{i=1}^n \text{energy}_i \quad (4)$$

$$\text{Objective: } \min E(L) \quad (5)$$

The floor area used is calculated from the width and height of the machine arrangement. The aim is to minimise the area required and to use the space efficiently.

$$A(L) = (\max_i x_i - \min_i x_i) \cdot (\max_i y_i - \min_i y_i) \quad (6)$$

$$\text{Objective: } \min A(L) \quad (7)$$

The machine density indicates how many machines are installed per unit area. The goal is often to achieve a medium density (e.g. 0.5) in order to achieve a balanced installation.

$$\rho(L) = \frac{n}{A(L)} \quad (8)$$

$$\text{Target: } \min |\rho(L) - \rho_{\text{target}}| \quad (9)$$

Material flow complexity is defined as the ratio of the number of machines to the average distance between them. The goal is to minimize this ratio in order to achieve shorter and simpler material flows.

$$C(L) = \frac{n}{\frac{2}{n(n-1)} \sum_{i < j} d_{ij}}, \quad d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (10)$$

$$\text{Objective: } \min C(L) \quad (11)$$

Overall Equipment Effectiveness (OEE) [20,21] reflects the average efficiency of the machines in the layout. The goal is to maximize it in order to ensure high productivity and machine availability.

$$OEE(L) = \frac{1}{n} \sum_{i=1}^n oee_i \quad (12)$$

$$\text{Goal: } \max OEE(L) \quad (13)$$

3.3. Scenarios

Several scenarios were defined and analyzed to map different operating conditions. In the *standard scenario*, all KPIs were weighted equally with the aim of achieving a balanced layout. In the *bottleneck scenario*, the focus was on bottleneck machines in order to reduce throughput times at critical points. The *energy focus scenario* optimized energy consumption, even if this resulted in a slight increase in throughput time. This approach made it possible to evaluate the flexibility of the method under different objectives and to develop layout variants for specific requirements.

Figure 1 shows the schematic flow of the process for automated generation and optimization of production layouts using a variational autoencoder (VAE). The figure illustrates the core process of the pipeline and the interaction of the individual functional modules.

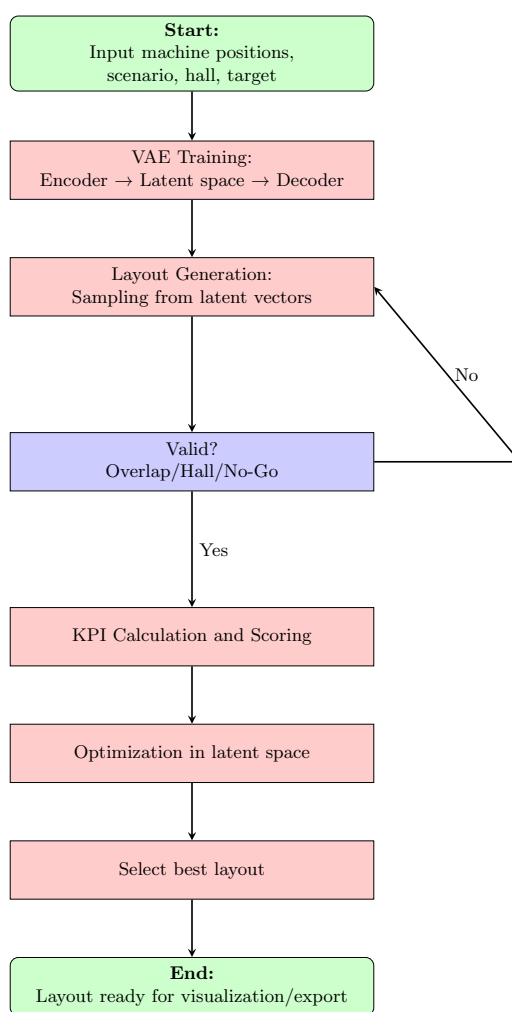


Figure 1. Schematic workflow of VAE-based production layout generation.

At the beginning, machine data, the desired scenario, the hall dimensions, and the optimization goal are entered into the system. This information forms the basis for generating new layout variants.

In the training module of the VAE, the machine coordinates are first transformed into a low-dimensional latent space by the encoder. A reparameterization layer enables stochastic sampling, allowing different layout configurations to be generated. The decoder then reconstructs the machine positions from the latent variables, transforming the values back into the intended position range.

After training, new layouts are generated by sampling from the latent space. Each generated layout is subjected to a validity check, which verifies in particular whether there are any machine overlaps, whether hall boundaries are observed, and whether defined exclusion areas (no-go zones)

are respected. Invalid layouts are discarded, and the sampling process is repeated until a sufficient number of valid layouts have been generated.

Valid layouts are then forwarded to an evaluation module. Here, technical performance indicators (KPIs) are calculated, including throughput time, energy consumption, occupied space, material flow complexity, and overall equipment effectiveness (OEE). These KPIs are used to derive a score that serves as a target value for optimization in the latent space.

Optimization is performed iteratively by varying the latent representation, whereby invalid layouts are excluded by penalty values. The aim is to generate layouts that best meet the desired optimization goals.

