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Original Research

Production Plant Layout Planning Supported by Selected CAx Tools and Artificial Intelligence

Roman Wdowik *, **Artur Bełzo**

The Department of Manufacturing Processes and Production Engineering, Rzeszów University of Technology, al. Powstańców Warszawy 12, 35-959 Rzeszów, Poland; abelzoktmip@prz.edu.pl (A. Bełzo)

*Correspondence: rwdowik@prz.edu.pl

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Abstract

The paper presents production plant layout planning techniques on the basis of selected Digital Tools (DTs) utilization including generative artificial intelligence (AI). The authors studied possible techniques that can be used in production plant planning and researched their implementations on the basis of three defined production cells and lists of machine tools assigned to each cell. The usage of 2D and 3D Computer-Aided Design (CAD) software tools such as LibreCAD and FreeCAD was studied. The CAD software was applied for the design of layout using traditional CAD modelling procedures and also by the AI support. Moreover, Matlab™ software usage was presented as an alternative planning solution. It demonstrated opportunities resulting from automated code creation in the ChatGPT™. The ChatGPT™ and Visual Studio Code™ were applied as tools supporting the AI-assisted layout design methodology. The performed study revealed that artificial intelligence support and utilization of DTs may contribute to the production plant planning process by the collaborative implementation of various software DTs.

Keywords: production plant, layout planning, artificial intelligence, manufacturing system

1. Introduction

Artificial Intelligence-based (AI-based) tools are becoming popular nowadays because they help expand the boundaries of knowledge by acceleration of data exchange and data utilization. The AI-based tools have a great chance to be used in production plants together with existing Computer-Aided (CAx) tools. CAx tools are software solutions that are part of a large group of Digital Tools (DTs). It is expected and discussed in the academic community that the general efficiency of workload shall be improved by implementation of the AI. The existing results in the area of industrial applications of the AI have an impact and a positive effect on scientific communities encouraging to carry out research focused on the abovementioned complex problems such as collaborative utilization of the AI, human knowledge and skills (CampusAI, 2025) and various DTs. The analysis of available literature and capabilities of DTs reveal that the topic and scope of the paper fit current expectations of innovative manufacturing environments.

The paper of Wang et al. (Wang et al., 2024) proposed a data and knowledge driven intelligent manufacturing system (AIMS) and its functionalities that support the existing vision of the factories of the future. Wan et al. (2021) presented the extended background of the Artificial-Intelligence-Driven Customized Manufacturing Factory. In addition, Li together with co-authors (Li et al., 2017) and Elbasheer with co-authors (Elbasheer et al., 2022) analyzed in the review-based paper the applications of artificial intelligence for intelligent manufacturing. The next analyzed paper that contributes to Proceedings of the NordDesign (Disselkamp et al., 2024) studies the selected use cases of the generative AI in a factory planning. It, inter alia, presents applications of ChatGPT™ by OpenAI in production environments. The paper of Terkaj and co-authors (Terkaj et al., 2015) proposed the use of a virtual factory, continuously synchronized with the real plant. In their presented scenario, the digital counterpart of the system can be used for integrated shop floor simulations to assess the future impact of production and maintenance planning decisions.

Additionally, Janecki et al. (2024) describe the use of virtual engineering in production facility planning, and they indicate discrepancies between reality and software generated models. The paper developed by Zhang and co-authors (Zhang et al., 2019) propose a general framework and algorithms of a simulation-based approach to design an optimized plant layout and production process. Lenin and co-authors in their paper (Lenin et al., 2013) propose a genetic algorithm for constructing a linear sequence of machines that minimizes flow distance in units, investment cost of machines, and number of machine types arranged in the final linear sequence. The proposed algorithm serves as a decision support tool useful in resolving layout problems in manufacturing facilities. Mengzhen and co-authors (Mengzhen et al., 2019) present research on intelligent manufacturing and process design of intelligent workshop. In their paper, the rationalization of workshop layout and logistics are proposed. Bi and co-authors (Bi et al., 2024) study workshop layout optimization in order to reduce the transportation distance, the production cost and improve the production efficiency. In their paper, a mathematical model of workshop layout is constructed and the sparrow search algorithm (SSA) is also used to find the optimal layout that satisfies the objective function. Moreover, Flexsim software is used to simulate the layout scheme. The authors of another topic-related study (Chao et al., 2015), present in their paper a computer-aided automatic production line layout planning and performance analysis system. In addition, Schäfer and co-authors (Schäfer et al., 2024) and Tearwattanarattikal and co-authors (Tearwattanarattikal et al., 2008) present the application of a simulation model to assist decision-making on plant layout design and planning. The simulation technique discussed (by the abovementioned authors) is a tool for analyzing and testing solutions before implementation in a real system. The paper of Vernadat (2020) provides development of Enterprise Modelling, listing key references and pointing out essential modelling principles, constructs, languages, frameworks and standards. The abovementioned work points out that enterprise models are essential for the understanding, analysis, engineering, improvement, optimization, maintenance and even management and control of enterprise systems especially in the context of smart manufacturing or Industry 4.0. Lin and Fu (Lin & Fu, 2001) focus on efforts to represent the virtual factory in an analytic form to apply mathematical analyses. The paper of Lindskog and co-authors (Lindskog et al., 2016) addresses methods of the design process and its support by using virtual representations of factory environments obtained using 3D laser scanning. They use 3D laser scanning to provide an accurate and realistic virtual representation of the current shop floor area along with 3D CAD models of infrastructure. In addition, the work of Fang-ying et al. (2010) presents the concepts of a digital factory. They present an analysis of the application and integration of various software for digital factory. The digital factory is defined by them as an integrated computer-aided environment.

