Intelligent planning process with adaptive quick response system for low volume manufacturing

John Frederick Dcoutho[1*], Akhlaqur Rahman3[3], Boris Eisenbart[2] and Ambarish Kulkarni[1]

[1*]School of Engineering, Swinburne University of Technology, John Street, Hawthorn, 3122, Melbourne, Australia.
[2]Department of Industrial and Architectural Design, Swinburne University of Technology, John Street, Hawthorn, 3122, Melbourne, Australia.
[3]School of Industrial Automation, Engineering Institute of Technology, Melbourne, 3000, VIC, Australia.

*Corresponding author(s). E-mail(s): jdcoutho@swin.edu.au;
Contributing authors: akhlaqur.rahman@eit.edu.au;
beisenbart@swin.edu.au; ambarishkulkarni@swin.edu.au;

Abstract

The automotive manufacturing industry in recent years has seen a paradigm shift in production. Increased customer individualization demands and shorter product life cycles have become the norm in the market. Traditionally, production planning methods in this sector are based on high volumes; thus, production lines used to be relatively rigid. With the current demand for individualized low-volume production, the line must be altered frequently, leading to increased downtime and additional cost. This shift in automotive manufacturing requires production planning to cater to faster, cost-effective adoption to changing low-volume individualized demands. This research discusses a novel Intelligent Planning Process (IPP) to address low-volume individualized manufacturing. The IPP model harnesses transformative technologies such as extended reality (xR) to facilitate faster and more adaptive planning. Further, artificial intelligence is embedded through xR models using various response nodes (e.g., quick response)

This provides a critical advantage in developing and evaluating multiple production layouts with considerably reduced efforts. A case study on positioning preloaded planning data to the real world with quick response nodes resulted in one-fourth of the time required by manual interactive positioning of physical assets. In addition, real-time control and synchronous optimization were other intangible outcomes.

Keywords: Production Planning, Low Volume, Individualized Product, Digital Twin, Extended Reality, QR Code Tracking.

1 Introduction

The automobile industry has been an integral part of both industrial and economic development in the global market. However, it is currently facing the need to cater to increased individualized customer demands. The automotive manufacturers must react swiftly to this increasing trend to stay competitive in the future market. This transformation in trends is pushing the automotive industry to its next evolution. But the challenge is to transition from mass manufacturing to low-volume customization without the high cost, time, or quality implications. The solution to specific demands is adopting an intelligent and adaptive production planning technique.

Customization is not an entirely new concept in the manufacturing industry. However, its effective and efficient implementation remains a challenge [1]. Even though automation makes modern manufacturing advanced and effective, human operators are still considered the epitome of flexibility and adaptability. Hence, human resources are an essential component in customized manufacturing to obtain high productivity, and quality [2]. The mass manufacturing techniques depend on repetitive automated systems for increased productivity. Therefore, it is vital to develop an intelligent system that is flexible as humans and efficient as machines to expedite customization. Current production environments are focused on mass manufacturing that deals with deterministic demands [3]. It cannot accommodate low volume individualized production without cost and time implications [4]. This indicates that production planning and processes need to be adaptable and intelligent compared to the rigid mass manufacturing techniques to implement customization without additional expense and production downtime.

Approximately 70% of final production costs are established in the conceptual stage, which involves critical decision-making. Validating the production plan for correctness in a simulated environment replicating the real world can help in accurate judgement [5]. A validated production plan can confirm the efficiency of the production line before its implementation. Traditionally, manufacturers use physical assets, including cardboard structures and physical prototypes, to create a mock-up of the workstations for validation. This process is time-consuming, inefficient, data-intensive, and thus costly to the manufacturer [6]. To develop an efficient and optimized factory layout, the functioning of the factory must be tested based on the user experience, data analysis, validations, and practical verifications. Without optimizing the factory plan, customization implementation cannot be successful. Innovative technologies, including Virtual Reality (VR), additive manufacturing, and Digital Twin (DT), are crucial to obtaining an efficient, customized manufacturing system [1]. The increased demands for individualized products and the various manufacturers' offers make it difficult to forecast and manufacture product demands without additional cost. Additionally, global issues involving disrupted supply chains and worsening energy crises create uncertainties for the manufacturing industry. Therefore, reconfiguring factory layouts and shuffling assembly sequences is inevitable for the manufacturing industry for smooth production.

The factory layouts are influenced by machine layout, inventory settings, machine capability, walkway design, warehouse material flow, etc. Any changes to the factory layout may have cost overruns, quality problems, and low equipment utilization [7]. One of the main issues in production planning is equipment positioning [8]. The diversified need of customers can lead to a prolonging development cycle and an increase in complexity. But the manufacturing industry is required to adapt to this new customer pattern. According to Kuo et al. [9], a company must undertake a market needs evaluation and create a model to fill the identified gap in incorporating customer needs. There is hardly any involvement of customer demands with manufacturers' Product Data Management (PDM) to evaluate factory changes.

Based on the limitations of the existing literature, our contributions to this manuscript are as follows:

- We propose an intelligent production planning framework that is capable of fast-tracking low-volume customized production. The framework incorporates extended reality techniques to couple product data, factory layout, and process data through an integrated data management system.
- We propose an enhanced data model that is dedicated to the visualization of the factory layout with quick changeovers for merit studies.
- We further incorporate a QR code tracking technique to the virtual assets for quick changeover between workstations.
- Finally, we implement a link between the virtual data and the real-world environment using QR code markers to position the pre-planning model and track layout changes in the real world.

The rest of the paper is organized as follows. Section 2 discusses relevant automotive industry production planning practices. Section 3 proposes the intelligent production planning framework incorporating transformative technologies to visualize and couple different data models that optimize customized, low-volume production plans. Section 4 discusses preloading and tracking the position of virtual content to designated real-world environments using quick response nodes. Finally, Section 5 concludes with a summary and discussion of potential future work.

