Cost-Based Decision Support System: A Dynamic Cost Estimation of Key Performance Indicators in Manufacturing

Foivos Psarommatis, Morad Danishvar, Alireza Mousavi, *Senior Member, IEEE*, and Dimitris Kiritsis

***Abstract*—An attempt is made to translate five generic key performance indicators (KPIs) into a continuous real-time cost function in a batch order-based manufacturing environment. The challenge of controlling and optimizing resource utilization, production efficiency, product-process quality, environmental impact, and inventory was specified by microelectronics and hard metal composite manufacturers. The motivation is to facilitate decision-making by converting operations management data into dynamic financial cost models. The process of interpreting engineering data of the physical level and operations management level into financial metrics creates a common language between engineers, managers, and financial departments of the company whose common objective is the profitability of the company, each with their own priorities. The proposed method provides a realistic representation of the performance of the system in monetary value. The integration may become an instrument of effective and efficient tactical and strategic collective decision-making. The main outcome is a near real-time formulation and prediction of manufacturing cost with respect to the five KPIs. The resultant cost function is verified according to several production scenarios. The case study demonstrating the proposed cost modeling methodology utilizes real-time and historical information from two different industrial partners in Tungsten metallurgy and electronic circuit manufacturing industries.**

***Index Terms*—Cost functions, hard metal, microelectronics, optimization, process planning, sustainable manufacturing, zero defect manufacturing (ZDM).**

I. Introduction

THE MANUFACTURING environment is highly competitive, and one of the most important aspects of this competitiveness is the accurate estimation of operational and capital expenditure that determines the final product cost [1]. Monetary evaluation of a state of a system is one of the most effective methods of communication between various decision-makers and stakeholders. Given a monetary value, the quality of business operations and decisions could be evaluated and improved [2], [3]. The importance of being able to predict the unit cost can be twofold. First, an accurate prediction of cost can help decision-makers meet the sales and business objectives (e.g., customer satisfaction, reduction of waste, and maximizing profit). Second, by using cost as a metric to integrate often conflicting objective functions (e.g., quality, production flow, delivery time, energy efficiency, etc.) then the balance can be struck.

The purpose of cost modeling is to translate a number of intrinsically different performance indicators into a common metric [4]–[6]. This helps to create a singular (integrated) point of reference in estimating and predicting the implications of interference with manufacturing operations. Having a reliable real-time cost estimation system involving most preponderant cost information and activities may lead to a competitive advantage [7]. The ability to obtain a continuous cost estimate and prediction as a tool for evaluating the impact of implementing new initiatives or continuing existing scenarios would be crucial to the survival of the manufacturing sector [6]. Early estimation and prediction of costs emanating from the translation of operations management data into financial cost models for timely and economic decision-making are essential to the sustainability of manufacturing enterprises. In recent years with high data availability and accessibility of real-time production data, manufacturing information, employee experience, and knowledge [8] which are key elements of the concept of smart factory and "Industry 4.0" revolution as well as advanced process mining techniques, forecasting of more accurate cost estimation through implementing an effective cost model is more demanding [6], [9], [10].

The task to genuinely capture, completely automates the process of continuous and real-time cost estimation in our experience has shown to be a major challenge, even in some of the most advanced manufacturing domains we have observed and studied. Existing manufacturing cost estimation methods such as ABC [11] are normally case-based and require extensive data acquisition and insight into the detailed cost of every element [12]. Such data acquisition is normally labor intensive and fixed into specified batches and process plans. They are normally one-off. Such methods fall short when we encounter high variety production plans that require adaptation in near

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real-time. This research intends to fill a gap to create a dynamic model that adjusts itself to such variations in production process and batch variety (batch oriented real-time cost modeling). This is thanks to the advent of Industrial Internet of Things (IIoT) and the capability of acquisition of real-time product tracking and traceability as well as machine state.

The motivation of the current study is to develop a solution to interpret sustainable manufacturing [13], inspired by practical implementation of Industry 4.0, AI-driven, and zero-defect manufacturing (ZDM) principles and technologies into monetary value. We present a novel cost estimation tool for properly selecting the manufacturing parameters that will allow productivity, but at the same time, they will give the opportunity to implement ZDM and have the desired product quality levels [13]–[15]. Decision-making process in complex manufacturing environments poses a major challenge for managers. Decisions are often taken based on complicated and, at times, conflicting objective functions. The key for successful monitoring and improving quality, productivity, energy efficiency, environmental impact, and inventory in a balanced way needs quality but simplified knowledge. In other words, the proposed approach will contribute besides other to the reduction of defects and by extent the related wastes. Waste is not only materials that are recycled of scraped but also time and environmental emissions and energy.

The proposed real-time cost modeler enables the translation of critical performance factors into singular common and universal metric, Cost. More specifically, the current cost model provides a systematic and easily deployable cost framework that addresses the shortcoming of the existing detail-oriented methods in batch order-based production environments. The proposed cost model uses a selection of five KPIs that represents the performance of the system in this article were defined by our industrial partners representing electronics and microelectronics, hard metal, and tool manufacturing sectors. The validation and verification process of the proposed cost models were conducted in the selected plants of the companies. By translating manufacturing process strategies and sustainability initiatives into real-cost, operations managers would possess a powerful tool to communicate with higher-level decision layers of the enterprise. Such seamless transition of information from shop floor to the board in a language understood by all allows justification for investments and divestment. At the shop floor tactical optimization can reduce instantaneous costs, while the integration of granular betterment actions may create nonlinear saving (combination of small actions) leading to larger impact and higher sustainability levels. Additionally, the proper selection of manufacturing parameters will significantly contribute to the reduction of defects and the related wastes. Waste is not only materials that are recycled of scraped but also time and environmental emissions and energy.

This article is structured in the following way; Section II presents the literature view, where relevant studies are analyzed shortly and using literature facts, the scientific gap is identified. Section III is devoted for presenting the proposed cost model. The section is divided into several subsections, one for each factor of the identified cost model. The developed model is tested using two real-life industrial use cases from semiconductor and hard metal domains (Section IV). The validation of the developed cost model takes place in Section V, where using a direct observation method for evaluation of the accuracy and performance of the model. Section VI presents several discussion points on the developed cost model and the results from the industrial cases. Finally, Section VII concludes this article.

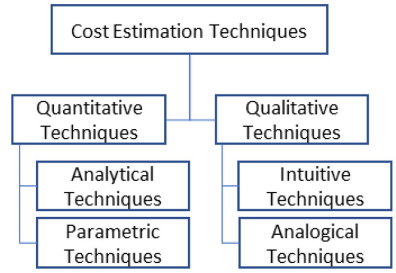

Fig. 1. Classification of cost estimation techniques according to [17].

