

A Stochastic Costing Model for Manufacturing Management and Control

Vishad Vyas*. Paulo Afonso*. Sergio Silva**. Bret Boris**

*University of Minho, Braga, Portugal (e-mail: b12192@algoritmi.uminho.pt; psafonso@dps.uminho.pt)

**Bosch Car Multimedia, Braga, Portugal (e-mail: sergio.silva@pt.bosch.com; boris.bret@pt.bosch.com)

Abstract: Due to global competition, manufacturing companies need to support decision making on sophisticated, timely and accurate costing systems. Traditional costing methods based on volume measures are not efficient in modern times characterized by product diversity, production complexity and market volatility and uncertainty. Activity-based cost models were introduced in the 1980s and can help to deal with the complexity. In this research project, a cost model has been developed to take into consideration uncertainty and variability in the computation of the product cost. Due to the existence of variability and uncertainty, product costing should be approached stochastically. The stochastic model presented in this paper showcases through its equation the different levels of product costs related to activities' cycle time, production line bottleneck, planned unused capacity (for operational or strategic reasons) and unplanned unused capacity (due to variability in production or market conditions). The model supports and can be extended for cost prediction and cost optimization under conditions of variability in resource costs, process and operations conditions, and demand changes imposed by the market or clients.

Copyright © 2022 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Keywords: Product cost, Activity-based cost model, Stochastic model, Variability, Uncertainty.

1. INTRODUCTION

Due to global competition, companies want to be prominent and continue in the market where competitors are available offering almost the same quality at competitive prices. In such context, product's specifications and quality tend to be commodities in the industry and that emphasizes the focus on the cost of the product. To survive in the market, it is necessary to provide a competitive pricing of the product, which asks for accurate costing systems. Such costing systems should help to control the cost of the products and to provide accurate information on the relevant cost objects (Cooper and Kaplan, 1987, 1988). Because if the costing is not done well then, the company might incur losses if the cost is underpriced and might not get the proper sales as the cost of the product is overpriced turning the company less competitive. Hence, a proper costing system and a good controlling of the cost is important (Pember and Lemon, 2015).

In this context, traditional costing methods based on volume measures (e.g., product quantities, labor hours) are not efficient in the modern times. Thus, in the 1980s, Kaplan and Cooper, proposed the new concept of activity-based costing (ABC), which can help to understand the product cost from a different perspective. Thus, differences in the cost will arise because the ABC system is a more sophisticated approach to allocate overheads that provides more accurate information on costs, supporting the costing of the relevant cost objects and of the activities and processes with more leverage for increasing the profitability (Robert S. Kaplan and Anderson, 2007).

There is empirical evidence about the impact of the use of ABC on the performance of the company. Nevertheless, many of the companies that had adopted and implemented activity-based costing systems faced difficulties during the

implementation process and eventually, abandoned their ABC projects (Gosselin, 1997). To overcome these drawbacks of activity-based costing, Kaplan and Anderson developed a new approach for ABC which they termed as time-driven activity-based costing (TDABC).

Time-driven activity-based costing models are focused on the relation between cost and time (which measures the available capacity of the resources employed) and how they can be used to determine the cost of the product. In a TDABC model, we can identify the resources used, their costs and practical capacity and from this information the cost per unit can be calculated. For each resource cost pool, the cost allocation is done using two sets of estimation 1) the capacity cost rate and 2) process time. The capacity cost rate is calculated as the cost of all resources used divided by the available time to perform the task. The process time is the time that each cost object needs (Hoozée and Hansen, 2018). The complexity of the product and of the production process can be represented through time equations. The Time equations are used to incorporate the time which is required for all sub-activities and related issues affecting the costs reducing the complexity that typically characterized ABC models.

The motivation of this research work is as there is space for improvement in the costing of the product in practice (approaches and tools used by companies) and conceptually (concepts and models). Particularly, the deterministic approach inherent to TDABC can be extended, namely, to take into consideration risk and uncertainty in the computation of the cost of the activities and cost objects.

