Responding to rapidly changing product demand through a coordinated additive manufacturing production system: a COVID-19 case study

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Abstract: COVID-19’s lockdown policies saw Modern Manufacturing Practice (MMP) – batch/mass/just-in-time supply chains – severed and societal demands rapidly change from products such as vehicles and clothing to Personal Protection Equipment (PPE), ventilators and equipment for remote working. The critical and, in many cases, life preserving, need for responsive manufacturing resulted in government and frontline services turning to society’s Additive Manufacturing (AM) capability in homes, schools, universities, and industry to provide essential products and product replacements. While AM managed to respond and support some government and frontline services, the highly distributed and diverse nature of the nation’s AM resources resulted in potentially avoidable production inefficiencies and delays. This paper develops and evaluates a series of strategies for coordinating AM for rapidly changing product demand to further enhance the responsiveness and productivity of AM. The strategies presented in the paper employ a host-client agent-based architecture that enable local governance of production thereby enabling distributed AM resource to come together to tackle society’s production needs without the need for centralised coordination. To enable and support local governance, it is necessary to understand how the combination of production logics impact the overall performance of the production system. Correspondingly, the contribution of this paper lies in the characterisation and quantification of the impacts of production logic through the metrics of Time in System, Lateness and Jobs in Queue and the consequences for responsive AM production systems.

Keywords: Responsive manufacturing, Additive manufacturing, Agent based modelling, Anarchic manufacturing, COVID-19.

1. Introduction

COVID-19 caused rapid and sweeping changes to product demand, particularly in its volume, variety and locality. Prior to the global lockdown, products, such as cars and fashion clothing, were in high demand but as lockdown measures were introduced, the profile of societal demand switched to food, toilet roll, Personal Protective Equipment (PPE), ventilators and remote-working equipment, with highly localised spikes in demand as lockdown regimes cascaded and tightened across the world.

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

A lack of agility of manufacturing resources and tooling. For example, an automotive production system
cannot be readily changed to produce other products (figure 1);
Sudden introduction of production constraints, such as restrictions on the number of operators on-site
which compromises and in some cases prevents effective operation of machinery; and/or,
Logistical challenges in delivering parts and materials to customers across the globe.

![Figure 1](image-url)

Figure 1. The manufacturing response to COVID-19: (a) MMP unable to respond, (b) Innovators
posting COVID-19 product. (c) FormLabs converting snorkel masks for utilisation as PPE (d) UoBristol ventilator. (e) Leading 3D printed news website detailing the AM community’s response
to COVID-19. (f) 3D systems looking to collaborate with innovators to create AM products to combat
COVID-19. (g) Innovators seeking 3D printers to manufacture their products to combat COVID-19. (h) Report on 3D printing being at the front lines of the manufacturing efforts to meet the crisis.

In an attempt to overcome these issues, society turned to its Additive Manufacturing (AM) capability
– homes, schools, universities and industry due to its affordances of (figure 1):

- Ease in producing manufacturing code from CAD models;
- AM design accessibility; and,
- Flexibility to produce all manner of products.

While AM managed to respond and contribute to national needs, the lack of coordination led to
production inefficiencies and unresponsiveness.

Coordinating AM production is non-trivial due to its highly distributed and diverse nature. And, while Modern Manufacturing Practice (MMP) coordination methodologies could be applied, they
neither take advantage of AM’s distinct capabilities nor provide an optimal production system.
Optimally coordinating AM production would not only provide significant gains in production
capability but also provide a production system that can complement existing MMP by filling the gaps
where MMP systems are unfeasible.

In this paper, we explore a host-client agent-based production system architecture to coordinate AM
production. The architecture enables local governance of production logics thereby enabling the AM
community to come as one to tackle society’s needs - i.e., the owners of the machines can determine
and select the logics they desire. Some operators may wish to set their machines to a First-Come First-Serve strategy while others may wish to select items based on manufacturing time, size, material, time remaining in the day and/or a combination thereof. However, the challenge with local governance is in evaluating how the combination of logics impacts the responsiveness and productivity of the production system and what combinations are desirable for different production scenarios. As a first step towards meeting this challenge, the study evaluates the impact of production logics (i.e., how important are they) on a manufacturing system’s responsiveness and productivity and starts to develop a landscape of what appropriate logics for different product demand scenarios would look like.