II. Literature Review

Conventional costing methods were used extensively in the manufacturing industry for many years. However, new techniques were proposed in the early 1980s. According to [16], cost modeling of the manufacturing system is a combination of scientific theory, engineering principles and established commercial practices for prediction and estimating the cost of processes. Manufacturing systems cost modeling can be found in various forms. Niazi *et al.* in [17] in Fig. 1, categorized cost estimating techniques into two qualitative and quantitative techniques. The qualitative techniques are further subdivided into intuitive and analogical techniques, and the quantitative ones are further divided into parametric and analytical techniques.

A. Analogical Cost Estimation Techniques

These techniques are based on a similarity comparison analysis which compares a new product with a known-cost product to estimate the new product cost [18], [19]. Regression analysis [20], neutral-networks (NNs) [21]–[24] and deep learning [25] techniques are examples of these techniques which use historical cost data to deploy a relationship between the cost of the past products and the value of the new product. Elmousalami [26] compared the accuracy of twenty Artificial intelligence (AI) and machine learning (ML) techniques that are applied for conceptual cost modeling. Urso *et al.* [27] proposed a model to estimate microelectro discharge machining costs, including both fixed and variable costs. Their research aimed to evaluate the overall manufacturing costs, considering production and manufacturing process, tool and workpiece information. A process-based cost calculation method was used for this purpose. The model was applied to two case studies using different electrode materials. This research result was limited to a change in workpiece/electrode combination and process parameters which can give rise to a change in machining time and tool wear windows.

B. Intuitive Cost Estimation Techniques

Intuitive cost estimation techniques are heuristic-based qualitative techniques that reply to past experiences and domains of expert knowledge. In these techniques, experts knowledge's are systemically used to build a summation of rules and decisions which finally identify a cost function—the techniques such as case-based methodology and decision support systems (DSS). As an example, [16] developed an intelligent knowledge-based model that was able to estimate the manufacturing cost modeling of a product at the conceptual design stage of the product life cycle for machining process of a different kind of material, where both the material and machine operational costs were considered.

Moreover, the fuzzy logic technique has been applied to generate accurate cost estimates for new designs and explore alternative materials and process. The required machining time and cost for the component are computed based on a feature-based manufacturing cost estimation developed in [28]. Therefore, all rule-based, fuzzy logic-based, and expert-based approach are categorized among intuitive cost estimation techniques.

C. Parametric Cost Estimation Techniques

The principle of parametric cost estimation is derived from the mathematical and statistical relationship between the costs of a product and its parameters. These techniques are useful where the cost of constituent variables could be easily identified. A wide range of parametric models is presented in the literature [29]. Like analogous cost estimation techniques, they require historical and past data. Unlike detailed breakdown techniques, these methods could be used in the early design stage without the need for any process plan.

D. Analytical Cost Estimation Techniques

Analytical cost estimation models in which the total cost is the sum of detailed components and relative activities and resources are reviewed in [30]–[32]. In this method, all work steps, with their costs for material, work, infrastructure, etc., are added up to produce the costs of the final product. For this kind of evaluation deep understanding of the process, the process interactions and the part design details must be available. The advantages of this method are the level of detail and the causation it can provide. However, the main drawbacks of this approach are the significant number of required product details and efforts. In literature, these methods can be found under different names like bottom-up cost estimation. Operation-based, breakdown, and feature-based approaches are examples of these techniques.

Recent developments in information technology aim to apply existing manufacturing event data to improve processes by process mining techniques application. Process mining aims to discover, monitor, and improve real processes by extracting knowledge from the system's event logs. A framework is proposed in [32] based on the obtained event logs, which aims to better management decisions on the control operations' real cost. This is achieved by merging cost data with historical data from event logs to predict and estimate process-related costs. This research followed by [33] to propose a framework for analyzing and predicting manufacturing cost by utilizing and extending process mining techniques. In this study, a cost prediction model based on production volume and time progress of manufacturing processes was presented. This model assumes that there are close relationships between time, cost, and production volume. Therefore, manufacturing costs can be estimated based on time prediction and production volume. The main drawback of this method is it only concentrates on processing cost and does not mention clearly how the relationship between time and process cost was calculated.

Some analytical cost methods divide the costs into direct and indirect and measure their cost individually [34]. Estimation of the indirect cost may profoundly impact the organization's business strategy and its total profit. The selection of a more reliable cost method that fits the organization is a complicated task. Misestimation of these direct and indirect cost leads to incorrect decisions. Examples of indirect manufacturing costs are depreciation of machines and tools, repair and maintenance, inventory and electricity consumption costs. The activity-based costing (ABC) method is an alternative approach to traditional cost functions. It is a useful tool to achieve a costing system more efficient since it identifies and analyses the production activities that lead to the product object of the cost [11]. The ABC methodology was developed by Cooper and Kaplan [35] as a way to address the problem of the increasing share that indirect fixed costs have on a product's cost structure. ABC is a costing system that assigns the cost of resources required by each activity to all products and services in each stage of production, marketing, sales process, and delivery. The goal of ABC is to measure and then price out all the resources used for activities that generate the production of goods and services for customers.

ABC has high estimation accuracy, although the estimation must be conducted after production completion. ABC leads to the greater competitive ability of businesses. Time-driven ABC (TDABC) [36]–[38] was developed to solve the ABC complexity problem. ABC and TDABC are approaches for more accurate product costing. Several research works [11], [37]–[40] describe innovative applications of ABC or TDABC methodology. For examples, [41] proposed a procedure for a cost model that helps in calculating any maintenance job cost, to a reasonable degree of accuracy, based on the actual activities performed. Psarommatis and Kiritsis [6] applied ABC method to define delay cost per unit, per time of/amount of delay, and its results in linear cost behavior, or Tsai *et al.* [42] proposed a green ABC model which considered carbon tax in the cost objects.

However, the complexity and high detail-orientation of ABC methodology is the primary reason for its universally abandoned by some organizations [24]. According to [43], the process of calculation under the ABC methodology is considerable time and labor-intensive, but the cost of products estimated through ABC methodology only by 2.5%–6.4% varies from the cost calculated using the conventional methods. Several authors have named labor intensity as the critical weakness of the ABC. The developed real-time product cost measurement method proposed in [38] is used to calculate the rates and nonproductive time and cases involving a mix of labor and machine times. The cost per unit of time combines both the cost per labor hour and the cost per machine hour, according to the operational relationships between the machines and operators. The use of analytical cost techniques is prevalent in many industries and sectors. For example, Hueber *et al.* [44] provide an analytical insight to cost estimation methods and models in aerospace composite manufacturing. The authors compared different cost estimation methods and then recommended models, which are combinations of these three basic methods with their various strengths. In the end, a summary of the advantages and disadvantages of them has been assessed.

