10th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16

Optimized assembly design for resource efficient production in a multiproduct manufacturing system

Oliver Gould[a], Alessandro Simeone[a], James Colwill[a,*], Elliot Woolley[a], Roy Willey[b] and Shahin Rahimifard[a]

[a]Loughborough University, Loughborough, Leicestershire, LE11 3TU, United Kingdom
[b]Safety and Environmental Assurance Centre, Unilever R&D, Colworth Science Park, Bedfordshire MK44 1LQ, United Kingdom

* Corresponding author. Tel.: +4401509225405; E-mail address: j.a.colwill@lboro.ac.uk

Abstract

Resource efficiency is one of the greatest challenges for sustainable manufacturing. Material flow in manufacturing systems directly influences resource efficiency, financial cost and environmental impact. A framework for material flow assessment in manufacturing systems (MFAM) was applied to a complex multi-product manufacturing case study. This supported the identification of options to alter material flow through changes to the product assembly design, to improve overall resource efficiency through eliminating resource intensive changeovers. Alternative assembly designs were examined using a combination of intelligent computation techniques: *k*-means clustering, genetic algorithm and ant colony algorithm. This provided recommendations balancing improvement potential with extent of process modification impact.

© 2017 Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license
(http://creativecommons.org/licenses/by-nc-nd/4.0/).
Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Material; Flow; Efficiency.

1. Introduction

Facilitating the sustainable use of the fundamental manufacturing resources (materials, water and energy), is a goal of tremendous importance. Resource efficient manufacturing (REM) is an established concept for much of industry as a means to financial competitive advantage and reduction of environmental impact [1] Resource efficiency may be improved in a variety of ways through changes to system design (e.g. factory layout [2]) and operational factors (e.g. production scheduling [3]). Decision making for REM improvement can be supported by tools and methodologies, such as digital modelling and simulation techniques, which capture the flow of resources in a defined system [4–6]. This kind of activity can help decision makers to examine and understand complex systems. For example, flow modelling can help to identify locations of inefficiency, thus targets for improvement. Material flow has inherently strong influence on overall resource efficiency [5]. The materials selected and how they are processed tends to define energy, water (and material) requirements and their impact across a product's life cycle. Material flow modelling can therefore be considered as a powerful approach for examining and improving not only material efficiency, but resource efficiency in general.

Previous work by the authors provided a framework for material flow assessment in manufacturing systems (MFAM [6]). The framework was developed with a view to providing a basis for modelling energy and water use as variables influenced (directly or indirectly) by material flow, thus providing an understanding of the interactions between different resources and how control of material flow can deliver net benefit. A previous publication by the authors describes the application of MFAM to model material flow in a case-study manufacturing system [7]. An opportunity to minimize resource consumption was identified and a corresponding tool to enable this was developed. This tool utilized intelligent computation in the form of a genetic algorithm to find the optimized production schedule (temporal material flow) for a given order of products (with varying material mix).

This paper examines another opportunity to improve resource efficiency, through modification of the assembly design. This approach was considered to have the potential to eliminate resource intensive procedures in the production schedule that are unavoidable when using scheduling optimization alone. A number of alternative assembly designs were analyzed and prioritized using intelligent computation techniques, including k-means clustering, genetic algorithm and ant colony algorithm.

2. Methodology

2.1. Assessment framework implementation

The manufacturing system used for a case study was a single site. Details of the first iteration of the MFAM study were previously published by Gould et al. (2015). The following sections expand the interpretation of this first iteration and the results of the second iteration.

2.2. Interpretation of the first MFAM iteration findings

In the first examination of the manufacturing system, a tool was developed to optimize resource efficiency using genetic algorithm to optimize the flow of materials in terms of product scheduling. The flow of 'potentially cross-contaminating materials' (PCCM) was determined as the critical flow for modelling and optimized resource efficiency was related to the minimization of resource intensive changeovers defined by the PCCM flow.

