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A digital twin architecture for effective product lifecycle cost estimation

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Abstract

Lifecycle cost estimation is crucial for high-value manufacturing sectors, in particular at the early product design stage, to maintain their product affordability and manufacturing profitability within the market. Accordingly, it is important to identify through-life cost reduction opportunities. However, this is a challenging task for designers at the early product lifecycle stage due to the lack of complete historical data and the existence of high-level uncertainties within the product and service cost data. Moreover, the complexity of maintenance, repair, and overhaul interventions during the operation stage reduces the designers' decision-making confidence level at the earlier stages. This paper aims to address these challenges by proposing a novel Digital Twin (DT) architecture that uses adaptive data structure and ontologies to automatically produce the cost model from data mined information throughout a product lifecycle. The DT architecture supports designers by capturing data in terms of consumed and caused cost and automates the data flow to provide an adaptive cost estimation method across the product lifecycle. The DT enables designers to estimate the lifecycle cost at the early stage and to identify the through-life cost reduction opportunities effectively. Thereby, it is expected that the proposed DT supports OEMs to reduce the total lifecycle cost and improve the efficiency of their product development. A case study of lifecycle cost estimation in the machine tool industry is considered for testing the validity of the DT architecture.

Keywords: Digital Twin; Product lifecycle; Cost estimation, Ontology; High-value manufacturing

1. Introduction

Lifecycle costing (LCC) aims to estimate the total cost of design, develop, operate and retire throughout a product's lifecycle. LCC, together with the 'design for X' realm, are utilized by designers to improve the design and reduce the cost of products. The LCC analysis and framework support designers by specifying the estimated total incremental cost of events for a particular item throughout its lifecycle [1]. Moreover, the LCC model supports reliability-based design at the early stage of a product lifecycle [2].

Cost estimation refers to the prediction of LCC by interpreting historical data and elicitation of experts' knowledge. Estimating LCC is vital to many sectors, and in particular to high-value manufacturing within defence and aerospace contexts. Niazi et al. [3] presented a classification for cost estimation approaches. At the top level, these approaches are categorized into qualitative and quantitative techniques. The quantitative methods consist of parametric and analytical approaches. Activity-based costing (ABC) is one of the analytical approaches, and is defined as a cost estimation approach that calculates the cost incurred on completing different activities throughout a product lifecycle [4], [5]. ABC is a bottom-up approach that can provide a relatively precise estimation.

According to existing literature, more accurate lifecycle cost estimation approaches such as ABC require detailed and through-life cost information. This necessitates a

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knowledge-based approach to enable retainment and management of lifecycle cost models' elements. Thus, the development of a Knowledge-Based System (KBS) enables the collection, management, interpretation and employment of relevant knowledge. The KBS is expected to assist with LCC prediction at the design stage, to support stochastic modelling for capturing potential changes and uncertainties throughout the product lifecycle. Such a KBS also require to be adaptive in a way to update LCC automatically. Deploying an automated bottom-up cost estimation tool can provide extensive support for engineers and designers to swiftly and effectively respond to changes in design, customer requirements, and market demands. Moreover, it provides critical insight to identify the cost reduction opportunities through the product lifecycle. Nonetheless, the main remaining challenge for industries is to determine the link to the design-related decisions by assessing LCC for major equipment [6].

A Digital Twin (DT) is a practical suite of technologies that can be deployed to support the KBS by providing automated data retrieval and management. In the manufacturing context, DT has been defined as a "digital representation of an observable manufacturing element with a means to enable convergence between the element and its digital representation at an appropriate rate of synchronization" (BS EN ISO 23247-1). The observable manufacturing element is also defined as the "item that has an observable physical presence or operation".

In high-value manufacturing sectors, accurate and reliable LCC at the product design stage is crucial. However, lack of complete historical data, high level of uncertainties within the cost data, and the complexities of maintenance, repair, and overhaul cause several challenges in LCC estimation. The digital twinning process at earlier stages of a product lifecycle supports designers and engineers to explore, evaluate and make confident decisions with the potential to increase performance, and quality, to optimize cost, and to reduce process time [7]. Integrating DT with cost models for lifecycle cost estimation can enhance data capturing for total lifecycle cost. DT-based cost estimation can provide support with identifying opportunities for performance improvement throughout an equipment life. In this paper, the DT architecture of a lifecycle cost estimation processes is presented. Moreover, this study attempted to answer the following research question: How to design a DT data architecture to effectively estimate product cost over its lifecycle?

