Distributed Manufacturing for Industry 4.0 Utilising Multi-Agent Based Simulations

Authors: Olatunde Banjo
Dr Kevin Rampersad

Distributed Manufacturing for Industry 4.0 Utilising Multi-Agent Based Simulations

Introduction

In Today's customer driven world, product development and innovation are constantly changing at a rapid pace (Frei et al. 2009). Especially through imposition of personal requirements and exigency for products with higher quality, functionality and shorter delivery times. Traditional manufacturing systems characterised by high volume, low flexibility and low variety of production are no longer appropriate for this type of demand. In addition, these systems are not designed to counteract disturbances, unforeseen events (e.g. market changes, more customized products, more product variants, availability of materials) that characterise the factory of the future. As a strategic industrial leverage, manufacturers need to be able to respond to these new trends. One method of production that allows manufacturers to produce only what the customer wants is described in literature as Mass Customisation (MC). However, the concept of MC introduces complexity within manufacturing operations. Furthermore, the time available for factories to manufacture a product at full plant capacity is continuously shrinking. This can be directly attributed to increased heterogeneity of customer demand and shorter product lifecycles.

Another method capable of coping with this type of demand is the Distributed Factory. This concept enables factories to cooperatively combine resources, skills, capacity to meet the requirements of the modern customer. The key advantage here is the flexibility available for a combination of factory nodes to distribute workload and make intelligent decisions with the objective of satisfying diverse customer requirements. In this paper, we present a new way of configuring a distributed factory to meet this type of demand.

The paper is structured as follows. Section 2 provides background information on manufacturing systems and decentralised manufacturing strategies. Sections 3 discusses the problem formulation and the proposed multi agent solutions and framework. Section 4 concludes the paper and suggests future work.

Background

With the introduction of the fourth industrial revolution – Industry 4.0, the need for customized product and services continues to increase. It is highly probable that the scope, scale and complexity of manufacturing will change. The need therefore arises for manufacturing systems and manufacturers to identify new methods, models and strategies to be able to cope with this level of complexity and variation.

Over the years, Flexible Manufacturing Systems (Khalid et al. 2013), Agile Manufacturing Systems (Bessant, et al., 2001), Evolvable Assembly Systems (Frei et al. 2009), Reconfigurable Manufacturing

Systems (Mehrabi et al. 2000), Holonic Manufacturing Systems (Botti & Adriana Giret 2008) have been adapted to deal with variation induced complexity. While these systems provide some level of flexibility, Vincente & Adriana criticised their inability to deal with the evolution of products within an existing production facility (Vincente & Adriana 2008). This issue poses a huge doubt on the ability of these systems to cater for intricate problems such as buffer sizes, material handling, planning, scheduling and control that could be a direct consequence of modern trends like Industry 4.0.

Various types of Distributed Control Systems (DCS) have been used to introduce modularity, real timeliness, integrated diagnostics and decentralised control in manufacturing activities (Memon 2009). Similarly, several heuristic and meta-heuristic methods and tools including Ant Optimisation, Simulated Annealing, tabu search etc. have been developed to tackle resource allocation, scheduling and optimisation problems in manufacturing. These tools however are mainly oriented towards predetermined large batch sizes and very little is known about their ability to deal with smaller batch sizes in the face of increasing product variation such as Mass Customisation. The objective of this paper is to develop a multi-agent framework to evaluate the functionality and adaptability of these methods to concepts of Industry 4.0.

Problem Definition

This paper addresses two main problems:

1. Optimising a distributed factory system to fulfil highly variant customer orders.

2. Reconfiguring factory characteristics to maximize efficiency and utilisation.

To tackle these problems, we have modeled the distributed factory as a multi-agent system whose objective is to find the optimum route i.e. the most efficient (cost effective) factory or set of factories within the system that can fulfil the customer order. To avoid ambiguity, we define cost here as a direct function of the lead time to fulfil the customer order. In addition, we have adapted concepts from the Traveling Salesman Problem (TSP), where we consider our factories as cities that a customer order must visit with the objective of finding the cheapest route. This sort of representation allows us to apply evolutionary concepts to solve this problem. These methods are described in more detail in the next section.