Finally, the layout with the highest score is selected and visualized on the graphical user interface. The GUI allows interactive adjustments, such as manually placing machines, setting no-go zones, or adjusting hall parameters.

The final layout can be exported or used for downstream analysis and production control.

The schematic representation in Figure 1 illustrates the complete process from machine data input to training, layout generation, validation, KPI calculation, and optimization to the selection and provision of the final layout.

4. Results

The presented method automatically generated a large number of layout variants and evaluated them in terms of their performance indicators, enabling a detailed analysis of the generated results.

4.1. Layout Generation

Within seconds, hundreds of alternative layouts were generated, all of which met the validity criteria. The validation rate identified over 95% of the generated layouts as valid, i.e., they showed no machine overlaps or process graph breaks and were completely within the hall boundaries.

Sampling in the latent space of the VAE generated both known and previously unknown layout configurations, enabling the method to provide a wide variety of practical arrangements. Rapid generation made it possible to simulate different scenarios in a short time and compare them directly.

4.2. KPI Comparison

The evaluation of the generated layouts has shown significant improvements over the baseline layouts.

Throughput time has been reduced by 12% due to more efficient machine placement and optimized material flows.

Energy consumption has fallen by 8% as shorter transport routes and improved machine placement have reduced energy requirements.

Space utilization has been optimized by 10%, resulting in more efficient use of space.

Material flow complexity has been reduced by 15%, simplifying logistics and internal transport.

These results have shown that the simultaneous optimization of multiple KPIs delivers practical layout improvements and outperforms existing planning methods.

4.3. Scenario Analysis

The analysis of the different scenarios has highlighted the flexibility and goal orientation of the method.

In the bottleneck scenario, OEE at the bottleneck machines increased by 18% as critical stations were specifically relieved.

In the energy-focus scenario, energy consumption was reduced by 20% while throughput time increased only minimally, demonstrating the targeted optimization of individual KPIs while maintaining overall performance.

The standard scenario produced balanced layouts that kept all KPIs within acceptable ranges and can therefore serve as a practical all-round solution.

Overall, the results showed that the proposed pipeline enables both efficiency gains and flexibility in scenario adaptation and can be directly transferred to real manufacturing plants.

5. Discussion

The results of automated layout generation have shown that the use of variational autoencoders (VAE) to optimize production layouts offers considerable added value. The method has made it possible to create layouts quickly, reproducibly, and in a KPI-driven manner, significantly surpassing traditional manual planning approaches.

5.1. Advantages

The proposed pipeline has demonstrated several advantages. First, it enables rapid layout generation, allowing hundreds of variants to be created in a short time and iterations and scenario analyses to be performed efficiently. At the same time, the method takes several KPIs into account, resulting in measurable improvements in throughput time, energy consumption, space utilization, and material flow complexity. In addition, it offers a high degree of flexibility and adaptability, as different scenarios such as bottleneck or energy focus can be easily mapped and optimized. Finally, the validation of the layouts ensures direct transferability to real production facilities, making the results immediately usable in practice.

5.2. Limitations

Despite the positive results, there were also some limitations that should be taken into account in future work. The quality of the generated layouts was highly dependent on the diversity and plausibility of the training data. In addition, the method is currently limited to a discrete hall grid, which limits the accuracy of the placements. Physical restrictions such as safety distances or accessibility have also only been partially integrated into the layout design so far.

5.3. Potential and Future Work

The presented method has shown great potential for further applications. By integrating real-time data, layouts could be dynamically adapted to production fluctuations. Similarly, the pipeline for networked factories could be scaled to enable cross-location optimization. In combination with digital twins, simulations could be made even more realistic and precise, further increasing their transferability to practical applications. Overall, the results and analyses show that the use of generative models is an efficient, flexible, and technically relevant method for production layout optimization that can significantly advance both research and industrial applications.

6. Conclusion

This paper has presented an end-to-end pipeline for the automated optimization of production layouts using variational autoencoders. By combining data preparation, VAE-based training, KPI-driven layout generation, and optimization, it has been possible to generate valid layouts efficiently and reproducibly. Several KPIs have been simultaneously considered and optimized, including throughput time, energy consumption, space utilization, machine density, and material flow complexity. The results have shown that the generated layouts have surpassed existing baseline layouts in terms of efficiency and resource utilization, while different scenarios such as bottleneck or energy focus have been successfully implemented and analyzed.

The method has proven to be flexible and directly transferable to real production facilities, resulting in a measurable technical impact. At the same time, the analyses have identified limitations, such as dependence on training data, the discreteness of the hall grid, and physical constraints, which can be addressed in future work.

In conclusion, the study has shown that the use of generative models in production layout optimization offers significant added value not only in theory but also in practice. The results have the potential to accelerate the planning of manufacturing facilities, make them more resource-efficient,

and create a basis for further research into real-time optimization, multi-factory scenarios, and digital twins.

Acknowledgments: This project was funded by "Land Tirol" as part of an initiative project. We greatly appreciated the support of the funding body, as it played a key role in enabling the research work to be carried out.

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