The paper is organized as follows: in Section 2. the theory and principles of existing research work on ontology-based and cost estimation are reviewed. The proposed digital twin architecture for product lifecycle cost estimation is presented in Section 3. The verification of the proposed architecture is presented in Section 4. using a case study from the machine tool industry. This is followed by conclusions and further work in Section 5.

2. Literature Review

The Total Cost of Ownership (TCO) was introduced in the late 90's. Subsequently, TCO was implemented within industries as a novel through-life cost estimation approach to support profitability for manufacturers, and suppliers. Moreover, LCC frameworks are mainly introduced in the literature to support designers in the earlier stages of the product development phase. Ellram [8] extended the TCO studies by developing a taxonomy for TCO models. The proposed taxonomy includes six main classes: capital cost of production and office support, Maintenance, Repair and Overhaul (MRO), components, raw material and services. Park et al. [9] stated that LCC becomes inadequate due to the lack of knowledge and information at the early design stage. They proposed a neural network algorithm to approximate LCC by considering over twenty attributes for a product throughout its lifecycle. Sandberg et al. [10] presented an LCC prediction model for the conceptual development of products. Their proposed model considers the activities at the manufacturing phase to estimate the cost of conceptual designs at the earlier stages of the lifecycle.

Kingsman and Souza [4] highlighted that cost estimation and making pricing decisions are challenging tasks, yet are required for remaining competitive within the market. They argued that static activity-based costing (ABC) is not sufficient, and therefore an assessment based on time, experience and expert judgment is required. Du et al. [2] proposed that analogical methods such as regression analysis and neural network models are more suitable to be implemented at the design and development stages and after the sale stage. Whereas, analytical techniques such as ABC, operation-based, and feature-based can be used at development, production and utilization stages.

Shehab and Abdalla [11] presented a knowledge-based approach to estimate the cost of products' machining and injection moulding at the design stage using the feature-based CAD system. A fuzzy logic approach was also implemented to analyze the uncertainty of the cost model. Tammineni et al. [12] presented a KBS for cost modelling of an aircraft gas turbine. Their proposed system integrates hierarchical trees and object-oriented knowledge to represent cost information. Germani et al. [13] presented a KBS for manufacturing cost estimation during the early stage of a machine design. Their proposed system comprises an automated link between the design features and manufacturing operation to predict manufacturing cost, effectively. Zhao et al. [14] presented a cost estimation approach using the knowledge-based engineering (KBE) technique to evaluate the production cost of an aircraft component. KBE refers to the application of KBS in manufacturing design and production. A parametric cost estimation approach was implemented by considering product and cost breakdown structures. They have argued that their proposed KBE enhances the integrity, efficiency, reliability and traceability of production cost estimation.

Chen et al. [15] presented an ontology-based mechanism for effectively allocating and sharing the heterogeneous product lifecycle knowledge among different enterprises. In a more recent study, a digital thread approach was presented by Siedlak et al. [16] to link aircraft performance, wing-box structural design, process-based costing, and production simulation tools. They have demonstrated how the digital thread approach can assist the affordability-based design. Recently, Erkoyuncu et al. [17] presented an ontology-based approach for model-traceability in DT solutions.

Existing literature on cost estimation and digital twin formation are isolated. Hence, this research work aims to present a DT architecture for effective lifecycle estimation to demonstrate how digital twins and cost estimation link.

3. DT architecture for effective LCC estimation

High-value and complex engineering assets evolve more rapidly when there exists their identical replica in a different form of representation, as the replica continues to provide resourceful information. DT is a virtual representation of a physical system throughout its lifecycle and enables the full integration of data, model, analytics, visualization, and decision tools to support continuous improvement of its physical counterpart. Based on the literature review and an academic-industry focus group workshop, a DT architecture for an effective LCC estimation is proposed, as presented in Figure 1. The proposed architecture demonstrates both physical and DT spaces. The two-layer physical space includes (i) physical item and, (ii) the associated lifecycle physical cost events; the extension of three layers in the DT conceptual model [18] adds three elements in the DT layer, which are: (i) data architecture, (ii) analysis, and (iii) decision element.