Uncertainty in costs can occur due to insufficient knowledge or information which implies that predictions might differ from the reality (Oberkampff *et al.*, 1999). During the estimation of costs, available information is usually historic or

past information, which can have a high level of uncertainty namely, related to processes cycle times (Scanlan *et al.*, 2006). An uncertain problem can be expressed as uncertain ratios also known as fuzzy numbers. Techniques based on the fuzzy numbers have been proposed to manage uncertainty in cost models by several authors (Nachtmann and Needy, 2003). There is research based on linear planning models using fuzzy numbers to deal with the uncertainty of the most relevant parameters of the cost model. Thus, fuzzy logic is an approach to deal with uncertainty that can be included into extended TDABC models which may provide more accurate results compared to deterministic cost models (Nachtmann and Needy, 2003).

A stochastic approach can also be used to accommodate the uncertainty and variability that prevails during the production process (Afonso *et al.*, 2021). A stochastic model can be built using the probability distribution of the possible results by allowing the random variable in one or more inputs over time. The random variables are based on the uncertainty and variability found in the historical data.

Hence, in this paper a stochastic cost model is proposed to extend the model proposed by Kaplan and Anderson. Firstly, a deterministic approach inherent to TDABC was developed and adapted to the context of manufacturing and production systems. Secondly, it was extended, namely, to take into consideration risk and uncertainty in the computation of the cost of the activities and cost objects. Thus, a TDABC to deal with the variation and uncertainty that prevails during the production is proposed in this paper. The proposed stochastic cost model is supported on a set of time equations structured around a cost hierarchy that highlights and differentiates the workstation specific cost, cost induced by the production line bottleneck, planned unused capacity cost and unplanned unused capacity cost. This novel cost hierarchy complements and extends Coopers' cost hierarchy proposed for the early ABC models (Cooper and Kaplan, 1988).

2. LITERATURE REVIEW

2.1 Activity-based Cost Models

Activity-based costing links resources to the activities needed to produce the relevant cost objects (e.g., products). The goal of activity-based costing is to allocate more accurately overhead costs using the best cost drivers of the process. There are mainly two stages in the application of activity-based costing, in the first one the resources are allocated to activities by resource drivers, and in the second stage, the cost of each activity is allocated to the cost objects by activity drivers. It has been assumed that the resources are consumed by the activities which are needed to produce the product (Robert S. Kaplan and Anderson, 2007). The allocation of the cost to the product by means of allocation bases related to activities results in more accurate costs of the cost objects (Cooper and Kaplan, 1988). ABC was developed to solve the problem of the increasing indirect costs of the product and its influence on the product cost structure which are derived from the process of industrialization and automation.

Nevertheless, the implementation and use of ABC was not feasible in many cases as the collection of the information is

very time-consuming resulting in a costly tool for decision-making. Furthermore, ABC ignores the potential of unused capacity.

To overcome these problems, Kaplan and Anderson derived a new method from ABC which was termed as time-driven activity-based costing (Kaplan, 2006). It facilitates the process of collecting the data considering time as the main driver of the cost and capacity measure. This approach also helps in understanding the capacity of each process/activity and uses the capacity needed for each product and the capacity cost rate to allocate resources' costs to products (Pember and Lemon, 2015).

But, activity-based cost models, both ABC and TDABC, have some limitations and must be extended and improved to deal with the complexity, volatility and uncertainty that characterize, nowadays, production and business processes, and market demands.

Furthermore, because the application of costing in organizations is characterized by several and different processes, products, and activities, measuring and identifying the parameters for the time equations may be particularly difficult. Costing systems demand for structured information systems and robust databases. Large companies have powerful Enterprise Resource Planning (ERP) systems, and the data is updated periodically. Nevertheless, in small and medium-sized companies, the process of data recording and analysis is much more complicated and time consuming. Finally, this costing model asks for constant reviews and regular maintenance over time what may turn it too expensive. Thus, measurement errors, subjectivity and dependence on homogeneity are the most cited problems related to the use of TDABC.

