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Required parameters for modelling heterogeneous geographically dispersed manufacturing systems

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Abstract

COVID-19 and global crises/events are driving governments to rethink their national manufacturing strategies. The drastic change of societal conditions has exposed our reliance on a constrained set of production practices. Furthermore, the future manufacturing landscape indicates – supply chain crises, trade agreements and natural disasters – a high level of volatility which requires a response that is far from being achieved.

While these emergent challenges have called the efficacy of established practices into question, new manufacturing technologies, such as Additive Manufacturing (AM), present the capability to provide a solution. One proposal is agent-based brokering of AM which could be a method for tackling local, regional, national, and international production needs. However, to achieve the reality of brokered AM, it is imperative that the diversity of AM capability is considered. Diversity that existing homogeneous modelling of AM and manufacturing systems rarely consider or capture. This paper conceptualizes the reality of AM systems and elucidates parameters that are necessary for successful modelling and subsequent co-ordination. Having presented the required parameters the paper continues to discuss requisite levels of abstraction, suitable performance metrics and the role of humans in agent-based manufacturing systems.

Keywords: Additive Manufacturing; Agent-Based Manufacturing; Brokering

1. Introduction

The COVID-19 pandemic has seen large and unforeseen changes in product demand. The introduction of lockdown measures saw product demand switch from cars and fashion clothing to toilet roll, personal protective equipment (PPE), ventilators and remote working equipment. Characteristics of this change in demand included large, highly localised spikes, with an urgent need for vastly increased supply of individual products.

Manufacturing's response to the rapid change proved mixed with dominant, centralised and highly developed manufacturing practices, such as batch/mass/just-in-time supply chains, struggling and in some case being totally disrupted. The variation in response can be attributed to the constrained and global nature of supply-chains to deliver specific products resulting in [1]:

- A lack of agility in the installed base. For example, an automotive production system cannot be readily changed to produce other products;
- Introduction of constraints – for example restrictions on on-site personnel compromising or preventing effective operation of machinery; and/or,
- Logistical challenges in delivering parts and materials to end-users.

The result of this was a shortfall in critical equipment amidst a global crisis.

Global distributed Additive Manufacturing (AM) capability was able to provide some relief to these shortcomings using a combination of professional and ad-hoc manufacturing capability. AM was used to manufacture vital items including medical equipment, PPE, ventilator valves, field respirators, hands-free tools and anti-microbial devices [2, 3, 4]. Its ability to respond was attributed to:

- Automated CAD to manufacturing code workflows;
- Design freedom with less cognitive load on manufacturing constraints; and,
- Production of a wide range of products.

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Whilst able to respond and contribute to national needs, this ability was reduced by issues including challenges around quality control, repetition in models causing overwhelming competition in design of the same product, and lack of exploitation of metal AM [4].

In addition, there was a lack of coordination of national AM which led to significant production inefficiencies and unresponsiveness. This is in part due to traditional means of manufacturing scheduling and control via hierarchical structures [5] being inappropriate for distributed, geographically dispersed manufacturing systems as their focus moves away from production maximisation and standardisation towards cost reduction and mass customisation [6]. These focal changes contribute to the phenomenon of *big demand*, the characteristics of which are volatility and rapid changes in the volume, variety and required location of products [7, 8]. When combined with the diversity of AM capability [9] (heterogeneity) these elements create a significant challenge in coordinating distributed manufacturing systems.

To address these challenges, agent based manufacturing systems [1] are proposed as a means of co-ordinating distributed AM capability [7]. Enabling this would not only provide significant gains in production capability but also provide a production system that can complement existing modern manufacturing practices (MMP) by filling the gaps where MMP systems are unfeasible either due to their lack of agility, inability to operate or offer unsuitable manufacturing characteristics.

While these systems share some characteristics with existing print services, such as hubs.com, the agent based system is decentralised with manufacturing decisions taken by agents (see [10, 11] for more information). This allows the system to respond to the characteristics of big demand through adaptation of individual agents rather than it being necessary to implement a top down overhaul of the entire system and its workflows. The decentralised nature would also make inclusion of more unregulated elements of AM capability, such as those in schools and universities, more straightforward. This could have improved manufacturing responsiveness during the pandemic for urgently required items such as PPE for which AM technologies such as FDM (with materials including PLA, PET and ABS) had a significant impact but could have been improved through access to more manufacturing resources.