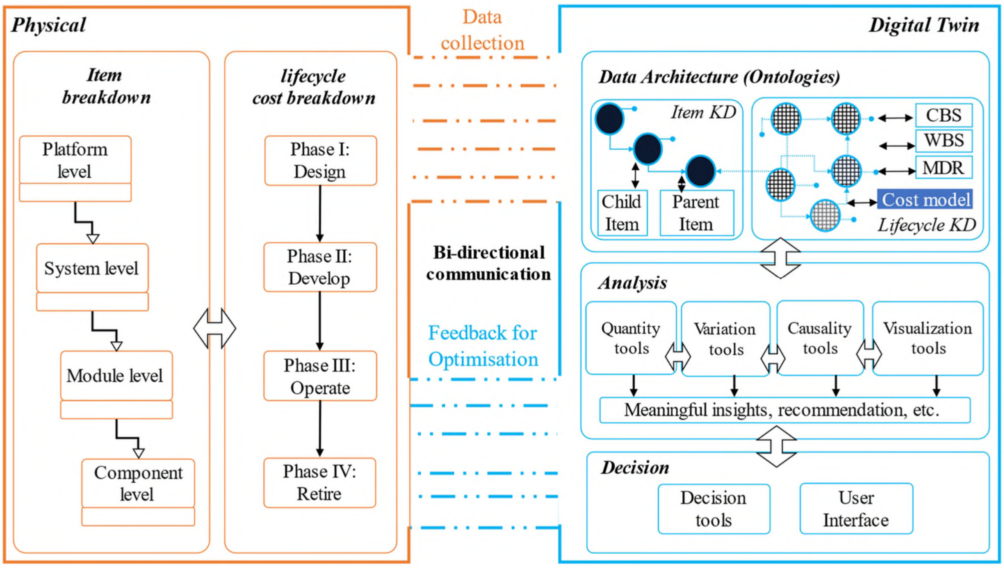

Figure 1: Digital twin architecture for an effective LCC estimation

Item breakdown: an item refers to a physical thing or entity that has potential or actual value to an organization. The item can be at platform (or asset system), system (or assembly), module (or sub-system), or component (or part) levels.

Lifecycle cost breakdown: refers to different physical tasks or processes that are applied to the item in which it triggers a cost throughout the design, develop (or manufacturing), operation (and maintenance), and retire (or end-of-life) stages of the item lifecycle.

Data architecture: DT is subject to evolve when its capability changes or its physical counterpart undergoes changes which entail modifications in the DT data structure. The proposed DT architecture adopts an ontology-based data architecture [17] in order to support adaptiveness in DT data. The design of DT data is divided into two stages.

The first layer is the modelling of the item knowledge domain (KD), which is only to be conducted once. The item has two sub-classes of ‘Child item’ and ‘Parent item’ in which the child item <isChiledOf> a parent item with ‘name’, ‘ID’, and ‘Batch’ (only for child items) as their attributes. The ‘item’ class has a transformation of <hasLifecycleCost’ to ‘Lifecycle’ class which is composed of two sub-classes of LCC_Event and LCC_Activity with ‘name’, ‘Unit Cost’, and’ Quantity’ as their attributed. The LCC_Activity <isPartOf> LCC_Event. The ontology structure for the item KD and lifecycle KD is presented in Figure 2.

