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Digital Manufacturing Pilot Study for Stepping Towards Mixed Reality Applications in Tertiary Education

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Abstract. Digital manufacturing is a comprehensive approach which includes the integration of information technology and automation into the entire product lifecycle, from design and engineering to production, logistics, and customer service. In education, mixed reality can be used to create interactive educational experiences. It has the potential to revolutionize the way products are designed, manufactured, and maintained in the digital manufacturing industry. One of the key-ways mixed reality can be used in digital manufacturing is by providing a more immersive and interactive design experience. Engineers and designers can use mixed reality to create virtual prototypes of their products and test them in a realistic, 3D environment. This can help identify potential issues early in the design process before they become costly to fix. The current paper explores the process of testing and selecting specific applications from a digital manufacturing university level course to be designed and integrated into mixed reality scenarios. Within the framework of an Erasmus+ funded project, the authors designed a Digital Manufacturing course which was implemented over 15 hours of face-to-face activities. Based on participant feedback and assessment of trainers the main areas of content were identified for further development into mixed reality applications. The paper presents one mixed reality application and pinpoints future areas of improvement and development into immersive environments for tertiary education.

Keywords. Digital manufacturing, Additive manufacturing, Simulation, Mixed reality

Introduction

A study by the European Commission, published in April 2016, shows that the progress currently being registered in the field of digital technologies has a special impact on the design, manufacture and marketing of products [1]. The rapid development of systems such as Internet of Things (IoT), 5G, Cloud Computing, Data Analytics and Robotics has led to the development of new industrial models and creates opportunities for increasing the competitiveness of industry worldwide in the long-term. Experts believe that the world is at the beginning of a new industrial revolution, the fourth, that of intelligent cyber systems [2]. This is characterized by the use of sensors, the expansion of wireless communications and networks, the introduction of smart machines, robots,

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increasing the processing capacity, the concept of "big data", etc. This new industrial revolution, anticipated since the ‘70s by Alvin Toffler, will lead to increased manufacturing flexibility, mass personalization, reducing manufacturing times, increasing productivity and increasing product quality [3]. Companies will be obliged to invest in equipment, information and communication technologies as well as in data purchase and analysis systems. Digital manufacturing plays a key role in the race for competitive advantage amongst enterprises wanting to secure a leading edge within the fourth industrial revolution [4]. The incorporation of digital technology in the manufacturing process can lead to increased efficiency and flexibility, reduced cost, improved quality, and greater design freedom. It offers companies a comprehensive approach which includes the integration of information technology and automation into the entire product lifecycle, from design and engineering to production, logistics, and customer service [5]. The digital transformation is enhanced by using immersive technologies in manufacturing, especially mixed reality (MR) utilities [6]. MR represents the fusion of the real world and the digital world, creating new environments and visualizations and enabling interaction amongst the elements of both real and digital worlds in real time [7]. It has the potential to revolutionize the digital manufacturing industry by improving design, training, logistics, quality control, and customer engagement [8]. With the technology continuing to evolve and more companies exploring how to implement MR into their processes, the potential use cases of MR in digital manufacturing are likely to grow and increase. As of now, MR is used by institutions in a variety of applications, such as [9,10]: design and creation of virtual prototypes; development of worker training and assistance by creating interactive training modules that allow workers to learn how to operate complex machinery or equipment in a safe and controlled environment; improvement of logistics and quality control, by allowing workers to visualize the layout of a warehouse or factory floors, and use the information to optimize the flow of materials and products; the creation of virtual inspection tools that can be used to check the quality of products at various stages of the production process; the development of virtual showrooms and product demonstrations for sales and marketing purposes. These are just some examples of the utilities of MR, whilst its possibilities within the digital manufacturing area are endless and limited only to the capabilities and requirements of user companies.

In this context, the authors developed and implemented a digital manufacturing pilot study for identifying the possibilities of integrating mixed reality applications in tertiary education modules. This approach aims at bridging the gap between companies and educational systems worldwide, creating a close loop for digital competence development for young professionals targeting specialized positions in the job market. This MR approach to teaching digital manufacturing concepts requires expertise in both digital technologies and pedagogy, as well as an understanding of how people learn and interact with technology integrating knowledge and approaches from different disciplines such as manufacturing engineering, computer science, and education sciences.