Moreover, products of several (various) software companies support the idea of production plant planning. For instance, the Autodesk™ software solution (Autodesk Factory Design™, 2024) indicates a variety of tools that allow for layout planning and optimization. For instance, a standard equipment library is available and these objects can be easily implemented to build a virtual environment together with self-made 3D models. Another option is provided by the DELMIA 3D Virtual Factory by Dassault Systèmes (Dassault Systèmes, 2024) that offers 3D modelling of industrial areas and processes. Also, The Siemens TECNOMATIX Plant Simulation (Siemens, 2024) solution also supports complex planning tasks. The existence of these tools proves that software developers invest in solutions that enable layout planning.

The presented literature review and growing importance of AI support in engineering triggered the efforts to look for new layout planning methodologies supported by AI and discuss with scientific community their real value at this stage of AI development. In this contexts, the presented study gives an overview of chosen techniques (called approaches) which can be used in production plant layout planning, presents their application and selected strengths and weaknesses. Moreover, the applications and definitions of selected parameters describing layout planning are discussed by authors of the study.

2. Experimental data and comparison of production plant planning approaches

This section presents experimental data and compares analyzed planning approaches. Table 1 presents exemplary dimensions of machine tools which are placed in the analyzed production plant. Three production cells are established representing different machining processes (turning, milling and grinding). The values of dimensions of machines are not taken from existing technical data, however, they are proposed for the study taking into account dimensions similar to the existing machine tools in order to preserve geometrical dependence of their dimensions to the dimensions of designed factory area. Moreover, for the aims of the study, authors assumed that the number of machines placed in one production cell is the same, however, this should not be assumed as industrial standard and it may vary. The production plant dimensions (area of production plant) are represented by a rectangular prism having dimensions of 70 m × 50 m × 4 m.

Table 1. Geometrical dimensions of CNC machine tools placed in the production plant which are applied in the study.

Test no.	Lathe production cell, length × width × height (m)	Milling machine production cell, length × width × height (m)	Grinding machine production cell, length × width × height (m)
1	3 × 1.5 × 1.8	3 × 3 × 2	3 × 1.5 × 1.5
2	3 × 1.5 × 1.8	3 × 3 × 2	3 × 1.5 × 1.5
3	3 × 1.5 × 1.8	3 × 3 × 2	3 × 1.5 × 1.5
4	2 × 1 × 1.5	3 × 2.5 × 2	2 × 1 × 1.5
5	2 × 1 × 1.5	3 × 2.8 × 2	2 × 1.5 × 1.5
6	2 × 1 × 1.5	3 × 2.8 × 2	2 × 1.5 × 1.5
7	3 × 2 × 1.6	4 × 4 × 2	3 × 2 × 1.5
8	3 × 2 × 1.6	5 × 4 × 2	3 × 2 × 1.5
9	3 × 2 × 1.6	5 × 5 × 2	3 × 2 × 1.5
10	4 × 2 × 2	4 × 3 × 2	3 × 2 × 2

Four approaches applicable to layout planning are presented in the following sections. They propose selected areas of AI implementation and collaborative data exchange useful in a production plant layout planning which can be utilized by planners.

2.1. Approach 1 – utilization of CAD software and manual layout of machine tools

This traditional approach allows to create a 3D assembly model of a production plant in CAD environment. 3D solid models of machine tools are created separately in the module supporting a part design and assembled by the use of the dedicated assembly tools. The placement of each machine tool is defined by a CAD user who manually arranges the layout details. Machine tools can also be easily moved and their location adjusted to specific requirements. Dimensions of the machines, distances between them or transportation details inside the plant can also be included. Figure 1 presents an exemplary layout developed on the basis of the defined dimensions. Three production cells were manually designed in three corners of the plant. The CAD models representing machine tools were created separately and the assembly was composed in the CAD module of the SolidWorks™ CAD software tool. Although this is a traditional approach and well known to CAD designers, it allows for manual adjustments to all required plant data.