In this context, some extended activity-based cost models have been proposed by several authors. Namely, Feature Based Cost Management (Filomena *et al.*, 2011), Efficiency Based Absorption Costing (Benjamin, Muthaiyah and Marathamuthu, 2009), Fuzzy Activity-Based Costing (Nachtmann and Needy, 2003; Chansaad *et al.*, 2012), Fuzzy Performance Focused Activity based Costing (PFABC) (Sarokolaei, Bahreini and Bezenjani, 2013), Activity-Based Life-Cycle Costing (Durán, Afonso and Minatogawa, 2020).

2.2 Stochastic Cost Model

The collection of random variables which are arranged in a specific mathematical set associated with elements of the set can be defined as a stochastic model (Anderson *et al.*, 1985). A stochastic model is a tool which can be used to estimate the probability distribution of the possible results by allowing the random variable in one or more input over time. The random variables are based on the variability and uncertainty found in the historical data for the selected time using time series methods. The mode of the curve which is also known as probability density function is the most likely estimate given by the distribution curve.

In manufacturing processes, there are significant sources of uncertainty associated to the cost estimation process. The uncertainty in the cost estimation can be reduced by providing more complete information about the manufacturing process.

Uncertainty and variability are present in costing because variation in the cycle time of assembly lines, production planning and scheduling, market variability and uncertainty and other unpredictable and unexpected events. Thus, lack of information, ambiguity, complexity in the information, errors in measurements, beliefs instead of real information cause variability on product costs (Zimmermann, 2000).

A sensitivity analysis can be used to estimate the cost under risk and uncertainty, but probabilistic methods can support better decision making by providing more information. Nevertheless, they require a larger amount of data and more sophisticated statistics than the sensitivity analysis (Datta and Roy, 2010).

There are a few examples in the literature. For example, a decision model based on activity based costing and stochastic programming was developed by (Oh and Hildreth, 2013). Stochastic programming has been incorporated considering uncertainty that prevails in energy demand and supply. In the optimization process under uncertainty, there are two types of stochastic programming that can be applied, which are resource type and chance constraint type.

Furthermore, (Chengjie, 2020) developed an activity-based bottleneck model considering the stochastic capacity in order to study the departure time choice behavior of commuters in the peak hours. Analytical solutions of the departure rate of each situation under equilibrium were calculated (Borrás Mora, Spelling and van der Weijde, 2021) proposed an advanced stochastic model to identify the most relevant parameters which influence cost and uncertainty. The variables which behave as the most important cost drivers were also highlighted. These variables are behind the effective reduction of the cost thus, providing information on where additional efforts are required and can effectively reduce the costs is very relevant. Stochastic variation is evident specifically in additive manufacturing, thus a method of time driven activity-based costing in collaboration with digital twinning will be advantageous to optimize the use of capacity and time available for manufacturing. In the case of stochastic variation, the standard time can be allocated to each and every element with a certain confidence level. The model proposed by (Anderson and Van Der Merwe, 2021) uses a digit twin, based on the statistical data available and stochastic variation, to predict the time required for each process element.

3. MODEL DEVELOPMENT

In the modern industry, there are a variety of products which require multiple operations to produce them from raw material to the final product. So, it is important to calculate the time and cost required for these operations which can be done using cost and time equations. Time equations represent a powerful tool for decision making and operational and strategic management particularly, in organizations characterized by complex production and business processes and those operating in very dynamic, competitive and uncertain markets. Using time equations, complex activities and processes can be easily modeled, making the costing process much easier, accurate and cheaper.

Thus, a general formula for both time and cost was developed that considers the cycle time cost by workstation, the bottleneck of the production line, the planned and real units produced, and cost rates.

