Ensembles of Heuristics and Computational Optimisation in Highly Flexible Manufacturing System

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Abstract. The objective of a Flexible Manufacturing System (FMS) is to respond faster to changes in products and demands with minimum changeover cost. However, layout changes in FMS are not automatic and required human intervention. Therefore, when requirements for layout changes are frequent, such as in a dynamic production environment, like mass personalisation production environments, layout reconfiguration becomes expensive and unrealistic. In this paper, we relax this core assumption of static FMS layout and introduce a decentralised approach to the design and coordination of manufacturing systems' entities, whereby both products and production machines are mobile and autonomous. We apply three different optimisation methods, of which two are ensembles of computational and heuristics optimisation approaches based on Gradient Descent and Ant Colony Optimisation (ACO), to optimise mobile machines locations under non-deterministic manufacturing conditions as obtainable in a mass personalisation context. These approaches enable mobile production machines to coordinate and autonomously adjust their location and layout in real-time to minimise the cost of material flow between production machines. The proposed approach offers a promising outlook on the design and coordination of manufacturing systems under unpredictable manufacturing conditions.

Keywords: nature-inspired optimisation · ensemble learning · flexible manufacturing system · real-time optimisation · mass personalisation

1 Introduction

Mass personalisation seeks to introduce individualised production into manufacturing systems, which will require the requirement for constant reconfiguration of assembly systems and layouts to manufacture at mass production cost [13,18]. Unfortunately, current assembly systems are limited in their reconfigurability capacities when additional processes and changes in process sequence or processing time are required at short notice, such as in minutes or hours. This is due to the physical constraints presented by the fixed transfer system of conveyor systems and fixed production machines locations [13].

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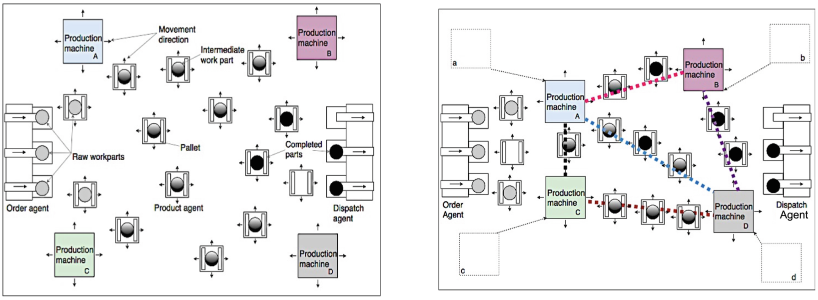
Indeed, finding innovative ways to reduce throughput times and increase product varieties within manufacturing firms is of long-standing interest within the operations research literature. Optimisation techniques such as in Assembly Line Balancing Problem (ALBP) [3,21], and Facility Layout Problem (FLP) [12] have also been suggested. However, the underlying assumption of these studies is that the production machines, workstations and employees remain fixed in their current factory layout. Up to date, virtually no studies have explored how throughput times can be improved by reconfiguring production lines and moving production machines during production (in real-time) to meet rapid changes in supply and demand in the context of mass personalisation [1].

To address this research gap in the manufacturing and operations research literature, we proffer a method for optimising production machine location and layout in real-time during production, depending on the mix of order inflow, using an ensemble of computational and heuristic means. This approach is analogous to performing assembly line balancing and facility layout in real-time and in a mass personalisation context, where order arrivals are non-deterministic, product mixes are stochastic, and real-time reconfiguration is required. The term ensemble is used loosely in this paper to refer to a combination of multiple optimisation approaches [30].

To achieve this, we explored the implication of relaxing the core assumption of static production machines and the use of fixed transfer lines for part movement by designing a decentralised and distributed manufacturing system, which we have labelled as the Lot Size-of-1 Manufacturing System (S1MS). In S1MS, we introduce mobile production machines and autonomous material handling systems to replace conveyor systems (see Fig. 1). We created a digital-object of the physical manufacturing system, called the virtual S1MS (V-S1MS), which connects and informs the real S1MS existing in the real world. The optimisation process is carried out in the V-S1MS, which informs the real S1MS in the real-world. This architectural change improves flexibility in material handling, minimises the cost of material flow by eliminating bypassing and backtracking, and minimises congestion that may occur when material flow is constrained by rigid conveyor movement.