2 Current Automotive Industry Practices

The societal paradigm shift has compelled the automotive industry to shift from the traditional manufacturing model to meet individualized demands [10]. The current market is transitioning from deterministic to probabilistic forecasting due to the fluctuating customer demands. The industry must be highly responsive with a critical focus on cost, quality, and flexibility to swiftly react to individualized customer demands. The industry's objective is to provide high-quality, individualized products to customers at a short lead time, matching the low-cost mass manufacturing techniques [8]. Mass manufacturing production line is rigid and can lead to large downtime and project delays when manufacturing new product variants [11]. These lines are focused on repetitive products and techniques, which isn't the case with individualized products. The automotive manufacturing line consists of multiple components or subsystems, including workers, procedures, facilities, data, suppliers, and technologies. All these factors influence the operations and efficiency of the manufacturing line, making change a complex task. These systems are interlinked, which requires an efficient data management system to optimize factory layouts [12].

2.1 Traditional Planning Process

Production planning is the system of putting together the settings to control the resources required to meet the expectations. The fundamental objective of production planning is to make decisions that help obtain maximum profit at minimum cost to provide customer satisfaction. Multiple production planning tools such as Advanced Planning and Scheduling Systems (APS) and Enterprise Resource Planning (ERP) are utilized to solve planning issues for mass manufacturing industries. Various research discusses production planning and proposes numerous strategies to support operations management. Garcia-Sabater et al. [13] discussed Mixed Integer Linear Programming (MILP) mathematical models to integrate production with logistics planning for production leveling. This technique lack interfacing between PDM and factory layout that can trigger an update mechanism and spot critical workstation revamping.

A seamless production plan requires integration between factory data, machines, operators, and material handling systems. Existing Autonomous Guided Vehicles (AGV) fleet management system cannot function efficiently in a flexible factory layout without real-time data tracking of the factory [14] making customized product picking a complex task. The current fixed production line with conveyor systems is unsuitable for customized production. Existing manufacturing processes emphasize improving the efficiency of the equipment. There is limited flexibility in terms of the arrangement and layout of the equipment. Rezig et al. [15] state that it is challenging to maintain a balance between productivity and flexibility. Changing factory layouts for certain automotive manufacturers is difficult as their production lines define them. Implementation of customized products into their production line requires redesigning, which can lead to downtime and reduction of productivity.

2.1.1 Customization and Complexity

The automotive industry has been following mass manufacturing techniques since its conceptualization by Henry Ford [16]. The traditional production planning and mass manufacturing techniques are unsuitable for low-volume individualized product manufacturing as they are focused on repetitive processes and preclude customization [17]. The mass manufacturing automotive companies are closely monitoring the increase in demand for individualized products in the market. They are gradually transitioning towards customization, and this shift poses several challenges to the industry. With the introduction of numerous product variants, the production process becomes complex leading to planning issues for several layout modules shown in Fig 1.

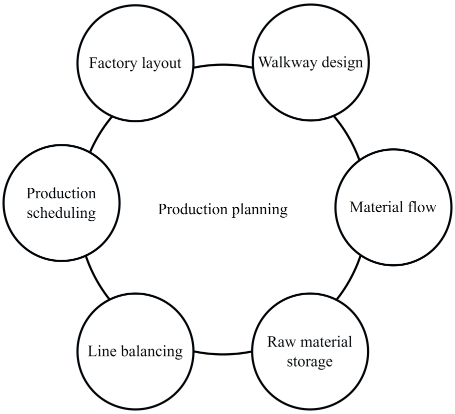

Fig. 1 Production planning modules

Volling et al. [18] point out that the automotive industry is moving from built-to-stock to built-to-order models. In the automobile industry, complexity is the variety and complexity involved within the product's system, subsystem, or structure. Complexity is driven by product variables and process variability, increasing product or process cost. These driving forces result in not just physical modification of the product, but a revamp of the whole process, including the logistic flow of the components. Furthermore, globalization plays a critical role in instigating complexity drivers due to the changing demand and the number of variants offered to the customers [19]. The product variants provided to the customers add complexity to the existing production line. This demonstrates that introducing a large variety of complex products without an intelligent and flexible manufacturing technique can escalate complexity in the conceptual and planning stages [20].

2.2 Low Volume

Automotive manufacturers with an annual production volume of fewer than 500 units with make-to-order production plans are classified as low volume manufacturers [20]. Systems that provide highly customized products, in low volume, with long delivery times are generally termed, intermittent production models. Individualized products are specific and are not produced in large volumes [11]. Introducing low-volume individualized products to the market implies a requirement for flexible production planning and variable characteristics compared to mass manufacturing [20]. Currently, automotive products are manufactured based on deterministic demand forecasting. With the introduction of customization, the deterministic forecasting model has moved to stochastic. Planning techniques must be collaborative to adapt to this varying demand by effectively utilizing the production layout, and manufacturing capacity [21]. Customization leads to complexity in supply chains, production lines, and data management influencing the planning process for low-volume individualized production. As depicted in Fig 2, the conceptualization of product variants depends on the process, the volume of units, process tracking, and data transfer. The lack of an intelligent framework for managing a coupled data field in conjunction with individualized customer demands makes traditional production planning techniques incompatible.

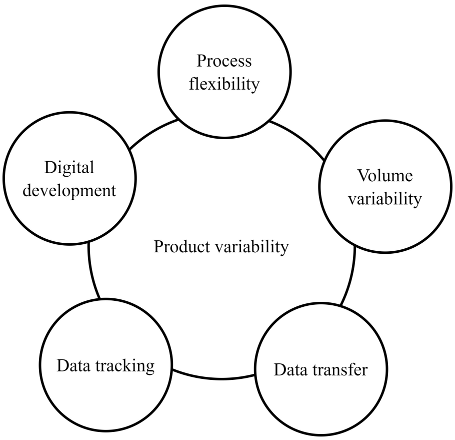

Fig. 2 Flexibility variables

2.3 Decision Framework and Optimization

Manufacturers aiming to capitalize on the competitive market are willing to introduce multiple variants of their products at less cost with fewer changes to their systems and techniques. Companies adopt mixed model assembly line that has a manufacturing configuration to produce different variants of an essential product. The mixed model assembly line is adaptive and can quickly respond to customer demands to manufacture new variants from a base model using the same facilities. However, developing a high variant mixed model assembly line is challenging due to random material transfer between stations leading to a shortage of parts and thereby resulting in disruption to the production line [22].