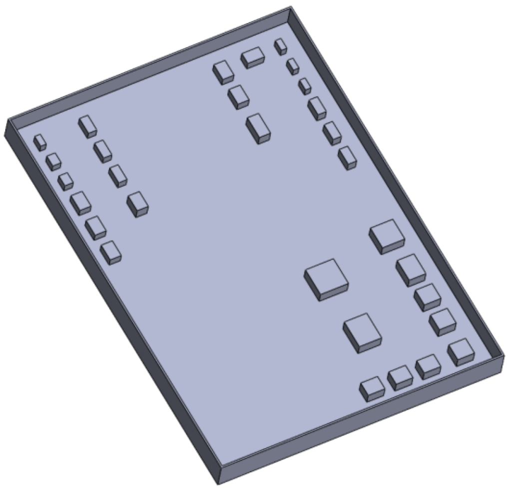

Fig. 1. CAD model of the production plant developed in the SolidWorks™ software.

New components can also be designed and assembled together with machines. Moreover, technical drawings can be developed using a dedicated module. This scenario requires any CAD software tool supporting the abovementioned requirements, hence, there is no need to install additional modules dedicated for factory layout planning tasks.

Nevertheless, additional layout planning capabilities are available if a dedicated module for the factory design such as the module offered by Autodesk™ is installed. For example, this enables designers to place additional 3D components existing in an available library such as furniture, shelves, robots, production lines, etc. Available tools of the module simplify planning details and help to optimize the entire manufacturing environment. The exemplary application of such a layout planning module is presented in Figure 2.

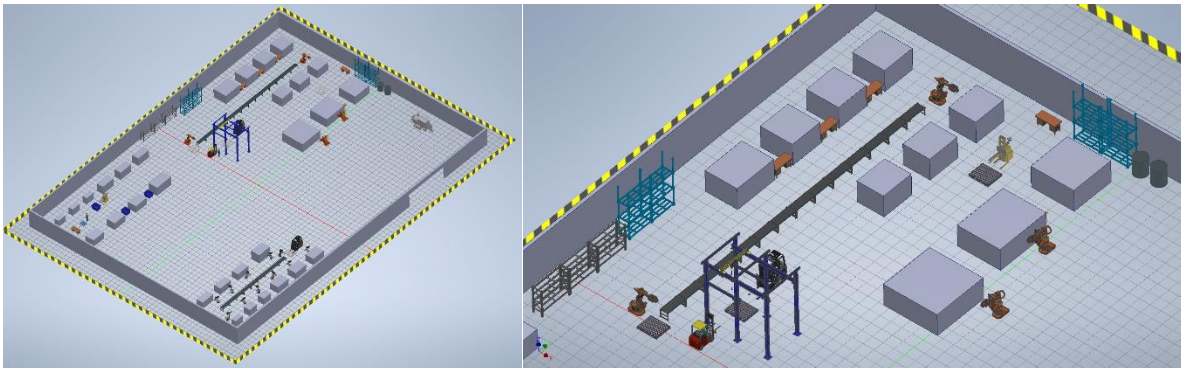

Fig. 2. Exemplary layout designed in the Autodesk Factory Design™.

2.2. Approach 2 – utilization of AI, Python programming environment and 2D CAD software

The second approach is based on the generative artificial intelligence utilization. The Python (Python, 2024) library *ezdxf* was used to generate **.dxf* files containing the developed layout of machine tools. The Python code was created on the basis of prompts developed in the ChatGPT™ by OpenAI (ChatGPT™, 2024) and tested/adjusted in the Visual Studio Code™ (2024) afterwards. It is presented in the Figure 3. The prompts pointed out the information about the required distance of 2 meters between machines. Moreover, the dimensions of machines were uploaded to the ChatGPT™ from the separate **.xlsx* file according to the Table 1. The several exemplary production cells graphical representations were obtained on the basis of requests (prompting) before the final acceptance of the factory layout. That layout shall be accepted by a planner who decides about the result which is best fitted to planner's general expectations and planning requirements.

```
def draw_machines(msp, start_x, start_y, specs, machines_per_row):
    for i in range(num_machines):
        x = start_x + (i % machines_per_row) * (specs["length"] + machine_spacing)
        y = start_y + (i // machines_per_row) * (specs["width"] + machine_spacing)
        msp.add_lwpolyline(
            [
                (x, y),
                (x + specs["length"], y),
                (x + specs["length"], y + specs["width"]),
                (x, y + specs["width"]),
                (x, y),
            ],
            close=True,
            dxfattribs={"color": specs["color"]},
        )
```

Fig. 3. Part of the Python code created by the ChatGPT™ to generate **.dxf* file (code lines used for creation of the layout).