$$T_{i,p} = \beta_i \times X_{i,1} + (\beta_b - \beta_i) \times X_{i,2} + (\beta_L - \beta_b) \times X_{i,3} + \left(\frac{Q_2 - Q_1}{Q_1}\right) \times \beta_L \times X_{i,4} + \varepsilon_i \quad (1)$$

$$C_{i,p} = \beta_i \times X_{i,1} \times \delta_i + (\beta_b - \beta_i) \times X_{i,2} \times \delta_i + (\beta_L - \beta_b) \times X_{i,3} \times \delta_i + \left(\frac{Q_2 - Q_1}{Q_1}\right) \times \beta_L \times X_{i,4} \times \delta_i + \varepsilon_k \quad (2)$$

$$C_p = \sum_i^n \beta_i \times X_{i,1} \times \delta_i + \sum_i^n (\beta_b - \beta_i) \times X_{i,2} \times \delta_i + \sum_i^n (\beta_L - \beta_b) \times X_{i,3} \times \delta_i + \sum_i^n \left(\frac{Q_2 - Q_1}{Q_1}\right) \times \beta_L \times X_{i,4} \times \delta_i + \varepsilon_p \quad (3)$$

$T_{i,p}$ - product p production time per unit or total units (respectively, $X = 1$ or $X =$ units produced) at workstation i

C_i - product p cost per unit or total units (respectively, $X = 1$ or $X =$ units produced)

C_p - product p cost per unit or total units (respectively, $X = 1$ or $X =$ units produced)

δ_i -cost rate of the workstation i

$X_{i,j}$ - 1 or 0 if time/cost component j is to be included or not, respectively

$X_{i,1}$ - related to the workstation

$X_{i,2}$ - related to the production line

$X_{i,3}$ - related to the planned flexibility/unused capacity of the production line

$X_{i,4}$ - related to the unplanned unused capacity

β_i - average cycle time of the workstation i

β_L - takt time

β_b - bottleneck time of the production line

$(\beta_b - \beta_i)$ - difference between the bottleneck time and the cycle time of the workstation

$(\beta_L - \beta_b)$ - difference between the takt time and the bottleneck time of the production line

Q_1 - real quantities

Q_2 - planned quantities

ε_i - residual and error measurement time

ε_k - residual and error measurement cost

The four components of the time and cost equations are explained below:

Workstation specific

This is related to the time required by the workstation to process the part in that specific workstation. It basically represents the cycle time of the particular workstation.

Production line Specific

This represents the difference between the cycle time of specific workstation and the bottleneck of the assembly line. This is non-value added for all the workstation except for the bottleneck workstation. This component will represent the waiting time of the workstation due to bottleneck instead of producing. Also, the workstation which is bottleneck will have value of 0 in the waiting time as it doesn't have to wait for any other workstation.

Flexibility or unused planned capacity

This component is also a non-value added which is the difference between the takt time and the bottleneck. Normally the assembly lines are designed in a manner which can produce excess quantities in case of more demand of the product, so this component can showcase how much excess time is been allocated to the assembly line.

Unplanned unused capacity

There is a planned value for the quantities that needs to be produced. If the real quantities are less than the planned ones, there will be additional unused time with non-value added by the workstations since the production line is installed with the purpose of producing the planned quantities required by the client and not less. It might happen due to various factors such as breakdowns of machines, insufficient supply of raw material or exceptional situations like the actual pandemic.

Hence, equation 1 can help to understand the overall time consumed for each workstation. In equation 2, δ has been added which represents the tariff cost associated to the resources allocated to the specific workstation. So, by multiplying the tariff with each component of the equation 2 it gives the cost of that respective component. Equation 2 will facilitate the computation of the total cost of each workstation. Summing the costs of all workstations as mentioned in equation 3, gives the overall cost of a product in the studied assembly line.

Stochastic variables

β_i represents the cycle time of the workstation which changes with each product produced.

β_b which represents the bottleneck workstation also changes. Sometimes the value of the bottleneck changes or the bottleneck workstation might also change.

ε_k is constant for a particular activity, but it is a random variable within the activities carried out, as they change stochastically from activity to activity.

These variables give the range of probable values capable enough to make a probability distribution, so they are considered to be stochastic variables.

4. ANALYSIS OF RESULTS

The model developed was implemented in a tier 1 of the automotive industry. The product under scrutiny uses 6 workstations in each assembly line. The equations can be used to know the total cost of each workstation including all the four

dimensions of the cost as can be observed in Table 1 that represents the cost for week 1.