The scope of optimization was therefore limited as in some circumstances resource intensive changeovers ('medium' or 'long') would be unavoidable given certain product requirements. For example, in the preceding publication, an optimum sequence was given for a selection of 50 products using genetic algorithm. However, the optimization was constrained by process and product design. The requirement for 2 'long cleans' (as well as 48 'short cleans', which require minimal resource consumption), was unavoidable in this sequence. Eliminating the intensive 'long cleans' would have additional resource efficiency benefits. To achieve this, alteration to process and production system design were considered.

2.3. MFAM second iteration: Production system scope, material flow inventory and assessment

The production system scope is as described previously [7]. The flow of PCCM was assessed and individual processes were characterized (in addition to previous characterization) by their contact with PCCM. This showed the level of isolation of PCCM *by design* and also showed the location of processes where the changeover cleaning protocols took place.

In Fig. 1, 'Process design A' shows an input-output diagram illustrating the processes included in the current system design, showing the processes where PCCM contact occurred in the system (highlighted with a grey background).
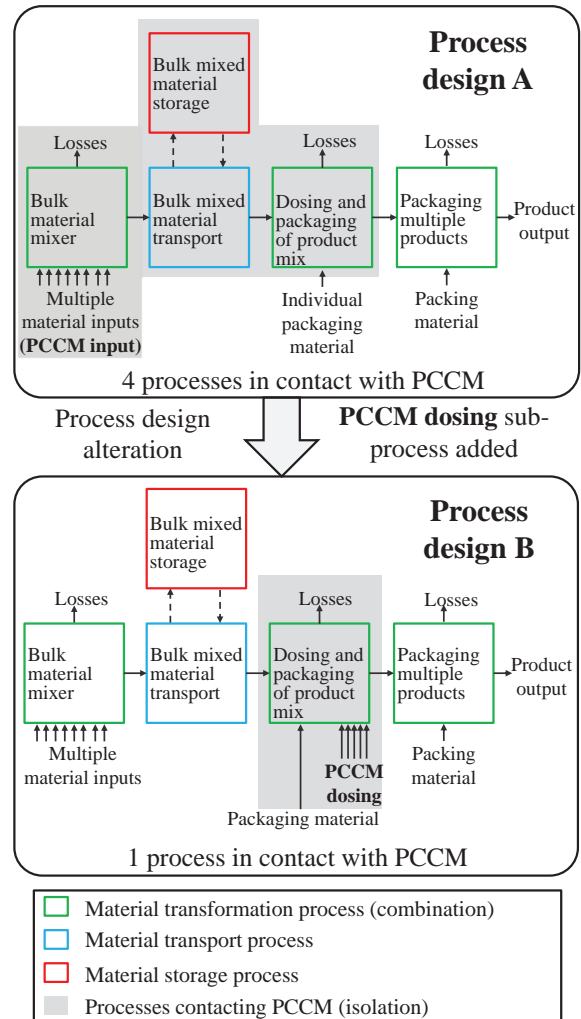

Fig. 1. Input-output schematic of the current and proposed alternative production system design ('A' and 'B', respectively). Processes are shown as boxes, descriptions inside. Green boxes indicate transformation processes, blue boxes indicate transport processes and red boxes indicate storage processes. Material flows (black arrows) are variable depending on product. Dotted arrow (to storage of bulk material mix) indicates that a material flow may be zero. Grey background area surrounding processes indicates where PCCM are in contact with processes (PCCM isolation).

2.4. MFAM second iteration: Improvement scenario modelling

The improvement scenario was based on the assertion that process and production system design could be altered to minimize contact between PCCM and processes, through isolation of specific PCCM to individual process equipment. The expectation was that process design modification could give additional benefits on top of optimized scheduling.

Initial exploration of process design alterations yielded a number of different broadly defined options (designs not shown). Of these, the option which provided the most localized PCCM processing was based on direct PCCM

dosing at the packaging process. This process modification ('Process design B') is outlined in Fig 1. This shows that PCCM input does not take place at the bulk material mixer; PCCM handling is contained within a single process stage (dosing and packaging of product mix), where the function of the process itself provides containment (packaging) of PCCM.