In order to develop and implement an agent based manufacturing system, it is necessary to first understand the characteristics of a distributed AM system that one wishes to model. As such, the aim of this paper is to elucidate the parameters that need to be included in an agent based system and then to subsequently propose a strategy for enabling the realisation of such a system. This will form the foundations of a modelling framework for the community to model heterogeneous geographically dispersed manufacturing systems.

The paper continues with the related work (Section 2). This is followed by the methodology in determining the characteristics that need to be modelled and how these can be parameterised (Section 3). The results are then presented in (Section 4). Equipped with this framework, two modelling approaches considering these parameters are presented in Section 5 to demonstrate how it can be used to support the community in building and describing their models of heterogeneous geographically dispersed manufacturing systems. Section 6 reflects on the completeness of the current framework and the next steps in developing it further. The paper then concludes with the key findings from the study (Section 7).

[1] where machine and jobs are agents that negotiate what will produce what.

2. Related Work

This section will explore two facets of modelling AM systems, modelling the manufacturing system as agents and modelling the individual manufacturing resource capability.

2.1. A manufacturing system of agents

Due the aforementioned unsuitability of hierarchichal systems for coordinating distributed AM, alternative heterarchical structures provide a radical alternative. One such example of this is Anarchic Manufacturing where the system features no central control or oversight, and manufacturing resources are agents with decision-making authority [12, 13]. Anarchic systems are shown to respond better than traditional hierarchical systems as scale and complexity of products increases [14]. The key elements required in these models are agents of which each has a set of optimising parameters that work as an objective function meaning that local objectives provide a global production system.

In the context of distributed manufacturing for AM, anarchic systems have been applied in a simulation context and have demonstrated the impact that production logics (part of a brokering strategy) have on system performance [1]. These agent based systems are controlled and maintained at the machine level meaning that governance and control remains with their own organisations.

Due to their existing applications in the area of distributed AM systems, and the demonstration that anarchic systems perform better that hierarchical alternatives when scale and complexity of products increases, it is evident that they are appropriate for modelling and coordinating distributed AM systems.

2.2. Modelling AM capability

AM permits considerable design freedom not permitted by traditional subtractive methods [15]. This is, in part, enabled by the variety of manufacturing parameters that can be controlled by the designer [16]. Many AM processes are considered heterogeneous as they have varying mechanical and dimensional properties depending on part orientation.

Through characterisation of the manufacturing process, previous work has sought to create predictive models of AM processes such as filament deposition modelling, in order to facilitate the prediction of the performance of finished parts [17]. These works have identified a number of manufacturing parameters such as build orientation, layer height and infill percentage that have significant impacts on the geometric and mechanical performance of parts.

Whilst a range of predictive models have been generated, none are able to work universally due to the wide range of AM capability [9]. At the same time, a range of benchmark artefacts for AM have been proposed [18], including an ISO standard [19], however, standardisation of AM technologies is still lacking. The result of this is that within the context of a manufacturing system, it is necessary to compare job requirements to the individual capabilities of the manufacturing resource.

3. Methodology

To determine the parameters required to model heterogeneous geographically dispersed manufacturing systems, a four step process was followed. Step 1 (in the previous two sections) consisted of a review of big demand, AM capability and agent based modelling to elucidate their respective requirements and constraints. Step 2 featured the construction of a high level process model to identify the necessary elements. Step 3 involved the extraction and expansion of these IDEF0 elements into a broader list of parameters that need to be included.

4. Results: A parametric framework for modelling heterogeneous geographically dispersed manufacturing systems

The literature reviewed as part of step 1 highlighted that modelling heterogeneous geographically dispersed systems could be achieved by considering it to be a manufacturing system of agents coupled with consideration of AM capability due to the heterogeneity of the manufacturing resources themselves.