The decision support system assists in optimizing the fixed factory layout and assembly sequence [23], and automotive manufacturers may depend on a decision support system to optimize their line. Tracking customer demands and pushing layout changes by coupling product data, process data, and factory is a complex process. Mathematical modeling coupled with an xR data pipeline can reduce the degree of complexity and shorten the development cycle.

The task of scheduling orders and sequencing them to ensure maximum efficiency without creating assembly constraints is a vital factor in obtaining maximum output. According to Fritzsche [24] heuristic approaches are suitable to tackle planning and scheduling problems. Research demonstrates that techniques such as colony optimization and greedy algorithms, simulated annealing (SA), and genetic algorithms (GA) are preferred for large and complex decision-making functions.

Production facilities are set up with high investments. Therefore, underutilization of any resource leads to loss and low productivity. Low volume individualization, if not adequately planned and implemented, can lead to time and cost burdens due to compromised quality and reworks. Different strategies can be formulated to solve optimization issues. MirHassani et al. [25] considered a multi-period, mixed integer, two-stage stochastic program to optimize capacity planning for supply chain issues. According to Chandra et al. [26] the optimization issues are solved subjected to demand satisfaction, capacity planning, the readiness of standard and unique parts, and judicial requirements. Researchers proposed different solution methods to overcome optimization problems 1) Mathematical Programming (M.P.), 2) Dynamic Programming, 3) Meta-heuristics, and 4) Heuristics [27]. Multiple algorithmic and heuristic methods exist for solving optimization issues. Both methods guarantee finding a solution, but heuristics do not promise an optimal solution even though it expedites the process. Conversely, algorithmic strategies provide an optimal solution but require significant computational times [28].

2.3.1 Heuristic Planning

Heuristic methods provide fast, feasible solutions but do not guarantee an optimal solution because it is a shortcut to decision-making based mostly on past experiences [28]. Meta-heuristics is another approach with algorithms used for complex optimization based on diversified strategies. This model is famous for obtaining solutions very close to optimum. Brahimi et al. [27] three meta-heuristics, namely GA, SA, and Tabu Search (TS), are applied to decision-making models. GA is utilized to optimize the manufacturing configuration based on a few demand requirements and reduce capital costs. Ye and Liang [27] recommended an optimization technique that uses GA to reduce manufacturing costs by identifying a sequence and layout for modular products. Carlo et al. [27] put forward a GA for different product variant manufacturing to reduce asset and operational costs.

Traditionally, production planning deals with takt time and material required to manufacture products in large quantities. However, this approach is unsuitable for large variety low quantity manufacturing considering individualization is not repetitive [28]. To capture new niche markets, the manufacturers reduce product life cycles and increase product variety. It leads to uncertainties within the organization, and different accurate and heuristic methods must be considered to solve decision-making problems [25, 28]. Using mathematical models, existing factory layout planning techniques optimize distance traveled, frequency, and other quantitative factors. This method is efficient for standard layout planning where ergonomics and worker feedback are not considered. Furthermore, it does not support customization and flexibility [29].

2.3.2 Modeling by Linear and Non-Linear Program

Researchers have proposed different mathematical modeling, including Mixed Integer Nonlinear Programming (MINLP), Mixed Integer Linear Programming (MILP), Integer Linear Programming (ILP), and Linear Programming (L.P.), to overcome optimization issues in production planning. Abbasi and Houshmand [27] proposed an MINLP model to optimize production tasks, configurations, and batch size. This model aims to identify the best sequence of functions to increase profit and improve cost-effectiveness. Rabbani et al. [27] proposed a bi-objective MINLP model to reduce the configuration, modification, and inter-cell movement costs. Carlo et al. [27] suggested an ILP model for a multistage single product manufacturing that helps to estimate minimum investment cost. In the MILP technique, the problem data and objective functions are described for solving optimization issues where the objective parameter aims at reducing resource costs [28]. The decision-making process can be accelerated and effectively optimized by collating a mathematical model with the proposed intelligent production planning framework.

3 Conceptual Framework Elements

The manufacturer's objective is to meet individualized customer demands by reducing development time [30] without compromising on product quality and minimizing manufacturing cost. Workers will see different parts for multiple variants requiring specific assembly steps. Quick changeover, upskilling and fast decision-making will be critical to addressing specific customer orders. Moreover, design and production planning must be digitized and interlinked to adapt to customer demands and market changes quickly.

3.1 Factory Layout and Planning

The factory layout should be flexible and adaptive for a seamless transition between product variants. Configuring the ideal production line to manufacture individualized products within deadlines is critical. Any delay in the process can lead to customer dissatisfaction and brand value diminution. Manufacturers can hastily launch new product variants or fast-track lowvolume individualized product manufacturing to gain a competitive edge in the market without proper validation. This may lead to poor facility planning and increased costs and reworks. Therefore, data management with effective visualization techniques is crucial to factory layout optimization.

Data is vital for planning virtual systems and digital layouts. Lee Lee [31] describes factory layout issues as a configuration of facilities with unequal areas possible fitting within the limits of the space of the factory to reduce material handling cost and optimize space usage. Studies suggest there is a lack of framework for low-volume individualization production planning. Implementing xR technology can facilitate production planning with real-time factory layout visualization as its design allows virtual verification and swift adjustments. Possible saving potentials expected to be achieved reduced prototypes, significant shortening of development cycles, or rework. Simultaneously xR can unlock the potential for effective design optimization early in the development process with attention to the ergonomic workplace design. As depicted in Fig 3, xR couples an industry's engineering and manufacturing aspects.

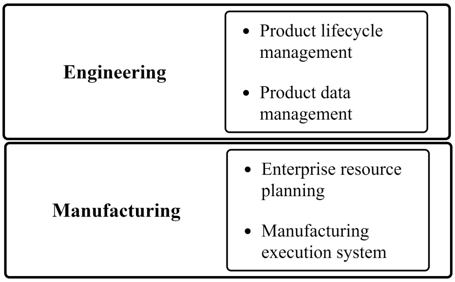

Fig. 3 State of the art data management

3.2 Transformative Technologies

Manufacturers have embraced digital manufacturing as a promising technology that can reduce cost and save time in implementing individualized product manufacturing. Technologies including VR augmented reality (AR) and xR assists in bridging the gaps between the physical and digital world [32]. Implementing these systems to the production planning techniques will provide the flexibility required to respond to low-volume individualized demands swiftly.