The exemplary result (Fig. 4) generated after Python code execution in the Visual Studio Code™ was opened by the use of 2D CAD software. The LibreCAD software (LibreCAD, 2024) was used as CAD software. Although the obtained layout is a quite simple representation, it meets the basic requirements and allows for further changes in the CAD software. The black rectangle represents the factory area while blue, green and red rectangles represent the proposed (by the ChatGPT™) layout within three designed cells. As stated above, the LibreCAD software (or any 2D CAD software tool) allows the geometry to be edited and adjust manually to the designer's requirements as well. Nevertheless, basic rectangles representing machines were created very quickly on the basis of input data from the **.xlsx* file. Moreover, the reached 2D layout representation requires further design of additional views in order to present height of each machine.

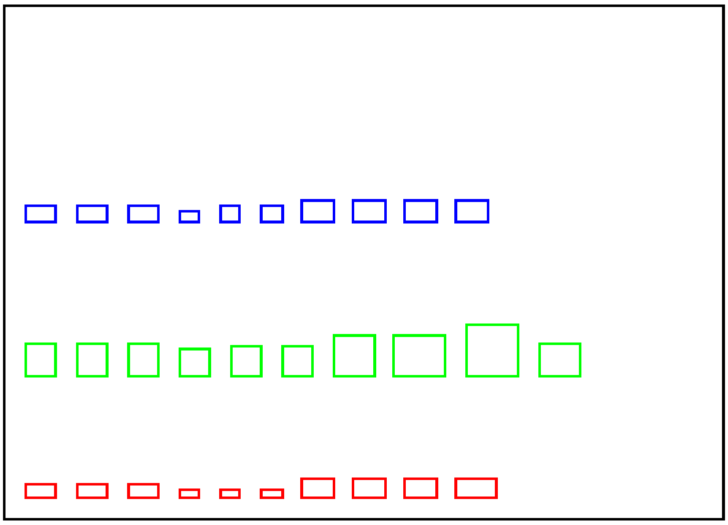

Fig. 4. The results obtained in the LibreCAD after the **.dxf* file import.

The Python code generated by the ChatGPT™ (2024) as a result of prompting attempts is presented in the Table 2. The authors present it as an exemplary result. The authors ran the chat by several various prompts until the final result presented in the table was obtained. The dimensions of machines were uploaded by using **.xlsx* file as it was mentioned above. The full chat is available on ChatGPT™ (2025a).

Table 2. The Python code generated by the ChatGPT™ as a result of authors' prompting.

```
import ezdxf
# Other parameters
machine_spacing = 2  # Distance between machines (2 meters)
cell_spacing = 10  # Distance between production cells (10 meters)
wall_margin = 2  # Minimum distance from the factory walls

# Factory hall dimensions
hall_length = 70  # meters
hall_width = 50  # meters
# Machine dimensions (previously read)
lathe_dimensions = [
    [3.0, 1.5, 1.8], [3.0, 1.5, 1.8], [3.0, 1.5, 1.8],
    [2.0, 1.0, 1.5], [2.0, 1.0, 1.5], [2.0, 1.0, 1.5],
    [3.0, 2.0, 1.6], [3.0, 2.0, 1.6], [3.0, 2.0, 1.6], [4.0, 2.0, 2.0]
]
milling_dimensions = [
    [3.0, 3.0, 2.0], [3.0, 3.0, 2.0], [3.0, 3.0, 2.0],
    [3.0, 2.5, 2.0], [3.0, 2.8, 2.0], [3.0, 2.8, 2.0],
    [4.0, 4.0, 2.0], [5.0, 4.0, 2.0], [5.0, 5.0, 2.0], [4.0, 3.0, 2.0]
]
grinding_dimensions = [
    [3.0, 1.5, 1.5], [3.0, 1.5, 1.5], [3.0, 1.5, 1.5],
    [2.0, 1.0, 1.5], [2.0, 1.5, 1.5], [2.0, 1.5, 1.5],
    [3.0, 2.0, 1.5], [3.0, 2.0, 1.5], [3.0, 2.0, 1.5], [3.0, 2.0, 2.0]
]

# Create DXF document
doc = ezdxf.new()
msp = doc.modelspace()

# Function to draw machines in a production cell
def draw_machines(msp, start_x, start_y, dimensions, color):
    x, y = start_x, start_y
    max_row_height = 0  # Maximum height of machines in the current row
    for machine in dimensions:
        length, width, _ = machine
        # Draw machine as a rectangle
        msp.add_lwpolyline(
            [
                (x, y),
                (x + length, y),
                (x + length, y + width),
                (x, y + width),
                (x, y),
            ],
```

```
            close=True,
            dxfattribs={"color": color},
        )
        # Update position for the next machine
        x += length + machine_spacing
        max_row_height = max(max_row_height, width)
        # If exceeding factory length, move to a new row
        if x + length + wall_margin > hall_length:
            x = start_x
            y += max_row_height + machine_spacing
            max_row_height = 0
    return y + max_row_height - start_y  # Returns total cell height

# Draw the factory hall boundary
msp.add_lwpolyline(
    [(0, 0), (hall_length, 0), (hall_length, hall_width), (0, hall_width), (0, 0)],
    close=True,
    dxfattribs={"color": 7},  # White color for factory boundary
)
# Arrange production cells
y_offset = wall_margin
cell_colors = [1, 3, 5]  # Colors: lathes - red, milling machines - green, grinders - blue
cell_dimensions = [lathe_dimensions, milling_dimensions, grinding_dimensions]
for dimensions, color in zip(cell_dimensions, cell_colors):
    cell_height = draw_machines(msp, wall_margin, y_offset, dimensions, color)
    y_offset += cell_height + cell_spacing
# Check if all cells fit within the factory
if y_offset > hall_width - wall_margin:
    raise ValueError("Production cells do not fit within the factory hall!")
# Save the DXF file
dxf_file_path = "factory_layout_variable_dimensions.dxf"
doc.saveas(dxf_file_path)
print(f"DXF file has been saved as: {dxf_file_path}")
```