In short, parametric and analogous cost estimation models require historical and past data, but analytical methods can be created, implemented, and used independently from historical data [45]. However, the latter methods are detail-oriented, labor-intensive, and difficult to deploy over large manufacturing systems with large-frequent variations in product batches and process plans [46]. Researching the gap in academia and industry shows a lack of a formally structured approach to estimate the manufacturing cost. In the following sections, a systematic and easily implementable cost framework will be proposed to cover the shortcoming of the existing detail-oriented methods. The proposed cost model estimates manufacturing costs through five major generic manufacturing KPIs that are well established and known in every manufacturing/industrial domain into a singular cost unit. This method can be adapted to various manufacturing systems with minor or no changes, and despite its simplicity, the final cost estimation has satisfactory accuracy, verified in the form of case studies by two different industrial applications, reported in this article.

III. Manufacturing Parameters Selection Cost Model

Quality and productivity were always contradictory terms. The current methodology aims to bridge that conflict and provide a cost model tool that will allow manufacturers to properly select manufacturing parameters in order to maintain productivity at acceptable levels and, at the same time, be able to implement ZDM [47]. In contemporary manufacturing environments, product quality is a crucial aspect of the sustainability of the company [48]. The outcome of the proposed tool will be a set of manufacturing parameters that will allow good performance KPIs and implementation of ZDM. The suggestion of those manufacturing parameters will be conducted based on the cost of the final product, and the model will incorporate five key performance indicators (KPIs), which demonstrate how efficiently and effectively a company operates [49]. These KPIs are productivity, efficiency, quality, environmental impact, and inventory. The number of KPIs to be considered in a manufacturing environment depends on the size, complexity of operations, as well as various business and economic principles. For instance, some of the universally measured parameters that define performance are greenhouse gas emissions, resource utilization, overall equipment efficiency, energy consumption, waste raw material and end-product quality, capital and operational expenditure, delivery, and flexibility of processes. The intention here is to translate relative gains in each parameter into monetary value (i.e., cost). In other words, it will calculate the final product cost given the expected order quality [47]. Fig. 2 illustrates the framework under which the current cost model is used. Once a new customer order has arrived to the factory the production planner uses the proposed cost model in order to identify the most suitable manufacturing parameters for the specific order that will allow both high productivity with low defect rates.

The product processing time (T_P) is the parameter that affects products quality significantly. Therefore, this parameter will serve as one of the key input parameters in the upcoming cost model. The calculation of the final product cost is not a one-step process; it is composed out of several steps. Fig. 3 depicts the overall steps that are needed in order to estimate the cost per unit of product for a given batch size. Those steps are correlated with the developed equations that will be explained in Section III A–E. For the ease of the reader, all the notations that the developed cost model uses are shown in Table I.

The proposed cost model consists of four different cost terms for each manufacturing stage (MFG). C is the respective operational cost for a specific MFG. This includes the operators, machines utilization, maintenance and depreciation, set up cost and energy consumption costs. C_R represents the cost of raw materials that are needed in order to produce a certain batch. The last two terms depict the inventory cost (C_v) and the environmental impact cost (P_E). These four cost terms will be analysed and calculated with respect to the previously introduced five KPIs in the following sections. The final manufacturing cost per product is summed up of these four cost terms divided by the batch size, as presented in (1)

$$\text{Product cost } = \frac{\sum_{z=1}^{\text{MFGs}} \left(\mathsf{C}_Z + \mathrm{C}_{RZ} + C_{VZ} + P_{EZ}\right)}{N} \quad (1)$$

$$\bar{Q} = a * {T_P}^2 + b * T_P + c \quad (2)$$

$$\dot{D} = \left(1 - \bar{Q}\right) * N * Q_R \quad (3)$$

$$D = \left(1 - \bar{Q}\right) * N * \left(1 - Q_R\right). \quad (4)$$

A. Production Quality and Cost

Product quality is a critical aspect of the manufacturing process and is directly affecting the final product cost. Quality may also affect the relations between customers and the manufacturer and by extent, the number of orders and the loyalty of customers [50], [51]. Quality control process could increase the cost of the product significantly, but also defective parts lead to yield loss. ZDM approach is one of the latest quality assurance paradigms that aims to eliminate defective parts ensuring that customers receive products free from defects and meet their requirements [13]–[15]. In this point should be mentioned that for achieving ZDM all parts need to be inspected for assuring that the quality meets the required levels and if the product is defective to identify if it is repairable or not [52]. In general, poor quality causes loss of operational and material yield. The percentage of manufactured parts that fail inspection during and post-process determines production yield [53]. Failed parts may be scrapped elements or reworked, both indicating monetary

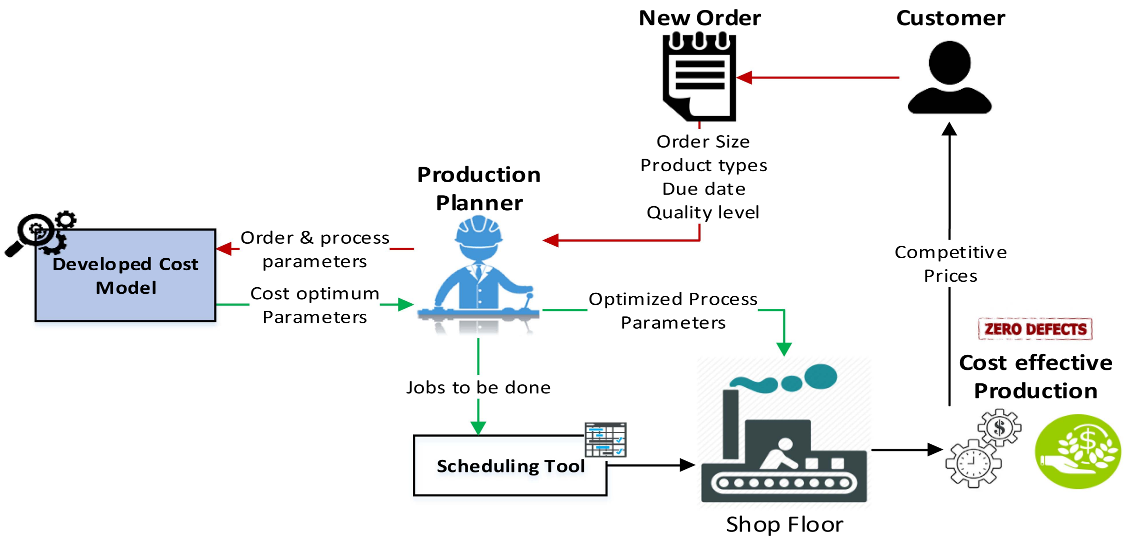

Fig. 2. Cost estimation procedure framework.