This diagram indicates that all PCCM types could be isolated and dosed directly into the packed product. A process modification of this kind could involve additional dosing equipment for up to 8 different PCCM types, each of which would need to be isolated from each other. This modification could be complex and potentially costly to implement, manage and maintain. Although this would provide complete isolation of all PCCM types and eliminate all long and medium changeovers, the extent of this process modification may not be completely necessary to deliver significant resource efficiency benefits.

Therefore, 'Process design B' required more detailed examination to establish recommendations for actions delivering the most benefit with the minimum disruption to process design, i.e. 'process impact'. This may include optimizing the number of individually dosed PCCM types and the number of products assembled using the PCCM dosing design. The optimum design would balance resource efficiency benefit with the extent of process modification.

To examine the material flow inventory and inform process design alteration, k-means clustering analysis was utilized in combination with genetic algorithm or ant colony algorithm. These techniques provided the near-optimized product schedules (determined as in previous work using genetic algorithm and additionally in this paper using ant colony algorithm) for different sub-set clusters of products from the product inventory (determined by k-means clustering). The following section describes the modelling and algorithm implementation steps.

3. Modelling: data collection and processing methods

3.1. Product inventory, selection and PCCM

The complete inventory of products (838) was included in the selection for analysis. According to the changeover rules reported in Gould *et al*., (2016), a corresponding source/destination matrix (838×838) was built and partially reported for illustration in Fig.2 for 25 products (25×25). Each cell of the matrix represents the changeover cleaning time specified when passing from the corresponding row (former) product to the corresponding column (latter) product entry.

3.2. k-means clustering

Data clustering is a data exploration technique that allows objects with similar characteristics to be grouped together in order to facilitate their further processing [8]. Clustering is a typical unsupervised learning technique for grouping similar data points.
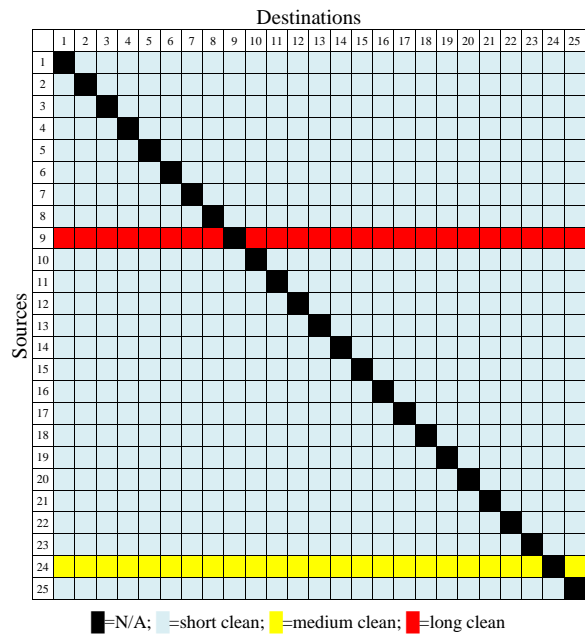

Fig. 2. Source/destination matrix illustrating a subset of products 1 – 25.

A clustering algorithm assigns a large number of data points to a smaller number of groups such that data points in the same group share the same properties while, in different groups, they are dissimilar [9]

Clustering analysis of the product inventory and PCCM content was carried out using k-means clustering technique: one of the best known and widely used algorithms [10]. The methodology represents each cluster by the mean value of the data points within the cluster which in this case is represented by the changeover time between the source and destination product. It then attempts to divide a data set S into k clusters to minimise the sum of the Euclidean distances between data points and their closest cluster centres [11]

The k-means clustering algorithm is described as follows [11].