Table 1. Component Cost by Workstation

WS Number	Specific Cost	Line Cost	Flexibility Cost	Unplanned Unused Capacity Cost	Total Cost
1	0,33 €	0,076 €	0,273 €	0,158 €	0,83 €
2	0,41 €	- €	0,272 €	0,157 €	0,84 €
3	0,38 €	0,038 €	0,477 €	0,276 €	1,17 €
4	0,36 €	0,067 €	0,286 €	0,165 €	0,87 €
5	0,39 €	0,102 €	0,261 €	0,151 €	0,90 €
6	0,32 €	0,068 €	0,596 €	0,345 €	1,32 €

Workstation 2 is the bottleneck so the line cost of that workstation will be 0. So, each component of the cost can be obtained along with the total cost of the workstation. The cost obtained consist of all the fixed and variable costs involved but only variable cost can be considered or overhead costs can be partially allocated. Using this method the cost of the entire assembly line can be known and compared during various weeks to understand the variability that persists in production.

Table 2 showcases the total cost of the assembly line (combining all the 4 cost dimensions by workstation). The analysis was made for 4 different weeks.

Table 2. Weekly Comparison of Total Cost

Week	Specific Cost	Line Cost	Flexibility Cost	Unplanned Unused Capacity Cost	Total Cost
1	2,19 €	0,351 €	2,165 €	1,252 €	5,95 €
2	1,98 €	0,20 €	1,522 €	1,108 €	4,80 €
3	2,32 €	0,442 €	2,526 €	1,391 €	6,67 €
4	2,06 €	0,271 €	1,565 €	1,154 €	5,05 €

It can be observed in Table 2 that total cost varies in each week. It is clear that there exists variability in the cycle time of the different workstations which results into different costs in the four weeks into consideration. It can be observed that in week 2 the total cost is at its minimum level compared to the other weeks. It signifies that cycle times and bottleneck were lower in week 2 which resulted into a lower cost. Whereas, week 3 has the highest total cost among all studied weeks, which resulted from higher cycle times and bottleneck.

As cycle time is stochastic in nature, further analysis was performed on it to understand the variability involved. Table 3 showcases the standard deviation of cycle time of each workstation.

Table 3. Cycle time, Standard Deviation and Interval of Values

WS Number	Cycle time (s)	Standard deviation (σ)	Lower limit cycle time $\underline{x} - \sigma$	Upper limit cycle time $\underline{x} + \sigma$
-----------	----------------	---------------------------------	---	---

1	34,40	7,21	27,19	41,61
2	56,23	9,95	46,28	66,18
3	44,41	3,33	41,08	47,74
4	37,75	3,08	34,67	40,83
5	46,57	5,41	41,16	51,98
6	33,23	14,14	19,09	47,37

After calculating the lower and upper limit for each workstation and multiplying it with the tariff enables to obtain the range of cost which are considered as optimistic and pessimist cost of the product. This approach was applied to the 4 different production lines which were used to produce the same product.

The comparison on the product cost for each line was done for 4 weeks. Figure 1 provides the aggregated cost of the product across the four production lines for 4 weeks. The variation in the cost can be seen evidently.

Using this information, it can be easy for managers to understand which week was more profitable and it can also help to identify the risks involved if the target cycle time is not achieved. Also, the impact of changes in external conditions can be assessed or estimated. This is important to manage the different production lines and evaluate how they perform under different internal and external conditions.

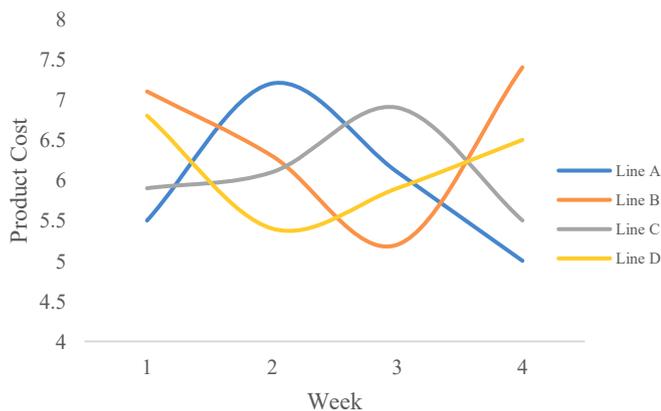


Figure 1. Weekly Product cost across different production lines.