Three different versions of S1MS were implemented using three distinct approaches to coordinate and autonomously organise and optimise the locations of the mobile production machines in real-time during manufacturing. Two of the approaches, referred to as the Gradient-Decent for Autonomous Resource Positioning (G-DARP), and Sensing Radius and Cluster Analysis for Autonomous Resource Positioning (SR-CAARP) are based on a combination of an iterative optimisation algorithm referred to as the gradient descent (GD) algorithm [14,20] and ant-based heuristic optimisation algorithm. The GD uses only local data and not global data to avoid computational overload and overfitting. The third approach, Ant Colony Optimisation for Autonomous Resource Positioning (ACO-ARP) is based on a nature-inspired algorithm referred to as the Ant Colony Optimisation Algorithm (ACO) [8,9].



(a) Initial S1M's layout.

(b) Final S1M's layout.

Fig. 1. Layout of Lot Size-of-1 Manufacturing System (S1MS). (a) Initial layout of S1MS during production. Production machines, which are aggregations of required resources for performing specific manufacturing processes on products, and with the capability to move during the manufacturing process depending on the mix of order in-flow. Product agents are aggregations of mechanisms relating to product handling, transportation, and routing, which can be implemented as mobile robots/AGV/AIV with integrated pallets for holding parts that are undergoing the production process. The product agents are capable of independently coordinating their production process by figuring out an optimal route based on order-mix through the use of a stigmergic coordination mechanism. (b) The layout of S1MS after a period, production machines A, B, C, and D have moved from their previous positions a, b, c, d to a new position. Product agents have also autonomously figured-out optimal routes for production based on the existing product mix using virtual pheromones. The coordination of the movement of the production machine is achieved using the optimisation techniques proposed in this paper.

We determined the viability of these three approaches using computer simulation. We explored how the introduction of mobile production machines in the different implementations of S1MS affects the throughput achieved in a mass personalisation context, compared with a base manufacturing system with stationary production machines. This system is referred to as the baseline system (BS). The throughput of the three approaches and that of the BS for processing personalised orders with a "lot size of one" were compared. This is achieved by measuring the average production rates and average cycle-time per unit during production. The performance of the three S1MS implementations was compared to determine which was best and in what scenarios the different approaches were most applicable.

Finally, we present a high-level description of the three approaches and corresponding simulation results. The output of the simulation shows that a combination of computational and heuristic approaches outperforms a pure heuristics approach, While the heuristic approach outperforms the base system. We conclude that a combination of computational optimisation using only locally available variables and heuristics optimisation has the potential to address the slow convergence of heuristics optimisation techniques.

2 Manufacturing Systems with Characteristics for Dynamic Production Environment

Manufacturing companies are investigating smart, flexible and adaptive manufacturing systems capable of autonomous self-adaptation, self-reconfiguration, and capability for lot size-of-1 manufacturing [22]. Examples of such systems include Flexible Manufacturing Systems (FMS), Reconfigurable Manufacturing Systems (RMS), Holonic Manufacturing Systems (HMS), and Evolvable Assembly Systems (EAS).

Flexible Manufacturing System is an integrated system of machine modules and material handling equipment under computer control for the automatic processing of palletised parts [6,23]. The objective of FMS is to respond faster to changes in products and demands by manufacturing several types of parts cost-effectively; within pre-defined part families that can change over time; with minimum changeover cost; on the same system and at the required volume and quality [10].

Reconfigurable Manufacturing System, on the other hand, is designed to enable rapid change in hardware and software components for quick response to sudden market changes by adjusting its functionality and production capacity [16]. RMS proposes a manufacturing system where machine components and material handling units can be added, removed, modified, or interchanged as needed to respond quickly to changes in requirements, demands, and functionality [17].

Holonic Manufacturing System is inspired by Arthur Koestler's holons concept [15]. Holons are autonomous, self-reliant units with a degree of independence, such that contingencies can be handled without being instructed by higher authority; and simultaneously subjected to control from single or multiple higher authorities [4,30]. This implies that holons can exist in complex systems like manufacturing systems as both a whole and a part simultaneously. The "whole" property ensures the stability of forms in the system, while the "part" property signifies intermediate forms and ensures stability for higher forms. The holons concept comparatively provides more flexibility for manufacturing systems through decentralisation, and aggregation [5,11].

The evolvable assembly system (EAS) is a holistic system approach to enhance the capability of the manufacturing system to respond to rapid changes in product demand, market and processes. The EAS architecture comprises four phases which are: the reconfiguration phase, operation phase, monitor phase, and adaptation phase [6]. These four phases provide the capabilities for EAS components to adapt to changing conditions of operations. Examples of EAS implementation are Instantly Deployable Evolvable Assembly Systems (IDEAS) and Smart Manufacturing and Reconfigurable Technologies (SMART), which have attracted several European Projects. An example is the IDEA Project sponsored by the EU with participating companies and institutions such as FESTO, and the University of Nottingham [28].

