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Green Material Optimum-Selection Driven by Digital Twins for Sustainable Manufacturing

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Abstract- In product design material selection and qualities are crucial. Environmental considerations should be incorporated in addition to technical and financial considerations in order to produce more sustainable products. The assessment indicators of the materials are supplied to meet the standards. This technique establishes an ideal evolution model first, which is a developing, high-fidelity digital twin of the actual object. The gathered digital and physical data are then combined. The performance of choosing green materials is analysed and simulated using the mode and fused data.

I.INTRODUCTION

Nowadays, material selection is crucial to consider the materials used in a manufacturing process. It has a significant impact on the product life cycle. Designers should take into account a wide range of criteria when choosing materials. Prior to now, the selection process was either cost- or product- or design-oriented. However, environmental worries have become worse recently. Thus, it turns into a decision issue with numerous criteria. Cost, mechanical qualities, process performance, among other factors, are taken into account when deciding which materials to utilise for a sustainable product design. Technical, economic, and environmental considerations are all part of the requirements for material selection. Sustainable manufacturing, which aims to cut costs, ensure product performance, and lessen environmental effect throughout the product's life cycle, heavily relies on the choice of green materials [1]. Although there are often trade-offs between physical property, cost, and the environment, the design aims and criteria in the material selection process are frequently in conflict. Additionally, each material performs differently in terms of its material properties [2].Green material optimal selection (GMOS) has historically been an optimization challenge that is reliant on the individual professional knowledge and experience of the designer. Furthermore, virtual layer algorithms and models served as the driving force for current GMOS research [3]. Numerous scholars used advanced computer software tools, optimization algorithms, and mathematical techniques to study this issue. Artificial neural networks and a genetic algorithm approach to GMOS optimization were proposed by Zhou et al. [4] in terms of optimization algorithms. Beiter et al. [5] created an expert system in complex computer software tools to do reasoning for the selection of plastics materials. Burkhardt et al. [6] investigated corrosion simulation and field analysis for the material selection of decoupling elements in simulation.

II DIGITAL TWIN-BASED EVOLUTION MODEL

Candidate materials are used in a variety of simulations, projections, and decision-making processes to simulate the whole life cycle of a sustainable manufacturing process, including design, production, transportation and logistics, recycling and remanufacturing, servicing, and so forth. The predicted characteristics derived from each simulation or careful examination in virtual space is compared to the anticipated qualities in actual space. If the comparison result is not achieved, the aforementioned simulation, prediction, and decision-making will proceed under different experimental conditions. The whole thing is an evolutionary process. Up until the predicted attributes are reached, the candidate material will be selected and manufactured. The ultimate objective of GMOS is to physically portray a product's true attributes. The mode of the GMOS based on DT is shown in Figure 2. Each possible material must have its properties anticipated via simulation in order to preserve consistency. The ultimate goal is to get the assessment results based on the predicted characteristics data and evaluation model.

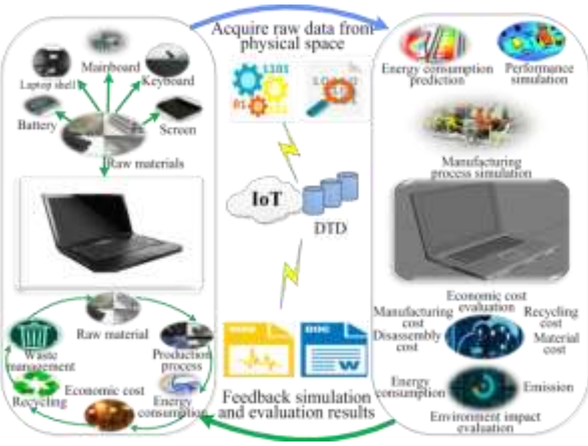

Figure.1.Digital twin driven green material optimal selection [7]

A. Digital Twin 5-D Model

The 5-D model proposed by Tao et al. [7] has currently gained widespread acceptance, and it can be represented as follows. M_{DT}=(PE,VE, DD, Ss,CN), where PE stands for physical entity, VE stands for virtual entity, DD stands for Digital Twin Data, Ss stands for Service for PE and VE, CN stands for connection among PE,VE,DD and Ss

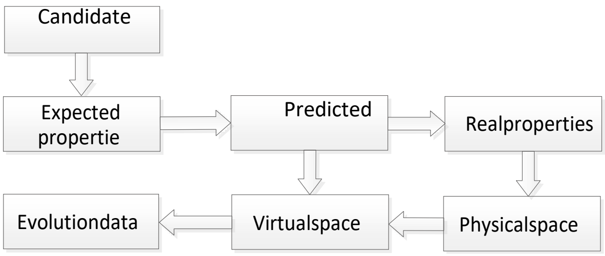

Figure.2. The mode of GMOS based on DT

III 5D-EDTM driven GMOS method

Over 277 million laptop were created in 2017, claims the report. Additionally, a laptop's shell is a crucial component that affects the device's functionality, price, and environmental impact. GMOS for laptop shell is a subject worth researching as a result. The method outlined above will be utilised to optimise the material choice for the laptop casing. 5D-EDTM.Three sets of indicators, namely physical properties, economic properties, and environmental qualities, are used to categorise the design requirements in step 1. Candidate materials are then screened in accordance with the design criteria [14]. These potential materials include engineered plastics, carbon fibre, magal, and titanium alloy (EP). In Step 2, X = {Magal, titanium alloy, carbon, engineering plastics} and define {x_1=magal, x_2=titanium, x_3=carbon, x_4=engineering plastics}, then load X to 5D-EDTM the GMOS is executed until i=4. As shown in Fig.3 .For the purposes of virtual space, physical space, and service modules, GMOS has evolved through four incarnations. Through data fusion and connection, the evolutionary optimization model is updated after each iteration. GMOS for the 5D-EDTM-based laptop shell is depicted in Fig.3.Data from the physical and virtual worlds are combined in step 3.