In this case we have a significant weekly cost variability between production lines but a much more stable average cost of the product. Indeed, the small production lines A and C have a similar trend which compensates changes in the big production lines B and D.

The product unitary cost varies considerably (by line, between approximately 5 and 7.5 euros, and globally between 5 and 6,7 euros) throughout the weeks studied and across all production lines. These results demonstrate that the different cost drivers (e.g., quantities produced, cycle times) impact significantly on product cost and that there are opportunities to optimise the process and reduce costs. This variability can be explained by a combination of factors internal and external to the company. Some of these factors might be interrelated (e.g., market demand and production planning) and other are independent (e.g. cycle times of bottlenecks in the different production

lines). Understand the behavior of these factors is fundamental for a better manufacturing management and control.

The variability studied in this paper is based on cycle time and bottleneck variations which are largely caused due to reasons such as time required for product setup on the machine, time to load/unload product on the machine, operator walking time between the machines etc. This affects the cycle time to a large scale, so overseeing some of this factors can have a very bad effect on the product costing. The stochastic analysis of production cycle times is fundamental to include variability and risk within costing systems. Besides the variability in the production processes, we can have also variability caused by changes in the demand and variability in the value of the resources used. Process variability is particularly relevant in costing systems and for optimization purposes.

5. CONCLUSIONS

In this paper, a stochastic costing approach has been developed based on the activity-based cost models. The variability of the quantities produced affects the cost to a great extent as required time and bottleneck may vary, so a single value for the cost is not enough. Thus, it is important to compute a complete range of possible costs. By the equations developed in this paper it is possible to obtain the past, real time or predictive cost of the product and it can help to understand the workstation specific cost, bottleneck cost, unused capacity cost and unplanned unused capacity cost. With this method, optimistic and pessimistic costs can be calculated and represented, helping companies to recognize which products and production lines are more profitable and which are the drivers of costs and profitability.

This cost model also allows to visualize and understand, in a transparent and accessible way, the cost and its breakdown by products and production lines. The outputs provided by the model turned possible to acquire a new cost breakdown of the product more relevant for decision making and grants an intelligible understanding and visualization of the cost from different perspectives. The model also permits to simulate what impact certain changes have on the cost and what is the most valuable approach to be adopted. With this division besides understanding the cost of the product, we can have a deeper understanding of the cost by process, activity, operation and specific workstation. Based on this breakdown of the cost in four components we can distinguish the value added and non-value-added cost of the product. For instance, it is possible to visualize the impact of the bottleneck workstation on product cost and what occurs when the company is producing more or less of then the planned quantities. Also by using this methodology, the production manager can have clearer insights about each manufacturing process which can help to identify value added and non value added activities in the manufacturing process. Along with that it can open opportunities to optimize the process as each process is minutely observed.

By using machine learning techniques, the cost of the product for each assembly line can be predicted which can benefit scheduling the production planning accordingly, in order to

achieve the maximum possible profit by incurring the minimum achievable cost of the product.

ACKNOWLEDGMENTS

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020.