Fig. 1 shows the output of Step 2 and how manufacture via distributed AM can be represented in IDEF0 [20]. The process requires inputs, outputs, mechanisms (physical aspects of the system that facilitate its function) and controls (that constrain and direct). In our case, these are:

- **Input**: Jobs & Raw Materials
- **Output**: Manufactured Parts
- **Mechanism**: Installed Base
- **Control**: Job Requirements, Demand Profile, Brokering Strategy

The process inputs and outputs are fairly self-explanatory; users submit jobs and when processed with raw materials (e.g., plastic filament, pellets, metal powders, energy), manufactured parts are created[2]. The mechanism for creating parts is the installed base consisting of the distributed manufacturing resources. The process controls are threefold and are job requirements, demand profiles and brokering strategy. Job requirements detail requirements of the completed part. These are important as they permit the identification of an appropriate manufacturing resource in the installed base for realizing the part. Demand profile considers the overall landscape of jobs submitted for manufacture which informs and impacts the brokering strategy which determines the manner in which the machine and job agents can communicate with one another to manufacture. An IDEF0 representation of this process is shown in Fig. 1

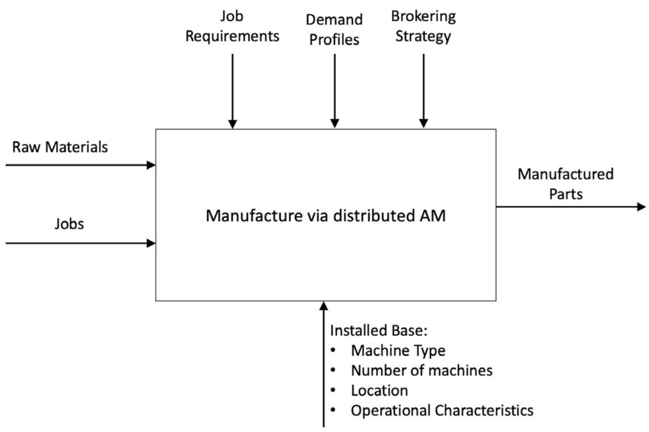

Figure 1. IDEF0 Process diagram

The mechanism and control of the manufacturing process can be grouped into four families of parameters:

1. **Demand Profile** is defined the same as in the IDEF0 diagram and refers to characteristics of all jobs entering and within the manufacturing system. It represents big demand to which the manufacturing must be able to respond to.
2. **Job** combines *Jobs* as an input, and *Job Requirements* as a control. It refers to an individual artefact within the system that requires manufacturing. It necessitates information about the part's size, quality and material.
3. **Installed base** is the same as the IDEF0 representation and refers to the collective manufacturing capability within the distributed AM system, its availability of materials and its operational characteristics.
4. **Brokering Strategy** dictates the manner in which the manufacturing responds to changing demand and is also the same as the IDEF0 representation

These high level families of parameters and are now discussed and elaborated. They are shown in (Fig. 2).

Demand profiles are defined by the jobs being submitted to the distributed system. This is important as the *frequency of arrival* of jobs (1.4) will greatly impact the brokering strategies employed by the system to maximise manufacturing performance. In addition to this Job *due date* (1.2) and *job duration* (1.3) determine the urgency. *Batch sizes* (1.1) impact the manner in which jobs are distributed to manufacturing resources.

Job as an an input and requirement can be represented as four parameters. *Quality* (2.1) considers the necessary mechanical

