Stochastic Cost Modeling for Operator Allocation and Workstation Planning in Manufacturing: Optimizing Resources and Minimizing Costs

Vishad Vyas
PhD Research Scholar at University of Minho - School of Engineering
Braga, Portugal

Paulo Afonso
Assistant Professor in Department of Production and Systems
University of Minho
Braga, Portugal

Lino Costa
Associate Professor in Department of Production and Systems
University of Minho
Braga, Portugal

Abstract

This paper presents the development of a stochastic cost model aimed at determining the optimal number of operators required for a workstation, considering the activities performed by them, the time required for each activity, and the associated costs. The model takes into account the inherent variability in task performance and the corresponding costs involved. By utilizing the derived time equations, the study identifies both value-added and non-value-added activities, along with their respective costs. The proposed optimization model not only enables the estimation of the required number of operators but also provides insights into the impact of addition of workstation on the overall cost of the product. By considering the variability in task performance and associated costs, the model offers a comprehensive approach to operator allocation and workstation planning. Through the application of this stochastic cost model, organizations can make informed decisions regarding operator allocation, optimizing the utilization of available resources while minimizing costs. The findings of this research contribute to the understanding of the relationship between operator allocation, number of workstation, and production costs. The developed model serves as a valuable tool for decision-makers in the manufacturing industry, enabling them to analyze and optimize their operations effectively.

Keywords
Stochastic, Cost management, Variability, Optimization, Time-equations

1. Introduction
Many companies are now including human resources as a core component of their business strategies due to the quickly evolving and fiercely competitive environment. Managers are looking for more effective tools to optimize the use and allocation of their available resources among the various services or systems in an effort to maximize or minimize certain functions related to performance and productivity. They are aware that human resources can play a significant role in the success of an organization. The issue arises in a number of real-world contexts, and research papers in the literature demonstrate a persistent interest in the human resource allocation problem and cover several useful applications. Costs are a relevant criterion that influences decision making and their estimation plays an important role in management. The key to a rising enterprise in the 21st century is product quality, competitive cost, fast delivery, and flexibility. The quality-functionality-price paradigm is a fundamental element of modern cost management that influences design changes that can be made collaboratively involving suppliers or clients towards the reduction of the costs of new products. Nevertheless, variability is a crucial aspect in costing models as it can have

a significant impact on the accuracy of cost estimates and the effectiveness of decision-making processes. Costing models that fail to consider variability may result in over or under-estimation of costs, leading to inefficient resource allocation, poor profitability, and ultimately, business failure.

Manufacturing systems are designed and controlled to satisfy the customer's orders and demands in a timely and cost-effectively manner; therefore, it is important to deliver the manufactured products at the exact time that was agreed upon with the customer. This practice encouraged to develop methods to determine the allocation of cross-trained operators to handle more than one machine. Keeping with the high production rate and performance, assigning the correct and optimal number of machines to each operator is essential, it will assure the utilization of the operators and not overload them and keep the machine running with minimum downtime due to changeover or loading/unloading activities. Therefore, knowing how many machines and how many employees are needed to accomplish a specific manufacturing job is vital.

It is not profitable to have more employees attending the production machines (fewer machines assigned to one operator) because this will act as a burden on the company as there will be extensive operator's idle time and will increase the usage/workload on the machines which require extra maintenance over the production period. On the other hand, having fewer employees (more machines assigned to one operator) will result in overloading the operators and decrease their work moral standards, and machines will be idling for the operator availability. Both scenarios will cause a delivery delay. The purpose in both cases is to accomplish the task of the production or the service for all the customers within the time and cost constraints. The number of machines should be higher than the calculated numbers because there is a possibility that some of these machines will fail down.

This paper focuses on development of the stochastic cost model on calculating the optimum number of operators required and their allocation considering the activities performed by them on the workstation and time to perform that activity taking into consideration the variability and associated costs. Using the time equations developed will help to identify the value-added activities and non-valued added activities along with their costs. Also, optimization model will help to understand requirement of workstation equipment in the assembly line and its effect on the cost of the product is analyzed.