The development in digital technology has enabled production planning engineers to test and validate assembly processes using digital factory layouts.

The last decade has developed multiple virtual models and motion planning algorithms. However, they rely on different motion generation algorithms. Interactive digital layouts require user feedback, as motions are not artificially generated. With the help of head-mounted devices and motion capture systems, we can develop manufacturing use case scenarios and validate the designs. Through this process, invalid simulations can be detected early, and the data can be used for further planning. Furthermore, the algorithms can evaluate the critical parameters and generate different process variants that can optimize production planning [33].

3.3 Virtual Reality

In the last few years, VR has been gaining wide attention in multiple industries due to its potential to adapt to changes swiftly. The automotive industry is among the many industries exploring the applications of VR Studies show that vast research is being conducted on the applications of VR in the automotive industry. It has shown that VR assists in optimizing factory layout, improving product design, and improving safety and training [29]. VR systems provide the perception of space by immersing the user in a virtual environment consisting of real size objects. Virtual environments allow one to experience factory layouts by walking within the environment without needing physical mock-ups [34].

3.3.1 Extended Reality

xR is a technique related to real and virtual environments with human-machine interactions created by computers and smart devices. Bridging both virtual and physical worlds can save time in design, development, supply chain, and guidance in the manufacturing industry. xR technologies can establish this link by engaging multiple stakeholders to plan and make fast and effective decisions [32]. As shown in Fig 4, the xR comprises three core technologies. Combining xR technologies with DT can enhance data management through interactive visualization and accelerate decision-making.

3.4 Intelligent Production Planning Framework

Low volume individualized product manufacturing is a critical issue in the manufacturing industry that requires immediate attention. The key gaps in the planning, design, development, and quality phases should be addressed by integrating ergonomics, engineering, and manufacturing data management with production planning to manufacture low-volume individualized products efficiently.

3.4.1 Input and Data Integration

The customer PDM act as an input to the organizational PDM to understand the customer demands. Capturing the data will assist in analyzing the factory layout planning and optimizing the process for low-volume individualized

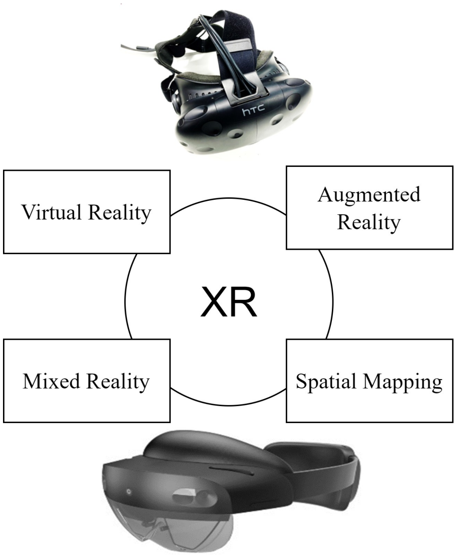

Fig. 4 Extended reality technologies

product manufacturing. The integration of PDMs with the physical assets of the factory data using the intelligent production planning framework help visualize the Computer-Aided Design (CAD) model in a virtual environment and perform merit studies. The production lines, workstations, and infrastructure must be reviewed and optimized to develop or re-layout the factory towards the low volume customized products. The math models of the factory layout act as the data source for visualization enabling interaction with the layout. An xR data pipeline integrated with factory data, process data, and PDM can identify relevant changes to data sessions before and after incorporating the customer demands.

A DT of the factory keeps track of the production plan, and the current factory layouts are visualized in an immersive environment by triggering the digital workstations created using the math models of the physical assets. The xR data management system evaluates the customer PDM with the current factory layout to establish if there is a need for changes in the layout to manufacturing the individualized product. To identify the product data changes, the factory assets are manipulated in the immersive environment to identify the key parameters influencing the complexity of the product. These changes are reviewed on a Head Mounted Display (HMD) or mobile apps for visualization purposes. The assembly lines are configured to facilitate the production of individualized products without developing physical prototypes. The key parameters that drive the production line are identified and optimized using mathematical models. Data tracking techniques embedded in the xR system provide the flexibility to update and analyze the layout for collisions.

The organizational manufacturing environment will be referenced to the DT when reconfiguring the factory layout. The intelligent production planning framework communicates with the manufacturing environment and the data management systems to analyze the updates. As depicted in Fig 5, the framework can adapt to the fluctuating customer demands, including environmental, socio, economic and political factors that can hinder a production line. Further analysis of the updated factory layout by visualizing and interacting with the assets determines the cycle time, thereby identifying bottlenecks and improving the assembly line. The data provision pipeline established using xR techniques assists in identifying the critical parameters.

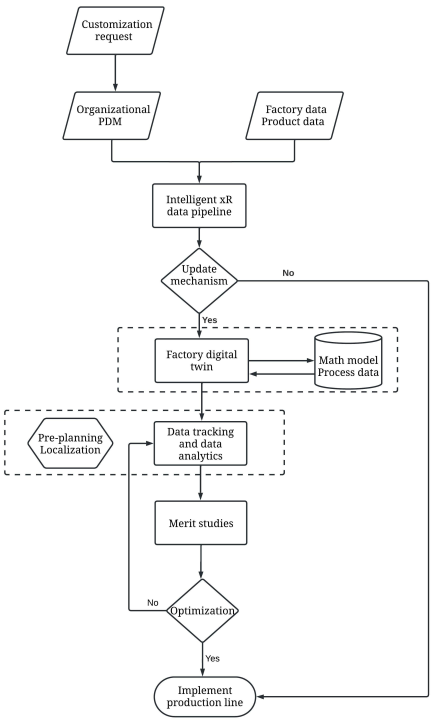

Fig. 5 Intelligent production planning framework

3.5 Data Management and Analytics

Qualitative goals for low-volume individualized product manufacturing can be achieved by transitioning the manufacturing processes towards an intelligent framework. Implementing transformative technologies, including xR, DT, and mobile apps will establish a real-time review of the product, factory, and process-related data. As depicted in Fig 6, a data management system comprises different factors, including data input, visualization, data management, and optimization.