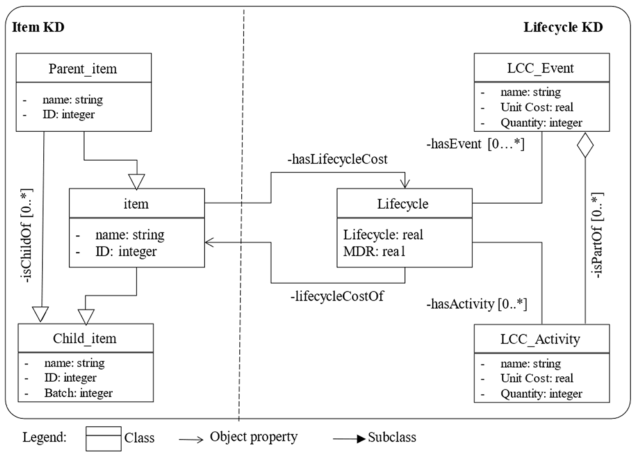

Figure 2: Ontology design for Item KD and Lifecycle KD

The second layer involves modelling the dynamic requirement over an item's life in the lifecycle KD. Item KD describes any single physical item that belongs to the platform breakdown throughout its lifecycle. Lifecycle KD provides interfaces to any possible DT software for data exchange in the item's lifecycle such as Cost Breakdown Structure (CBS), Work Breakdown Structure (WBS) and Minimum Data Requirement (MDR) [19]. The adaptiveness of DT data is required when there is a change in the DT system requirement to include a new KD i.e. a new model or software, for instance, the lifecycle cost model. This paper demonstrates how the proposed framework facilitates new KD, e.g. cost model, to be incorporated into the existing DT data to realize added capability for the DT system. When this new KD is modelled, all relevant data related to the physical asset lifecycle cost can be collected and represented in the DT layer for estimating the cost of an asset over its lifecycle. An effective cost estimation model using CBS, WBS and MDR has been recently introduced in [19] to be integrated into the proposed DT architecture in this study.

Analysis: In line with Grieves' concept [18], DT contains a set of virtual entities that each has a specific purpose in representing its physical counterpart. For cost estimation, these entities can include the digital quantitative models that process cost data to emulate the cost profile of its physical twin in the computational form. Digital cost models not only allow the simulation of the current status of the physical system, but also facilitates the analysis of what-if scenarios to derive meaningful information for optimizing operation and performance. The other types of entities may also include data analytic tools, which can be used to extract insights from the physical system and digital twin data.

Moreover, the virtual entity can incorporate variation tools such as sensitivity and uncertainty analyses to identify where the greatest proportion of the caused cost is laid. Furthermore, it can integrate with causality tools to enhance the visibility and mapping of root-causes to understand why the cost caused in the first place. The other important entity in DT is visualization modalities for representing DT data and models. The visualization tools enable the experts to perceive and to interact with DT for identifying useful information to improve and control the physical system.

Decision: DT also has the functionality to realize changes to its physical twin. This layer determines the flow of DT information to its physical representation to reach the desired state and maintain symmetrical status between both systems. There are some modules that provide a mechanism to act on the physical space based on the information generated in DT: 1) decision tools such as condition-action rules, decision matrices, and etc. to facilitate decision making, and 2) user interface, which consists of a means to receive data input and control output to aid users in the decision making process. The actions made from any modules in this layer can be realized either manually through the human operator or automatically using a controller or an actuator.

4. Case study: a machine tool

Item breakdown: A CNC machine tool at platform level from [19], with the same specifications, is selected as a case study to test the proposed DT architecture in our study.

Lifecycle cost event: The physical cost events, including CBS and WBS for the case study, are summarised in Table 1. The lifecycle of the machine is assumed as T=30 years.

Table 1: Case study – Lifecycle cost and work breakdown structures.

Lifecycle CBS	Lifecycle WBS
Acquire & Install	Purchase price; Legal fee; Dis-assembly; Transport; Assembly; Specification; Installation; Testing; Integration
Lost Opportunity	Penalty
Operate	Operator
Investigation	Investigation
Monitor & Support	Baseline maintenance; Standby support
Remove & Inspect	Remove; Inspect
Reject	Preventive maintenance; Corrective maintenance; Part disposal (including the cost of spares)
Re-Install	Re-install
End-of-life	Uninstallation; Dis-assembly; Transport; Retrofit

Data architecture: The implementation of the DT architecture started by identifying the two main classes; the item (item KD) and lifecycle cost event (Lifecycle KD) to describe the item (machine tool as the parent item) and its associated cost events, as shown in Figure 3.