In finding the optimal factory configuration, each factory is modelled as an intelligent agent. Using concepts from evolutionary algorithms, we design each agent to comprise of chromosomes which are made up of individual genes. To clarify further, chromosomes represent the high-level functionalities of the factory such as the ability to perform assembly operations, production, manufacturing a specific product or its variant etc. the genes represent the individual skillset required to fulfil an objective e.g. drilling, cutting, gluing etc. Together, the chromosomes and the genes are jointly responsible for describing the characteristics of the factory.

At the system level, each factory within the system is unique. The advantage here is that we are also able to identify the characteristics in factories that make them efficient for meeting heterogenous customer demand. As generations evolve, factories with low performance or credibility gradually become extinct within the system and only the fittest factories survive. This survival of the fittest setup ensures that the fittest configurations of factories are available within the distributed system over time. To maintain the number of factories within the distributed system, we perform a random combination of mutation and cross-over to create replacement factories with new genes i.e. configuration to replace extinct ones. Eventually, the system converges to present the factories with the strongest characteristics within the system for the type of demand being evaluated.

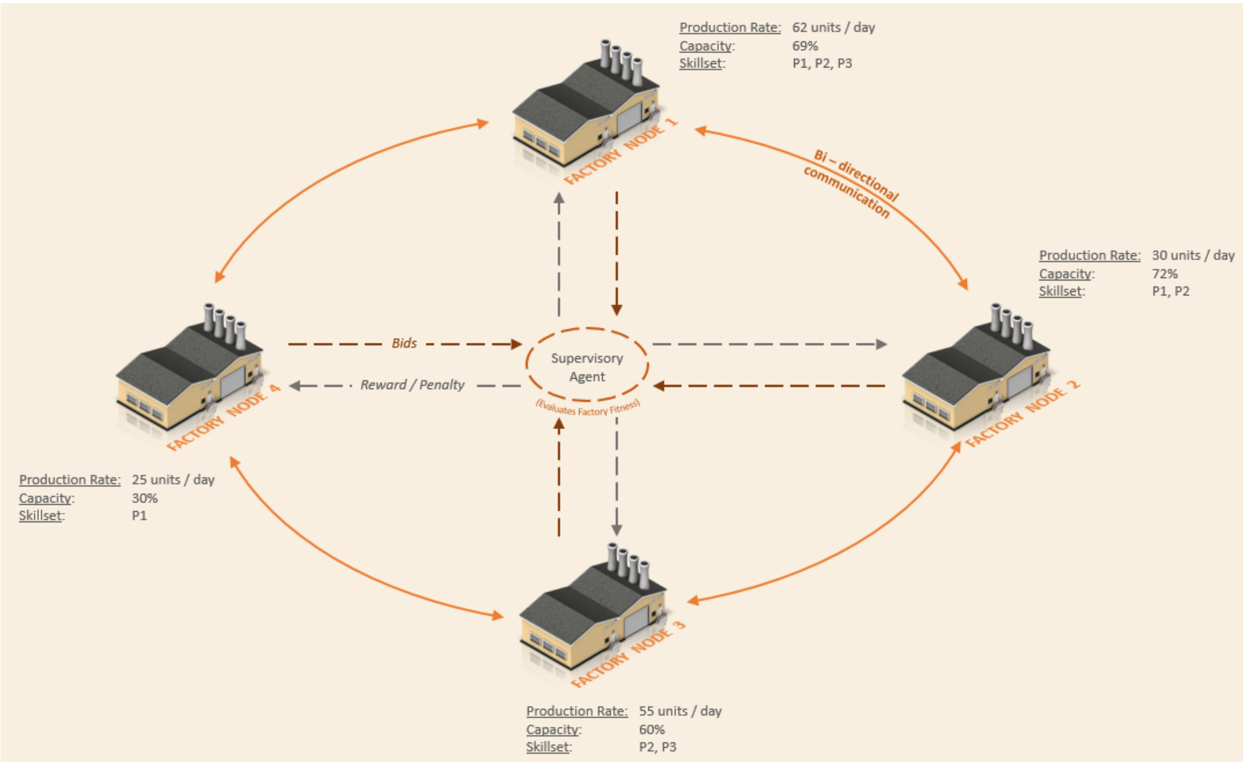

Figure 1*: The Distributed Factory System - A Multi Agent Systems Approach*

As shown in Figure 1 above, each factory has unique characteristics i.e. production rate – the amount of product units per day that the factory can make (this varies from product to product), capacity – the percentage of the total capability of the factory that the factory is currently working at i.e. if the factory is not at 100% capacity this implies that there are improvement opportunities to improve the production rate of that factory and skillset – the total number of product types that the factory can make. In addition, the factories have a bi-directional communication link to each other and to the Supervisory Agent. This facilitates factory interactions using either competitive or cooperative strategies. This is described in much detail in the next section.