Given an integer number of clusters k and a set of n data points $X \subset \mathbb{R}^d$, the objective is to choose k centres C so as to minimise the potential function:

$$\phi = \sum_{x \in X} \min_{c \in C} \|x - c\|^2$$

1. Randomly choose an initial k centre $C = \{c_1, c_2, ..., c_k\}$;
2. For each $i \in \{1, ..., k\}$, set the cluster C_i to be the set of points in X that are closer to c_i than they are to c_j for all $j \neq i$
3. For each $i \in \{1, ..., k\}$, set c_i to be the centre of mass of all points in C_i: $c_i = \frac{1}{|c_i|} \sum_{x \in c_i} x$

4. Repeat Steps 2 and 3 until C no longer changes

In *k*-means clustering, the number of clusters must be defined *a priori*. The analysis was carried out by selecting up to 4 clusters ($k = 2$ to 4) i.e. subsets of products which were then analyzed individually.

3.3. Travelling salesman problem (TSP)

The travelling salesman problem is analogous to the scheduling sequence for products in the inventory, where each product represents a node and the distance is analogous to the changeover cost.

Let $V = \{a, ..., z\}$ be a given complete digraph, $A = \{(r, s): r, s \in A\}$ be the vertex set, and $\delta(r, s)$ be a cost associated with the arc $(r, s) \in A$. (with $\delta_{rr} = +\infty, for\ r \in A$). The TSP is the problem of finding a minimal cost closed tour (*Hamiltonian circuit*) of V that visits each vertex of A exactly once [12]. If $\delta(r, s) \neq \delta(s, r)$ for at least some (r, s) then the TSP becomes an asymmetric TSP (ATSP) [13]. The scheduling constraints in this work dictate that the problem is described as ATSP. In this work, the cost $\delta(r, s)$ is represented by the changeover cleaning time and the minimal cost closed tour represents the production scheduling sequence that minimizes the associated resource consumption.

3.4. Genetic Algorithm (GA)

The GA procedure for solving the ATSP used the steps reported previously [7] with the following parameters: population size = 100 and number of iterations 30000.

3.5. Ant colony optimization (ACO) [14]

Let $b_i(t)(i = 1, ..., n)$ the number of ants in town (where town means product in the inventory) I at time t and let $\sum_{i=1}^n b_i(t)$ be the total number of ants. Each ant is a simple agent with the following characteristics:

- It chooses the destination town with a probability that is a function of the town distance (where town distance is changeover time between two products) 'visibility' and amount of trail present on the connecting edge;
- To force the ant to make legal tours, transitions to already visited towns are disallowed until a tour is completed (this is controlled by a tabu list);
- When it completes a tour, it lays a substance called *trail* on each edge (i,j) visited.

Each ant generates a complete tour by choosing the towns according to a probabilistic state transition rule:

$$p_k(r, s) = \begin{cases} \dfrac{[\tau(r, s)]^\alpha \cdot [\eta(r, s)]^\beta}{\sum_{u \in J_{k(r)}} [\tau(r, u)]^\alpha \cdot [\eta(r, u)]^\beta} & if\ s \in J_{k(r)} \\ 0, & otherwise \end{cases}$$

Where τ is the pheromone, $\eta = 1/\delta$, $J_{k(r)}$ is the set of towns that remain to be visited by ant k positioned on city r, α and β are parameters which determine the relative importance of pheromone versus distance ($\alpha, \beta > 0$).

Once all ants have completed their tours a *global pheromone updating rule* is applied according to*:*

$$\tau(r, s) \leftarrow (1 - \rho) \cdot \tau(r, s) + \sum_{k=1}^m \Delta\tau_k(r, s)$$

Where

$$\Delta\tau_k(r, s) = \begin{cases} \dfrac{1}{L_k}, & if\ (r, s) \in \text{tour done by ant } k \\ 0, & otherwise \end{cases}$$

$0 < \rho < 1$ is the pheromone trail persistence. L_k is the length of the tour performed by ant, and m is the number of ants. In this work, $\alpha = 1$, $\beta = 5$, $\rho = 0.35$, m=n.

4. Results and discussion

4.1. k-means clustering

Clustering analysis of the product inventory and PCCM content was carried out using the *k*-means clustering technique. The analysis initially yielded 4 different sets of clusters ($k = 1$ to 4 containing I to IV discrete groups of products): subsets of products in the inventory which were determined to be closely related according to PCCM content. The number of products n, in each cluster k, is shown in Table 1.