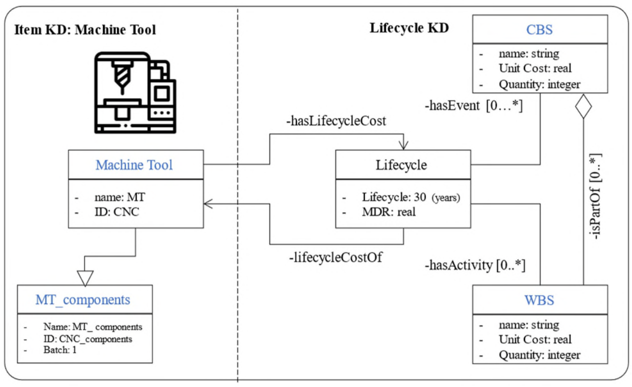

Figure 3: Case study - Ontology data architecture for cost model

This case study used the life cost estimation model proposed by Farsi et al. [19] and uses CBS, WBS and the MDR from different phases of the machine tool lifecycle. For this case study, the MDR is summarised in Table 2.

Table 2: Case study – Minimum data requirement

MDR	Symbol	Value
Time Between Overhaul (or MTBF)	TBO (years)	0.1
Removal rate (RR) for inspection at overhaul	RR	1
Overhaul Inspection Interval $OII = TBO/RR$	OII (years)	0.1
Rejection rate (Rej) after inspection	Rej	1
Replace strategy rate ($Repl$) after rejection	$Repl$	0.5

The data architecture is designed in the lifecycle KD following the ontological design architecture. This enables data interoperability among different DT software to address:

1) the accuracy of the cost model and 2) the opportunities for lifecycle cost reduction. Table 3 shows the example of cost model data attributes in terms of unit cost and quantity over the lifecycle in a tabular format.

Table 3: Case study – Lifecycle KD attributes, unit cost and quantity

Lifecycle cost events	Unit cost of events (K£)	Quantity (/Lifecycle)	Proposed total cost (K£)
Acquire & Install	£406.40	1	£13.55
Lost Opportunity	£0.55	30	£0.55
Operate	£1.35	1	£0.05
Investigation	£1.50	60	£3.00
Monitor & Support	£3.75	30	£3.75
	£0.50	360	£6.00
Remove & Inspect	£0.48	300	£4.75
	£1.90	300	£19.00
Reject	£20.00	150	£100.00
Re-Install	£0.48	300	£4.75
End-of-life	£55.50	1	£1.85
Total LCC over 30 years			£4.72m

As shown in Figure 1, DT can continuously collect data from the physical asset and log any unregistered events and activities which incur a cost to the machine tool's lifecycle. The data structure for cost model can be dynamically modified using ontologies for machine tool, and its lifecycle and the changes can be easily spread across the DT software systems. As a result, the DT improves the cost estimation accuracy by progressively updating the current model throughout the lifecycle. Ontologies also have the reasoning capabilities that permit semantic query to the data stored. This feature enables the retrieval of both explicitly and implicitly derived meaning from the semantic that was contained within the data. The data structure of the cost model has been formalized with attributes and relationships to describe lifecycle cost based on the events, activities, unit costs, and quantities which allow the provision of information based on the contextual query. Figure 4 shows the Protégé interface that captured the element of the cost estimation model.

Analysis: To identify the opportunities for reducing the lifecycle cost, the machine tool cost profile should be developed. The example of a contextual query can be expressed as *"Which cost event has the most cost proportion throughout the item lifecycle?"*.