Multi-Agent System

Each factory within the proposed system is modelled as an intelligent agent. The entire system can then be described as a MAS where agents compete with one another to fulfil a customer order. The MAS comprises of two main agent types.

1. The Supervisor Agent (SA) – An individual agent responsible for receiving, awarding or rejecting bids from factory agents. This agent is also responsible for broadcasting customer orders to all agents.

2. The Factory Agent (FA) – A population of agents representing individual factories within the distributed system.

When a customer order arrives at the distributed factory (see Figure X.xX below), the SA broadcasts the order to all FA's within the system. In response, each FA makes the decision to submit a bid to fulfil the customer order or not. If an FA decides to submit a bid, the SA collates all the bids for that round and awards the contract to the FA with the best offer through what is commonly describes as an auction protocol. This determines the route i.e. factory or set of factories that will fulfil the customer order as shown in Figure 2 below.

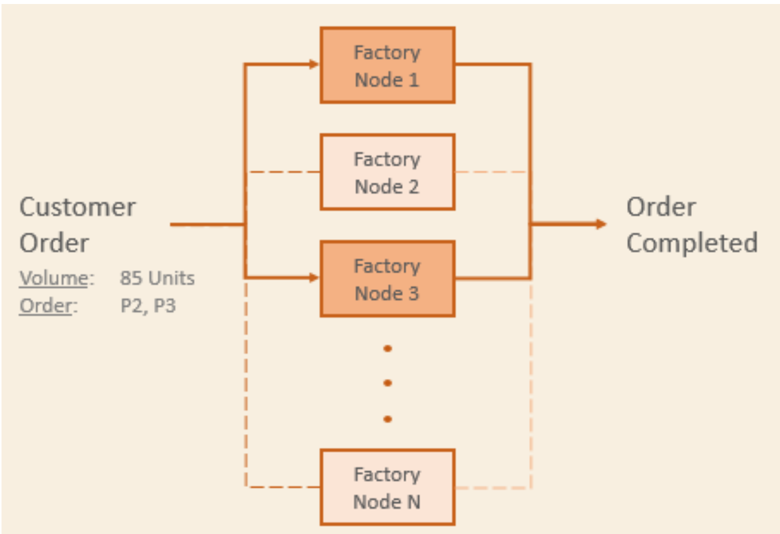

***Figure 2**: Customer Order Route to completion*

Consider the use case described in Figure 2 for a customer order of Product P2 and Product P3; a total of 85 units, when we run this through the system described in Figure 1, we find that Factory Node 1 and Factory Node 3 are favorites if we consider the trivial case of simply using the factory production rates. Likewise, since the order request includes Product P3 Factory Node 4 and 2 do not have the skillset and therefore cannot fulfil this order. However, in considering a more industrial situation, we might apply a different strategy for example where factories can cooperate with each other. This means that Factory Node 4 and 2 can now bid to fulfil part of the customer order in collaboration with either of Factory Node 1 and 3 who have the required complementary skillset. This collaborative approach is implemented using a multi-agent protocol adapted from contract net.