4.2. Genetic algorithm and ant colony optimization applied to clusters

Each cluster of products was used as a subset for optimized scheduling using GA and ACO. The results of which are summarized in Table 1. Fig. 3 shows the total cleaning time required for each cluster, optimized using the two computation techniques. For clusters of two or more subsets (i.e. clusters II, III and IV), the total changeover time required for each cluster are summed and stacked in Fig. 3. This shows that having two clusters ($k = 2$), scheduled using ACO provided the minimum total changeover time of 13545 min. This indicates that altering process design to handle two separate clusters of products presents a significant improvement over the use of RES alone (by either GA or ACO).

Table 1. . Summary of clustering analysis for clusters k = 1 to 4, showing number of products(n) per cluster as well as changeover cleaning time for each cluster, optimized using genetic algorithm (GA) and ant colony optimization (ACO)-based resource efficient scheduling.

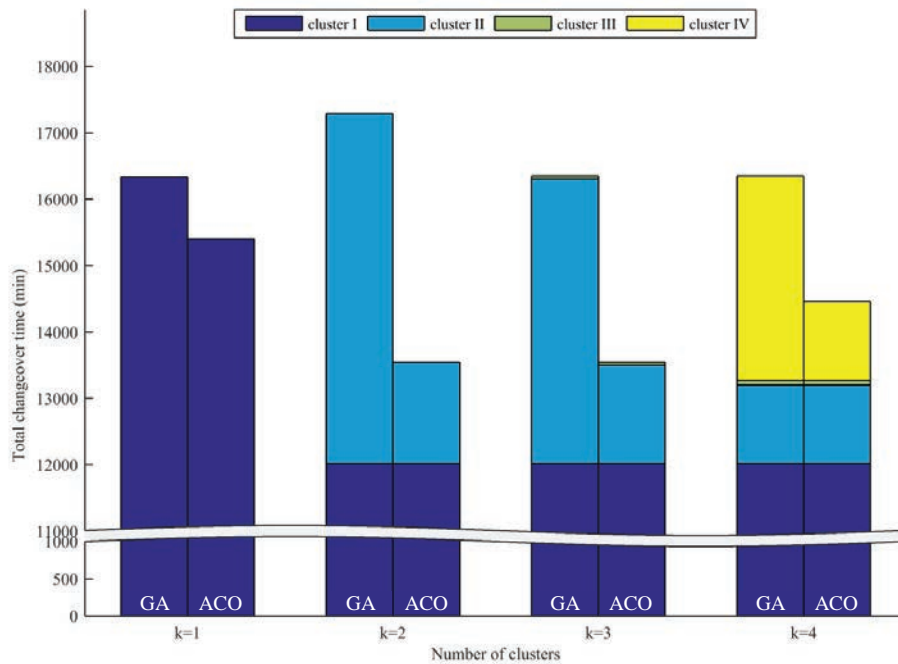|	Cluster	n	GA	ACO
k=1	**Tot**	**838**	**16335**	**15405**
	I	801	12015	12015
k=2	II	37	5280	1530
	Tot	**838**	**17295**	**13545**
	I	801	12015	12015
k=3	II	34	4290	1485
	III	3	45	45
	Tot	**838**	**16350**	**13545**
	I	801	12015	12015
	II	16	1185	1185
k=4	III	5	75	75
	IV	16	3075	1185
	Tot	**838**	**16350**	**14460**

Fig. 3. Graph showing total changeover cleaning time required for clusters (k = 1, 2, 3, and 4), containing corresponding product subsets (I, II, III and IV), optimised by genetic algorithm (GA) and ant colony optimisation (ACO).

It is noted that an order requirement to produce *ca.* 800 products would not likely be required in a real world scenario; however, it represents a potential 'worst case' scheduling problem.