The paper starts by discussing research in agent-based production systems and related studies aimed at enhancing the productivity of AM facilities, and a summary of how the pandemic affected product demand (Section 2). This is followed by a description of the proposed host-client agent-based production system (Section 3). The study is then presented that sought to evaluate four sets of production logic with respect to four production scenarios, evaluating responsiveness and productivity via the metrics of Jobs in Queue, Lateness and Time in System (Section 4). The results are presented (Section 5), followed by a discussion (Section 6). The paper then concludes by highlighting the key findings and future work (Section 7).

2. Related work
To frame this paper, this section provides a brief overview of work in coordinating production systems and evaluating the changes in demand as a result of the COVID-19 pandemic.

2.1. Coordinating production systems
Traditionally, manufacturing scheduling and control is centrally managed via hierarchical and centralised structures, managing complexity through decomposition and simplification [1]. Recent manufacturing system paradigms, however, have shifted their focus; away from production maximisation and standardisation to cost reduction and mass customisation [2].

One of the biggest challenges yet to be realised is the coordination of production systems for mass customisation at mass production prices [3]. This is due, in part, to the increased complexity in coordinating diverse production jobs (e.g., type, size, quantity) [4]. Cloud Based Manufacturing (CBM) is proposed to achieve mass customisation which in itself brings its own elements of complexity due to the diverse resource(s) provided by participants [5].

Alternative heterarchical structures provide a radical approach to coordinating production systems. An example of this is Anarchic Manufacturing where there is no central control or oversight, and manufacturing resources have decision-making authority [6, 7]. They are shown to respond better than traditional hierarchical systems as scale and complexity of products increases [8]. Thus, anarchic principles appear to be a sensible approach to take for the coordination of distributed and diverse AM.

2.2. Changes in demand during COVID-19
The COVID-19 pandemic has demonstrated the fragility of global supply chains. This is driven, in part, by changes in demand of products – with surges in products, such as toilet paper [9], online food deliveries [10] and personal protective equipment [11] where in the US mask production was 72% lower than demand.

Challenges in a reduced workforce at production facilities contributed to reduced production and inability to meet demand, particularly in the early stage of the pandemic. It has been suggested that digital manufacturing technologies can be employed to reduce workforce sizes and subsequently risk of viral spread to create resilient supply chains [12]. In addition, recovery models have been developed for how firms can respond for high demand items [13] and it has been proposed that to effectively respond to shortages in essential products we need to transcend traditional profit motives that underpin business decisions [9]. This work shows COVID-19 demand profiles are multi-faceted and thus, requires a highly adaptive and responsive coordination of manufacturing capability in order to maintain supply of essential products.
2.3. Summary
To complement and act on previous work, this paper evaluates anarchic principles as a means to better coordinate distributed and diverse AM. Existing research looking at disruption due to pandemics has sought to develop methods of supply chain recovery. The contribution of this paper is novel as it investigates the development of supply chains that are robust and can manage supply of essential items through disruptions, such as pandemics.

3. A host-client production system for coordinating additive manufacturing
The host-client production system architecture evaluated in this paper is shown in figure 2a. The host, most likely a cloud provider, manages and maintains the queue of jobs to be manufactured by the AM machines. An Application Programming Interface (API) is provided that enables AM machines to query the jobs in the queue and assign themselves to produce the job. The API allows the machines to query the entire queue and extract information concerning the job such as, material requirements, estimated production time, quantity, and its current status (i.e., queued, selected, manufacturing, manufactured).

The architecture allows each AM machine connecting to the queue to feature its own Production Logic (PL), such as First-Come First-Serve, and Shortest/Longest Processing Time. This enables local governance of PLs enabling the AM machines to operate in a manner that is desired by their owning organisation, for reasons such as commercial contracts, operator availability, materials and capacity.