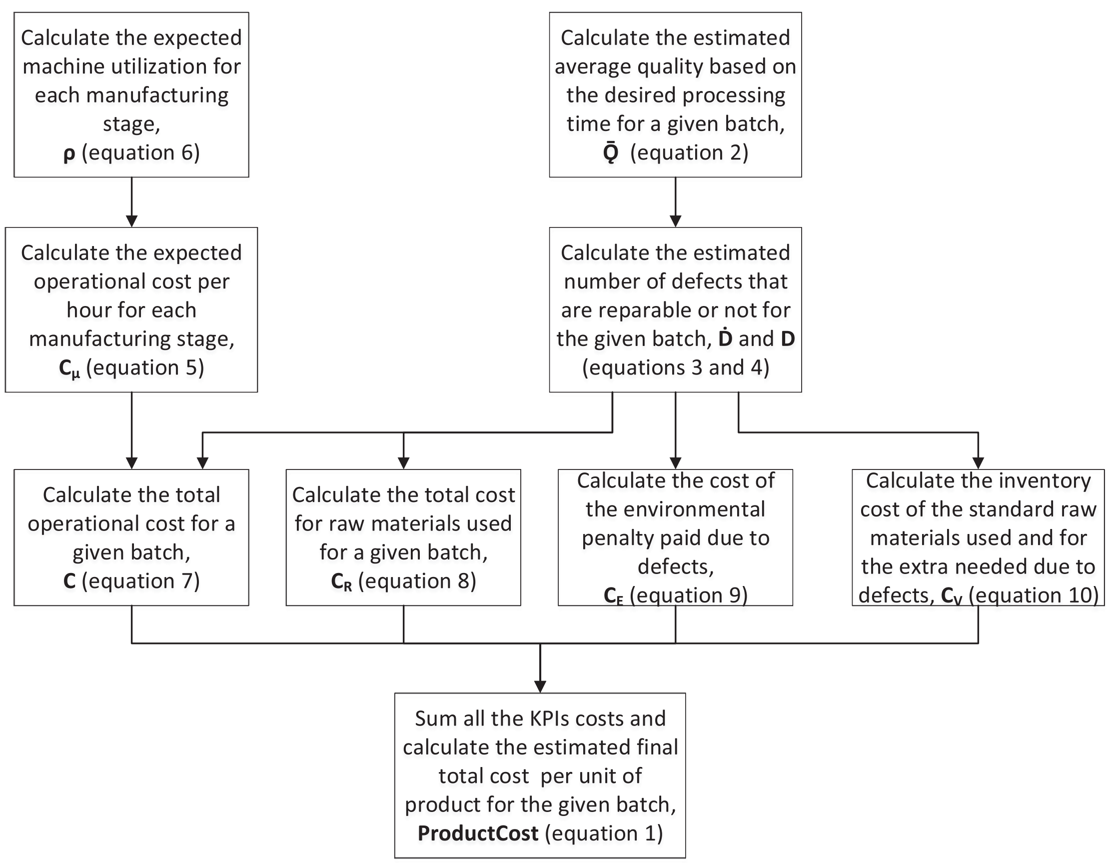

Fig. 3. Cost model calculation procedure.

expenditure [6]. Numerous factors can affect the quality of the final product. For example, in the present work experiments, the quality of the manufactured products deteriorates as the speed of the machines increase, although this is not a general rule. It is a tradeoff that needs to be balanced according to each individual order and specification that the customer has set. The average quality percentage of the manufacturing system is depicted with the $\bar{Q}$ and shows what percentage from the production of the total parts are nondefective. The relation between the processing time and the average quality can be described by a quadratic equation (1). This quadratic equation is changing according to the use case. Furthermore, the defective parts are classified into two categories those that can be reworked $[\dot{D}, (3)]$ and those that cannot be repaired and they have to be discarded $[D, (4)]$. Rep

TABLE I
NOTATIONS USED IN THE DEVELOPED COST MODEL

Notation		Description
a,b,c,d,e,f	:	Quadratic equation coefficients
$*\rho$	:	Resource utilization
z	:	Manufacturing stage
$*\omega$	:	Weight factor for evaluating the cost of raw materials needed for repairing a part
$*W$	:	Materials weight
D	:	Number of estimated defected parts that are not reparable
$\dot{D}$	:	Number of estimated defected parts that are reparable
P_E	:	Penalty for energy consumption per unit of time
$*P_M$	:	Penalty for each kg of materials used
C_O	:	Normal operational cost
C_E	:	Energy consumption penalty cost
C_Q	:	Quality inspection cost
$*C_I$	:	Inspection machine operational cost
$*C_\mu$	:	Machine operational cost
C_v		Inventory cost
$*C_u$	:	Inventory cost per unit of product and time, constant rate
$*C_R$	:	Cost of raw materials per unit
C_M	:	Normal materials cost
C	:	Total operational cost
X	:	Extra materials needed for non-repairable products
X'	:	Extra materials needed for repairable products
X''	:	Extra operational cost for non-reparable defected parts
X'''	:	Extra operational cost for reparable defected parts
$*T_I$	:	Inspection processing time
$*T_P$	:	Processing time (for one part for a specific machine)
$*T_R$	:	Repair processing time
$\bar{Q}$	:	Estimated/expected average percentage of "good" parts from the total produced
$*Q_R$	:	Percentage of reparable parts in a certain batch
E_μ	:	Machine energy consumption
*N	:	Number of parts in the orders
τ	:	Order shipping date
τ'	:	Order finish date
τ''	:	Order starting date

*model input parameters

denominates the average percentage of the defective parts that are repairable in a certain product type.

B. Production Productivity and Cost

Slower machine throughput or higher cycle times than the ideal throughput/cycle time are signs of productivity loss. Some of the causes of low throughput are a high frequency of breakdown, low quality or deficient materials, start-up delay, human factors, as well as imbalanced production lines. One of the main measurable indicators of productivity is machine utilization and overall equipment effectiveness (OEE) [54]; the ratio of machine value-adding a business to machine availability. Fluctuation in resource utilization affects the cost of production per unit of the product [55]. The machine cost per unit of time is a term that can be either a fixed value for each machine, as described in [56] or can vary, depending on the usage of the machine. The proposed cost function in this paper is a function of dynamism of machine equipment (resource) utilization. The algebraic value of the actual resource utilization cost is calculated as the summation of cost of operator set up time energy consumption at each state of the machine (i.e., standby, idle, busy), maintenance, and machine depreciation (some of these costs called indirect cost in analytical cost models). Equation 6 calculates instantaneous resource utilization. The total processing time corresponds to the average processing time from all the products in the current batch. The shift time, expressed in hours, is the available time to complete the batch. Machine processing time is a dynamic variable; therefore, in order to calculate the resource utilization, the average of processing time is used. Each instantaneous resource utilization is associated with the cost of process and delivery penalties (production throughput). Further to that, C_μ is following a quadratic trend against resource utilization (ρ). C_μ incorporates the following terms: the cost of the operator, machine maintenance, set up cost, consumed energy and machine depreciation. C_μ is calculated for each machine (i) in the production (5)

$$C_{\mu i} = d * \rho_i^2 + e * \rho_i + f \tag{5}$$

$$\rho_{\boldsymbol{i}} = \frac{\text{Total processing time } (T_P)_i}{\text{Shift time}} \tag{6}$$