2.3. Approach 3 – utilization of AI and 3D CAD software

The Python-based code may also be directly utilized in the existing Python console of the FreeCAD software (FreeCAD, 2024). The newest stable version 1.0 of this open source FreeCAD software has been recently (November 2024) released. The prompts lead to creation of the Python code which can be implemented in the Python console and it enables designers to create the layout very quickly in the software (Fig. 5). However, similarly to the previous approach (Approach 2) a user needs to experiment with prompting to achieve the best results. In the case of the presented example the prompt contained requests similar to those implemented in Approach 2, however, the final code was utilized for creation of 3D models placed in the production plant. Also the difference between this approach and the previous one exists - here the basic CAD model is generated in the CAD software while in the 2nd approach it was generated by the use of the appropriate Python library in the Visual Studio Code^{TM}. It is also noticed that the layout is not the same as in the previous approach but existing CAD tools allow to make the desired changes such as shifting of machine location, rotations and other necessary changes to the 3D model.

Similarly to the Approach 2 the full chat regarding the Approach 3 is available on ChatGPT^{TM} (2025b).

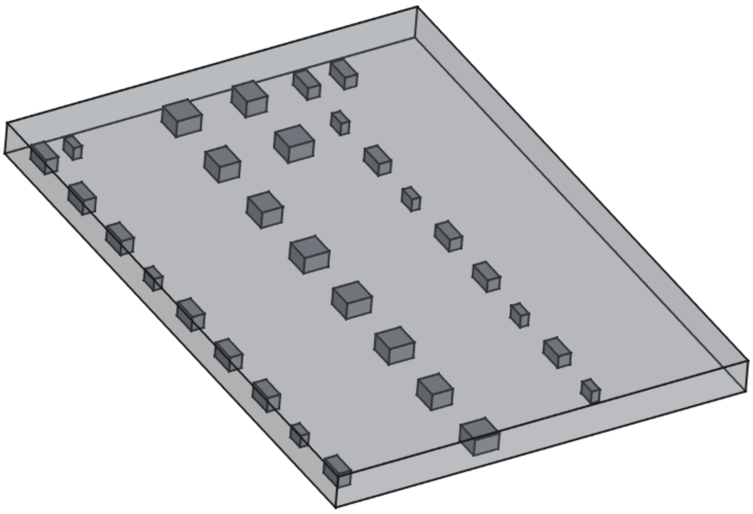

Fig. 5. Properly generated model of the production plant and machine cells created in the FreeCAD software on the basis of prompting.

2.4. Approach 4 – Utilization of the Matlab™ software

This approach, leading to a visual representation of the production layout, utilizes plotting tools in the Matlab™ software (Matlab™, 2024). An exemplary plot is presented in the Figure 6. The Matlab™ software-ready code can be generated by the use of artificial intelligence (ChatGPT™ by OpenAI was used) and directly pasted/edited in the Matlab™ environment. Several tests in that area revealed that if the code is properly formulated than the final plot shall be correctly generated too. However, authors obtained quite a few wrong layouts before an acceptable one. It is not possible to change the fundamental and substantive results of visualization without changing the code. A possibility of direct height visualization is a positive results within that approach.

The chat is available on the webpage ChatGPT™ (2025c).