1. Research methodology

1.1. Background

The current study is developed under the ReCap 4.0 Erasmus+ project led by the Asian Institute of Technology (AIT) from Thailand and implemented together with seven other consortium partners. The project is aimed at enhancing the capacity and ability of the non-university sector at the tertiary level in Thailand for the effective delivery of engineering and technology knowledge and skills related to Industry 4.0. As a part of this project and to achieve this aim, the authors developed an innovative training module on Digital Manufacturing, together with training materials and the delivery process for the Industry 4.0 competence development training program according to ECTS Implementation of modern ICT tools and methodologies for effective training. The training program involved, amongst other activities, a three-day face-to-face teaching module for training the trainers of Thai partner universities. The final sample of participants consisted of 12 trainers, three from each Thai partner. Participants had various technical background, but not specific to the content of the module.

1.2. Digital manufacturing training module

The Digital Manufacturing training module was designed by the University POLITEHNICA of Bucharest (UPB) partner with the aim of developing two competences, namely: C1. Apply digital technologies for product design and manufacturing (instrumental, systematic); C2. Apply digital technologies for improving industrial performance (instrumental). The construction of the module was based on six learning outcomes. The first module learning objective (MLO) refers to understanding of how to use digital technologies for design, simulation and analysis of production systems and will be achieved through activities like: an overview of scope of the use of digital technologies for the design of the production systems, a brief description of the digitalized production systems; case studies for a better understanding of digital design technologies; hands-on workshops. The assessment of the first learning objective was done using discussions based on existing case studies and feedback on systems the trainees used. The second MLO entails the selection and application of digital technologies for product design and manufacturing, achieved through three main targets: analysis of the requirements for the product design, the inputs of the process of designing a product; understanding the process of manufacturing and the differences between a traditional one and a digitalized one; understanding the advantages and disadvantages of the digital technologies applied in product design and manufacturing. Hands-on labs and case studies were used to assess performance. Simulation and analysis of a specific production cell/ production line was the third MLO of the module and was undertaken by using general data and case studies on simulation of the dynamic behaviour of a production cell/ production line and utilisation of a specific simulation software. The last three MLOs are related to additive manufacturing and include: Identify main Additive Manufacturing (AM) technologies for specific areas of applications and explain the advantages of the technologies in each of the domains; Build product specifications for AM and optimise 3D printing parameters considering the used technology and product function; Analyse and design products for additive manufacturing. The main assessment tools used for all three were applied case studies, technical assignment presentations and discussions based on existing case studies.

The Digital manufacturing module was designed to be implemented through face-to-face training (15 hours), coaching activities (30 hours) and group projects (60 hours). The current study focuses on the face-to-face activities which were delivered throughout a 5-day event. The first two days involved organisation of available infrastructure at AIT teaching laboratory. The three UPB trainers set up and tested six Adventurer 3D printers which were available for all module activities. The training and teaching activities took place during three days, as follows: Day 1 - Digital Manufacturing – Introduction and main areas (1 hour); Advantages of Digital Manufacturing and Manufacturing simulation (2 hours); Digital Twin (2 hours); Assignment presentation and discussions (1 hour); Day 2 - Introduction to Additive Manufacturing (AM), presentation of facilities, resources and large-scale manufacturers (1 hour); Additive Manufacturing process flow and technologies (2 hour); Additive Manufacturing Industries and Applications (2 hours); Day 3 - Design for Additive Manufacturing (3 hours); AM - Assignment presentation and discussions (1 hour). All teaching materials and applications were made available for the participants through the projects' GDrive.

1.3. Quantitative analysis

All throughout the 15-hour teaching activities on-the-spot active feedback was collected from the participants through open discussions on the content of the module. After implementing the three-day Digital Manufacturing module, participants were asked to give overall feedback using a training evaluation sheet. This was constructed in four main parts: general information about the participants; overall feedback; impact of training; further comments. To incorporate both quantitative and qualitative analysis, closed and open-ended items were used. The overall feedback was constructed from 10 items (Table 1) which used a 5 – point Likert Scale, where value 1 corresponds to "totally disagree" and value 5 corresponds to "totally agree". The scale provided one neutral opinion along with two extremes and two intermediates to the respondents. Construction of this data set allowed the application of an Analysis of Variance (ANOVA) as a quantitative analysis tool.