4.3. Investigation of clusters and process design recommendations

Further investigation of the content of the two clusters ($k = 2$) was carried out to determine the PCCM distribution, in terms of their locations and frequency of occurrence. Figure 4 shows the distribution of PCCM type within cluster ($k = 2$) I and II, showing the frequency of PCCM contained within products at concentration level zero, one, two or three.

In cluster I, PCCM types $4 – 6$ are found at zero concentration in the 801 products. PCCM types $1 – 3$ are found at concentration level one with a frequency of < 200 products and concentration level two is found in < 20 products. Cluster II, containing 37 products, shows much greater variety of PCCM types contained, with occurrences of concentration level three and more frequency of level one and two. Importantly, PCCM types $1 – 7$ appear in at least one product at concentration level three.

The result that 2 clusters outperformed 3 or 4 clusters indicates that process design alteration should be differentiated based on the 2 clusters of products identified.

The group of products within cluster I would be assembled according to the current process design ('A') and this would include a small number of products which could have PCCM added at the bulk material mixer, which are predominantly specified at concentration level one and for PCCM types $1 – 3$ only. RES applied to this cluster would eliminate resource intensive changeovers.

Products within cluster II would be assembled using direct dosing of the highest concentration PCCM into individual packets immediately before sealing. The assertion is that cleaning of this additional dosing process would 1) be much less intensive in terms of resource consumption than current changeover cleaning requirements, 2) would be localized and 3) potentially take place off-line (by isolating the additional dosing system), whilst production was in process on the existing line, therefore eliminating the requirement for changeover 'downtime'. In effect, intensive cleans can essentially be eliminated from the current production system through the recommended alteration to the process design in combination with ACO-based RES.

Inspection of cluster II products indicated that there were a number of products ($n = 13$) that contained more than one PCCM type in their formulation; however, the PCCM type that defined the changeover protocol (the PCCM with highest concentration) in each product was accompanied by other PCCM at concentration level one. In these cases, the lower concentration PCCM can be added at the bulk mixing process and will not lead to intensive changeovers (through RES), whilst the high concentration (level two or three) PCCM will be dosed individually according to the new process design.
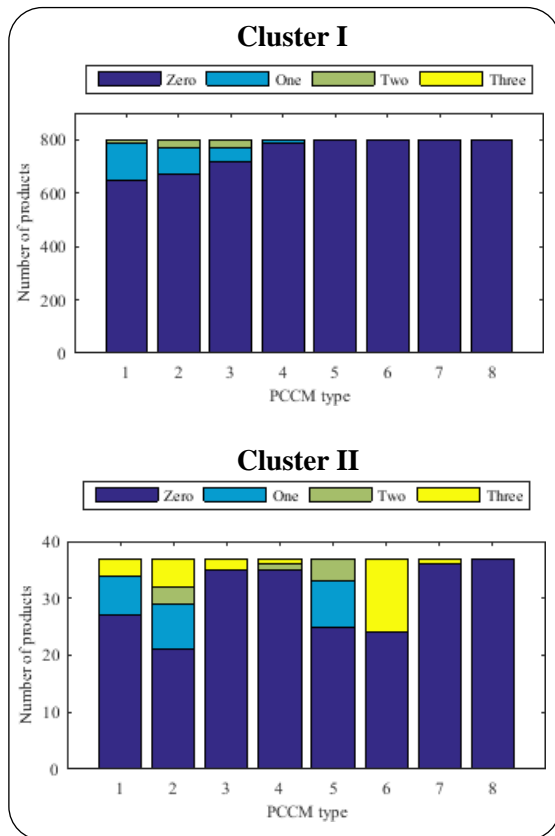
Fig. 4. Graphs showing the frequency distribution of PCCM types (1 to 8) and corresponding concentration levels (zero, one, two or three) in clusters I and II (k = 2).

5. Conclusions and further work

The modelling analysis showed that a combination of 2 clusters and ant colony optimization was found to provide the most resource efficient material flow with minimum changes to process design.

The practical implication of this conclusion was that a process design modification incorporating a single additional dosing apparatus (sub-process) in the dosing and packaging process would be required.