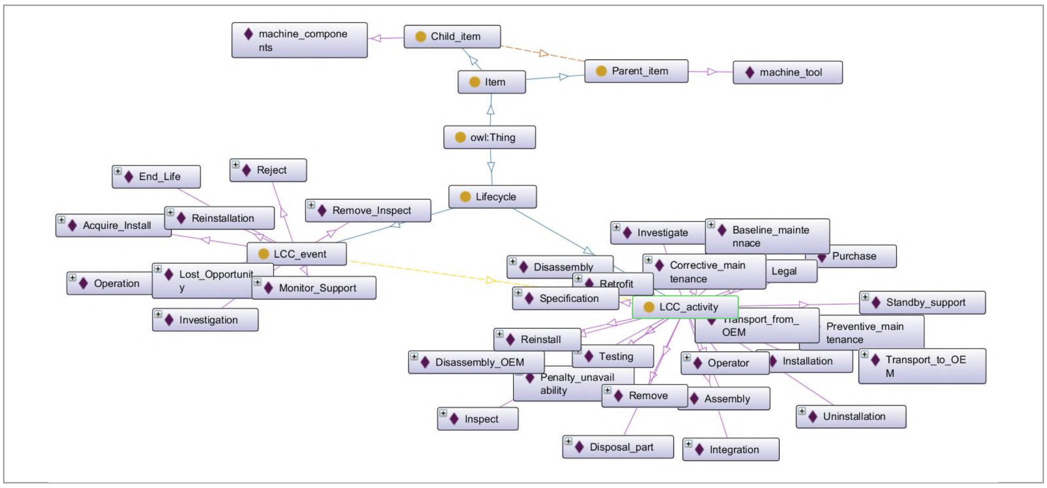

Figure 4: Case study – Protégé interface for item and lifecycle ontologies

The cost of events and the total LCC is calculated over the 30 years using the activity-based costing approach as detailed in [19]. The cost composition heatmap outlines the through-life cost profile across the lifecycle of the machine tool, as illustrated in Figure 5. The variation analysis results show that 75.61% of the LCC caused by the 'Reject' event.

Decision: as mentioned earlier, the proposed DT architecture is capable of providing feedback to its physical twin from the analysis and decision layers. There are a number of modules that provide a mechanism to act on the physical system based on the information generated in these DT layers. The outcome from the analysis layer presents the area(s) (i.e. cost event) with the greatest potential for a tangible and positive change with a view to reducing the LCC. In this case study, the 'Replace strategy' event caused 63.4% of the LCC. Accordingly, the appropriate decisions should be made by the engineers to minimize this cost. For instance, how designers can change the design of the machine tool's components to maximize their remaining useful life. How can the cost of replacement be reduced – including the cost of spares, inventory and logistics? What are the components with the highest failure rate? How can a repair strategy be conducted to reduce the cost of replacement?

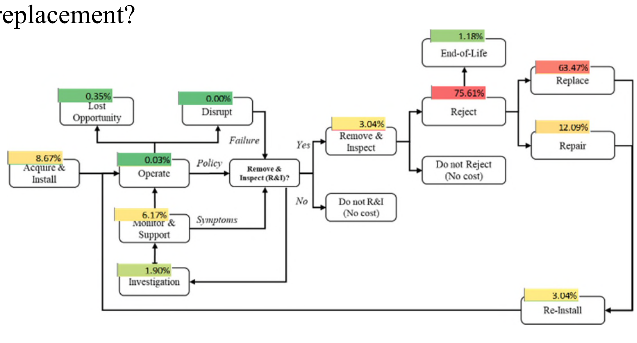

Figure 5: Case study – Cost breakdown heatmap flow chart

5. Conclusion and further work

In this study, a digital twin architecture for effective product lifecycle cost estimation is proposed. The DT architecture collects data from physical space (item and lifecycle events) to create the DT space with three main layers of data architecture, analysis and decision. The DT architecture has been tested on a machine tool case study. The collected data is used to develop an ontology-based data architecture as detailed in this study. The DT analyzes and visualizes the costs caused by the machine tool across its lifecycle. The accuracy of the proposed cost estimation using the bottom-up activity-based costing approach had been discussed in Farsi et al. [19]. The results indicate that the 'Reject' event with the 'Replace' strategy is the most potential area to look at for reducing the LCC of the machine tool.

This study contributes to the digital twin research by demonstrating an effective DT architecture for product lifecycle cost estimation using an ontology-based approach for synchronization between the physical and the digital spaces to establish a closed-loop DT. The developed ontology-based approach is flexible to spot the cost opportunity areas of an item over its lifecycle. The proposed DT supports manufacturers to reduce the total lifecycle cost and, ultimately, to improve the efficiency of their product development. There are a number of limitations in this study that induces the need for further work to demonstrate automated bi-directional communication, and the use of further analysis approaches by tracing the 'causalities' to identify the cause of costs which are often difficult to capture and visualize.

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