3 Optimimisation Approaches in S1MS

3.1 Gradient-Descent Approach

We created a digital simulation of the physical manufacturing system, called the virtual S1MS (V-S1MS), which connects and informs the real S1MS existing in the real world. We present the structure and the layout optimisation process of the V-S1MS in this study, hence corresponding production entities are virtual. We modelled the shop floor as a two-dimensional plane. We assume Euclidean distance as a distance measure instead of rectilinear distance; this is because the movement of materials by the AIVs/AGVs and the movement of production machines are not constrained by any physical means. We then approximate the space of possible location h of production machines as a linear function of the location of AIVs/AGVs. Then we approximate the optimal location H, referred to as the global-hotspot as a function of h.

Therefore, we define a cost function $J_H(\theta_0, \theta_1)$, which evaluates the closeness of $h_\theta(x)$ to the desire AIV.

$$J_H(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}(H_\theta(x^{(i)}) - y^{(i)})^2 = \frac{1}{2m}\sum_{i=1}^{m}\left(\frac{1}{n}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)}\right)^2 \quad (1)$$

To minimise the cost function $J_H(\theta_0, \theta_1)$, we use the gradient descent algorithm, which searches for potential *hotspots* and eventually arrives at a global-hotspot by starting with some initial-guess for θ and repeatedly changes θ to minimize $J_H(\theta_0, \theta_1)$, until it cannot be minimised further.

The gradient descent algorithm is expressed as follows:

$$repeat\left\{\theta_j = \theta_j - \alpha\frac{\partial}{\partial\theta_j}J(\theta_0, \theta_1)\colon (For\, j = 0\, and\, j = 1)\right\} \quad (2)$$

The final algorithm for finding the global hotspot is expressed as follows:

$$H_\theta(x) = \frac{1}{m}\beta\sum_{i=1}^{m}\left((\theta_0 - \alpha\frac{1}{n}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)})) + (\theta_1 - \alpha\frac{1}{n}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)}))\right) \quad (3)$$

where β is the location bias, α is the learning rate, θ_0 and θ_1 are the intercept and slope of the line joining the different possible *hotspots* $h_\theta(x)$. $H_\theta(x)$ is the *global-hotspot*, which is the optimal location for the production machine, based on the location x, y of AIV with matching operation task.

3.2 Nature-Inspired Approach

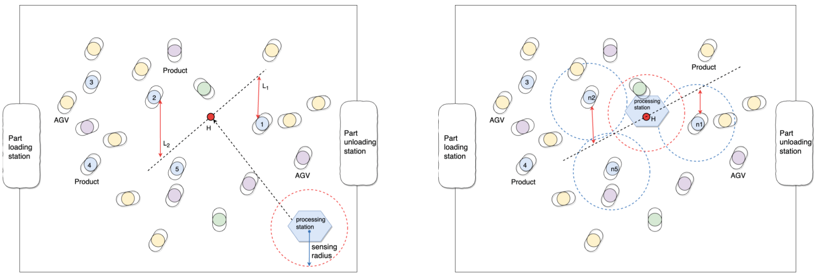
A nature-inspired approach referred to as stigmergy is used as the coordination mechanism for coordinating the movement and re-positioning of production machines in real-time to minimise the cost of material flow and the distance between production machines without overlapping. The type of stigmergic coordination used is called *ant-based algorithm*. It is based on the stigmergic coordination found in an ant colony. This is generally referred to as Ant Colony Optimisation (ACO) algorithm or simply Ant Algorithm [8,9]. This algorithm has been extensively used as an approach to solving optimisation problems in manufacturing, operations research and supply chain [2,7,12,19,24,25].

However, ACO in the context of S1MS requires an abstraction within the problem domain. This will allow for seamless integration of the ACO algorithm into S1MS for effective coordination of production processes. To achieve this, the production environment is modelled as a Direct Acyclic Graph G and the ACO algorithm is used to find a feasible minimum cost path between two nodes over the graph $G = (C, L, W)$, where C is the node, L is the edge, and W is the weight associated with the edges, and feasibility is defined with respect to a set of constraints Ω. The minimum cost path in the context of S1MS implies the optimal positioning of production machines for the production of varied product mix with minimum cycle time. Details of the algorithm are given in [29].

