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AN OVERVIEW OF ARTIFICIAL INTELLIGENCE IN PRODUCT DESIGN FOR SMART MANUFACTURING

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Abstract— **Artificial intelligence (AI) has received significant attention nearly from every part of the world because it is a critical technology approach to develop intelligent systems. The manufacturing sector is one part which exploits AI, especially in the product design stage towards smart manufacturing. The aim of this paper is to present an overview on how AI enhances the product design stage for smart manufacturing. First, the paper gives the overall understanding of smart manufacturing about its definition, importance, and characteristics. Then, it delivers a brief overview of product design and product design stages. The essential concepts of AI techniques as well as various AI applications in product design ranging from conceptual design, embodiment design and detail design are discussed. Finally, research challenges and future directions for using AI in product design are provided and discussed.**

Keywords - smart manufacturing; product design; artificial intelligence; machine learning; deep learning.

I. INTRODUCTION

The fourth industrial revolution is characterised by smart manufacturing, which plays an essential role in the world. The crucial features of smart manufacturing are the complete integration of the various technologies to increase flexibility through real-time responses and collaborations [1-3]. All features aim to serve the product to customers on time with high efficiency so customer needs can be satisfied through personalisation and customisation. Each process in the manufacturing industry, especially product design and development [4], needs to significantly improve its efficiency [5] in terms of shortening operation time for high performance.

To achieve smart manufacturing, various technologies (e.g., internet of things, cyber-physical), are combined in the manufacturing sector. Because most of the techniques follow a data-driven strategy, a vast amount of data is created during the operation stages of a manufacturing process. Artificial Intelligence (AI) has been applied in the manufacturing operations [6] to analyse the data to make decisions for operating systems to reduce any effect that impacts the cost and quality, such as a human error, operation time, and downtime. AI system aim to response in real-time to process issues. More advanced AI aims to even self-monitor and self-control in an autonomous style.

The product design is a crucial activity in the manufacturing industry that takes a long time to develop [7]. A designer normally spends more than half of the time on organising data and designing knowledge [8]. To develop a smart design, meet customer needs, increase market competitiveness, and design effectively, this stage requires the employment of essential tools such as AI to support developing design, analysing data, and managing design knowledge efficiently.

This paper contributes to developing product design by using AI in smart design for smart manufacturing. In addition, this paper provides an overview of smart manufacturing characteristics, an introduction to the concept of AI, and a background into smart product design.

II. UNDERSTANDING OF SMART MANUFACTURING

A. Definition of Smart Manufacturing

The fourth industrial revolution or "Industry 4.0" is well-known in the industrial sector [9]. The main concept of Industry 4.0 is the digitalisation of manufacturing by the integration of various innovative technologies. Smart Industry 4.0-systems utilise real-time data between devices and machines, machine-to-machine and machine-to-systems [10] for real-time response, self-planning, self-control, self-monitoring [11].

Smart manufacturing as a concept has been used to describe manufacturing system which are driven by data-driven technologies [12, 13]. Smart manufacturing implemented as a completely integrated intelligent system serves customer needs in real-time to react to changing demands and conditions in a factory [14]. Technologies that have been used in smart manufacturing are e.g. the Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, data mining, robotics and artificial intelligence (AI) [15].

B. Characteristics of Smart Manufacturing

Customers and market demand require manufacturing flexibility to serve their needs quickly. Agile operation in manufacturing requires real-time response. Accordingly, conventional manufacturing requires improving its systems to be more intelligent and more flexible [5].

The Royal Thai Government for Janjira's PhD study.

Smart manufacturing consists of six pillars: manufacturing technology and process, materials, data, predictive engineering, sustainability, and resource sharing and networking [2, 3]. The naming of the pillars vary depending on time, organisation, or researcher (e.g., production planning has been used instead of predictive engineering). This paper focuses on the characteristics rather than the names. The characteristics of smart manufacturing (Fig 1.) are as follows:

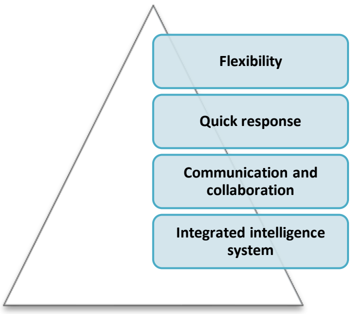

Figure 1. Characteristics of Smart Manufacturing

- **Flexibility:** it is defined as the ability to adjust and operate due to changing requirements [3], as well as increasing market demand in terms of customisation and personalised products (e.g., changing colour, changing the part, more features added). Therefore, the manufacturers require to develop the systems, methods, and tools for more flexibility and cutting down the lead time, leading to meeting customer needs and launching the products in time and increasing market competition.
- **Quick response:** when the market changes due to new trends, new innovative technology or other disruptions, it is necessary for manufacturers to improve or adjust their strategies to minimise the operation time and serve products in time, especially in product development, product design and manufacturing stages [4].
- **Communication and collaboration:** the objective is to meet the specification of the product accurately and with high efficiency in time. Thus, communication and collaboration in the respective section such as marketing, design, production, service, etc. is very important because stakeholders should be up to date on all information in real-time, leading to more efficient monitoring and problem prevention.
- **Integrated intelligent system:** integrating the innovative technologies like IoT, CPS, cloud computing, AR, robotics and AI together to make the smart manufacturing system, such as smart design, smart monitoring, smart machining, smart control, and smart scheduling [11], to support all the requirements mentioned above. Integration of intelligent systems causes lower cost, higher quality, shorter lead time, quick response, and increased market competition.

III. Product Design

A. Product Design

Product design in this context is the process of designing a product that begins with receiving the market needs or customer needs until generating the product's overall detail before production. Moreover, product design can be defined as a crucial step because many factors need to be considered to meet requirements. Broad information in manufacturing is set in this stage that affects the success of market competitiveness [15].

Fig.2 shows factors in product design that are affecting a product. For example, the materials selection process not only means selecting by the properties of materials but also considering aesthetic issues (texture, colour) and cost.

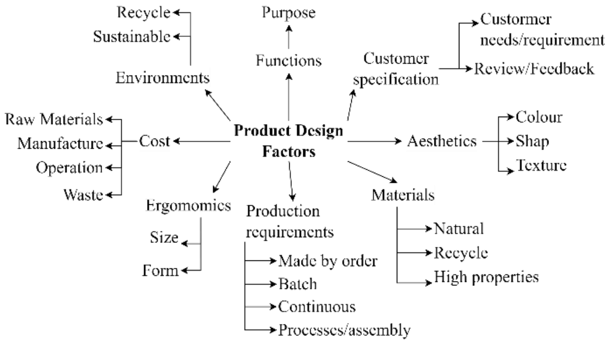

Figure 2. Factors that affect product design

B. Stages of Product Design

There are many activities in a product design stage, including the translation of customer needs to technical requirements, designing the shape and form, selecting materials, and considering the possibility of manufacturing and assembly process until complete the overall product detail before transferring to the production stage.

Product design can be separated into three stages: conceptual design, embodiment, and detail design [16], as shown in Fig.3.

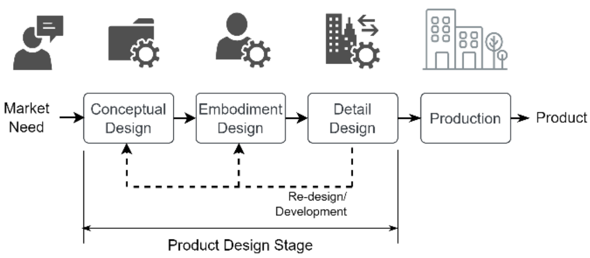

Figure 3. Product design stage

- **Conceptual design:** in this crucial stage, an unwise decision becomes the root of complexity in operation [7]. All the activities in this stage deal with the needs and requirements, such as analysing customer needs and design requirements, specifying the main function, and searching for principles for solving the fundamental design problem [10]. Moreover, evaluating the conceptual design, an overview of the design, to select the feasible concept.

- **Embodiment design**: outcomes from the stage are to clarify, confirm or optimise the details in primary design functions [17], such as the form design (shape and material of part), manufacturing process, assembly, and cost, as well as provide a solution for auxiliary functions if possible. If all the activities are done, the design in this stage will become the best solution, and it is chosen for the detail design stage [17, 18].
- **Detail design**: this step determines the complete overall specification, overall cost, and other key factors in detail [4, 18], such as a method of operation, aspect of assembly, and packaging, for transfer to the production phase. At this stage, the designer should have explored all of the potential possibilities that might impact the design and complete with only one choice and manufacturable solution [17].

IV. Artificial Intelligence in Product Design

A. *Artificial Intelligence*

There are multiple definitions of artificial intelligence (AI) because it has attracted much attention from many researchers in various industries. Hence, AI has been defined in many ways. Some AI definitions are shown in [4, 19-21]. Wang, et al. [4] have provided the following high-level definition of AI : "The theories, methodologies, technologies, and tools that are intended to understand human intelligence, develop artificial systems with intelligence, empower artefacts to perform intellectual tasks, and leverage computational means to simulate intelligent behaviours".