2. Literature Review

Most manufacturing companies compete in global markets, in which competitors are offering similar products with almost the same quality and price. Due to these reasons the focus then turns towards the cost of the product. To survive in the market, it is mandatory to provide a competitive price of the product, which in turn asks for the use of accurate costing systems (Barth et al. 2008). There can be severe effects if the costing is not done well, namely, the company might lose money if the selling price of the product is underpriced or might not achieve proper sales target if the product is overpriced. Therefore, it is important to have a proper costing system and good control over the cost (Pember & Lemon 2015).

Production lines managers are working non-stop to maximize profits by increasing yields and reducing the cost of manufacturing at the same time (Tirkel & Rabinowitz 2014). An important approach to achieve that goal is to determine the optimum number of operators needed to run the production machines. Using the fuzzy logic controller provide an easy tool where management can determine the optimal number of operators to be assigned, and the number of workstations that should be used by the operator in terms of controlling, or operation to reach the production goals (Keren & Hadad 2016) .

Assigning several workstations to one operator may not increase the system's overall performance (Chien et al. 2014). Although assigning the proper number of workstations to an operator is a critical and non-trivial decision. Trade-offs will take place and the manager will need to select trade-offs in the best scenario. Too many workstations assigned to one operator may increase overworked operator occurrences, idle workstation, defects and failures, safety, and health problems, and so on. On the other hand, few workstation assignments may cause unnecessary labor costs associated with idle or bored operators.

The operator-workstation assignment affects both workstation and operator utilization and production yields' cost (Haque & Armstrong 2007). The number of operators assigned to a given number of workstations, and the number of machines that will be controlled by each operator, must both be optimized. Additionally, different objective functions such as minimizing cost, maximizing profit, minimum idle time, and/or minimum overload, may require different assignments. Many papers in the literature dealt with similar problems assigning the operations to workstation/ operators, both in job-shops or flexible manufacturing systems (Park et al. 2014).

The notion of a bottleneck is important in many planning methods. A bottleneck is the group of similar machines that limits the production rate. As a result of this, the importance of an efficient machines capacity plan for this tool is required. Capacity planning problems appear in many forms and have attracted thousands of research papers. In order to structure this large body of research, comprehensive literature reviews by Costa et al. (2014) and Wu et al., (2005) have been published. As stated by Costa et al. (2014), deterministic models have got much attention in solving capacity allocation models. To illustrate, Huang et al. (2014) considered the problem associated with the decentralized allocation of the finite capacity of a single facility among different business organizations with fuzzy demand. Simultaneously, game theoretic approaches have been widely applied to capacity planning problems in strategic and tactical levels of manufacturing organizations (Renna & Argoneto, 2010) . Renna & Argoneto, (2010) developed a distributed approach, for a network of independent enterprises, able to facilitate the capacity process by using a multi-agent architecture and a cooperative protocol. In another application of game theory concepts in solving capacity allocation problems. Seok & Nof, (2014) proposed an adaptive collaborative demand and capacity sharing (CDCS) protocol based on dynamic contract mechanism. Liu et al. (2015) proposed a model of cloud manufacturing resource service sharing based on the Gale-Shapley algorithm and analyzed it in the context of fluctuating resource service supply and demand.

With regard to machine capacity allocation models in photolithography, one of the earliest studies on both capacity allocation problem and machine capability is the study by (Leachman & Carmon 1992), in which they defined a production plan by presenting a linear programming (LP) model in order to maximize total profit. A similar production plan with an LP model was also presented by Hung & Cheng (2002). The former study scrutinized machine process capability constraints by introducing 'alternative machine set' that is defined to represent a capability for a particular operation, and the capacity limitations of these machine sets are indicated by proposed models (i.e., step-separated, workload allocation and direct mix formulations) with the assumption of identical or proportional processing times. For LP formulations, the number of decision variables increases due to revisits of products to process areas because of the number of alternative machine types to the power of the number of re-entrant visits.

With regard to a latter study, Hung & Cheng, (2002) presented the capacity partition generation procedure (CPGP) in which the uniformity assumption is relaxed in the direct mix formulation provided by Leachman & Carmon, (1992) with the capacity set generation procedure (CSGP). Toktay & Uzsoy (1998) transformed the capacity allocation problem into a maximum flow network problem for maximizing throughput. Their mathematical formulation includes not only machine capabilities but also tooling and set-up constraints together with integer side constraints. They compared results of the problem by two proposed heuristics, i.e., greedy, and extended heuristics. Toktay & Uzsoy (1998) decomposed the shift-scheduling problem into two sub-problems which are capacity allocation and lot sequencing, in order to analyze them sequentially. To solve the problem, capacity allocation routine (CAR) was applied by the greedy heuristic defined by Toktay & Uzsoy (1998), and embedded in a simulation model. Also, two different sets of capabilities (i.e., operation-stepper matrices) were defined as fully flexible and nested sets. That is, the fully flexible set was defined for processing capability of all operations, and the nested set was defined for the processing capability of a partial set of operations. Their simulation experiments included analyses of stepper capabilities, reticle, and setup constraints.