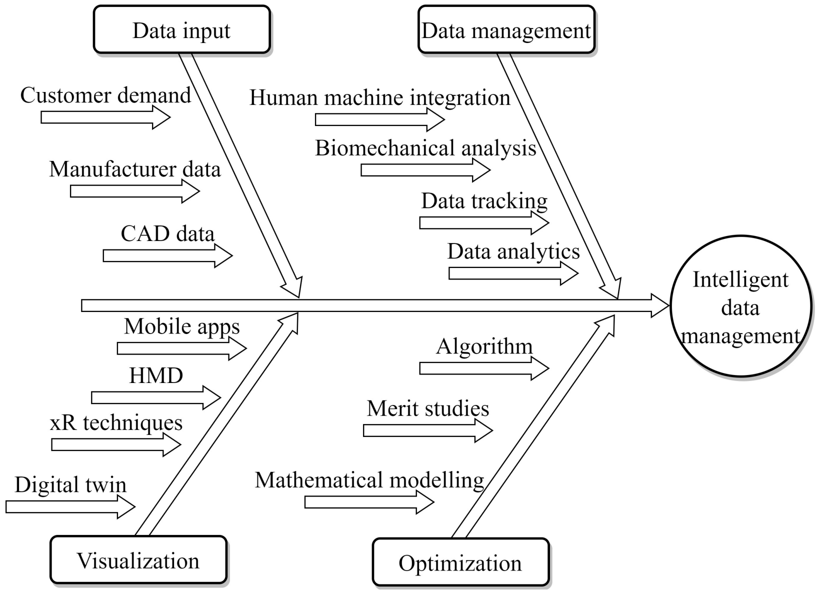

Fig. 6 Data management system

Analytical tools generally considered for data analytics include statistical data, data visualization, data mining, and AI [35]. The coupling of various data systems requires a complex data management system for effective administration. In the proposed framework, the customer product data is integrated into the digital model of the factory to analyze the process and components involved in the manufacturing process in the xR environment. The product data act as the input to the framework for decision-making. It is crucial to interlink different product and manufacturing data segments to establish an optimized layout for individualized products. The xR data pipeline connects the customer product data with the organizational data management systems. The initial data supply evaluates the factory data and triggers the update mechanism. The update mechanism identifies the changes from the initial and final phases of the planning, and the updates are visualized. All relevant changes to the data sessions are highlighted and considered for review.

Fig 7 illustrates a product and production environment-based data management system that couples production planning-related information. Integrating the product data into the production environment assists in data analysis for product variants. The intelligent production planning framework assembles the information required for the update mechanism and is further verified using visualization methods.

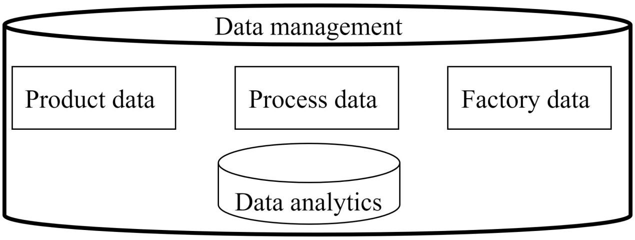

Fig. 7 Data augmentation and analytics

Virtual walkthroughs of the workstations further optimize the assembly lines to understand the design intent and identify potential issues. Utilizing the equipment and product data, the material flow and equipment locations are visualized in the virtual layout allowing to quickly identify the changes to the layout to meet the customer demands. Early detection of unwanted simulations helps in faster layout planning and proper utilization of the factory space.

The operational environment is reviewed, and merit studies are conducted to optimize the factory layout faster. The human-machine integration facilitated by the xR framework will generate a data pipeline that can track real-time worker movement. Since the factory layouts are visualized in the virtual layout, the data is stored, and workstations are reviewed based on the customization requirements. The digital layouts and models are positioned in the real world using QR code tracking to represent the physical factory accurately. Furthermore, the integration of the human through motion capture evaluates and validates the worker movement for productivity and ergonomic studies. A biomechanical analysis is obtained to review worker movement and ergonomics. The DT developed with xR technology bridges the digital and real-world provides the opportunity to set up, assemble and guide workers. The data-based framework can optimize the factory layout, assembly, walkway planning and development process.

4 Preplanning and Positioning with Quick Response Nodes

In the planning phase, it is vital to understand the layout and decide the optimal position for the equipment. Any changes to the physical resources during the production stage involve cost overruns, low productivity, low equipment utilization, increased operational costs, and safety issues. Implementing a digital layout planning can prevent approximately 70% of the planning errors in the planning phase and reduce almost 15% of the change costs [36].

The introduction of customized products and product variants increased complexity and a shorter product life cycle requiring fast decision-making. The dependency on various planning parameters makes the planning process cumbersome using physical prototypes. Therefore, it is ideal for visualizing the digital factory layout, evaluating its feasibility, and fast track the process for customized product manufacturing. The proposed intelligent production planning framework evaluates the customer demand with a real-time factory layout and fast-track workstation layout for low-volume customized manufacturing.

4.1 Data Loading

Companies with digital infrastructure use VR to visualize their product and factory models. However, loading a pre-planning model takes considerable time and lacks reference to the real-world position tracking [37]. Often reconfiguring issues are caused by minor changes made to the assembly line by the workers, which are not notified to the planning department leading to inaccurate planning [38]. Therefore, the layout must be continuously monitored and reconfigured to accommodate low-volume customized production. Digital factory layout assists in tracking the workstation design in real-time.

The virtual scene lack reference to the real world without registration with the physical environment. However, it is vital to establish a tracking method to gain an accurate representation of the digital layout. Multiple tracking methods, including object-based tracking, optical tracking, simultaneous localization, and mapping (SLAM), are considered in the industry [38]. The QR code technique is used in the proposed concept to track the scene and its content.