REFERENCES

- Afonso, P. et al. (2021) ‘A stochastic approach for product costing in manufacturing processes’, *Mathematics*, 9(18). doi: 10.3390/math9182238.
- Anderson, A. M. and Van Der Merwe, A. (2021) ‘Time-driven activity-based costing related to digital twinning in additive manufacturing’, *South African Journal of Industrial Engineering*. doi: 10.7166/32-1-2271.
- Anderson, O. D. et al. (1985) ‘The Forecasting Accuracy of Major Time Series Methods.’, *The Statistician*. doi: 10.2307/2988175.
- Benjamin, S. J., Muthaiyah, S. and Marathamuthu, M. S. (2009) ‘An improved methodology for absorption costing: Efficiency Based Absorption Costing (EBAC)’, *Journal of Applied Business Research*, 25(6). doi: 10.19030/jabr.v25i6.998.
- Borràs Mora, E., Spelling, J. and van der Weijde, A. H. (2021) ‘Global sensitivity analysis for offshore wind cost modelling’, *Wind Energy*. doi: 10.1002/we.2612.
- Chansaad, A. P. et al. (2012) ‘A Fuzzy Time-Driven Activity-Based Costing Model in an Uncertain Manufacturing Environment’, *Proceedings of the Asia Pacific Industrial Engineering & Management Systems Conference 2012*.
- Chengjie, G. (2020) ‘An activity-based bottleneck model with stochastic capacity’, in *IOP Conference Series: Earth and Environmental Science*. doi: 10.1088/1755-1315/587/1/012028.
- Cooper, R. and Kaplan, R. (1988) ‘Measure costs right: make the right decisions’, *Harvard business review*, 66(5), pp. 96–103.
- Cooper, R. and Kaplan, R. S. (1987) ‘How Cost Accounting Systematically Distorts Product Costs’, *Accounting and Management Field Study Perspectives*, pp. 49–72.
- Datta, P. P. and Roy, R. (2010) ‘Cost modelling techniques for availability type service support contracts: A literature review and empirical study’, *CIRP Journal of Manufacturing Science and Technology*. doi: 10.1016/j.cirpj.2010.07.003.
- Durán, O., Afonso, P. and Minatogawa, V. (2020) ‘Analysis of long-term impact of maintenance policy on maintenance capacity using a time-driven activity-based life-cycle costing’, *Mathematics*. doi: 10.3390/math8122208.
- Filomena, T. P. et al. (2011) ‘Manufacturing feature-based cost management system: A case study in Brazil’, *Production Planning and Control*, 22(4). doi: 10.1080/09537287.2010.497505.
- Gosselin, M. (1997) ‘The effect of strategy and organizational structure on the adoption and implementation of activity-based costing’, *Accounting, Organizations and Society*. doi: 10.1016/S0361-3682(96)00031-1.
- Hoozée, S. and Hansen, S. C. (2018) ‘A comparison of activity-based costing and time-driven activity-based costing’, *Journal of Management Accounting Research*. doi: 10.2308/jmar-51686.
- Kaplan, R. S. (2006) ‘The Competitive Advantage of Management Accounting’, *Journal of Management Accounting Research*. doi: 10.2308/jmar.2006.18.1.127.
- Kaplan, Robert S. and Anderson, S. R. (2007) ‘Time-driven activity-based costing: a simpler and more powerful path to higher profits’, *Harvard Business School Press Books*.
- Kaplan, R. S. and Anderson, S. R. (2007) *Time-Driven Activity-Based Costing: A Simpler and More Powerful Path to Higher Profits*. Harvard Business School Press.
- Nachtmann, H. and Needy, K. L. (2003) ‘Methods for handling uncertainty in activity based costing systems’, *Engineering Economist*. doi: 10.1080/00137910308965065.
- Oberkampf, W. L. et al. (1999) ‘New methodology for the estimation of total uncertainty in computational simulation’, *Collection of Technical Papers - AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*. doi: 10.2514/6.1999-1612.
- Oh, S. C. and Hildreth, A. J. (2013) ‘Decisions on energy demand response option contracts in smart grids based on activity-based costing and stochastic programming’, *Energies*. doi: 10.3390/en6010425.
- Pember, A. and Lemon, M. (2015) ‘Measuring and managing environmental sustainability: Using activity-based costing/management (ABC/M)1’, in *2nd Environmental Considerations in Energy Production Conference*.
- Sarokolaei, M. A., Bahreini, M. and Bezenjani, F. P. (2013) ‘Fuzzy Performance Focused Activity based Costing (PFABC)’, *Procedia - Social and Behavioral Sciences*, 75. doi: 10.1016/j.sbspro.2013.04.039.
- Scanlan, J. et al. (2006) ‘DATUM project: Cost estimating environment for support of aerospace design decision making’, *Journal of Aircraft*. doi: 10.2514/1.17362.
- Zimmermann, H. J. (2000) ‘Application-oriented view of modeling uncertainty’, *European Journal of Operational Research*. doi: 10.1016/S0377-2217(99)00228-3.