Table 1. Feedback statements used for ANOVA.

No.	Statement
1	I have sufficient background for this training.
2	The training was useful and relevant for the project activities.
3	I understood the concepts presented in the training.
4	The themes/topics developed in the training were relevant for my teaching practice
5	I had an active participation during the training activities.
6	The trainers had an effective approach during the activities developed.
7	The training materials were useful for the project activities.
8	The training was a valuable experience for my professional growth.
9	After the training, my knowledge and experiences in this subject have been improved.
10	I will recommend this training to somebody else.

The statistical analysis was conducted to examine the differences between groups on a particular measure. The groups in the data set were the different statements and the measures being analysed were the responses given to each statement. To accurately identify the improvement areas and the fit of MR applications within the content of the digital module, ANOVA was followed by a qualitative analysis of the open-ended feedback sheet. Although this analysis provided a better insight on participants' experiences, solely the quantitative data for this particular study is further discussed because firstly we aimed to explore statistical relationships, patterns, and trends related to our research.

2. Results and discussions

2.1. Quantitative analysis

For this analysis statement S1 was removed from the data set as it is not related to the content of the Digital Manufacturing module, but rather to the technical background of each participant. Although the results for this statement are important to the overall feedback, the internal consistency of the study is influenced by items that do not measure the same underlying construct. After conducting the ANOVA with Two-Factor Without Replication the results include the source of variation, the sum of squares (*SS*), the degrees of freedom (*df*), the mean squares (*MS*), the *F*-ratio, the *P*-value, and the *F* critical value (Table 2). The results show that there is a significant difference between the means of the groups on the measure being analysed if the *P*-value is less than 0.05, and the source of variation was broken down into three main parts: *Rows, Columns, and Error*.

Table 2. ANOVA Two-Factor Without Replication for the 9-statement data set.

Source of Variation	***SS***	***df***	***MS***	***F***	***P-value***	***F crit***
Rows	9.074074074	11	0.824915825	3.802133851	0.00017648	1.899171018
Columns	0.685185185	8	0.085648148	0.394762367	0.920686304	2.045414315
Error	19.09259259	88	0.216961279			
Total	28.85185185	107				
Cronbach's Alpha = 0.736989796						

The *Rows* source of variation demonstrates that there is a significant difference between the means of the groups that were formed by rows. For this particular ANOVA the *Rows* source of variation indicated the variation in responses between the different statements. The results for the *Rows* source of variation suggest that there is a significant difference in the responses given to the 9 statements, with a large *F*-ratio (*F* - 3.802133851 > *F crit* - 1.899171018) and a very small *P-value* (0.00017648). Thus, all values are significant, indicating that there is a difference in means among the groups. The relevance of these values is that they can be used to identify which statements are most important to the participants, which statements are not well understood, and which statements are measuring different aspects of content creation. With a *P*-value of 0.92, which is larger than 0.05 the *Columns* source of variation shows that there isn't a significant difference between the means of the groups that were formed by columns. Also, since F < F crit (0.394762367), the null hypothesis will not be rejected [11]. The *Columns* source of variation in this analysis refers to the variation in responses between the different statements, which in this case were only values of 4 and 5 on the Linker scale, so the results are consistent with anticipated values. Moreover, the ANOVA performed for the digital manufacturing feedback has a Cronbach's Alpha of 0.736989796, which is an acceptable indicator of the questionnaire internal consistency. This indicates that the results are reliable and that the items on the scale or survey are assessing the same underlying construct [12].

Each question was further analysed in terms of its' significance, developing Table 3 which reveals the number of respondents (*Count*), the sum of scores (*Sum*), the average of scores, the variance and standard deviation (*Std. Dev.*) for each of the nine statements.

Table 3. Standard deviation and variance for the 9-statement data set.