4.2 Preplanning and Quick Response Nodes

The virtual content has no reference to the real environment in its placement and position, making it tedious to determine the virtual model's posture and path. Further, estimating the distance moved while reconfiguring the equipment location becomes cumbersome and inaccurate. The proposed framework captures real-time data of the digital factory layout and avoids manually positioning them to the intended world space using QR code tracking. Additionally, it simplifies and fast-tracks loading the planning data compared to physical prototypes and cardboard modeling of the workstations.

Most AR applications use the marker-based system to identify the relative position of virtual objects within the scene [39]. A user position tracking system is also applied to track user position [40]. Development tools such as ARToolkit, and AR Tag consist of various markers, including dot markers, frame markers, data matrix markers, and ID markers. These markers are usually standard primitives, text, or patterns in greyscale, providing the advantage of recognizing the patterns quickly in dim light or under reduced camera pixels [39].

Most current HMDs can detect QR codes within their frame of sight. The QR marker system provides a reference coordinate to the real world, establishing a scale for indication. Fig 8a represents a user interface for the digital factory prompting to place the marker and Fig 8b demonstrates the virtual asset positioned with respect to the QR code. The virtual assets appear on the device after registering the QR code by scanning it. When triggering the QR code, the PLMXML activates the virtual models linked to it, which are visualized. The QR marker represents a location in the virtual factory layout and displays the content relative to its position in the real world. Furthermore, it eliminates the need for pre-registration, unlike azure spatial anchors. Virtual models are linked using PLMXML, which calls the function.

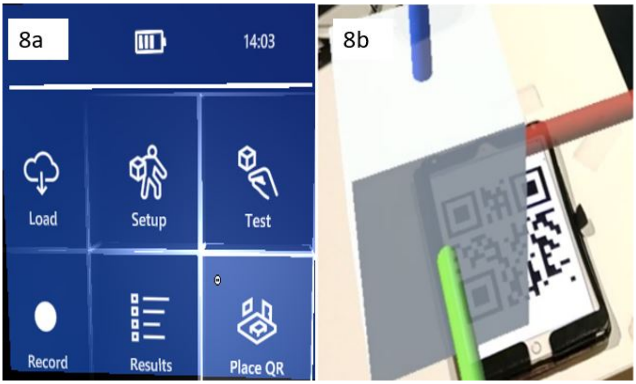

Fig. 8 (a) User interface for QR marker placement (b) QR code positioning virtual asset

4.3 Loading and Positioning Operations

To visualize the virtual layout, an HMD is required. HMDs accept a default feature point to load a virtual scene in xR. It does not provide accurate referencing of the virtual content with the real world when visualizing the layout. To track positional changes to the equipment in the factory, it is critical to precisely position the scene with the real world. The QR code positioning generates a reference point enabling the tracking of its position relative to other components in the scene. Any updates to the workstation position are captured for merit studies. The worker movement captured in the scene provides data for analysis and further validated for improvement.

The digital factory layout was visualized on an HMD by importing the CAD models to the game engine. The project is set up based on the current planning data. The CAD models are imported to the project and further reviewed on the HMD. The digital factory is displayed on selecting the application, and QR code can be triggered from the user interface (UI). The position of the workstation is analyzed based on QR code tracking. Fig 9a depicts the augmentation of digital factory for scene positioning and Fig 9b represents a part of the factory layout prompted by the application.

Not all the workstation needs to require an update. Therefore, a quick changeover between workstations provides the opportunity to review bottlenecks between connected workstations and review for collisions in the material flow. It assists in conducting merit studies of the workstation design. Real-time feedback assists in fast-tracking the review process and re-initialize tracking

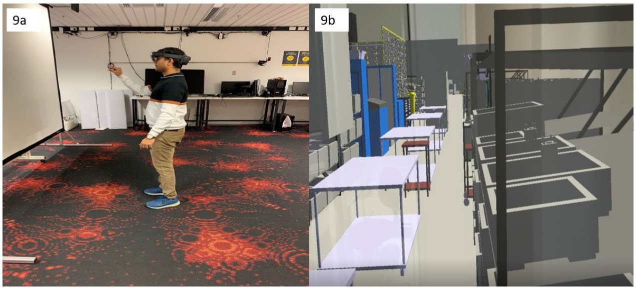

Fig. 9 (a) Augmentation of virtual assets (b) Digital factory visualization

to see the changes. Fig 10a displays a virtual workstation and Fig 10b demonstrates the UI used for quick changeover between workstations. The work

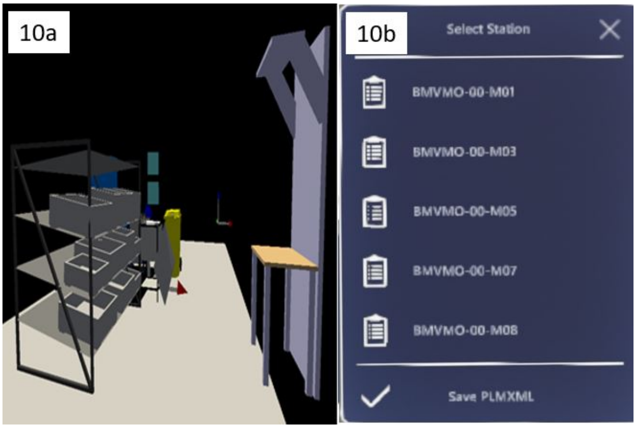

Fig. 10 (a) Virtual workstation (b) Quick workstation changeover User interface

points on each workstation were considered anchor points, which enabled securing each workstation to the real world. Each workstation can be analyzed and reviewed for improvements once it is positioned in the real world.

4.4 Results

The pre-planned virtual models were loaded and positioned accurately to the real world using quick response nodes proposed by the framework. The virtual factory models were loaded and positioned faster without interference with the real-world environment. The workstations were loaded and positioned manually in the case study using QR code. A HoloLens2 was used to load pre-planned virtual assets.