The optimization problem is an important issue that has been studied by many types of research throughout the last decade in various manufacturing fields such as structural design (Yildiz, 2013), cell formation (Anbumalar & Sekar, 2015, U-shaped manufacturing lines (Sirovetnukul & Chutima, 2009) and others. The research is related to applying Fuzzy logic to the machine operator allocation problem in the cellular manufacturing setting. Few researchers did utilize fuzzy logic to analyze facility layouts, working conditions, lighting effect on employee behavior, dynamic layout, and even the selection of the layout and machine allocations to estimate the downtime and Fuzzy Inference System (FIS) had been utilized to determine the machine criticality levels for maintenance activities (Kunduracı & Kazanasmaz 2019; Osuch et al. 2020; Torun & Çetinkaya, 2019; Zha et al. 2020).

3. Methods

In the manufacturing process, there are a variety of products which require multiple operations to transform 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 the TDABC model and time equations. Time equations are an important building block of TDABC

(Hoozée & Bruggeman 2010), resulting in a powerful tool for both operational and strategic management decision making. Using time equations, complex activities and processes can be easily modelled, making the costing process much easier, accurate and cheaper.

There are several activities performed during the production. But from a managerial perspective it is important to understand which activities are actually adding value to the product, and which are non-value added. The model developed helps to calculate the value-added time, non-value-added time, and unused unplanned time.

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

$\beta_i \times X_{i,1}$: Value added time

$(\beta_b - \beta_i) \times X_{i,2}$: Non-value-added time

$\left(\frac{Q_2 - Q_1}{Q_1}\right) \times \beta_L \times X_{i,3}$: Unused unplanned time

$T_{i,p}$ – Total time taken by the operator to perform all manual operations at workstation i per unit or total units
β_i – Value added time by operator on the workstation i
β_L – takt time for manual operations
$X_{i,j}$ - 1 or 0 if time component j is to be included or not, respectively
Q_1 - real quantities
Q_2 - planned quantities
ε_i - residual and error measurement time

The three components of the time equations are important elements of this model and are described below.
Value added time:
This is related to the time required by the operator to perform certain manual operations, which adds value to the product. By multiplying the labor cost rate by the time required, the costs for value added operations can be obtained.

Non-value-added time:
This represents the cost of all the non-value-added operation costs such as setup, travel time between workstations, allowances etc. These operations are needed for the production, but they don´t add any value to the product so the cost incurred by these operations will be considered as non-value-added costs.

Unplanned unused capacity time:
There is a planned value for the quantities that need 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 operators.

As the target cycle time of the line is defined by the production manager based on the availability of the operators and it is assumed here that operators are the bottleneck. So, it is important to understand the optimum number of operators required, so an optimization model is implemented to fulfil this requirement and along with that it will also give an overview of on which workstation the operator should work.

Labour cost optimization model:
The objective of the optimization model was to understand how many operators are required and to minimize the cost of the labor. But there are certain conditions that work done by the operator shouldn´t exceed the target cycle time. The work on each workstation has to be done by just one operator.

Objective function: To calculate and allocate the optimum number of operators to the workstation to achieve target cycle time of assembly line

$$\sum_{i \in Op} \sum_{j \in WS} c_{ij} x_{ij}$$

where, c_{ij} - time needed on workstation by operator i on workstation j

x_{ij} – allocation of operator i on workstation j

Constraints*:*

The work in each WS is done by just one Operator

$$\sum_{i \in Op} x_{ij} = 1, \ \ \forall j \in WS$$

Each Operator can work on zero or more WS

$$\sum_{j \in WS} x_{ij} \geq 0, \ \ \forall i \in Op$$

Each Operator works no more than the bottleneck

$$\sum_{j \in WS} c_{ij} x_{ij} \leq Bottleneck, \ \ \forall i \in Op$$

Workstation specific cost optimization:
Increasing the number of workstations brings the advantage of achieving the target cycle time and reduce the bottleneck time of the assembly line, but it also comes with the disadvantage that having more workstations will result in the higher fixed cost of the resources and the amortization cost which will directly result in higher cost of the product as the cost tariff will be increasing.