C. Production Efficiency and Cost

Manufacturing efficiency is the level of performance of a manufacturing system. Manufacturers rely on the efficiency of their manufacturing processes to create quality products and achieving good financial and operational performance [57]. The more expensive and inefficient your manufacturing process, the higher the cost of producing products. Nowadays, the selection of the proper manufacturing parameters for achieving satisfactory resource efficiency and product quality levels is one of the primary and most crucial goals of manufacturing companies in order to stay competitive because they need to adapt production plans and volumes continuously according to the demand fluctuations [58], [59]. The proposed cost function incorporates the production efficiency in terms of operational time cost [C, (7)] and raw materials cost [C_R, (8)]. C is composed out of four terms; the first one C_O corresponds to the operational cost under ideal condition, which means there are no defects and therefore, no extra costs. The next three terms are the terms which include additional costs for achieving ZDM. More specifically, X'' is the extra operational cost required for counteracting defected products that are nonreparable. Using the same logic X''' is the extra operational cost required to repair the defected products that are reparable. Finally, as it was stated earlier, all the parts are inspected in order to verify the level of quality. Therefore, the last term represents the quality inspection cost

$$\begin{aligned} \mathsf{C} &= C_O + X'' + X''' + C_Q \\ &= \sum_{i=1}^{N} C_{\mu z} * T_{Pi} + \sum_{j=1}^{D} (C_{\mu z} * T_{Pj}) \\ &\quad + \sum_{k=1}^{\dot{D}} (C_{\mu z} * T_{Rk}) + \sum_{i=1}^{N} C_I * T_{Ii} \end{aligned} \tag{7}$$

$$C_R = C_M + X + X' = \sum_{i=1}^{N} C_{Ri} + \sum_{j=1}^{D} C_{Rj} + \sum_{k=1}^{\dot{D}} C_{Rk} * \omega_k. \tag{8}$$

D. Production Environmental Impact, Energy Efficiency, and Cost

Production environmental awareness and conformity are becoming compulsory and will be a major factor in the management of production systems [60]. One of the indirect methods of calculating CO_2 emissions is measuring the energy consumption of plants. The other method is a direct observation by environmental probes and toxic material release from production systems. Such emissions based on the designated country rules could imply direct financial penalties to be used for measuring production costs. The calculations cover both passed, defective and reworked production environmental impact. An effective way of controlling the environmental impact of production is to minimize the number of defective products throughout the production process. One of the major objective functions of ZDM strategy is to reduce the cost of environmental impact. Thus we strongly believe an environmentally friendly production system set up will lead to increased profitability per unit of production [13], [14]. Equation 9 shows how environmental impact cost is calculated. The term in the parenthesis derives the total time that the machines were working, and this is multiplied by a factor P_E which is the penalty cost per unit of energy consumed. The second term is about the raw materials that were used for the manufacturing of a certain batch

$$C_E = P_E * \left(\sum_{i=1}^{N+D} E_{\mu z} * (T_{Pi} + T_{Ii}) + \sum_{k=1}^{\dot{D}} (E_{\mu r} * T_{Rk}) \right) + W * P_M. \quad (9)$$

E. Inventory and Cost

The cost of inventory represents all the costs that are linked to the storage of products for sale as well as the raw material that is stored and gradually fed into the production lines [61]. The cost of holding, replenishing, and replacing products in the inventory depends on the type of product/material and the decay time, size, and value. Inventory cost in analytical methods is considered under a fixed indirect cost category. In the current study, the inventory cost is a fixed cost per unit of time. The type of material used in the presented industrial cases has a long shelf life, and in the case of adhesive glue, this requires a special cold storage facility that increases the cost of an inventory. Equation 10 shows how inventory cost is calculated

$$C_v = [(\tau - \tau') + (\tau' - \tau'')] * (N + D) * C_u. \quad (10)$$

IV. Industrial Case Studies Description

The accuracy of the developed cost model was tested and validated through two real-world industrial scenarios coming from the semiconductor and hard metal manufacturing domains. Two industrial use cases were selected in order to capture the accuracy of the model in different production systems. In the semiconductor scenario, the production line is automated, whereas in the case of the hard metal manufacturer, the production is semiautomated. The machine processing time was selected as the controlling parameter in this cost model since it affects the final product quality and the order finish time for meeting the due dates. Noteworthy, meeting due dates and product quality are the ingredients of customer satisfaction. In both use cases, the quality deterioration follows almost a linear trend as the machine's throughput increases.

The developed cost model was deliberately designed to be simple and not requiring extensive detailed and cumbersome and frequent data acquisition procedures. Such a solution in estimating production cost can be deployed in practice with minimum interference by operators. The input parameters of the developed model are 13 and presented in Table I with "$*$."

A. Semiconductor Automated Production System Use Case and Results

The manufacturing of printed circuit boards (PCB) is a complex and highly precise process, dealing with micron-scale components. Deviation from the planned process and desired product quality are costly. In the micro-semiconductor assembly process, a machine is responsible for dispersing adhesive and positioning components on an electronic wafer. Defects occur when insufficient or excess adhesive is dispensed. The faulty dispensing of glue causes failure to contact the die or short circuit. In both cases, the product is discarded costing on average 80€ per unit. Fig. 4(a) presents the relationship between product quality and production throughput. In other words, it shows the ratio between the healthy parts versus the total produced. In both industrial cases, there are four quality curves that are the outcome of different setups for the manufacturing of the part under investigation (QC_1, QC_2 ,QC_3, and QC_4). The differences between the four setups are in terms of setup time, the hardware used during the process. The values and the effect of those parameters were given based on the experience of the industrial partner for the specific process. Fig. 4(b) shows the relationship between resource utilization and the machine operational cost for the particular machine used in the use case. Further to that, the relation between operational cost and resource utilization can be depicted by the following quadratic equation $20.59\rho^2 - 2900.9\rho + 1213.5$.