3.3 The Three Optimisation Approaches in S1MS

Gradient Descent for Autonomous Resource Positioning (G-DARP)

In Fig. 2(a), mobile production machines, referred to as processing stations, move toward the global-hotspot H, which is equidistant from the product (the AGV + loaded parts for operations) with product-ids 1 & 2. This is because of the number of products selected for optimisation, which is the node-count = 2. Therefore, the spot that is optimum for production machine discovery, which is the global-hotspot, will be a location between the two products. Figure 2(b) shows that as the processing station approaches the global-hotspot H, it will be able to execute production tasks for other products with matching production processes (depicted as those with the same colour as the production machine)



(a) (b)

Fig. 2. V-S1MS using G-DARP for navigation and autonomous positioning of production machines (node-count = 2): product → AGV + loaded parts for operations, AGV → AGV without loaded parts for operations.

and are within its sensing-radius (for example, product with node-id = $n1, n2$ and $n5$). The products that have already located the hotspots use pheromones to lead other products to the hotspots. The final global hotspot is passed to the S1MS in the real world.

In Fig. 3, the processing station moves toward the global-hotspot H, which is equidistant from the products with product-id 1 to 5, but with a bias towards products with a smaller distance from each other. Therefore, computing a global-hotspot using the G-DARP algorithm is biased towards the centre of the floor-space between the closest products. Thus, the G-DARP algorithm tends to over-fit when node-count is high and thus providing a sub-optimal solution. It also tends to under-fit and provides a less optimal solution when node-count is low. However, it is intuitive to expect a better solution as the number of node-count increases, hence the poor performance is assumed to be a weakness of the algorithm and thus, a new algorithm that overcomes this deficiency is implemented and juxtaposed.

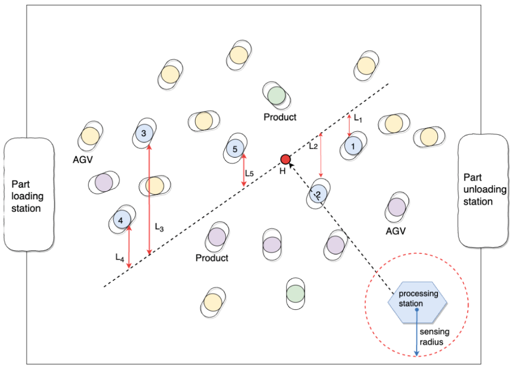
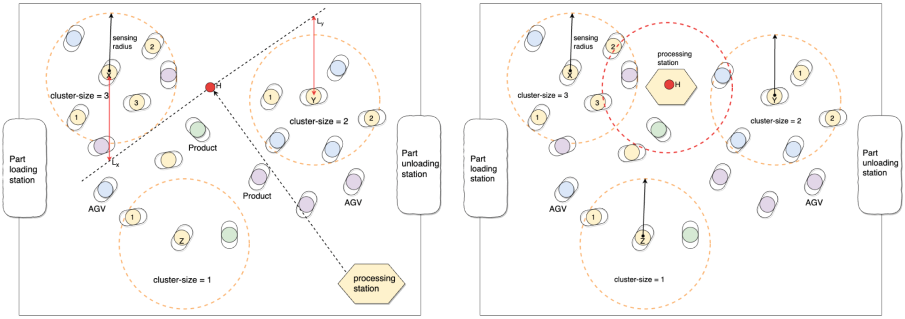


Fig. 3. V-S1MS using G-DARP for navigation and autonomous positioning of production machines (node-count > 2): product → AGV + loaded parts for operations, AGV → AGV without loaded parts for operations.

Sensor Radius and Cluster Analysis for Autonomous Resource Positioning (SR-CAARP)

In Fig. 4(a), each products compute a value called the cluster-size, which is the number of similar product within a specified radius. The product with node-id = X has the highest cluster size (cluster-size = 3) followed by the product with node-id = Y (cluster-size = 2). These two clusters have the highest cluster-size and are selected for optimisation (i.e. node-count = 2). Therefore, the global-hotspot H will be a location between the two clusters. In Fig. 4(b), as the production machine approaches the global-hotspot H, it can execute production tasks for products within the clusters that are with matching production operations (depicted as those with the same colour as the production machine) and are