Some terminologies are referred to a AI, such as Machine Learning (ML) and Deep Learning (DL); however, these technologies are subsets of AI [22]. The relationship between AI, ML, and DL is shown in Figure 4. Here is a brief introduction to help understand the elements:

- **Machine learning:** a branch of AI focused on the ability of programs to perform data-driven calculations such as classification, regression, or clustering, etc. [22]. There are various ML algorithms such as neural networks (NN), K-means, Decision Trees and Random Forests [1, 23], k-nearest neighbours, multi-regression, logistic regression, and Latent Dirichlet allocation (LDA) [21],
- **Deep learning:** a branch of ML and a subset of AI focused on the operational data using multiple layers of neural networks [24]. The "deep" in DL refers to the number of layers of neural networks [22]. In the industrial sector, DL algorithms such as multi-layer perceptron and convolutional neural networks (CNN) are used for estimating costs in the conceptual design stage [25].

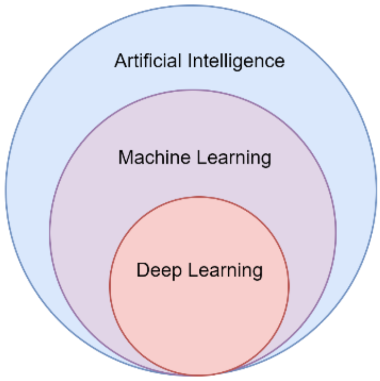

Figure 4. The relation between artificial intelligence, machine learning and deep learning

B. *Artificial Intelligence in Product Design*

Product design can be a time-consuming process in manufacturing. However, the product design step is crucial and can affect marketing, production, maintenance. Furthermore, there is a multitude of factors to be considered to satisfy customer needs, such as ergonomics, function, shape, service, and price resulting to designers spend a lot of time organising the many data and design knowledge. Thus, product design should employ the best cutting-edge technologies, such as AI, to facilitate the development and analysis data to serve a smart design decisions, meet customer needs on time, boost market competition, and design efficiently.

1) *Conceptual Design*

This step is to determine the concept function and design of the product by considering the needs translated into the concepts. Analysing the market or customer needs should be done carefully; otherwise, it will be complex to the next step and might not meet the absolute requirements.

Many researchers focused on systematically understanding the needs of the whole product, whereas, previously, the needs were captured by focus group and interview approaches [26]. The customer needs are generally expressed in natural language. Natural Language Processing (NLP) is a powerful branch of AI. However, the analysis of spoken language is challenging because the corresponding data can be unstructured, biased and prone to human error, thus making data analysis complex [21]. Wang, et al. [27] adopt a deep learning approach to improve the efficiency of mapping the customer needs and design parameters due to a large number of review data customers using natural language. Zhou, et al. [21] applied a machine learning approach to analyse customer needs for product ecosystem, which is collected by an online product review system to cut analysing time, improve effectiveness and efficiency of the online product review system. The result improved the designer's understanding of customer needs but fails in a part of product configurations by considering the capability of the manufacturers.

In this stage not only translating needs to concept functions but also required to finding the possibility of concept design candidate for the subsequent embodiment and detail design. Some research points out that in the recent year applying AI, especially DL, in computer-aided design (CAD) and Computer-aided Engineering (CAE) have increased as can be seen in [28-30]. Yoo, et al. [31] research generating 3D model and evaluation of engineering performance of a vehicle wheel by integrate AI, deep learning, into CAD and CAE system. The advantage of this system is AI estimate the engineering performance and generate a large number of 3D model candidates, which is engineer and industrial designer can be review and discuss the candidates togethers. However, some points still challenging such as expand the scope for consider the manufacturing constraints, generate 3D model without using 2D images and integrated AI to CAE simulation for predict nonlinear problems.

Apart from the customer need for translation and concept design generate, another part of the conceptual design stage also applies the AI, such as estimating the cost and visualisation of machining features to be a guidance for a designer to reduce the manufacturing cost during the conceptual design stage [25].

2) Embodiment and Detail Design

This paper presents the AI application in these stages simultaneously. The main activities in these design stages will be shown in two main activity groups: material selection and product form design.

a) Material Selection

Materials selection is one key point of product design, especially engineering design in general [32], due to the fact that materials play an essential role during the product design and production stages.
Ashby [33] studied materials and developed a diagram that helps designer select materials; this is well-known as the Ashby diagram. Some study points out that there is some gap in the method for selecting materials and several researchers point out that traditional material selection depends on designer experience. Hence, many researchers became interested in adopting AI for material selection. Merayo, et al. [23] summarised and compared the related AI tools for materials selection in various aspects of detail. This study has confirmed the importance of AI for making a decision in materials selection. Liu, et al. [34] used AI to classify the microstructure of graphite. The microstructure of each type is quite similar and difficult to classify by humans, but the properties are different. In case misclassifying will impact product failure [33]. Recently, Das, et al. [35] used AI to rank the candidate material and select materials for storage tanks and flywheels by comparing the result with Multiple-attributed decision-making (MADM) framework from the previous study, which lacks of evidence in the part of geometry. It was found that, their results were like the real-world practice and other previous methods.

b) Product form design

Mechanical design is a broader term covering the design of various parts, components, products, or systems of mechanical nature [36], and sometimes refers to the designing of machine elements. Product form design will be used in this paper. The term ‘Product form design’ or form design will be used solely when referring to designing the shape, features, and form of a product.