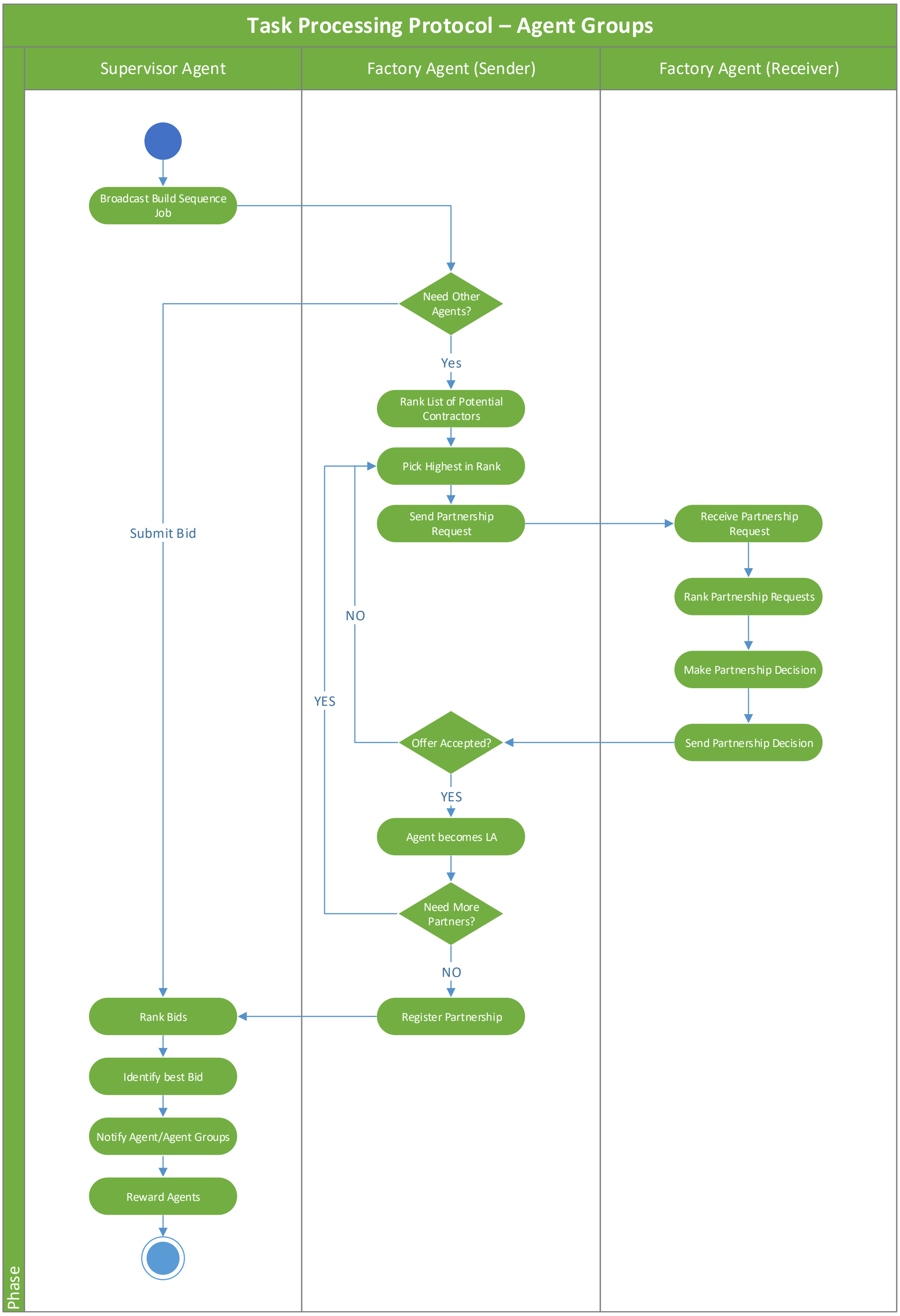

Figure 3 gives an overview of the protocol used by the FA to work in coalition.

As shown, the SA ranks the bids and awards the contract to the best FA or group of FA. For simplicity, the term FA will be used interchangeably going forward from here to describe both individual and group of FAs depending on the context.

More generally, a typical bid gives an indication of the lead time within which the FA can fulfil a customer order. For clarification, the lead time here is defined to consider internal and external supply chain, availability of parts, current utilisation of the plant, workload and transport network i.e. customer location and distance trade off. The SA agent evaluates these parameters before deciding which FA to award the bid to.