[2] this is inclusive of any required post processing

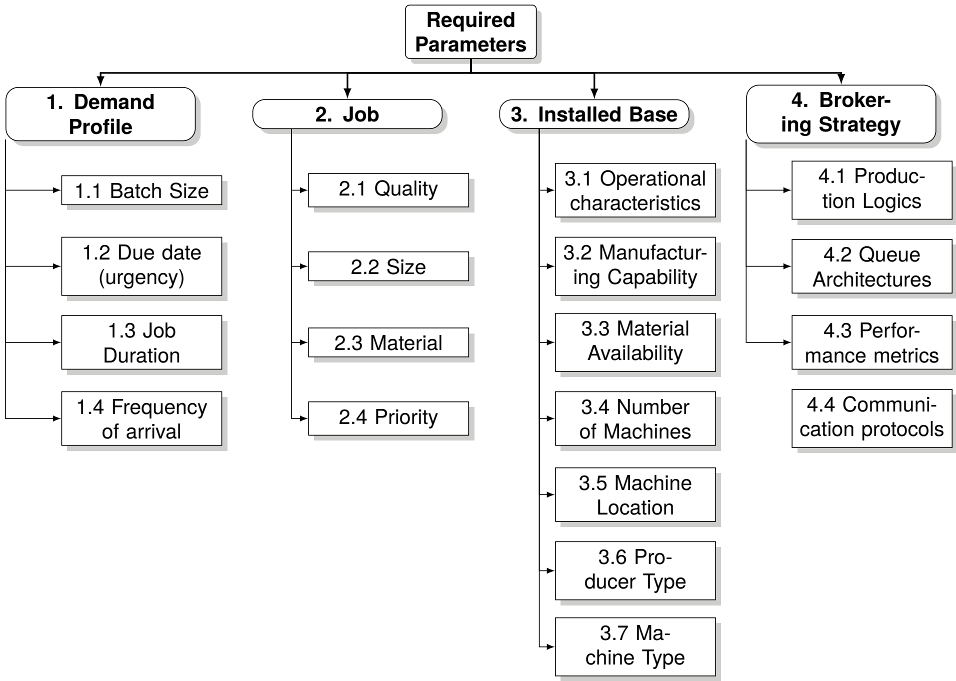

Figure 2. High level of elements to consider

properties, geometric accuracy and durability of a completed job. *Size* (2.2) considers how large the part is with respect to manufacturing dimensions and required mass of material. *Material* (2.3) refers to the type of material(s) that the job can be manufactured from. *Priority* (2.4) refers to how production is prioritised, for example at lowest cost, fastest delivery or lowest environmental impact.

Installed base is a term referring to a collection of manufacturing resources (in our case AM resources). This can be broken down into:

- *Operational Characteristics* (3.1) - incorporating factors that determine when the installed base is productive such as day/night and maintenance cycles.
- *Manufacturing Capability* (3.2) - considers elements such as print sizes, geometric accuracy, mechanical properties of printed parts, materials that can be printed in and manufacturing complexity (such as multi-material printing).
- *Material Availability* (3.3) - materials that are available and their respective lead times.
- *Number of machines* (3.4) - the quantity of machines that are part of the installed base.
- *Machine Location* (3.5) - where the different machines are located.
- *Producer type* (3.6) - AM capability is distributed across a range of different 'producers' such as schools, universities, OEMs and individuals. These will all have different operational characteristics, manufacturing capability and motivations for participating in a distributed network
- *Machine Type* (3.7) - refers to the type of AM machine. This could refer to a manufacturing technique or a brand of machine.

Brokering strategy is the approach that the manufacturing system takes to coordinate distributed manufacturing and assign jobs to the installed base. The research team identified there was a spectrum by which one can broker work between the machine and job agents. At one end of the spectrum is *co-ordinated manufacture* where job agents are submissive and exist in a pool together with the machines agents negotiating/deciding what to produce. At the other end is the *marketplace* where the machine agents are submissive and jobs to determine which machine they will be machined on. In the middle is brokering where both machine and job agents negotiate and determine which manufacturing resources will process which jobs. The brokering strategy used to achieve this requires:

- *Production logics* (4.1) define how manufacturing and job agents determine which machine will receive which job.
- *Queue architectures* (4.2) refer to how job queues are constructed. Within the installed base, individual resources could for example have their own queue enabling the creation and curation of their own backlog, or a facility with multiple resources could have a local queue, or the manufacturing system features one global queue.
- *Performance metrics* (4.3) serve as an objective function for the system and permit comparison of different brokering strategies.

- *Communication protocols* (4.4) define which agents can communicate together and in what capacity.

5. Modelling approaches

Having presented required parameters it is necessary to consider methods of modelling. Section 2 demonstrated the two areas that need to be incorporated for modelling distributed AM systems - modelling of production systems and AM capability. Both of these are non-trivial, complex modelling challenges in themselves. We propose that is necessary to tackle these individually before combining to resolve the entire system. Stages of achieving are detailed as follows.

Modelling level one - Level one consists of production system modelling featuring discrete AM capability and AM capability modelled separately.

Production system with discrete AM capability: Key tenets of this modelling are categorisation of installed base manufacturing capability and job requirements. This requires the inclusion of the following parameters:

1. **Demand Profile** – all parameters shown for (1) in Fig. 2.
2. **Jobs** - parameters abstracted to simple classifications (e.g., A,B,C,D) incorporating material, process, quality, volume and a derived print time.
3. **Installed base** - includes operational characteristics (3.1), number of machines (3.4), machine location (3.5) and producer type (3.6). All other parameters are abstracted to classification as in jobs above.
4. **Brokering strategy** – all parameters shown for (4) in Fig. 2.