Observation from the production line showed that as the production throughput increases (i.e., drops per minute) the quality deteriorates [see Fig. 4(a)]. Also, the higher the process throughput, the lower the resource utilization [62]. The proposed cost model was used for the identification of the optimum process throughput for several different batch sizes under the different product and process quality scenarios. Five different batch sizes were used for the empirical study and cost modeling of the production process. The results are presented in Fig. 5. Each diagram represents one quality curve ($Q.C.$) [see Fig. 4(a)]. Note that according to the available information, 10% of the failed products are repairable [see Rep in (2) and (3)]. Referring to the figures, the quality control scenarios QC_2-QC_4 demonstrate similar patterns of cost trends and where they reach the minimum value. In QC_1 the different curves are closer to each other compared to the other $Q.C._S$, and they converge toward a single point as the machine throughput increases. One observes that in all quality scenarios, the optimum point is on

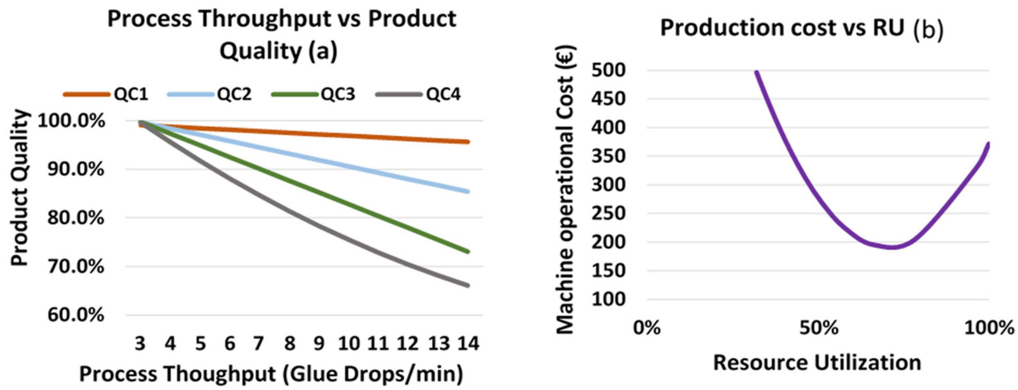

Fig. 4. Semiconductor use case: Quality curves vs machine speed in the top (a) and machine operational cost vs resource utilization in the bottom (b).

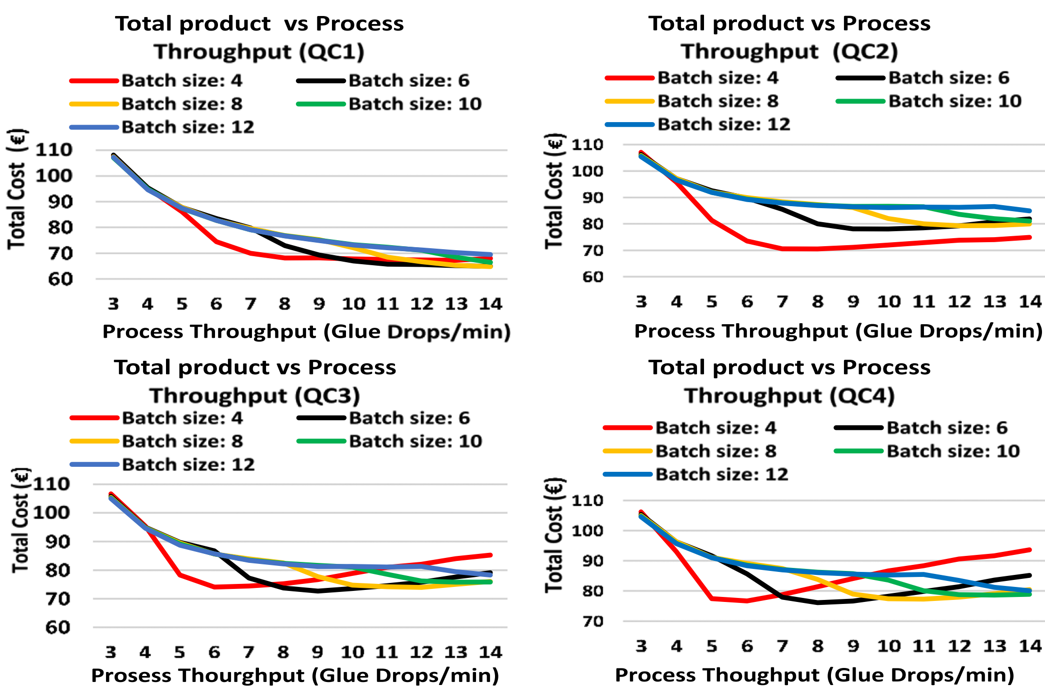

Fig. 5. Cost model results for the semiconductor use case.

machine throughput of 6 drops/min and batch size 4. In addition, the curves of batch sizes 4 and 6 have a behavior that they start from a high point, they reach a minimum point, and after that, they increase. This is because, in small batches, the appearance of defects has a more significant impact on the final cost. Something that is not the case in batches with more products.

In this use case, the minimum product cost for each quality scenario are as follows: for QC_1 the product cost is €66.30 for batch size 8 and machine speed 14 drops/min, and for QC_2 the product cost is €70.44 for batch size 4 and machine speed 7 drops/min. For the QC_3 the product cost is €72.43 for batch size 6 and machine speed 8 drops/min and for the QC_4 the product cost is €75.88 for batch size 6 and machine speed 8 drops/min. The minimum cost follows an expected trend which is aligned with the quality curves. What is noticeable is that in QC_2 the cost for batch size 4 is always lower than the rest of the cost curves except for process throughput 3, while in the other $\mathrm{QC_S}$ different speeds indicate a lower value in various batch sizes.

B. Hard Metal Semiautomated Use Case and Results

Tungsten carbide (WC-Co) is an intensive user of precision grinding, milling and turning operations, particularly for the final stages of hard metals wear tooling for numerous industrial applications. Surface finishing, including surface roughness, dimensional tolerances, and structural integrity must meet precise standards, which demand continuous measuring and quality control. Low process and product quality are costly. Rejected material and final products can be recycled through the chemical dissolution of the parts to recover the primary powder, which is an expensive and time-consuming process. The manufacturing stage that is investigated is the so-called "green machining" which is the machining of the compressed powder part prior to sintering. This stage is very critical because the part is very fragile and very prone to defects such as cracks and pores. Further to that, after sintering, which is the next process in the chain, if defects were not detected during the "green machining"

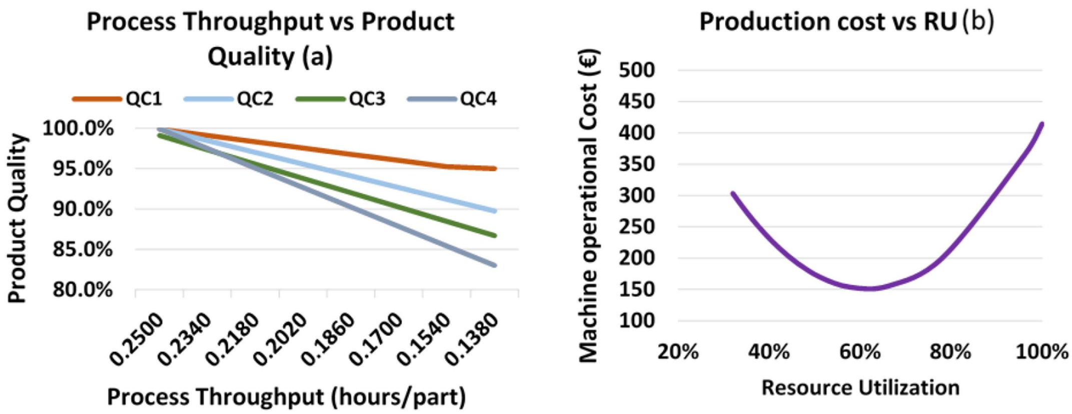

Fig. 6. Hard metal use case: Quality curves vs processing time in the left (a) and machine production cost versus resource utilization in the right (b).