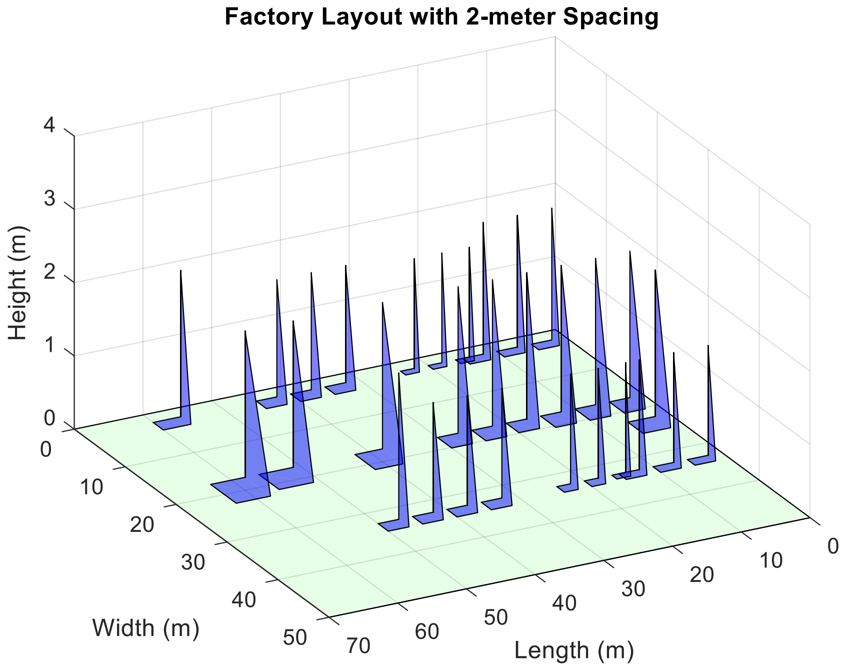

Fig. 6. Exemplary layout obtained in the Matlab™ software.

2.5. Comparison of used approaches

The Table 3 compares the approaches and presents their strengths and weaknesses. The analysis of the table leads to some general conclusions regarding the used approaches:

1) AI accelerates creation of the layout tentative proposals, however, it often requires several reps (prompting attempts) to achieve an accepted final result.
2) 3D visualization seems to be more effective in the case of 3D analysis of any production plant because it displays three dimensional environment, however, 2D layout is sufficient in many cases such as placing machine tools on the available area of a production plant.
3) The utilization of 3D model creation by the use of AI and Python code automates the 3D visualization. Moreover, existence of Python console in the software such as FreeCAD simplifies 3D assembly creation.
4) There is still a need of advanced training for designers who would like to design complex layouts because AI-supported results may require some changes.

Table 3. Selected pros and cons of the proposed approaches.

Approach 1 *Traditional CAD or/and layout module*	**Approach 2** *AI, Python and 2D CAD software*	**Approach 3** *AI, Python and 3D CAD software*	**Approach 4** *AI, Matlab™ software*
Main Pros: - Enabled detailed construction, - Full layout control, - Existing libraries utilization. **Main Cons:** - Longer time of design process (no AI support), however, macros may be also utilized.	**Main Pros:** - Simple 2D visualization - Fast code and **.dxf* file creation, - Open source 2D CAD software (or simple commercial) utilization even for less experienced users. **Main Cons:** - AI-based errors may occur.	**Main Pros:** - 3D visualization, - Fast code and model production and possible improvements in CAD environment, - Open source software utilization. **Main Cons:** - AI-based errors may occur, - Knowledge and skills are required to operate in the 3D CAD environments.	**Main Pros:** - Plot-based visualization - Fast code and model production **Main Cons:** - AI-based errors may occur, - Difficult reconfiguration without code changes, - Software license requirement.

It can be stated that every approach presented in the paper can be used in production plant layout planning. Traditional CAD environments still allow to use various, well-developed tools that support existing CAD design methodology which is based on a designer's vision, layout requirements (input data) and steps performed in the software by a designer. In the case of AI and utilization of prompting in chats the main role of a designer is to focus on the appropriate information that will be given in a prompt. Prompts may also have attachments such as text or data file. In some cases, several attempts are required to obtain the satisfactory final result. However, with many machines and existing dimensional data, the CAD model or plot creation process may be accelerated leading to the overall design time reduction. The examples of layouts presented in the paper confirm this statement. It shall be also noticed that existing CAD tools support changes of models even if only simple models of machines can be effectively generated by the AI. For instance, necessary changes of CAD model geometry such as a rotation of an element, moving from point to point in the coordinate system, scaling (enlarging or reducing dimensions), layering (assigning the designed layer features to elements of CAD geometry) and other similar CAD model changes may be implemented. Moreover, the basic knowledge in the area of Python programming and console operating is required to execute the code properly and save the results.