Table 1 shows that it took approximately 251s and 263s to load the four workstations using manual tracking and QR code tracking, respectively. This signifies there isn't a big difference in loading preplanning data due to the execution of QR code. However, in the case study, the positioning of models

Table 1 Workstation pre-planning loading and positioning

Modeling	Manual orientation		QR code tracking	
Factory stations	Loading	Positioning	Loading	Positioning
Workstation 1	60s	120s	70s	30s
Workstation 2	55s	90s	55s	25s
Workstation 3	48s	92s	50s	25s
Workstation 4	88s	135s	88s	32s

in the real world showed a significant difference. It took approximately 437s to manually position the virtual models of the four workstations and reference their position to the intended design for a real environment. But using the QR code marker, the workstations were oriented within 112s. Overall, positioning workstation assets using QR code takes 25.6% of the time required to position assets using manual positioning by interacting with the virtual assets.

5 Conclusion

The focus of this paper is to underline the gaps in the current industry practice when planning low-volume individualized product manufacturing. The proposed intelligent production planning framework couple's different data systems and workstations are optimized by virtual analysis using xR techniques. Additionally, it highlights the challenges the automotive industry is facing to fast-track low-volume production planning and the solution to fast decision making:

- Mass manufacturers are finding it challenging to fulfill low-volume personalized demands due to their dependability on traditional mass manufacturing production planning techniques.
- Poor integration between process planning, factory layout, and customer and factory PDM leads to inefficiencies in production planning, increased cost, and time delays.
- The quick response nodes implemented in the automotive preplanning layout review resulted in positioning virtual assets within 25.6% of the time required using manual interactive positioning using VR techniques.
- The lack of a framework for low volume individualized production planning has led to quality depreciation for manufacturers due to the lack of appropriate data management strategies.

The intelligent production planning framework can fast-track the development cycles for an individualized product by xR techniques embedded with data tracking and analytics. The linking of data management with xR applications enables faster decision-making and reduction of downtime. Integrating customer PDM, factory data, manufacturer PDM, product data, and process data can quickly detect production planning issues and track information in real-time. Future research will be conducted by optimizing the walkway and testing and validating the framework in a real-world scenario for shortening layout development for individualized products.

Statements & Declarations

- Funding: This work was supported by FFG Austria's Beyond Europe Scheme (Project ID [874154] and Magna Steyr in collaboration with Swinburne University. The authors acknowledge their support without which this research would not be possible.
- Conflict of interest/Competing interests: The authors do not have financial or non-financial interests to disclose.
- Availability of data and materials: The authors do not have no data and materials to disclose.
- Code availability: The authors have no code to disclose.
- Ethics approval: Ethics approval is not applicable.
- Consent to participate: The authors have no consent to disclose.
- Consent for publication: The authors have no consent for publication to disclose.
- Authors' contributions:

References

[1] Zawadzki, P., Żywicki, K.: Smart product design and production control for effective mass customization in the industry 4.0 concept. Management and Production Engineering Review **7**(3), 105–112 (2016). https://doi.org/10.1515/mper-2016-0030

[2] Mourtzis, D., Zogopoulos, V., Xanthi, F.: Augmented reality application to support the assembly of highly customized products and to adapt to production re-scheduling. The International Journal of Advanced Manufacturing Technology **105**(9), 3899–3910 (2019). https://doi.org/10.1007/s00170-019-03941-6

[3] Hoffmann, M., Meisen, T., Schilberg, D., Jeschke, S.: Multi-dimensional production planning using a vertical data integration approach: A contribution to modular factory design. In: 2013 10th International Conference and Expo on Emerging Technologies for a Smarter World (CEWIT) (2013). https://doi.org/10.1109/cewit.2013.6713754

[4] Scholz, M., Hußnätter, M., Kreitlein, S., Franke, J.: E|flow - from production line concept to a physically and digitally full-meshed production network. Applied Mechanics and Materials **805**, 94–101 (2015). https://doi.org/10.4028/www.scientific.net/amm.805.94

[5] Bonnema, G.M., Houten, F.J.A.M.V.: Use of models in conceptual design. Journal of Engineering Design **17**(6), 549–562 (2006). https://doi.org/10.1080/09544820600664994

[6] Dyck, F., Stöcklein, J., Eckertz, D., Dumitrescu, R.: Mixed mock-up – development of an interactive augmented reality system for assembly planning. In: Virtual, Augmented and Mixed Reality. Design and Interaction, pp. 37–49 (2020). https://doi.org/10.1007/978-3-030-49695-1_3

[7] Minner, S.: Planning Production and Inventories in the Extended Enterprise: A State of the Art Hand book. JSTOR (2011)

[8] Shofa, M.J., Widyarto, W.O.: Effective production control in an automotive industry: Mrp vs. demand-driven mrp. In: AIP Conference Proceedings, vol. 1855, p. 020004 (2017). https://doi.org/10.1063/1.4985449. AIP Publishing LLC

[9] Kuo, C.-M., Chen, W.-Y., Tseng, C.-Y., Kao, C.T.: Developing a smart system with industry 4.0 for customer dissatisfaction. Industrial Management & Data Systems (2020). https://doi.org/10.1108/IMDS-12-2019-0656

[10] Xia, L., Lu, J., Zhang, H., Xu, M., Li, Z.: Construction and application of smart factory digital twin system based on DTME. The International Journal of Advanced Manufacturing Technology **120**(5-6), 4159–4178 (2022). https://doi.org/10.1007/s00170-022-08971-1

[11] Zennaro, I., Finco, S., Battini, D., Persona, A.: Big size highly customised product manufacturing systems: a literature review and future research agenda. International Journal of Production Research **57**(15-16), 5362–5385 (2019). https://doi.org/10.1080/00207543.2019.1582819

[12] Tang, H.: Automotive Vehicle Assembly Processes and Operations Management, (2017)

[13] Lalami, I., Frein, Y., Gayon, J.-P.: Production planning in automotive powertrain plants: a case study. International Journal of Production Research **55**(18), 5378–5393 (2017). https://doi.org/10.1080/00207543.2017.1315192

[14] Yao, F., Keller, A., Ahmad, M., Ahmad, B., Harrison, R., Colombo, A.W.: Optimizing the scheduling of autonomous guided vehicle in a manufacturing process. In: 2018 IEEE 16th International Conference on Industrial Informatics (INDIN), pp. 264–269 (2018). https://doi.org/10.1109/INDIN.2018.8471979

[15] Rezig, S., Ezzeddine, W., Turki, S., Rezg, N.: Mathematical model for

production plan optimization—a case study of discrete event systems. Mathematics **8**(6), 955 (2020). https://doi.org/10.3390/math8060955