So, it is important to find a balance between the required number of workstations, bottleneck, and the cost of the product which can be calculated using cost equations developed by Vyas et al. (2022). Because the focus of the production manager will be to decrease the bottleneck time but also controlling the cost of the product. Using the Stochastic cost model developed, cost of the product will be calculated which will help us to understand the effect of increased cost tariff. Some iterations of the cost calculation can be made by increasing the number of workstation and effects of that on the cost can be observed. Reducing the bottleneck time will help reduce the cost and increasing the workstation will increase the cost so the optimised scenario must be chosen that how much bottleneck time should be reduced and increase the workstation in order not to have drastic increase in the cost of the product.

4. Results and Discussion

It is important to understand the optimum allocation of the operator as the variability persists even in their operation time. Also, it is important to understand the bifurcation between the value-added time and the non-value-added time by the operators along with the optimum number of operators required in the assembly line. Table 1 mentions the time spent in all the 3 components of Equation 1 along with standard deviation, upper and lower limits.

Table 1. Time for Operator tasks for Line A

WS number	Value added time	Non-value-added time	Unplanned unused time	Total time	Standard deviation	Lower limit time	Upper limit time
1	2	3	1	6	1.2	4.8	7.2
2	5	6	2	13	2.5	10.5	15.5
3	5	7	2	14	2.1	11.9	16.1
4	3	6	2	11	1.9	9.1	12.9
5	5	7	3	15	1.5	13.5	16.5
6	4	6	2	12	1.8	10.2	13.8
7	3	4	1	8	1.4	6.6	9.4
8	4	4	2	10	2.1	7.9	12.1
9	3	3	1	7	1.9	5.1	8.9
10	5	5	2	12	2.3	9.7	14.3
11	2	2	1	5	1.4	3.6	6.4
12	3	4	3	10	1.9	8.1	11.9
13	3	4	1	8	1.7	6.3	9.7
14	3	4	2	9	1.5	7.5	10.5
15	2	3	2	7	1.6	5.4	8.6
16	4	8	4	16	2.4	13.6	18.4
17	6	7	5	18	2.6	15.4	20.6
18	2	2	1	5	1.8	3.2	6.8

The target cycle time for the operator was 34 seconds for line A. The total time spent by the operator on 18 workstations is around 186 seconds, as in the model it was defined in the constraint that an operator cannot work more than the target cycle time so based on that we got the solution that there is requirement of 7 operators. Based on the standard deviation considering the worst-case scenario i.e., the upper limit time which totals to 219 seconds is still less than 238 seconds (34 seconds x 7 operators). Hence, even considering the extreme situation 7 operators will be sufficient enough to work on these workstations. Using the optimization model, we can solve the allocation problem to understand what the best possible workstation for each operator is. Solving the problem, results can be seen in table 2.

As it can be observed in the table 2, operator 1 will be working on workstation 1, workstation 2, and workstation 4. Operator 2 will be working on workstation 3 and workstation 5. Operator 3 will be working on workstation 6,8, and 9. Operator 4 on workstation 7 and 10. Operator 5 on workstation 11,12,13, and 14. Operator 6 on workstation 15 and 16. Lastly, operator 7 on workstation 17 and 18. The details on the total allocation for each operator can be found in table 3

Table 2. Operator Allocation to Workstation on Line A

Workstation	Operator
WS1	Operator 1
WS2	Operator 1
WS3	Operator 2
WS4	Operator 1
WS5	Operator 2
WS6	Operator 3
WS7	Operator 4
WS8	Operator 3
WS9	Operator 3
WS10	Operator 4
WS11	Operator 5
WS12	Operator 5
WS13	Operator 5
WS14	Operator 5
WS15	Operator 6
WS16	Operator 6
WS17	Operator 7
WS18	Operator 7

Table 3. Total Allocation of Operator in Line A

Operator	Total allocation (s)	Allocation (%)
OP1	30	88.24
OP2	29	85.29
OP3	29	85.29
OP4	20	58.82
OP5	32	94.12
OP6	23	67.65
OP7	23	67.65