This modelling permits the generation and validation of an appropriate brokering strategy but requires a representative approximation of real demand profiles and installed based. Means of generating these will be considered in Section 6.

AM capability modelling: AM capability modelling necessitates a comparison of job requirements and manufacturing capability of a production resources. It requires parameters omitted in Section 5, namely:

2. **Job** - quality (2.1), size (2.2), material (2.3).
3. **Installed Base** - manufacturing capability (3.2), material availability (3.3) and machine type (3.7).

Modelling of AM capability vs job requirements will enable the development of a manufacturing triaging strategy for AM and subsequent determination of which jobs need to go to which machines.

Modelling level 2 - bringing it together. Level two modelling builds on level one by combining the production system model with the AM capability modelling. This permits the refinement of the brokering strategies developed as they can be applied to realistic job requirements and manufacturing capability. In place of modelling this entire manufacturing system, this would likely need to be carried out for job use cases and sub-sections of the installed base such that the modelling strategies can be tested and verified.

6. Discussion and Future Work

This section will consider three areas: key known unknowns; interdependencies of parameters; and, operationalising the model - all of which are considered for further work.

In addition to the modelling challenges presented, realistic information for feeding into these models needs to be garnered. Of particular importance are the key known unknowns regarding the elucidation of realistic demand profiles and understanding the characteristics of the installed base – a particular challenge due to the paucity of reliable data [21]. Required stakeholders to determine AM installed base include a representative range of AM users (to elicit for example, key producer types, the AM technologies they use and their applications), manufacturers of the AM machines, design repositories (to define and understand the makerscape), trade associations, AM networks and policy makers. Demand profiles can be investigated by considering the fluctuations in demand of business as usual products that are produced under normal and crisis (e.g., changed constraints due Covid) conditions for a range of industry sectors. In addition to this, it is possible to build demand profiles around emergency items that have been necessary during the pandemic as highlighted in the media and in literature (e.g., [4]).

Further to these known unknowns, it is important to recognise the interdependencies between many of the parameters presented. For example, brokering strategies are dependent upon characteristics of the installed base, types of jobs and demand profiles. The installed base is related to producer type and will vary greatly dependent upon the range of producers types included. It is therefore necessary to map the interdependencies between parameters and understand the impact that each will have on other areas of the system and the assumptions underpinning the modelling approach.

As defined in Section 4, performance metrics need to be defined as these are necessary as objective functions for the system and to compare different brokering strategies and are required to operationalise the model. Challenges exist in that for distributed AM both big demand and the installed base are amorphous, evolving concepts so traditional ideas of 'optimisation' (e.g., minimise cost, maximise output) in manufacturing systems (where installed base and demand are fixed) are perhaps not wholly relevant. Ideas of resilience (as used in infrastructure [22]) may be pertinent, as manufacturing capability could be viewed as a key piece of societal infrastructure. A well coordinated system may therefore be one that is able to keep functioning in the face of adverse and rapidly evolving conditions rather than performing well with respect to a simple cost/output metric.

Initial implementations of such brokering strategies in simulation environments can be seen in [1, 23, 11]. These demonstrate how manufacturing system performance is impacted even at the small scale of a university workshop by production logics that define which jobs are selected for processing. Architecture for a brokered physical system to validate the modelling can be seen here [10]. Future work will involve the creation of a living lab to demonstrate the function of a brokered manufacturing system.

While machine and job agents will coordinate production and could theoretically function autonomously, humans can (and most likely will) exist in the system and are considered by the agent as a type of logic. For example a job agent could be assigned locally by a human identifying which printers are available and selecting an appropriate resource for manufacturing. Considering the role humans play in these systems will be critical in their uptake and will therefore need to be considered in associated business models and policy relating to brokered manufacturing systems.

7. Conclusion

This paper has presented a framework defining requisite parameters for modelling heterogeneous, geographically dispersed manufacturing systems. Having presented the framework, it considers incremental modelling approaches eventually permitting representation of the entire system. The discussion identified key unknowns, reflected on the interdependencies of these parameters, considered how to operationalise the model and considered existing implementations of brokered systems.

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