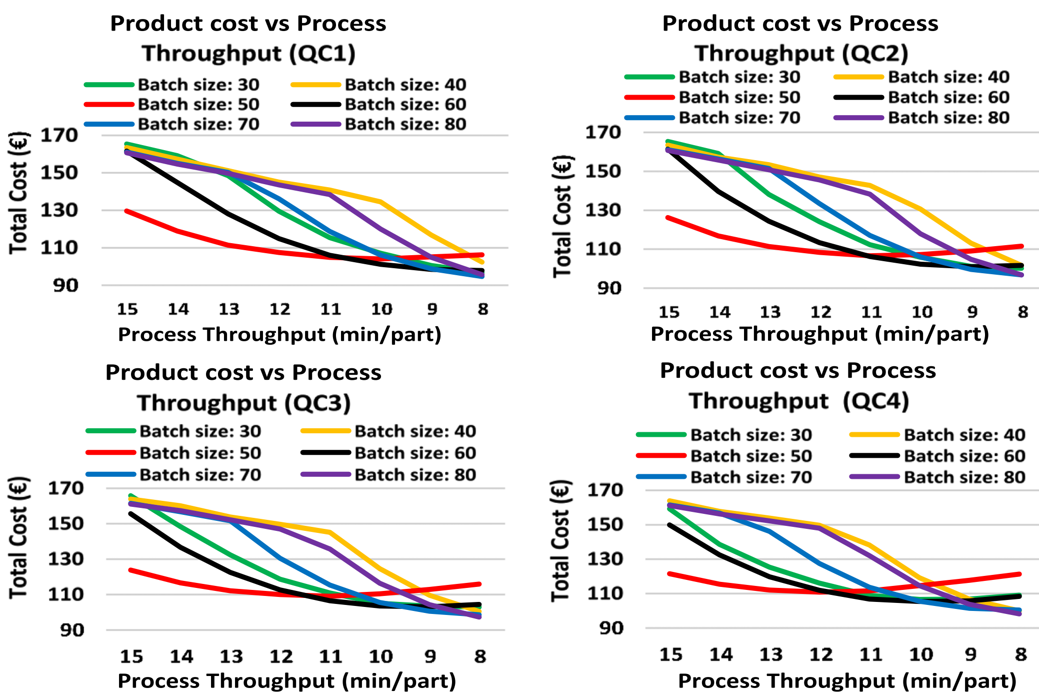

Fig. 7. Cost model results for the hard metal use case, processing a time-oriented approach.

the part could not be repaired, and it was discarded. The average cost for this part is 110€. Additionally, the structuring of this use case is identical to the semiconductor use case. Fig. 6(a) shows the ratio between the healthy parts versus the total produced for four different sets up configurations, resulting in QC_1 to QC_4. Fig. 6(b) illustrates the machine operational cost versus resource utilization, and it is described by the following quadratic equation $17.59\rho2$-$2158\rho+813.5$.

It is conceivable to deduct from the differences in the optimum regions of cost of resource utilization for both cases of semiconductor and hard metal that the effect of human factors plays a role. This empirical study confirms [63], [64] regarding the impact of human factors in manual production systems. The optimal point of resource utilization for a fully automated system is higher than the system with human intervention. As human intervention increases, the optimal cost of resource utilization becomes lower.

Six different batch sizes scenarios were studied. Fig. 7 illustrates the results. Also, the results for all the $\mathrm{QC_S}$ have an almost identical form, and they vary only to a few points compared to each other. The minimum product values are €95.35, €96.48, €96.65, and €97.52 for QC_1-QC_4, respectively. These values are very close with a maximum relative difference of 2.25%, due to the current process is insensitive to the different setups and by extension to the quality trend.

Observation: An interesting discovery from the two different case studies reveals an empirically inferred relationship between production cost and resource utilization [see Fig. 4(b) and 6(b)]. A quadratic function with well-defined and comparable parameters. Such a pattern may be true in other industrial cases,

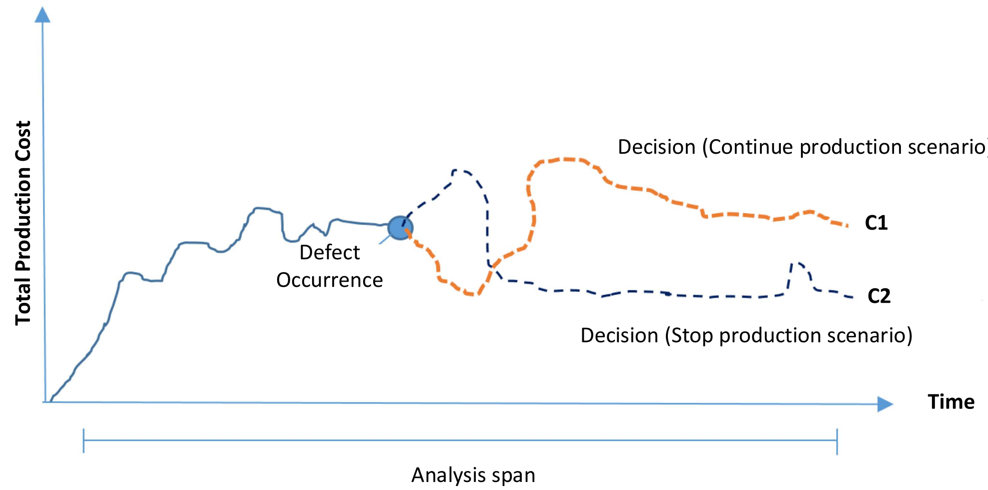

Fig. 8. Cost implications of two different decisions the dilemma of the production manager.