The result is a production system that is an ensemble of PLs that are not determined centrally. This enables all manner of AM capability – homes, education and industry – to all connect to the same queue thereby increasing the production capacity of the entire system. It also enables operators to change PL ‘on-the-fly’ on a per machine basis providing a wealth of configurability to the production system, which increases the flexibility of the system and allows matching of local constraints and demands. A potentially critical capability in order to meet varying product demand. However, the responsiveness and productivity of the system is based on the ensemble, and it is thus necessary to understand the degree to which the ensemble impacts the system.

4. Study
A study was devised to investigate the performance of a host-client production system and how the ensemble of production logics perform with varying product demand. An agent-based model, using Anylogic, was constructed to replicate the host-client architecture. The study consisted of:

- Building the Agent-Based Model;
- Determining the Production Logics to be used by the machines;
- Selecting the utilisation (Product Demand) scenarios that will be explored; and,
- Evaluating production system responsiveness and productivity in terms of Time in System, Jobs in Queue, and Lateness.
These are now discussed.

4.1. Agent-based model of the host-client production system
The agent-based model of the host-client production system followed the methodology set out by [7]. Monte-Carlo simulation was applied to observe the impact of varying experimental factors. The model features three agents: AM Machine, Job and Queue Coordinator.

The model is initialised with a fixed set of AM machines. In this case, the number of machines was set to 12 to be representative of a university workshop or makerspace. Each machine features a Production Logic (PL). The PLs describe how an AM machine queries and selects jobs from the queue coordinator, this is also set during initialisation.

The queue coordinator is a stateless agent that stores the jobs that have not been selected by an AM machine and in effect, represents the queue of jobs to be manufactured. Jobs are also agents whose state informs on whether they are in the queue, being manufactured by an AM machine or have been completed (Figure 2c). Jobs, on creation, join the queue coordinator. A machine agent (Figure 2b) can exist in two states, idle, where the machine will periodically query the queue for jobs to select, and manufacturing, where the machine decrements the manufacturing time remaining on the selected job. When a job is selected by a machine, it leaves the queue and assigns itself with the machine. It is then processed by the machine and exits the system on completion.

Demand profiles were normalised against system utilisation\textsuperscript{1}, $U$ and were subsequently converted to determine the inter-arrival time, $t_a$, of jobs to the model. The inter-arrival time is a function of utilisation, the mean job duration, $\bar{\delta}$ and number of machine tools, $M$. This is shown in equation (1).

\[ t_a = \frac{j}{\bar{\delta}U} \]

4.2. Production logics
Four Production logics were investigated:

- First-Come First-Serve (FCFS) - Job with earliest arrival time to the queue is selected. This is akin to a standard queue (e.g., at the post office).
- Shortest Processing Time (SPT) - Job with the shortest manufacturing time is selected.
- Longest Processing Time (LPT) - Job with the longest manufacturing time is selected.
- Earliest Due Date (EDD) - Job with the earliest due date is selected.

The distribution of logics across the 12 AM machines were as follows:

- All First-Come First-Serve (FCFS) - to evaluate a standard queuing system.
- All Earliest Due Date (EDD) - to evaluate a queuing system based around ‘fire-fighting’ to deal with jobs according to urgency.
- Half SPT and Half LPT- to evaluate a queuing system based on assessment of a job’s manufacturing requirements\textsuperscript{2}.
- Equal Distribution of Logics (EDL) - investigating the affordances of hybrid strategies.

To evaluate how the production system in its four configurations would respond to rapidly changing demand, the system was subjected to four demand scenarios.

\textsuperscript{1} A demand of 1.0 should result in the production system being fully utilised.
\textsuperscript{2} A combination of these logics is required to ensure that at both ends of the queue (longest and shortest) jobs would be completed
4.3. Demand scenarios

Four theoretical demand scenarios were generated to evaluate the responsiveness of the coordinated AM system. All scenarios allowed for suitable simulation ramp up, by maintaining an initial constant demand with all changes starting at 1,500 h. Demand scenarios then either stayed within or exceeded 100% machine utilisation for stress testing and/or cycling. These demand profiles can be seen in figure 3a.

- Scenario 1: Steady-State. Scenario 1 provides a steady-state demand input into the system and forms the baseline to compare the three other scenarios. The steady-state demand was set to 70% for the model.