Statement	*Count*	*Sum*	*Average*	*Variance*	*Std. Dev.*
S2	12	55	4.583	0.265	0.515
S3	12	56	4.667	0.242	0.492
S4	12	54	4.500	0.273	0.522
S5	12	54	4.500	0.455	0.674
S6	12	53	4.417	0.265	0.515
S7	12	53	4.417	0.265	0.515
S8	12	55	4.583	0.265	0.515
S9	12	55	4.583	0.265	0.515

Results show an average range between 4.417 to 4.667 and a variance range between 0.242 to 0.273, indicating that there is not a significant difference between the means of the statements being analysed. Nevertheless, the variance indicates the spread of the data, the larger the variance, the more spread out the data is. In this case, it can be concluded that no outliers are involved in the analysis. A low standard deviation for all nine statements shows that most of the scores are near the mean, with no dispersed scores. Higher average scores imply that the statements are more significant to the participants. Moreover, statements with a lower standard deviation implies that the responses are more consistent amongst participants, thus it is more likely that the statement is considered more important. Statement S3 *"I understood the concepts presented in the training",* has both the highest average of 4.667 within the range, and the lowest standard deviation of 0.492 within the range. Thus, it is considered the most significant to the trainers involved in the study. On the other hand, statement S5 *"I had an active participation during the training activities"* registered the highest values for variance (0.455) and standard deviation (0.674) within all statements. Although not high enough to suggest the presence of outliers, the variability in responses for S5 can be accounted to several factors, such as differences in individual learning styles, personal preferences or teaching styles. Given the ANOVA study, we can conclude that the results of the analysis show that although the digital manufacturing module was well designed and implemented, all the trainers agree that activities should involve different types of active participation throughout the delivery of course content.

To substantiate the findings of the ANOVA research, authors propose the development of a MR application which could generate active participation of trainees within the learning process, whilst using immersive environments to interact with elements from both the real and digital worlds in real time.

2.2. Development of MR application

Based on the previous findings, a didactical MR application based on a digital twin for a simple manufacturing process of an electronic assembly made from a case, cover and an electronic board was designed. The focus was on building the model, simulate and optimize a comprehensive digital twin of this manufacturing process.

It was chosen a digital twin concept within MBSE (Model Based Systems Engineering) Framework [13]. A customized representation of this concept it is shown in Figure 1.

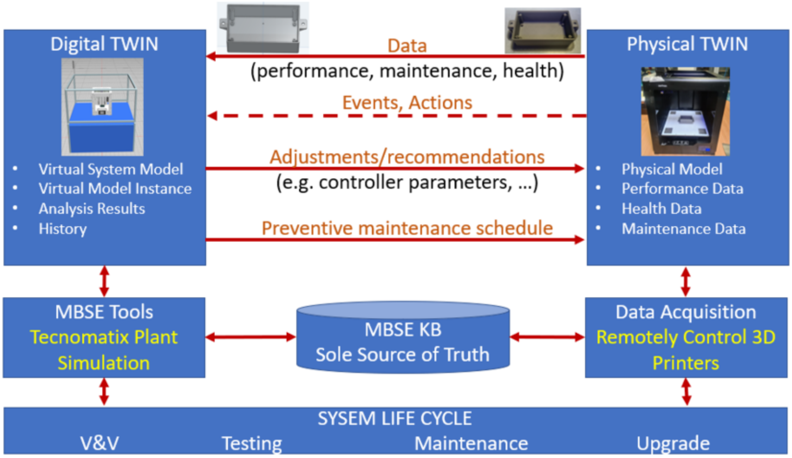

Figure 1. Customized Digital Twin Concept within MBSE Framework [Adapted from 13].

The digital twin starts with a 3D model of the case and cover, which is created using Computer-Aided Design (CAD) software. The 3D models are then used to create the necessary Z-codes for the physical twin model that consist of two 3D printers' type Zortrax M300 Plus, post-processing workplaces and an assembly workplace. One printer is used to create the case, and the other to create the cover (see Figure 2). After post-processing of the 3D printed parts, the electronic board is then inserted into the case, and the cover is placed on top to complete the assembly.