TABLE II
DIRECT OBSERVATION AND MEASUREMENT OF OPERATION OF SEMICONDUCTOR USE CASE

Parameter	Value
Product cost /module	\$109.52 (€91.53)
Batch Size	4 Batch (4*18 modules)
Speed for the machine	7 dots/min
Machine utilization	58%
Number of defective products	13 defective modules (Quality Rate: 82%)
Repairable products	None

TABLE III
DIRECT OBSERVATION AND MEASUREMENT OF OPERATION OF HARD METAL USE CASE

Parameter	Value
Product cost /part	€ 115
Batch Size	50
Process throughput	0.1860 hrs/part
Machine utilization	70%
Number of defective products	2 defective parts (Quality Rate: 96%)
Repairable products	None

and generic cost functions predicting Resource Utilization costs could be implemented in various industrial scenarios.

Fig. 7 presents that the batch size of 50 is distinctive from other scenarios. In this scenario, the smallest cost fluctuation can be observed, the minimum and maximum processing time have a greater cost, and the optimum configuration is 12 min per part. Regarding batches 40, 70, and 80, they show a high-cost decrease between machine speeds 10 and 13 min per part.

V. VALIDATION

A direct observation method is conducted to validate the proposed cost model based on the availability and accessibility of production data and manufacturing information from the use cases shop floors. The validation is based on comparing the cost model projections with the actual financial performances of both companies. The direct operational and management observation results for the same machine, production line, and products used in the proposed model are presented in Tables II and III for the semiconductor and hard metal use cases. The overall results showed an accurate prediction of the overall production costs of the firms and were validated by the finance departments.

To employ the proposed cost model in the semiconductor use case, first, we find the nearest quality fit graph to this case QC_4 curve in Fig. 4, with a machine speed of 7 dots/min. Then in Fig. 5(d) with the same machine speed, find the cost estimation, which is €89. The semiconductor financial department calculated the cost of €91.52 (see in Table II), which shows a deviation of 2.3%. And in the hard metal use case, there are two defects in a batch size of 50 products, and we used the QC_1 curve from Fig. 6, with a process throughput of 0.1860 hrs./part. Then in Fig. 7(a) with the same process throughput, cost estimation is €108 while the estimated cost by the hard metal company is €115 (see in Table III), i.e., a deviation of 6.4%.

VI. DISCUSSION

The proposed cost model is proven to be able to accurately translate multiple manufacturing KPIs into a singular metric (i.e., monetary value) simplifying decision-making (i.e., objective function definition). The proposed analytical method covers direct and indirect manufacturing-related costs. For example, the indirect costs such as depreciation of machines and tools, repair and maintenance are included with the resource utilization KPI and translated into cost. Other indirect costs like inventory and energy consumption as other KPIs are also included in the general cost model. Based on this approach the dynamism of the system is captured, thus the model adjusts to sudden and real-time changes, making it practical, flexible, and adaptable.

The translation of production systems KPI into cost unit allows for simplification of knowledge dissemination and facilitating tactical and strategic decision-making. The singular metric integrates information, making it understandable among larger groups of stakeholders in the enterprise. Justification of alternative strategies is made easier to demonstrate for the broader audience, e.g., engineering, operations, accountancy, and board level.

For example, the dilemma of the production manager in the event of a defect generation is to either stop the line and adjust; or continue the production to meet customer demands (see Fig. 8)—the dilemma of waste versus customer satisfaction. On the operational scale, any of those alternative actions will have a significant impact on the other production KPIs (productivity, efficiency, WIP, etc.). Typically, the most frequent decisions in the manufacturing area fall into either normal trend (i.e., what previously happened or which department production or marketing has the upper hand) and actions are taken without real understanding or projection of actual costs.

In the long term, the scenario with the lowest cost will and should prevail. The main impact of such a solution is the overall reduction of production costs at the specific dichotomy of decision and risk to the business. Two case studies used for validating and verifying the dynamic cost model generated showed on average less than 5% deviation from the actual costs of the production for the period of the analysis.

VII. Conclusion

The challenge of translating operations information into financial metrics in manufacturing systems persists. To address this problem, a cost model of production KPIs was proposed, capable of translating five KPIs into one single value, which has monetary units. The purpose of the developed model is to provide an easy to use tool that will assist production managers during the decision-making process for achieving an efficient and sustainable manufacturing. The proposed model considers both direct and indirect manufacturing costs. The developed model is designed to utilize real-time, historical, and data from each individual customer order to accurately estimate the product cost, with respect to system state (a continuous measurement of indicators of performance). The goal is that manufacturers use the proposed tool on a daily basis to select properly the manufacturing parameters keeping productivity at the desired levels and at the same time be able to implement ZDM. The implementation of ZDM contributes toward high-quality products without losing the performance of the system and minimizing the different type of wastes. The developed tool is able to adapt to a variety of use cases with very minor or no changes. As conditions of production vary, having a real-time indication of production cost and being able to conduct what-if-scenarios and have accurate cost implications could improve the quality of decision-making (especially quick response cases) and reduce overall production costs. The goal of the proposed tool was not only improving the efficiency of the production but also the sustainability. The selection of the proper manufacturing parameters has as an effect to the product defects reduction and by extent the wastes reduction.

The validation and the performance measurement of the proposed cost model was performed using data from two individual real-life industrial cases coming from metallurgy and electronic circuit manufacturing domains. The presented cost model was developed and validated based on a single machine, a single queue, with random arrival rates. Despite the simplicity of the proposed cost model, the results from the developed model had less than a 5% deviation from the actual values measured. An interesting observation was that we discovered the cost of resource utilization in two different manufacturing settings proved to follow near-identical quadratic patterns. Both industries are a combination of manual and automated operations, which is common in many other manufacturing environments (e.g., machining and assembly).

Due to accessibility to real production lines in the project and to avoid disruption to daily production, the case studies were limited to a single machine, single queue, with random arrival rates (M/M/1). It could be considered a limitation of the study. However, the experiment was the first step to demonstrate the capabilities of the proposed approach and verify it in a practical environment. Furthermore, determining whether a relationship between various parameters of the system is linear or nonlinear depends on the nature of the system and its specific data acquisition trends. The two industrial cases in this article demonstrated with no bias that the ratio between healthy and defective parts had a linear relationship. In the case of resource utilization this relationship was nonlinear (i.e., quadratic). Our next effort will be to connect multiple machines (processes) to explore whether the linear relations persist or otherwise. The models will shortly be implemented on the shop floor and expanded to more complex processes and multimachine scenarios. Noteworthy that the testing and evaluation of the models considered the average processing time. In the future, the actual readings from the processing times of the machines can be extracted from the live controllers so that the cost functions will become more accurate, and a further reduction of 5% deviation from the actual costs can be achieved.

Longer-term aim and future work will be to focus on the expansion of the model incorporating the circularity, environmental impact and inventory KPIs meeting future sustainability targets of the manufacturing sector. One of the implications of this research is the ability to evaluate the efficacy of green scheduling and sustainability initiatives with monetary values, something that is currently missing in sustainable manufacturing strategies.

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