The target cycle time for the assembly line was 34 out of which operator 1 will be working for 30s which accounts for 88.24% of allocation. Operator 2 and 3 will be working for 29s which account for 85.29% of the total capacity. Operator 4 has comparatively less allocation of 20s which is 58.82%. Operator 5 will be working for 32s out of 34s with allocation of 94.12%. Operator 6 and 7 will be working for 23s with 67.65% of the allocation. Furthermore, the hourly cost of the operator is 13€/hr so based on the allocation and time spent by the operator it is important to calculate the cost of the labor for each unit. Table 4 presents the range of cost based on the tariff.

Table 4. Cost of operator tasks for line A

WS number	Lower limit time	Upper limit time	Lower limit cost	Upper limit cost
1	4.8	7.2	0.017	0.026
2	10.5	15.5	0.038	0.056
3	11.9	16.1	0.043	0.058
4	9.1	12.9	0.033	0.047
5	13.5	16.5	0.049	0.060
6	10.2	13.8	0.037	0.050
7	6.6	9.4	0.024	0.034
8	7.9	12.1	0.029	0.044
9	5.1	8.9	0.018	0.032
10	9.7	14.3	0.035	0.052
11	3.6	6.4	0.013	0.023
12	8.1	11.9	0.029	0.043
13	6.3	9.7	0.023	0.035
14	7.5	10.5	0.027	0.038
15	5.4	8.6	0.020	0.031
16	13.6	18.4	0.049	0.066
17	15.4	20.6	0.056	0.074
18	3.2	6.8	0.012	0.025

In table 4, it can be observed the total labor cost on each workstation per piece of the product which ranges from 0.55€ to 0.79€ per unit which includes all the three components of value-added cost, non-value added cost and unused unplanned.

From a total of 18 workstations in the assembly line, four workstations with the highest cycle time were chosen. Workstation 17 is the bottleneck workstation among all the other workstations in the assembly line. As the bottleneck time is also stochastic in nature, the range of the bottleneck was from 58 seconds to 62 seconds. Since the target cycle time of the assembly line is 34 seconds, there will be a need for 2 equipment on Workstation 17 to achieve the desired cycle time of the assembly line. But this increase in the equipment comes with the disadvantage of increased cost tariff which directly results in an increase in the cost of the final product.

Since this cost was measured after installation of 2nd equipment the bottleneck of the assembly line was shifted to workstation 16 so the line cost is zero for that particular workstation. It is important to notice that line cost component decreased as the waiting period for all the workstation decreased which is somehow compensating the increased cost tariff. But considering the bottleneck time is stochastic in nature it is important to calculate the range of the cost.

Table 5 . Component cost after installing 2nd equipment on WS 17

WS Number	Specific Cost	Line Cost	Flexibility Cost	Unplanned Unused Capacity Cost	Total Cost
5	0.68 €	0.062 €	0.392 €	0.240 €	1.374 €
17	0.82 €	0.004 €	0.40 €	0.212 €	1.436 €
16	0.85 €	- €	0.391 €	0.274 €	1.515 €
3	0.63 €	0.067 €	0.389 €	0.268 €	1.354 €

After installing the 2nd equipment in the workstation 17 and performing this analysis, the new bottleneck of the assembly line is workstation 16. So, one more iteration was made to test if adding 2nd equipment on workstation 16 will be still advantageous to reduce the cost of the product. So, following this model a simulation was made assuming to add an equipment to this workstation which resulted to the following results:

Table 6. Component cost after installing 2nd equipment on WS 16

WS Number	Specific Cost	Line Cost	Flexibility Cost	Unplanned Unused Capacity Cost	Total Cost
5	0.96 €	0.059 €	0.413 €	0.448 €	1.88 €
17	1.09 €	- €	0.40 €	0.432 €	1.923 €
16	1.12 €	0.003 €	0.423 €	0.512 €	2.058 €
3	1.10 €	0.063 €	0.441 €	0.491 €	2.095 €