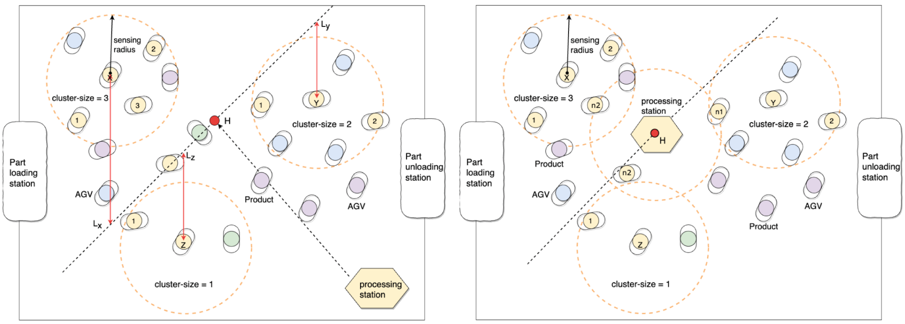


(a) (b)

Fig. 4. V-S1MS using SR-CAARP for navigation and autonomous positioning of production machines (node-count = 2): product → AGV + loaded parts for operations, AGV → AGV without loaded parts for operations.

within its sensing-radius (for example, product-agent with node-id $= n1, n2$ and $n3$).

In Fig. 5(a), the products with node-id = X, Y, Z are selected for optimisation (node-count = 3). Therefore, the global-hotspot H will be a location between the three clusters. In Fig. 5(b), as the production machine approaches the global-hotspot H, it can execute production tasks for products within the clusters that are with matching operations requests (depicted as those with the same colour as the production machine) and are within its sensing-radius (for example, product-agent with node-id $= n1, n2$ and $n3$). In both cases, the products that have already located the hotspots use pheromones to lead other products to the hotspots. The final global hotspot is passed to the S1MS in the real world.

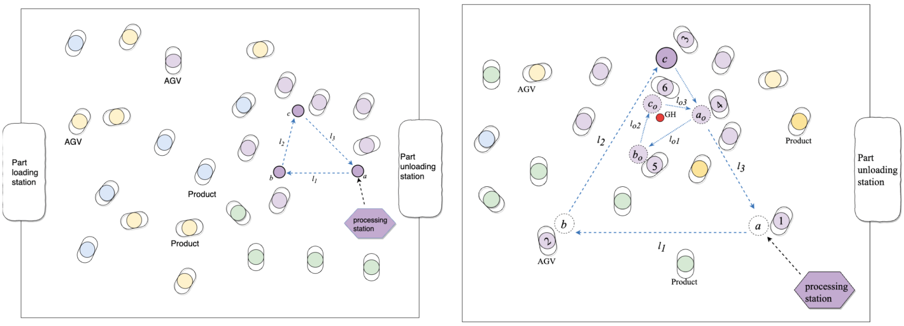


(a) (b)

Fig. 5. V-S1MS using SR-CAARP for navigation and autonomous positioning of production machines (node-count = 3): product → AGV + loaded parts for operations, AGV → AGV without loaded parts for operations.

Ant Colony Optimisation for Autonomous Resource Positioning (ACO-ARP)

In the ACO-ARP, the production machine randomly explores the shopfloor and drops pheromones on spots (hotspots) where operations were executed. In Fig. 6(a), the production machine creates hotspots a, b and c, with l_1, l_2 and l_3 distances from each other respectively. The production machine switched to the exploitation strategy if the maximum hotspots are reached, and visits the different hotspots in the order in which they are created ($a \rightarrow b \rightarrow c$) with speed $s = log(\beta \cdot \frac{1}{n} \sum_{i=1}^{n} l_i)$. In Fig. 6(b), the production machine creates new hotspots (a_0, b_0, c_0) while navigating a, b, c, the new hotspots are at distances $(l_{0_1} \ll l_1; l_{0_2} \ll l_2; l_{0_3} \ll l_3)$ which are better hotspots due to their closeness to each other. At this instance, the speed $s = log(\beta \cdot \frac{1}{n} \sum_{i=1}^{n} l_i) \approx 0$ for the production machine and thus it remains stationary at a distance close to the hotspots, which becomes the global hotspot GH. The final global hotspot is passed to the S1MS in the real world.



(a) (b)

Fig. 6. S1MS using ACO-ARP for navigation and autonomous positioning of production machines: product → AGV + loaded parts for operations, AGV → AGV without loaded parts for operations, processing stations → mobile production machines

4 Simulation, Results and Discussions

There are a total of 24 product mixes. These product mixes are a function of the number of production machines available to perform different production tasks. Thirty simulation runs were performed in each of the developed simulations for 140,000 simulation steps each. The distribution of product mix in the system was skewed at an interval of 20,000 simulation steps during the simulation to further observe the behaviour of S1MS during unpredictable changes in product mix.