[16] Dörmer, J., Günther, H.-O., Gujjula, R.: Master production scheduling and sequencing at mixed-model assembly lines in the automotive industry. Flexible Services and Manufacturing Journal **27**(1), 1–29 (2015). https://doi.org/10.1007/s10696-013-9173-8

[17] Volling, T., Spengler, T.S.: Modeling and simulation of order-driven planning policies in build-to-order automobile production. International Journal of Production Economics **131**(1), 183–193 (2011). https://doi.org/10.1016/j.ijpe.2011.01.008

[18] Volling, T., Matzke, A., Grunewald, M., Spengler, T.S.: Planning of capacities and orders in build-to-order automobile production: A review. European Journal of Operational Research **224**(2), 240–260 (2013). https://doi.org/10.1016/j.ejor.2012.07.034

[19] Sabadka, D., Molnár, V., Fedorko, G.: Shortening of life cycle and complexity impact on the automotive industry. TEM journal **8**(4), 1295 (2019). https://doi.org/10.18421/TEM84-27

[20] Javadi, S., Bruch, J., Bellgran, M.: Characteristics of product introduction process in low-volume manufacturing industries: A case study. Journal of Manufacturing Technology Management (2016). https://doi.org/10.1108/JMTM-03-2015-0017

[21] Parry, G., Graves, A.: Build to Order: the Road to the 5-day Car, (2009)

[22] Fathi, M., Ghobakhloo, M.: Enabling mass customization and manufacturing sustainability in industry 4.0 context: a novel heuristic algorithm for in-plant material supply optimization. Sustainability **12**(16), 6669 (2020). https://doi.org/10.3390/su12166669

[23] Küttner, R.: Production planning for a supply chain in a low-volume and make-to-order manufacturing environment. Estonian Journal of Engineering **15**(1) (2009). https://doi.org/10.3176/eng.2009.1.05

[24] Fritzsche, A.: Implications of agile manufacturing in the automotive industry for order management in the factories-evidence from the practitioner's perspective. Procedia CIRP **72**, 369–374 (2018). https://doi.org/10.1016/j.procir.2018.03.127

[25] Günther, H.-O., Meyr, H.: Supply Chain Planning: Quantitative Decision Support and Advanced Planning Solutions, (2009)

[26] Chandra, C., Everson, M., Grabis, J.: Evaluation of enterprise-level benefits of manufacturing flexibility. Omega **33**(1), 17–31 (2005). https://doi.org/10.1016/j.omega.2004.03.004

[27] Brahimi, N., Dolgui, A., Gurevsky, E., Yelles-Chaouche, A.R.: A literature review of optimization problems for reconfigurable manufacturing systems. IFAC-PapersOnLine **52**(13), 433–438 (2019). https://doi.org/10.1016/j.ifacol.2019.11.097

[28] Ghezzi, L., Hömberg, D., Landry, C.: Math for the Digital Factory vol. 27, (2017)

[29] Gong, L., Berglund, J., Fast-Berglund, Å., Johansson, B., Wang, Z., Börjesson, T.: Development of virtual reality support to factory layout planning. International Journal on Interactive Design and Manufacturing (IJIDeM) **13**(3), 935–945 (2019). https://doi.org/10.1007/s12008-019-00538-x

[30] Lima, M.B., Kubota, F.I.: A modular product design framework for the home appliance industry. The International Journal of Advanced Manufacturing Technology **120**(3), 2311–2330 (2022). https://doi.org/10.1007/s00170-022-08896-9

[31] Mustafa, K., Cheng, K.: Improving production changeovers and the optimization: A simulation based virtual process approach and its application perspectives. Procedia Manufacturing **11**, 2042–2050 (2017). https://doi.org/10.1016/j.promfg.2017.07.356

[32] Fast-Berglund, Å., Gong, L., Li, D.: Testing and validating extended reality (xr) technologies in manufacturing. Procedia Manufacturing **25**, 31–38 (2018). https://doi.org/10.1016/j.promfg.2018.06.054

[33] Agethen, P., Gaisbauer, F., Otto, M., Rukzio, E.: Interactive simulation for walk path planning within the automotive industry. Procedia CIRP **72**, 285–290 (2018). https://doi.org/10.1016/j.procir.2018.03.223

[34] Kunz, A., Zank, M., Fjeld, M., Nescher, T.: Real walking in virtual environments for factory planning and evaluation. Procedia Cirp **44**, 257–262 (2016). https://doi.org/10.1016/j.procir.2016.02.086

[35] Chen, T., Wang, Y.-C.: Hybrid big data analytics and industry 4.0 approach to projecting cycle time ranges. The International Journal of Advanced Manufacturing Technology **120**(1), 279–295 (2022). https://doi.org/10.1007/s00170-022-08733-z

[36] Biesinger, F., Meike, D., Kraß, B., Weyrich, M.: A case study for a digital twin of body-in-white production systems general concept for automated

updating of planning projects in the digital factory. In: 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA), vol. 1, pp. 19–26 (2018). https://doi.org/10.1109/ETFA.2018.8502467

[37] Nakamura, T., Kaneko, J., Abe, T., Horio, K.: Developing a support system for loading planning. International Journal of Automation Technology **13**(4), 475–481 (2019). https://doi.org/10.20965/ijat.2019.p0475

[38] Rohacz, A., Weißenfels, S., Strassburger, S.: Concept for the comparison of intralogistics designs with real factory layout using augmented reality, slam and marker-based tracking. Procedia CIRP **93**, 341–346 (2020). https://doi.org/10.1016/j.procir.2020.03.039

[39] Lin, P.-Y., Wu, W.-C., Yang, J.-H.: A qr code-based approach to differentiating the display of augmented reality content. Applied Sciences **11**(24), 11801 (2021). https://doi.org/10.3390/app112411801

[40] Anggoro, P.D.W.: User position tracking system using marker-based AR for exploring VR museum galleries. Jurnal Teknologi dan Sistem Komputer **7**(4), 134–140 (2019). https://doi.org/10.14710/jtsiskom.7.4.2019.134-140