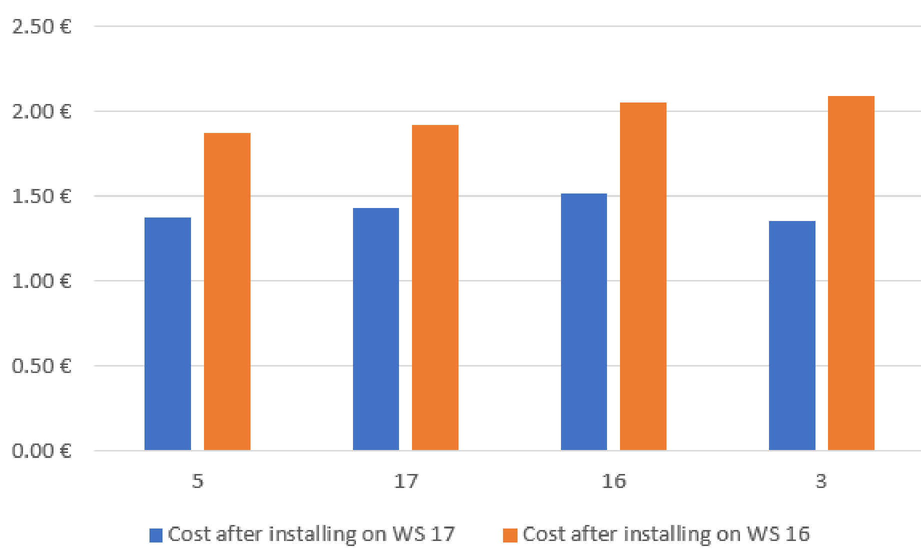

Figure 1. Cost Comparison between WS16 and WS17 after installing 2nd equipment

As it can be observed in figure 1 and table 6 that by adding an equipment on workstation 16 it increases the cost tariff drastically which results into significant increase in the cost of the product and the bottleneck than is shifted back to workstation 17. The decrease in the bottleneck time and cost is so negligible that it cannot manage to balance the cost of equipment. So, it is not worth to add an additional equipment to any workstation as it will only result into increased cost of the product.

6. Conclusion

It is evident that there exist huge variations in the demand from the customer. So based on that changes it is required to adjust the allocation of the resources accordingly. Over allocation or under allocation of the resources can have a huge impact on the production abilities and eventually on the profitability of the company. To avoid these situations, it is very important to design this allocation of resources carefully. But for allocation of resources, it is important to understand how much time is spent on each activity and variability that comes along and the calculation of the cost.

In this paper, the optimization of resource allocation was divided into two parts namely Operators and Equipment of Workstation. Using the time equations, the variability in the operator tasks were measured and costs were calculated. As the assembly line had the target cycle time, it was necessary that the total time spent by the operator should be less than the bottleneck or target cycle time. By using the traditional linear programming resource allocation problem to obtain the optimum number of operators required and best possible workstations that should be allocated to them was decided. With the equations developed it was possible to understand the activities performed by operator which were value added and non-value added to the product. So, it was possible to bifurcate between them and calculate the cost for it to clearly understand how much it costs for value added activities and non-value-added activities along with the inclusion of the variability.

Based on the target cycle time it is possible to calculate the number of equipment needed in order to achieve that target. Following that, various iterations were performed to find a balance between the cost and adding an equipment to the workstation, as adding an equipment had direct effect in the increase of the cost of the product. But in some cases, adding the equipment was advantageous as the waiting time for other workstations decreased along with the bottleneck of the assembly line. Therefore, the cost component of bottleneck decreased (might as well change to some other workstation) which compensated the increased cost tariff, so the cost of the product was reduced.

But it is not always the case, as it was observed in table 6 that when the extra equipment was added it didn't have much effect on the bottleneck, so the cost of bottleneck component didn't reduce much but the tariff cost increased a lot which resulted into significant increase in the final cost of the product.

Hence, it can be concluded that using this methodology in order to calculate value added time and non-value added time of the operator along with the information about the optimum number of operators needed and their allocation of the workstation will help a lot to take some managerial decisions as they will have clear picture about the cost and focus can be then shifted on the optimization of the non-value added activities. Also, in terms of decision making for the designing of the line this approach can be helpful to understand better the effect on the cost of the product by adding the equipment to the workstation.