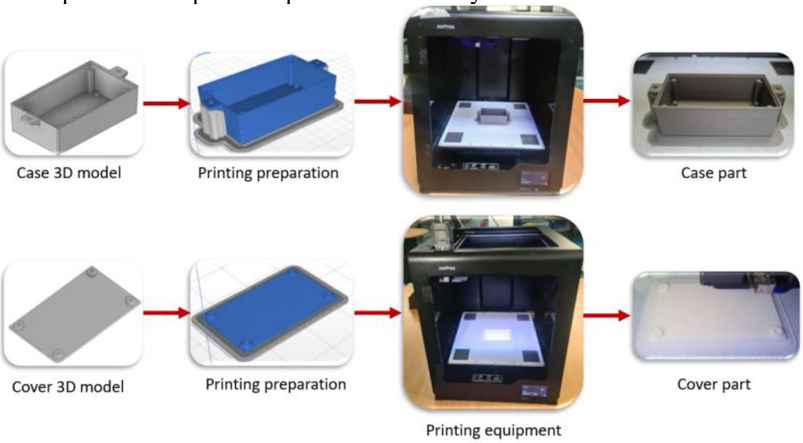

Figure 2. Main steps of the proposed AM process.

The simulation model made in Tecnomatix Plant Simulation is used to create a virtual representation of the manufacturing process (see Figure 3). Both, the simulation and the physical models were designed in parallel and include the same number of workplaces. The 3D models of the parts and data extracted from the Z-codes were also used as an input data, for example parts representation and processing times. This simulation model includes a variety of parameters, such as the time it takes to complete each step including set-up time for each workplace and the processing time which can be 3D printing time, post-processing of the printed parts or assembly time, machines failures (5% of the time), the involvement of the worker in the manufacturing process activities and the quality control checks that are performed.

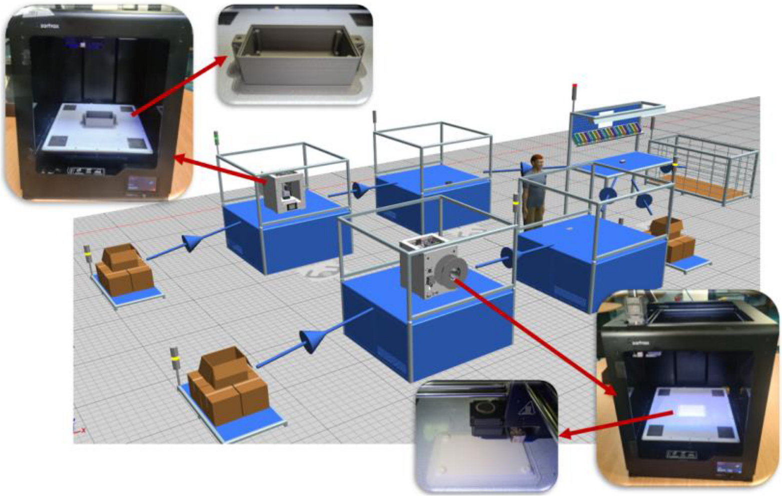

Figure 3. Simulation model developed in Tecnomatix software.

The simulation model results show that the printing time of the Case (10h and 51min) has a great influence on the total manufacturing time of the final assembly, on the utilisation of resources (see Figure 4) and, consequently, on the total number of products that can be obtained in a fixed period of time. The statistics of the drain show that only 2 products can be assembled in 24 hours (see Figure 5). Potential solutions for eliminating the waiting times can be to use the AM station used for printing the cover also for printing the case, to print more parts at the same time or to use two AM stations for printing covers. However, the model created is only for didactic purposes and it is used to give to the students/ trainers an insight regarding a digital twin and how MR can be applied in this type of manufacturing line.

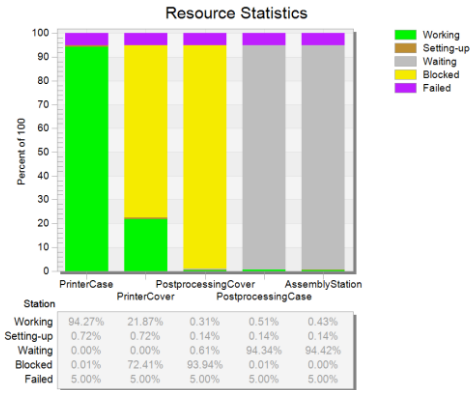

Figure 4. Resources utilisation.