- Scenario 2: Step-Change. Scenario 2 provides a step-change in demand of the model simulating a sudden surge of jobs. Post initialisation, a step change is introduced demanding jobs that would theoretically push the system to 1.08, beyond the capacity of the production system, and lasting 1,000 hrs. Thus, leading to a queue (backlog) of jobs to process. After which, the demand returns to the original state of 70% for the remaining time. This enables us to investigate how the system can accommodate a sudden change in demand and how quickly it can return to steady-state operation.

- Scenario 3: Saw-Tooth. Scenario 3 represents a saw-tooth demand profile where the service is receiving cyclic high and low-demand. Post initialisation, the simulation enters the saw-tooth profile with min and max demand set to 51% and 117%, respectively, and cycling every 250 h. The cycling continued through the remainder of the simulation to evaluate if the system could react to and sustain the demand being placed upon it.

- Scenario 4: Two stage linear ramp. Scenario 4 introduces to two stage linear ramp to simulate an increasing demand before returning to almost no demand. Post initialisation, a first stage ramp increasing linearly from 1500 h to 2500 h at a rate of 6% is set. Between 2500 h and 2750 h, the rate is increased to 34%. A maximum demand of 137% is set before dropping to 8% for the remainder of the run.

4.4. Job duration

The duration of jobs submitted to the model were randomly selected from a triangular distribution with minimum job duration of 0.8 h, maximum job duration of 10 h and mode job duration of 4 h (figure 3b). These values were calculated by fitting a triangular distribution to a range of facemasks and face-shields that were manufactured in response to COVID-19 and can be found on the Open Source Hardware repository Thingiverse [14]. The machines in the system therefore represent desktop 3D printing machines that one would typically use to manufacture products found on Thingiverse.

4.5. Evaluating production performance

Three metrics were derived to evaluate production system responsiveness and productivity and are common in agent-based manufacturing literature. These are Jobs in Queue (JIQ), Lateness and Time in
System (TIS).

JIQ captures the number of jobs in the queue throughout the simulation run and gives an insight into the backlog in the system. Lateness is calculated as the time the job was completed against the desired completion time for the job. Jobs completed early have a negative lateness. The desired completion time was set as a function of job print time multiplied by a random value taken from a uniform distribution between 2 and 4 h. TIS is the total time a job spends in the production system.

![Graphs showing simulation results for different demand profiles.](image)

**Figure 4.** Simulation results for each Production Logic (PL) set in response to different Demand Profiles (DP). Steady State DP: (a) JIQ, (b) Lateness, (c) TIS. Step Change DP: (d) JIQ, (e) Lateness, (f) TIS. Saw Tooth DP: (g) JIQ, (h) Lateness, (i) TIS. Ramp Up DP: (j) JIQ, (k) Lateness, (l) TIS.
5. Results

Figure 4 shows the response of the four PL sets for the four demand profiles. In the Scenario 1, we observe little to no difference in the responsiveness and productivity of the production system for the different logic sets. Moving to Scenario 2, we start to see differences in production behaviour. FCFS provides the fewest JIQ, Lateness and time in queue throughout the simulation. The other logics behave similarly with the exception of EDD featuring some peculiar behaviour with high Lateness and TIS being observed.

This may be due to SPT and EDD logics prioritising manufacturing capacity to shorter jobs at the beginning of the simulation (via SPT logic). As longer prints become more urgent (due to EDD), manufacturing capacity becomes saturated with longer jobs, which ramps up average TIS and Lateness.

In Scenario 3, all logic sets were able to respond and meet the demand being placed on the system with them being able to clear the backlog prior to the next peak in demand. In this scenario, Half SPT and Half LPT respond better to the change in demand where it maintains the fewest JIQ, lowest Lateness and lowest TIS.

Half SPT and Half LPT results in polarisation of the manufacturing capability with half the machines considering longer jobs, and half short jobs. This combination works well as long as these polarised sets overlap which occurs if the system is not saturated. When jobs are in excess, these polarised sets no longer overlap, and a gap arises which jobs fall through greatly increasing backlog and queue length. The former of these occurs in Scenario 3 as the number of jobs are manageable by the system.