In the case of very complex layouts of production plants, and at this stage of generative AI-supported tools development, authors would like to recommend to divide the entire factory layout design into smaller parts which could be easier to be described in prompts and in the next step to add (by the use of existing tools) the separate results for in CAD environment.

3. Proposed parameters describing layout planning process and their application for studied approaches

In order to extend knowledge about possible areas for further analysis the authors would also like to propose the selected parameters (Table 4) that can be assigned to the approaches in order to describe their general characteristics and describe the design process not only by qualitative indicators but also by quantitative ones. Their characteristics and general definitions are developed within sections 3.1 ÷ 3.4.

Table 4. List of selected parameters linked to the production plant layout reconfiguration process.

Parameter no.	Parameter name and designation	Parameter unit
1	Reconfiguration time, t_r	second, s
2	Reconfiguration cost, c_r	Euro, Eur
3	Experimental number of reps, r_n	number
5	Reconfiguration criteria number, n_c	-

3.1. Basic model reconfiguration time (t_r)

Basic model reconfiguration time (t_r) is counted from the beginning of the reconfiguration process to its completion. The basic configuration of layout is required to be defined as satisfactory, however, requiring further changes. In the case of the CAD software it is devoted to the time of manual changes of the basic configuration. It also involves utilization of AI-based tools, prompts preparation, data transfer and a test run in the software. It can be stated that the decreased time of reconfiguration process improves overall process efficiency before the implementation in the production plant.

3.2. Reconfiguration cost (c_r)

Reconfiguration cost (c_r), calculated on the basis of Eq. (1), is directly linked to the expenses related to the reconfiguration of the basic project. Among others, it involves software cost (c_s), AI-based tool cost (c_{AI}), remuneration of a planner (c_p), energy consumption cost (c_e) and other costs (c_o). In authors opinion, at this stage of broadly-available AI tools there is a need for research focused on this matter and individual cost analysis performed on every single example in necessary.

$$c_r = c_s + c_{AI} + c_p + c_e + c_o \quad (1)$$

3.3. Experimental number of prompting reps (r_n)

Experimental number of reps (r_n) concerns a number of unsuccessful code generation reps plus the final one successful prompting. It is linked to the AI-tool, such as ChatGPT by OpenAI, usage only. It should be also stated that prompting methodology is a desired area for future research.

3.4. Reconfiguration geometrical criteria number (n_{gc})

Reconfiguration criteria number (n_{gc}) is calculated based on geometric parameters that affect the layout of machine tools. The following parameters may be considered: distance between machines, required space over them, distance from walls and other equipment, plant geometry, machine tools geometry, placement on the floor, etc.

4. Discussion of the results

Presented approaches regarding layout planning allow to create correct layouts, however, the best designer control over the process can be reached during manual planning or after reconfigurations of the basic AI-supported layout proposals. In authors' opinion and from the industrial application point of view the most complicated is the approach that utilizes Matlab^{TM} software, because layout changes are reachable only by reprompting in the ChatGPT^{TM}. It has an impact on the total reconfiguration time linked to the reprompting process. For other approaches, at the current stage of development of large language models (LLMs) in AI, it is very difficult to assess whether the application of automated layout planning using AI brings only beneficial results. However, the authors were able to generate the basic layouts according to the expectations indicated in the prompts. Moreover, these basic layouts can be changed.

The parameters proposed in the section 3 shall be measured and analyzed taking into account the defined example. Basic model reconfiguration time *(t_r)* (Fig. 7) may be linked to all studied approaches. In the case of manual CAD design (please refer to Approach 1, Section 2) it consists of time necessary for feedback collection and necessary changes implementation such as rescaling, replacing, reshaping the basic layout elements. In fact, these changes and the time linked to them depend strongly on a designer's assumptions and needs resulting from feedback analysis and skills of a designer. It should also be taken into account that due to the designer's awareness of the company's expectations, reconfiguring a manually prepared basic layout may be easier than rebuilding a layout proposed by AI – even if prompts are created by humans. In this context, the additional time used for the major changes can be quite short compared to other approaches, however, the final time depends on the characteristics of layout.

Reconfiguration cost *(c_r)* is analyzed as a parameter linked to the financial effectiveness of the entire layout planning process. The tools such as chats which are based on language models require at this stage quite small financial contributions. In the authors' opinion the main difference can be considered for the remuneration of a planner. Longer reconfiguration time leads to the cost increase in that context.

Experimental number of prompting reps *(r_n)* is a parameter that characterizes the approaches that utilize the artificial intelligence and large language models (LLMs). A person who uses these approaches actually does not know the result of the prompting process and this experimental number may vary depending on the prompting skills and LLM architecture.