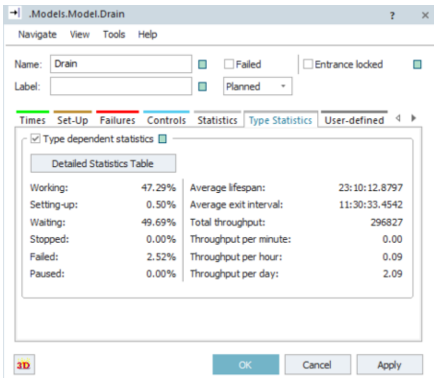

Figure 5. Drain statistics.

The digital twin combines the physical twin with the simulation model, allowing for real-time monitoring and optimization of the manufacturing process. For example, if the simulation model identifies a bottleneck in the assembly line, the digital twin can be used to test and optimize potential solutions, such as increasing the speed of the assembly line or adding additional workers. The developed digital twin can be used for simulation and monitoring of any other manufacturing process that involves 2 parts that can be obtained using AM.

For using virtual reality with simulation software (Tecnomatix Plant Simulation) a bridge software should be used to work together, so scripted objects can be triggered from within the VR environment. This bridge software is a bidirectional virtual reality interface plugin which allows to connect Tecnomatix Plant Simulation with a virtual reality headset, such as the HTC Vive or Oculus Rift.

Mixed reality can be used to enhance the visualization and interaction capabilities of the digital twin. One way to use mixed reality in Tecnomatix Plant Simulation is to visualize the simulation model in a mixed reality headset or device. This enables the user to see the simulation model in a more immersive and interactive way, which can help with monitoring and optimizing the production process. For example, the user will be able to monitor the state of each AM machine in order to know when should be at a specific workplace.

Mixed reality can also be used to overlay real-time data onto the simulation model, such as production data (3D printing, post-processing of the parts and assembly real times), maintenance instructions for the printers, or assembly instructions. This can help the user to monitor the performance of the production process and to identify potential issues in real-time. Therefore, it can be a helpful while training, making it easier for the users to learn and follow procedures.

3. Conclusions

The paper discusses the integration of mixed reality (MR) technology into a digital manufacturing module intended for higher education. The digital manufacturing approach merges automation and information technology into the entire life cycle of a product. The integration of MR has the potential to transform the traditional design, production, and maintenance process by offering a more engaging and interactive design experience. The technology enables the development of virtual prototypes that can be simulated and tested in a realistic 3D environment, allowing for the identification and resolution of possible issues in the initial stages of the design process.

The study analyses the process of testing and selecting specific digital manufacturing applications for university-level courses to be integrated into MR scenarios. Feedback from participants in a 15-hour digital manufacturing course was collected through open discussions, training evaluation sheets, and closed and open-ended questions. The evaluation sheet had ten items rated on a 5-point Likert scale. ANOVA was applied to examine the differences between groups on each measure. The results show a significant difference in the responses given to nine statements, with a large F-ratio and a very small P-value. Based on the feedback and assessment of trainers, the authors identified the main areas of content to be developed into MR applications.

To support the ANOVA research findings, the authors suggest creating a MR application which would encourage trainee engagement in the learning process by providing immersive environments allowing them to interact with elements from both the physical and digital realms in real time. MR applications in digital manufacturing education can potentially address the skill gap by enhancing the practical application of theoretical knowledge.

Overall, mixed reality can significantly enhance the capabilities of a digital twin that combines a simulation model and a physical twin, providing an intuitive and interactive way to monitor and optimize the production process. Future developments include the integration of a virtual headset with the Tecnomatix simulation software to perform monitoring and optimization of additive manufacturing process in real time, within an immersive production environment. Also, in order to compare the effectiveness of 2D versus VR visualization for simulation a quantitative and qualitative study will be considered as further research. The study will provide more insight into the benefits and limitations of each approach and will help to determine which one is more effective in certain contexts by providing a more comprehensive understanding of the users' experiences with each visualization method.

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