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

Anbumalar, V., & Sekar, R. C. Methods for solving cell formation, static layout and dynamic layout cellular manufacturing system problems: A review. *Asian Journal of Science and Technology*, *6*(12), 2107–2112, 2015.
Balakrishnan, J., & Cheng, C. H. Multi-period planning and uncertainty issues in cellular manufacturing: A review and future directions. *European Journal of Operational Research*, *177*(1), 281–309, 2007.
Balakrishnan, J., & Hung Cheng, C. Dynamic cellular manufacturing under multiperiod planning horizons. *Journal of Manufacturing Technology Management*, *16*(5), 516–530, 2005.
Barth, M., Livet, A., & de Guio, R. Effective activity-based costing for manufacturing enterprises using a shop floor reference model. *International Journal of Production Research*, *46*(3), 621–646, 2008
Brauner, N., & Finke, G. Optimal moves of the material handling system in a robotic cell. *International Journal of Production Economics*, *74*(1–3), 269–277, 2001.

Chen, J.-H., & Ho, S.-Y. A novel approach to production planning of flexible manufacturing systems using an efficient multi-objective genetic algorithm. *International Journal of Machine Tools and Manufacture*, *45*(7–8), 949–957, 2005.

Chien, C.-F., Zheng, J.-N., & Lin, Y.-J. Determining the operator-machine assignment for machine interference problem and an empirical study in semiconductor test facility. *Journal of Intelligent Manufacturing*, *25*(5), 899–911, 2014.

Cılasun Kunduracı, A., & Kazanasmaz, Z. T. Fuzzy logic model for the categorization of manual lighting control behaviour patterns based on daylight illuminance and interior layout. *Indoor and Built Environment*, *28*(5), 584–598, 2019.

de Iuliis, M., Kammouh, O., Cimellaro, G. P., & Tesfamariam, S. Resilience of the Built Environment: A Methodology to Estimate the Downtime of Building Structures Using Fuzzy Logic. In *Resilient Structures and Infrastructure* (pp. 47–76). Springer Singapore, 2019.

Gupta, Y., Gupta, M., Kumar, A., & Sundaram, C. A genetic algorithm-based approach to cell composition and layout design problems. *International Journal of Production Research*, *34*(2), 447–482, 1996.

Haque, L., & Armstrong, M. J. A survey of the machine interference problem. *European Journal of Operational Research*, *179*(2), 469–482, 2007.

Hoozée, S., & Bruggeman, W. Identifying operational improvements during the design process of a time-driven ABC system: The role of collective worker participation and leadership style. *Management Accounting Research*, 2010.

Huang, M., Song, M., Leon, V. J., & Wang, X. Decentralized capacity allocation of a single-facility with fuzzy demand. *Journal of Manufacturing Systems*, *33*(1), 7–15, 2014.

Hung, Y., & Cheng, G. Hybrid capacity modeling for alternative machine types in linear programming production planning. *IIE Transactions*, *34*(2), 157–165, 2002.

Keren, B., & Hadad, Y. ABC Inventory Classification Using AHP and Ranking Methods via DEA. *2016 Second International Symposium on Stochastic Models in Reliability Engineering, Life Science and Operations Management (SMRLO)*, 495–501, 2016.

Leachman, R. C., & Carmon, T. F. On capacity modeling for production planning with alternative machine types. *IIE Transactions*, *24*(4), 62–72, 1992.

Liu, Y., Zhang, L., Tao, F., & Wang, L. Resource service sharing in cloud manufacturing based on the Gale–Shapley algorithm: advantages and challenge. *International Journal of Computer Integrated Manufacturing*, 1–13, 2015.

Martínez-Costa, C., Mas-Machuca, M., Benedito, E., & Corominas, A. A review of mathematical programming models for strategic capacity planning in manufacturing. *International Journal of Production Economics*, *153*, 66–85, 2014.

Nakade, K., & Nishiwaki, R. Optimal allocation of heterogeneous workers in a U-shaped production line. *Computers & Industrial Engineering*, *54*(3), 432–440, 2008.

Nakade, K., & Ohno, K. An optimal worker allocation problem for a U-shaped production line. *International Journal of Production Economics*, *60–61*, 353–358, 1999.

Osuch, A., Osuch, E., Rybacki, P., Przygodziński, P., Kozłowski, R., & Przybylak, A. A Decision Support Method for Choosing an Agricultural Machinery Service Workshop Based on Fuzzy Logic. *Agriculture*, *10*(3), 76, 2020.