To implement the evolutionary concept, each FA has an account which is credited with predefined metric units as a measure of the FA's wellness or health. This metric determines the existence of the FA within the distributed network i.e. an FA with zero health value become extinct or dies and is removed from the system. In this way, we can redefine our MAS as comprising of individual agent units whose objective is to survive by winning bids to fulfil customer orders. Generally, when a FA wins a bid, its account gets credited and when a FA loses a bid, it's account gets debited. Furthermore, each FA's account is modelled to decay by a fixed percentage over time. On one hand, this creates an incentive for each FA to strive to participate in bidding for contracts to ensure its survival, on the other since each FA is modelled as an intelligent agent they are therefore able to evaluate their chances of success for each contract bid to minimize the possibility of being penalized for loosing the bid.

Conclusion

The proposed work presents a new method for implementing the distributed factory using a hybrid combination of evolutionary computing and Multi Agent systems. By considering manufacturing in the context of the fourth industrial revolution, we propose a new method of managing heterogenous customer demands.

As observed in literature, very little implementations of the concepts of the distributed factory has been done. All the existing complexity measures to the knowledge of the author have not considered the complexity introduced by Industry 4.0. In previous work done by the author (Banjo, et al., 2016), operational complexity was studied and used as a measure of optimizing material handling for a major car manufacturer in the UK. Knowledge from this work was used to corroborate the concepts presented here.

This research contributes to the knowledge gap using two main streams. Firstly, we design a multi-agent framework with the objective of identifying the optimum route for a customer order in a distributed factory system. Secondly, we propose an evolutionary configuration of factories that can identify the most effective configuration of factories to meet heterogenous and unpredictable customer demands.

Finally, we show that the concept of Industry 4.0 has huge potential to introduce complexities in manufacturing activities. An overview of the advances in manufacturing systems was presented showing how manufacturers currently tackle the issue of increasing product variation. Current literature was used to guide the initially proposed research objectives. New objectives were presented based on key literature in the research domain.

In conclusion, while new concepts like factory of the future and distributed factory are becoming common place in current manufacturing, very few methods currently exist to facilitate the evolution of traditional manufacturing plants to meet the requirements proposed by this new method of manufacturing. This research therefore presents one method of implementing these manufacturing systems by proposing a state of the art AI approach, validated by a UK based manufacturing plant.

Bibliography

Banjo, O., Stewart, D. & Fasli, M., 2016. *Optimising Mixed Model Assembly Lines for Mass Cusomisation - A Multi-Agent Systems Approach.* Loughborough, IOS Press, pp. 1-6.

Bessant, J. et al., 2001. Developing Manufacturing Agility in SMEs. *International Journal of Technology Management,* 22(22), pp. 28-54. Botti, V. & Adriana Giret, 2008. *Holonic Manufacturing Systems*, London: Springer-Verlag London.

Frei, R., Serugendo, G.D.M. & Barata, J., 2009. Designing Self-Organisation for Evolvable Assembly Systems. *Assembly*, pp.1–24.

Khalid, M.N.A., Yusof, U.K. & Khader, A.T., 2013. Solving flexible manufacturing system distributed scheduling problem subject to maintenance: An artificial immune system approach. *ICIC Express Letters*, 7(3 A), pp.805–810.

Mehrabi, M.G., Ulsoy, a G. & Koren, Y., 2000. Reconfigurable manufacturing systems : Key to future manufacturing. *Journal of Intelligent Manufacturing*, 11(4), pp.403–419. Available at: http://www.springerlink.com/index/Q5634H3416XT2306.pdf.

Memon, Q.A., 2009. *Automation Control - Theory and Practice* A. D. Rodic, ed., InTech.

Skobelev, P. (2011). Multi-agent systems for real time resource allocation, scheduling, optimization and controlling: industrial applications. *Holonic and Multi-Agent Systems for Manufacturing*, 1–14. http://doi.org/10.1007/978-3-642-23181-0_1

Vincente, B. & Adriana, G., 2008. *ANEMONA*, Springer-Verlag London. Vrabic, R. & Butala, P., 2011. Computational mechanics approach to managing complexity in manufacturing systems. *CIRP Annals - Manufacturing Technology*, 60(1), pp.503–506.