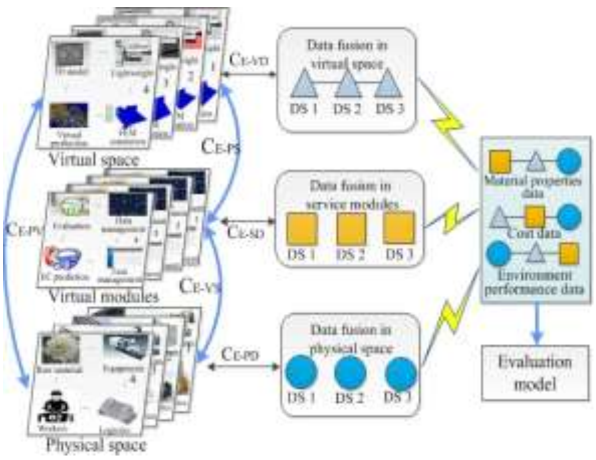

Figure.3. Green material optimal selection for laptop shell base on 5D-EDTM

These data include predictions, material property data, simulation data, and more. These combined data will be utilised as assessment criteria and indicators to assess the effectiveness of the item.$Evaluation\ Grade = \sum_{i=1}^{i=n} \frac{I_1+I_2+I_3}{n} + \cdots (0 < I < 1)$. I_i is evaluation for related indicators from evaluation models [15].

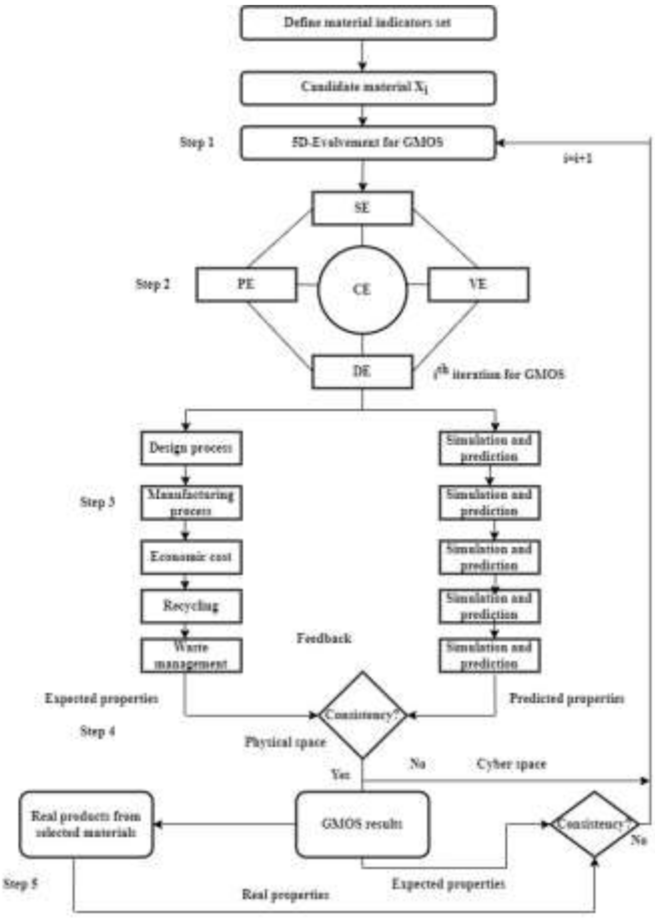

Figure.4. The process of 5D-EDTM driven GMOS Method

Table 1. The Result of Material Iterative Optimization

Iteration	Material	Design Objects	Parameters	Evaluation Score
1	Magna	Effectiveness	Strength, Toughness, Density Stress, Compressive stress, Heat Resistance, Cost of Processing, Material, After Sale, Recycle Waste, Energy Consumption	M1
		Worth		M2
		Atmosphere		M3
2	Ti Alloy	Effectiveness		T1
		Worth		T2
		Atmosphere		T3
3	Carbon	Effectiveness		C1
		Worth		C2
		Atmosphere		C3
4	Engg Plastics	Effectiveness		E1
		Worth		E2
		Atmosphere		E3

IV CONCLUSION AND FUTURE WORK

The GMOS is the primary process in product design, and its effects can be quite important because they have an impact on not only the cost, EC, manufacturing method, and recycling of the product, but also its function and quality. This research offers insight into DT driven GMOS and a direction for future work in order to accomplish the accuracy and efficiency of GMOS. The primary contributions are summarised as follows: (1) GMOS was the first system for which the 5D-EDTM idea was developed. (2) The DT-driven GMOS approach was presented and investigated. (3) The evolution of the 5D-EDTM is demonstrated using a laptop shell casing. The research still needs a lot more effort and is now in the early exploring stage. Future research will concentrate on the following topics: (1) analysing data fusion in 5D-EDTM, (2) exploring feature synchronisation in 5D-EDTM, (3) evaluating the rules and system of DT driven GMOS, and (4) using DT driven GMOS in sustainable manufacturing.

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