Park, J., Bae, H., Dinh, T.-C., & Ryu, K. Operator allocation in cellular manufacturing systems by integrated genetic algorithm and fuzzy data envelopment analysis. *The International Journal of Advanced Manufacturing Technology*, *75*(1–4), 465–477, 2014.

Pember, A., & Lemon, M. Measuring and managing environmental sustainability: Using activity-based costing/management (ABC/M)1. *2nd Environmental Considerations in Energy Production Conference*, 2015

Renna, P., & Argoneto, P. A game theoretic coordination for trading capacity in multisite factory environment. *The International Journal of Advanced Manufacturing Technology*, *47*(9–12), 1241–1252, 2010.

Seok, H., & Nof, S. Y. Dynamic coalition reformation for adaptive demand and capacity sharing. *International Journal of Production Economics*, *147*, 136–146, 2014.

Sirovetnukul, R., & Chutima, P. Worker allocation in U-shaped assembly lines with multiple objectives. *2009 IEEE International Conference on Industrial Engineering and Engineering Management*, 105–109, 2009.

Sirovetnukul, R., & Chutima, P. The Impact of Walking Time on U-Shaped Assembly Line Worker Allocation Problems. *Engineering Journal*, *14*(2), 53–78, 2010.

Sparling, D., & Miltenburg, J. The mixed-model U-line balancing problem. *International Journal of Production Research*, *36*(2), 485–501, 1998, Stafford, E. F. On the Development of a Mixed-Integer Linear Programming Model for the Flowshop Sequencing Problem. *Journal of the Operational Research Society*, *39*(12), 1163–1174, 1988.

Tirkel, I., & Rabinowitz, G. Modeling cost benefit analysis of inspection in a production line. *International Journal of Production Economics*, *147*, 38–45, 2014.

Toktay, L. B., & Uzsoy, R. A capacity allocation problem with integer side constraints. *European Journal of Operational Research*, *109*(1), 170–182, 1998.

Torun, H., & Çetinkaya, S. Machine criticality level assignment with fuzzy inference system for RCM. *International Conference on Intelligent and Fuzzy Systems*, 1363–1370, 2019.

Venugopal, V., & Narendran, T. T. Cell formation in manufacturing systems through simulated annealing: An experimental evaluation. *European Journal of Operational Research*, *63*(3), 409–422, 1992.

Vyas, V., Afonso, P., Silva, S., & Boris, B. A Stochastic Costing Model for Manufacturing Management and Control. *IFAC-PapersOnLine*, 1116–1121, 2022.

Wu, S. D., Erkoc, M., & Karabuk, S. Managing Capacity in the High-Tech Industry: A Review of Literature. *The Engineering Economist*, *50*(2), 125–158, 2005.

Yildiz, A. R. Comparison of evolutionary-based optimization algorithms for structural design optimization. *Engineering Applications of Artificial Intelligence*, *26*(1), 327–333, 2013.

Zha, S., Guo, Y., Huang, S., & Tang, P. A hybrid optimization approach for unequal-sized dynamic facility layout problems under fuzzy random demands. *Journal of Engineering Manufacture*, *234*(3), 381–399, 2020.

Biographies

Vishad Vyas is a PhD research scholar at University of Minho (Portugal) in the field of Industrial and system engineering with a focus on product costing and process optimization and hold master´s in Mechanical Engineering – Industrial management and bachelor’s degree in mechanical engineering. Have published various papers in renowned journals and conferences and have participated in various conferences.

Paulo Afonso works as an assistant Professor at the University of Minho (Portugal) with a focus on Management Accounting & Control and also on Strategic Analysis & Business Modelling. Current research focus on Supply Chain Cost Management and Performance Measurement and also Business Modelling in Startups. Education: PhD in Management Accounting at Manchester Business School - University of Manchester (UK), 2008; master’s in industrial engineering at University of Minho, 2002; Diploma in Economics at ISEG (Economics and Business School) - Technical University of Lisbon (UTL), 1997.

Lino Costa holds PhD in Production and Systems Engineering, MSc in Informatics, DEng in Informatics and Systems Engineering and is Associate Professor at the Department of Production and Systems, School of Engineering, University of Minho, Portugal. He conducts his research activities in the ALGORITMI R&D center and is a member of its Systems Engineering and Operational Research (SEOR) group, with interests in the fields of multi-objective optimization, nonlinear optimization, evolutionary algorithms, and applied statistics.