Through inspection of Scenario 4, we observe all the logic sets performing well with little difference between them. Apart from Equal Distribution, which again features some peculiar behaviour with high Lateness and TIS being observed – possibly for the same reasons as put forward for Scenario 2. In terms of response, it shows that a steady change in demand profile can be responded to well by all PL sets but sudden changes in demand is where you see the PL set having an effect.

Table 1 provides ranking of the PL sets against the demand scenarios based on the desired characteristics of maintaining fewest JIQ, low Lateness and low TIS. We observe that different PL sets were able to respond better for different demand scenarios with all FCFS being suited for a step-change scenario, Half SPT and Half LPT suited for saw-tooth and two-stage ramp. This highlights that those optimisations can occur for a production system based on the PL set and production system providers may wish to change their logic sets for the demand profile they are receiving.

Table 1. Ranking Production logics against the demand profiles. Units in brackets are the peak values from the simulation results as shown in Figure 4.

| Demand Profile | Jobs In Queue [#] | Lateness [h] | Time In System [h] | Overall |
|----------------|-------------------|-------------|--------------------|---------|
| Steady-state   | –                 | –           | –                  | Either  |
| Step-change    | FCFS (174.6), EDD (176.4), SPT/LPT (198.1), EDL (198.7) | FCFS (64.1), SPT/LPT (70.1), EDD (70.4), EDL* (164.0) | FCFS (79.3), SPT/LPT (85.2), EDD (85.3), EDL (179.5) | FCFS |
| Saw-tooth      | SPT/LPT (12.5), EDL (14.2), FCFS (14.6), EDD (16.9) | SPT/LPT (5.2), EDD (4.6), FCFS (4.3), EDD (3.5) | SPT/LPT (9.8), EDD (10.2), FCFS (10.7), EDD (11.4) | SPT/LPT |
| Ramp           | EDL (103.9), FCFS (107.3), SPT/LPT (111.1), EDL (118.4) | SPT/LPT (33.5), EDD (35.9), FCFS (37.5), EDL* (58.8) | SPT/LPT (49.2), EDD (50.6), FCFS (53.8), EDL* (101.3) | SPT/LPT |

6. Discussion and further work

The study has revealed that the production logic sets significantly impact the ability of a production system to respond to demand and it is more apparent when the demand profile is either highly frequent or has a high magnitude, or both, which is in line with what we have observed with COVID-19. Thus, under these conditions, it is important to select the right combination of logics to tackle the incoming demand.

The next step in this research is to build on this model and investigate this behaviour at scale (e.g., 100,000+ machines). The model could also be refined to include day/night cycles where production may
need to cease and/or reduce but demand can continue. Other extensions include maintenance of the machines and machines of varying capability (e.g., dual extrusion, max job size). This will enable us to determine optimal logic sets for a given AM host-client production system and provide society with the most responsive overall manufacturing capability.

The model can also be extended to look at logic set transitions alongside the demand profiles and how these transitions should be performed. Should the production logics be changed in one instance or over a period, for example.

Lastly, real-world validation needs to be undertaken with the architecture being implemented on a real set of AM machines and utilised in a real-world setting. In addition, real-world demand profiles need to be captured to enable researchers to design appropriate production logic sets to respond to real-world production demand profiles. The authors are currently pursuing this with local University workshops trialling a platform that we have developed.

7. Conclusion

The need for responsive manufacturing has never been greater with COVID-19 highlighting the limits of Modern Manufacturing Practice in responding to extreme changes in societal demand. This has resulted in society turning to new technologies for an answer with Additive Manufacturing revealing itself as a means to overcome the limits in terms of responsiveness, capacity and flexibility.

This paper has shown that agent-based AM production systems have the potential to improve regional and national manufacturing resilience to rapidly changing demand profiles caused by global crises. This ability is afforded by the fact that each machine can feature a different production logic that determines how it selects a job from a global queue enabling local manufacture of nationally required products.

A study of different demand scenarios and production logic sets reveals the optimal combinations exists for each scenario. The simulation also shows that there is no one dominant logic set and that agent-based AM production systems will need the ability to transition from one combination to another based on the demand profile.

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