This distribution is estimated based on the probability of selecting a product mix with a particular machining sequence among the 24 possible product mixes. This probability is referred to as mix probability. The distribution of the different order types within the product mix is shown in Fig. 7.

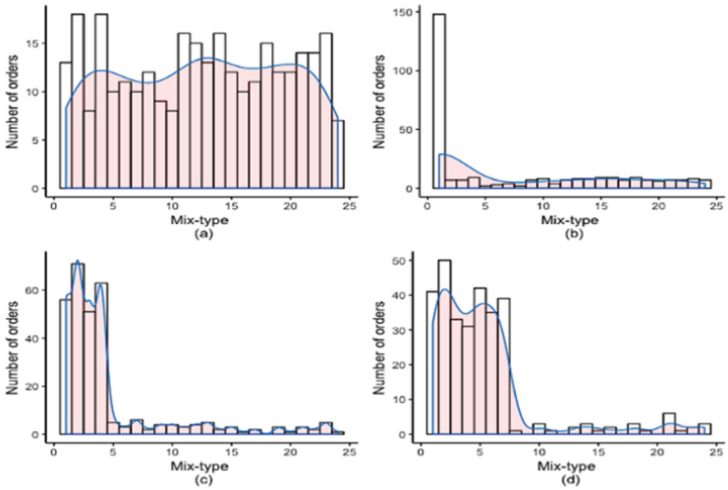


Fig. 7. Distribution of products within the product mix during simulation: (a) the default scenario, (b) scenario 1, (c) scenario 2, and (d) scenario 3

The following parameters were measured in each of the simulation setups to investigate differences in performance in the different approaches:

1. *Production rate*: This is the average number of products produced per 1k simulation steps during the simulation runs (140,000 simulation steps in total).
2. *Average cycle-time per product unit*: This is the average time (measured in simulation steps) taken to manufacture each product, i.e. the time each product spent in the production system.

G-DARP, SR-CAARP, ACO-ARP were compared with the BS using the production rate and average cycle-time per unit. The outcome of these two measures is referred to as performance afterwards. Four separate experiments were designed for this purpose, as shown in Fig. 7. The performance and behaviour of the different systems during production and unexpected changes in the product mix were compared (see Fig. 8).

Figure 8 showed that the production rate and average cycle-time when the total number of work-in-progress $N = 50$. It was observed that the three systems with mobile production machines, namely ACO-ARP, G-DARP and SR-CAARP, outperformed the BS. This is as a result of the capability of the three approaches to effectively minimise the cost of material flow and distances between production machines in real-time.

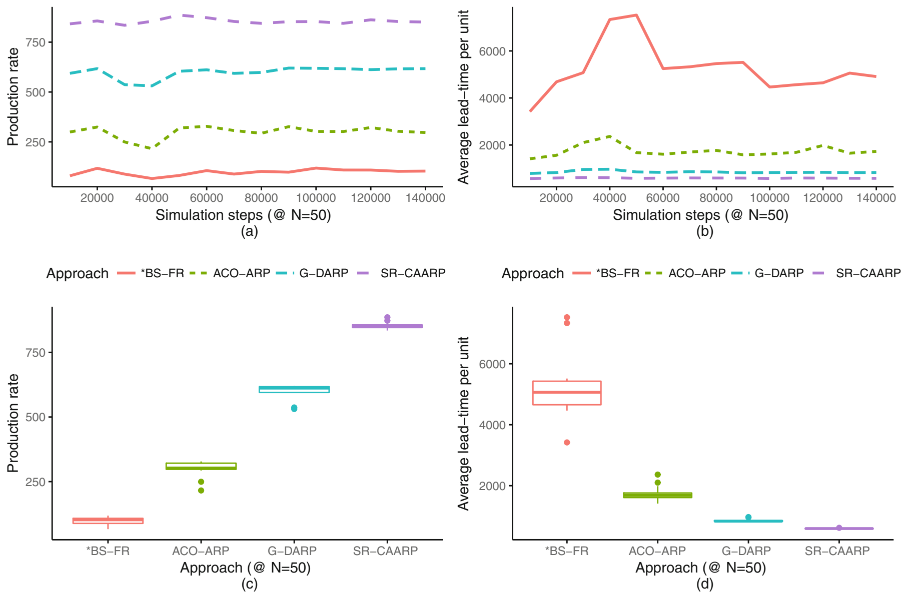


Fig. 8. Comparing S1MS performance based on ACO-ARP, G-DARP, SR-CAARP and baseline system (BS) approaches

The SR-CAARP approach, which is the optimised version of the G-DARP has the highest performance followed by the G-DARP, i.e. it has the highest production rate (see Fig. 8(a) and Fig. 8(c)) and lowest average cycle-time per unit (see Fig. 8(b) and Fig. 8(d)). Both of these approaches employed a local interaction mechanism complement with the ant-inspired algorithm for coordinating and autonomously positioning production machines to minimise the cost of material flow and distances between the production machines. The ACO-ARP comes just below the two ensemble approaches in performance, but its method for coordination and autonomous positioning of production machines is based on local interaction and heuristics optimisation algorithm, and, therefore, far less computationally expensive. The baseline system with fixed production machines records the least performance.