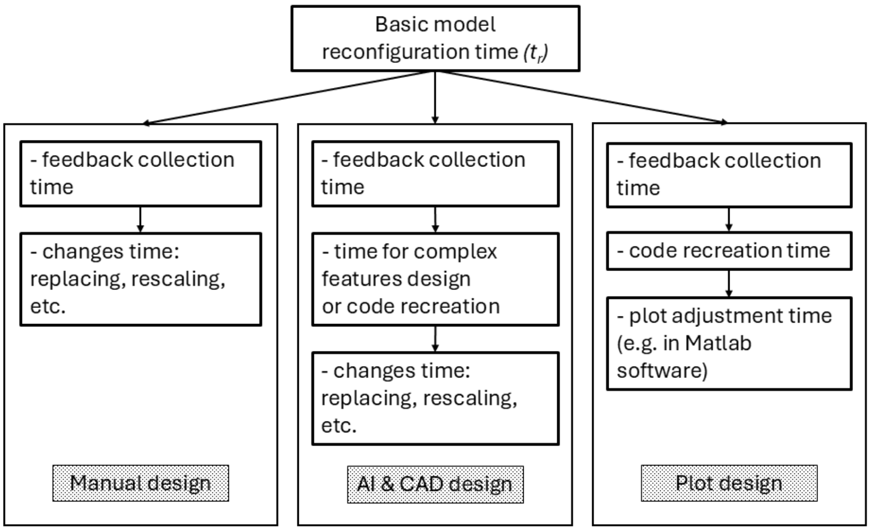

Fig. 7. Basic model reconfiguration time (t_r) analysis for studied approaches.

Reconfiguration geometrical criteria number (n_{gc}) is mostly linked to the AI assistance and these criteria shall be implemented in prompts, however, also in the case of a manual design a designer shall define the criteria used in the process.

5. Conclusion

Presented techniques linked to factory layout planning can be successfully used within the process of factory planning. There are individual characteristics of presented approaches as well as their individual pros and cons. The use of AI (in this case text conversation e.g. with the ChatGPT™) has a great perspective in terms of layout planning automation, however, further research is needed in the area of prompting methodology. Simpler layouts limited to machine tools can be easily and efficiently prepared with further correction possibilities. Moreover, software-AI collaborative approaches enabling fast and effective data exchange could improve planning process. It is also necessary to develop and continuously research quantitative indicators helping to describe planning process efficiency, however, in authors' opinion, at this stage of AI progress, the final results regarding indicators can be analyzed only on the basis of specific layout examples. Future research will be focused on the abovementioned issues along with the research on applications of various LLMs from different software firms.

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Artificial Intelligence usage statement

ChatGPT™ by OpenAI was used to generate Python code lines. Sentences presented in the paper were developed by authors. Figures were captured as print screens in the CAD software (Figs. 1, 2 and 5), in the Visual Studio Code™ (Fig. 3), exported from the CAD software as image (Fig. 4) or Matlab software (Fig. 6) or developed by authors using PowerPoint™ software (Fig. 7). Table 2 content was generated by the ChatGPT™ on the basis of authors' prompting.

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Projektowanie Położenia Maszyn na Hali Produkcyjnej Wspomagane Wybranymi Narzędziami CAx i Sztuczną Inteligencją

Streszczenie

Artykuł przedstawia proces projektowania rozmieszczenia maszyn na hali produkcyjnej, w którym wykorzystuje się wybrane programy komputerowe oraz generatywną sztuczną inteligencję (SI). Autorzy przedstawili możliwe techniki, które mogą być wykorzystane podczas projektowania oraz poddali analizie ich zastosowanie na podstawie trzech gniazd produkcyjnych z uwzględnieniem listy obrabiarek. Zastosowano oprogramowanie CAD 2D oraz 3D (LibreCAD i FreeCAD). Oprogramowanie CAD zastosowano w procesie projektowania położenia modeli maszyn – zarówno w sposób tradycyjny jak i uwzględniający sztuczną inteligencję. Przedstawiono także alternatywne wykorzystanie programu Matlab™. ChatGPT™ oraz program Visual Studio Code™ wykorzystano jako narzędzia wspomagające projektowanie położenia maszyn przez wykorzystanie sztucznej inteligencji. Oprogramowanie Matlab™ umożliwiło zautomatyzowane opracowywanie wykresów przedstawiających położenie maszyn. Przedstawiona analiza uwidoczniła możliwości zintegrowanego wykorzystania różnych narzędzi w procesie projektowania ich rozmieszczenia na hali produkcyjnej. Dodatkowo zaproponowano w artykule wybrane parametry opisujące ilościowo proces projektowania rozmieszczenia maszyn na hali produkcyjnej.

Słowa kluczowe: hala produkcyjna, projektowanie rozmieszczenia maszyn, sztuczna inteligencja, system wytwarzania