Coupled with ACO-based RES, this would provide the greatest resource efficiency benefits in terms of minimized time (including energy overheads), but also water and auxiliary cleaning material consumption.

This work proposed process design recommendations with the understanding that they would require fully detailed design and cost-benefit analysis before implementation in the facility. Further work would require more detailed design of the dosing process, with appropriate revision of operational procedures. The specifics of which would need to be

examined, including an assessment of the technical feasibility of dosing small masses of PCCM with sufficient isolation to produce a sufficiently mixed product. The cost of retrofitting additional apparatus into existing apparatus is clearly a potential constraint.

References

[1] Delmas, M. a., Pekovic, S., 2013, Resource Efficiency Strategies and Market Conditions, Long Range Planning, 48:80–94, DOI:10.1016/j.lrp.2013.08.014.
[2] Ojaghi, Y., Khademi, A., Yusof, N. M., Renani, N. G., Hassan, S. A. H. B. S., 2015, Production layout optimization for small and medium scale food industry, in *Procedia CIRP*, pp. 247–251.
[3] May, G., Stahl, B., Taisch, M., Prabhu, V., 2015, Multi-objective genetic algorithm for energy-efficient job shop scheduling, International Journal of Production Research, /March:1–19, DOI:10.1080/00207543.2015.1005248.
[4] Caggiano, A., Marzano, A., Teti, R., 2016, Resource Efficient Configuration of an Aircraft Assembly Line, in *Procedia CIRP*, pp. 236–241.
[5] Caggiano, A., Marzano, A., Teti, R., 2016, Sustainability Enhancement of a Turbine Vane Manufacturing Cell through Digital Simulation-Based Design, Energies, 9/10:790, DOI:10.3390/en9100790.
[6] D'Addona, D., Teti, R., 2011, Queuing network modelling techniques for response time enhancement in electronics assembly, International Journal of Computer Aided Engineering and Technology.
[7] Rieckhof, R., Bergmann, A., Guenther, E., 2015, Interrelating material flow cost accounting with management control systems to introduce resource efficiency into strategy, Journal of Cleaner Production, 108:1262–1278, DOI:10.1016/j.jclepro.2014.10.040.
[8] Gould, O., Colwill, J., 2015, A framework for material flow assessment in manufacturing systems, Journal of Industrial and Production Engineering, 32/1:55–66, DOI:10.1080/21681015.2014.1000403.
[9] Gould, O., Simeone, A., Colwill, J., Willey, R., Rahimifard, S., 2016, A Material Flow Modelling Tool for Resource Efficient Production Planning in Multi-product Manufacturing Systems, Procedia CIRP, 41:21–26, DOI:10.1016/j.procir.2015.12.139.
[10] Pham, D. T., Dimov, S. S., Nguyen, C. D., 2005, Selection of K in K-means clustering, *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*. pp. 103–119.
[11] Pham, D. T., Afify, A. A., 2006, Engineering applications of clustering techniques, in *Intelligent Production Machines and Systems*, pp. 326–331.
[12] Jain, A. K., Dubes, R. C., 1988, Algorithms for Clustering Data.pdf. .
[13] Arthur, D., Arthur, D., Vassilvitskii, S., Vassilvitskii, S., 2007, k-means++: The advantages of careful seeding, Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms, 8:1027–1035, DOI:10.1145/1283383.1283494.
[14] Roberti, R., Toth, P., 2012, Models and algorithms for the Asymmetric Traveling Salesman Problem: an experimental comparison, EURO Journal on Transportation and Logistics, 1/1–2:113–133, DOI:10.1007/s13676-012-0010-0.
[15] Dorigo, M., Gambardella, L. M., 1997, Ant colony system: A cooperative learning approach to the traveling salesman problem, IEEE Transactions on Evolutionary Computation, 1/1:53–66, DOI:10.1109/4235.585892.
[16] Dorigo, M., Maniezzo, V., Colorni, A., 1996, Ant system: Optimization by a colony of cooperating agents, IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 26/1:29–41, DOI:10.1109/3477.484436.