5 Conclusion

The three different approaches in S1MS were effective in seamlessly coordinating the movement and positioning of production machines during manufacturing. However, the ensemble approaches, G-DARP and SC-CAARP, performed better than the ACO-ARP. This is because the ensemble approach explores clusters of locally available information, such as product position, cluster size, and sensing radius, to optimise the location of production machines, while it uses the pheromones to speed up convergence. However, as the complexity and volume of this information grow as the value of N increases, slightly more computational resources may be required for cluster computation and analysis. The nature-inspired approach (ACO-ARP) used only locally available information and followed simple but effective rules to achieve seamless coordination of the movement and positioning of production machines.

Overall, the ACO-ARP has a computation advantage, but it does not outweigh the poor performance compared to the ensemble approaches. However, the ACO-ARP can serve as a backup in situations when local information required for computation suddenly becomes unavailable, such as network failure.

References

1. Andersen, A.-L., Brunoe, T.D., Nielsen, K., Rösiö, C.: Towards a generic design method for reconfigurable manufacturing systems: analysis and synthesis of current design methods and evaluation of supportive tools. J. Manuf. Syst. **42**, 179–195 (2017). https://doi.org/10.1016/j.jmsy.2016.11.006
2. Bautista, J., Pereira, J.: Ant algorithms for a time and space constrained assembly line balancing problem. Eur. J. Oper. Res. **177**(3), 2016–2032 (2007). https://doi.org/10.1016/j.ejor.2005.12.017
3. Becker, C., Scholl, A.: Balancing assembly lines with variable parallel workplaces: problem definition and effective solution procedure. Eur. J. Oper. Res. **199**(2), 359–374 (2009). https://doi.org/10.1016/j.ejor.2008.11.051
4. Botti, V., Giret, A.: Holonic manufacturing systems. In: Bowen, H.K., Robert, S., Carin-Isabel, K. (eds.) A multi-Agent Methodology for Holonic Manufacturing. New Balance Athletic Shoe, Inc., Harvard Business School Case, 606-094, April 2006. https://doi.org/10.1007/978-1-84800-310-1. Revised June 2008
5. Brusaferri, A., Ballarino, A., Carpanzano, E.: Distributed intelligent automation solutions for self-adaptive manufacturing plants. In: Ortiz, Á., Franco, R.D., Gasquet, P.G. (eds.) BASYS 2010. IAICT, vol. 322, pp. 205–213. Springer, Heidelberg (2010). https://doi.org/10.1007/978-3-642-14341-0_24
6. Chaplin, J.C., et al.: Evolvable assembly systems: a distributed architecture for intelligent manufacturing. IFAC-PapersOnLine **28**(3), 2065–2070 (2015). https://doi.org/10.1016/j.ifacol.2015.06.393
7. De Santis, R., Montanari, R., Vignali, G., Bottani, E.: An adapted ant colony optimization algorithm for the minimization of the travel distance of pickers in manual warehouses. Eur. J. Oper. Res. **267**(1), 120–137 (2018). https://doi.org/10.1016/j.ejor.2017.11.017
8. Dorigo, M., Blum, C.: Ant colony optimization theory: a survey. Theoret. Comput. Sci. **344**(2–3), 243–278 (2005). https://doi.org/10.1016/j.tcs.2005.05.020
9. Dorigo, M., Di Caro, G.: Ant colony optimization: a new meta-heuristic. In: Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), vol. 2, pp. 1470–1477 (1999). https://doi.org/10.1109/CEC.1999.782657
10. El Maraghy, H.A.: Flexible and reconfigurable manufacturing systems paradigms. Flex. Serv. Manuf. J. **17**, 261–276 (2006). https://doi.org/10.1007/s10696-006-9028-7