Feng, et al. [8] point out that designers spend a lot of time organising the data and design knowledge in the mechanical design stage. Thus, many researchers tried to implement AI for managing these data to reduce a workload for the designers and increase the quality of product design.

Recently, Bermejillo Barrera, et al. [19] study AI-aided design by implement AI and the CAD model library to predict the structure and properties of tissue engineering scaffolds to serve in different design requirements. The interesting point is simulation and conventional design cannot be applied due to the geometry complexity and aspect ratio of tissue engineering scaffolds. The paper validated possibility way for using AI-aided design of tissue scaffolds which might lead to an automated design. In addition, Krahe, et al. [20] aim to automate product design by implementing Deep Learning algorithms to identify design patterns to a product family out of their underlying latent representation, in this study focus on a class of table, chair and sofa, and use the extracted knowledge to automatically generate new latent object representations fulfilling different product feature specifications. Obviously, this study provides the trend to become an automated design to support smart manufacturing, the product family can be created according to give a product specification, but still need to improve in term of dimension error.

TABLE I. APPLICATION OF AI TECHNIQUES IN PRODUCT DESIGN

Applications	Related AI Techniques
Customer needs analysis	bi-directional long short-term memory or bi-directional LSTM (BLSTM) [27], Latent Dirichlet Allocation (LDA) [21]
Cost estimation for design guidance	Convolution neural network (CNN) [25]
Material selection	Decision trees, Multi-Layer Perceptron, and K-means Clustering [23], Nearest Neighbour Search (NNS) [35], CNN [37]
Prediction of structure and properties	3D Convolution Neural Network (3D-CNN) [34]
Predictive 3D model	3D Convolution Neural Network (3D-CNN) [19], Generative Adversarial Networks (GANs) [20] Probabilistic methods using N-Grams, Neural Network (NNs), and Bayesian Networks (BNs) [38]

It can be observed that existing data (e.g., CAD library, existing pattern of product family, previous data design) is attractive to many researchers in order to facilitate designers to reduce design time-consuming and design mistake during product design stage. As mentioned above, Bermejillo Barrera, et al. [19] and Krahe, et al. [20] aim to use the historic data to transfer the conventional design into automate by using AI. On the other hand, Vasantha, et al. [38] use the previous data design, such as features and configurations, to provide a predictive CAD system in order to suggest design engineer for valve design. The successful of the study is this system, which is use AI as a tool, can be suggested the designer for valve already. However, this study believed that the system should be a user’s interaction rather than automate due to designer interaction could be used to improve the accuracy of the system. While this study has completed to facilitate to design the valve, there are also opportunities to improve the functionality of the system, such as expand the scope to multitype of feature.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

According to the overall review on AI application for product design for smart manufacturing, the challenges and the future research directions can be summarised as follows:

- Analysing the customer needs faces the challenge of dealing with natural languages. Natural language often does not use technical terms which makes directly translation into a technical design language difficult. Moreover, understanding and analysing the whole product ecosystem is complex and can be time-consuming. Zhou, et al. [21] pointed out that mapping customer needs to product attributes still needs more research.
- Material selection also still poses research challenges. Firstly, dealing with the materials selection in the part of a balanced manner between technical design and industrial design are difficult due to the industrial design can be subjective and difficult to technically specify (emotion, aesthetic, perception, for instance). In addition, the lack of dataset and structured method for industrial design can lead to unpredictable outcomes [39]. Ferreira, et al. [33] highlighted that 96% of designers require smart material selection tools which are not available yet.
- Product designers, especially during product development, often use previous knowledge and know-how. Design procedures based on designer's experience becomes very individual. This makes knowledge transfer between designers challenging. Know-how and designer experience is valuable. Efficient knowledge capture and use through AI is still an open challenge.

VI. CONCLUSIONS

As the fourth industrial revolution plays a significant role globally, various industries pay more attention to transforming traditional systems into smart systems. AI is one crucial tool that is used for transferring a conventional system into an intelligent system. This paper has presented an overview of smart manufacturing and AI application. It shows how AI can and has enhanced the product design stages. Three substages, i.e. conceptual design, embodiment design, and detail design have been considered in terms of using AI. Examples of using AI for converting the customer needs to design requirements in the conceptual design stage, implementing AI for decision making in materials selection correctly in the embodiment design stage are discussed. The paper also highlights that some activities in product design still require further research. This includes analysis of customer needs to find a hidden requirement, managing product design historical data to improve design from reconstruction of historical data, and developing tools for materials selection.

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