11. Frayret, J.-M., D'Amours, S., Montreuil, B.: Coordination and control in distributed and agent-based manufacturing systems. Prod. Plann. Control **15**(1), 42–54 (2004). https://doi.org/10.1080/09537280410001658344
12. Hani, Y., Amodeo, L., Yalaoui, F., Chen, H.: Ant colony optimization for solving an industrial layout problem. Eur. J. Oper. Res. **183**(2), 633–642 (2007). https://doi.org/10.1016/j.ejor.2006.10.032
13. Huettemann, G., Gaffry, C., Schmitt, R.H.: Adaptation of reconfigurable manufacturing systems for industrial assembly - review of flexibility paradigms, concepts, and outlook. Procedia CIRP **52**, 112–117 (2016). https://doi.org/10.1016/j.procir.2016.07.021
14. Kiefer, J., Wolfowitz, J.: Stochastic estimation of the maximum of a regression function. Ann. Math. Stat. **23**(3), 462–466 (1952). https://doi.org/10.1214/aoms/1177729392
15. Koestler, A.: The Ghost in the Machine. Arkana Books, London (1989)
16. Koren, Y., Shpitalni, M.: Design of reconfigurable manufacturing systems. J. Manuf. Syst. **29**(4), 130–141 (2010). https://doi.org/10.1016/j.jmsy.2011.01.001
17. Koren, Y., et al.: Reconfigurable manufacturing systems. CIRP Ann. Manuf. Technol. **48**(2), 527–540 (1999)
18. Pine, B.J.: Mass Customization - The New Frontier in Business Competition. Harvard Business School Press (1993). ISBN 0-87584-372-7
19. Rajendran, C., Ziegler, H.: Ant-colony algorithms for permutation flowshop scheduling to minimize makespan/total flowtime of jobs. Eur. J. Oper. Res. **155**(2), 426–438 (2004). https://doi.org/10.1016/S0377-2217(02)00908-6
20. Robbins, H., Monro, S.: A stochastic approximation method. Ann. Math. Stat. **22**(3), 400–407 (1951)
21. Samadhi, T.M., Hoang, K.: Shared computer-integrated manufacturing for various types of production environment. Int. J. Oper. Prod. Manag. **15**(5), 95–108 (1995). https://doi.org/10.1108/01443579510083695
22. Sanderson, D., Chaplin, J.C., De Silva, L., Holmes, P., Ratchev, S.: Smart manufacturing and reconfigurable technologies: towards an integrated environment for evolvable assembly systems. In: Proceedings - IEEE 1st International Workshops on Foundations and Applications of Self-Systems. FAS-W 2016, pp. 263–264 (2016). https://doi.org/10.1109/FAS-W.2016.61
23. Sethi, A.K., Sethi, S.P.: Flexibility in manufacturing: a survey. Int. J. Flex. Manuf. Syst. **2**(4), 289–328 (1990). https://doi.org/10.1007/BF00186471
24. Shishvan, M.S., Sattarvand, J.: Long term production planning of open pit mines by ant colony optimization. Eur. J. Oper. Res. **240**(3), 825–836 (2014). https://doi.org/10.1016/j.ejor.2014.07.040
25. Silva, C.A., Sousa, J.M.C., Runkler, T.A., Sá da Costa, J.M.G.: Distributed supply chain management using ant colony optimization. Eur. J. Oper. Res. **199**(2), 349–358 (2009). https://doi.org/10.1016/j.ejor.2008.11.021
26. Valckenaers, P., Van Brussel, H.: Holonic manufacturing execution systems. CIRP Ann. Manuf. Technol. **54**(1), 427–432 (2005). https://doi.org/10.1016/S0007-8506(07)60137-1
27. Valckenaers, P., Hadeli, G., Saint, B., Verstraete, P., Van Brussel, H.: MAS coordination and control based on stigmergy. Comput. Ind. **58**(7), 621–629 (2007). https://doi.org/10.1016/j.compind.2007.05.003
28. Weirather, J., Institutsleitung, M.D., Muenchen, T.U.: Instantly deployable evolvable assembly systems. Project Final Rep. **49**, 1–69 (2015)

29. Ogunsakin, R., Marin, C.A., Mehandjiev, N.: Towards engineering manufacturing systems for mass personalisation: a stigmergic approach. Int. J. Comput. Integr. Manuf. **34**(4), 341–369 (2021)
30. Valentini, G., Masulli, F.: Ensembles of learning machines. In: Marinaro, M., Tagliaferri, R. (eds.) WIRN 2002. LNCS, vol. 2486, pp. 3–20. Springer, Heidelberg (2002). https://doi.org/10.1007/3-540-45808-5_1