

Manufacturing for the Masses: A Novel Concept for Consumer 3D Printer Networks in the Context of Crisis Relief

Bart Raeymaekers,* Kam K. Leang, Maurizio Porfiri, and Shenghan Xu

Local or national crises, such as natural disasters, major infrastructure failures, and pandemics, pose dire threats to manufacturing. The concept of a rideshare-like distributed network of consumer-type 3D printers is proposed to address the limited ability of the industrial base to quickly respond to abrupt changes in critical product demand or to disruptions in manufacturing and supply-chain capacity. The technical challenges that prevent the implementation of such a network are discussed, including 1) remote qualification of 3D printers, 2) dynamic routing algorithms with reactive and predictive components, which take advantage of real-time information about current events that may affect the network, and 3) performance evaluation of the network. Furthermore, a cyber-infrastructure that enables autonomous operation and reconfiguration of the network to render it “crisis-proof” by minimizing human involvement is introduced. The concept of a distributed network of consumer-type 3D printers allows anyone with a 3D printer and access to the internet to manufacture critical supplies, triggered by actual and predicted customer demand. Beyond crisis relief, distributed networks of manufacturing assets have broad relevance, and they can establish a virtual marketplace to exchange manufacturing capacity. Thus, this future manufacturing platform has the potential to transform how to manufacture for the masses.

personal protective equipment, and other critical, high-demand products ramped up slowly because the industrial base required time to adjust its production and distribution to meet the unexpected surge in demand.^[4–7] In contrast, grass-roots, do-it-yourself (DIY) efforts that used consumer-type 3D printers successfully manufactured small quantities of basic parts and supplies, including medical devices (e.g., ventilator valves and nasal swabs) and personal protective equipment (e.g., face masks and door openers).^[8–11] While the 3D-printed parts were not identical to their commercial equivalents, they were economic and functional substitutes. Similarly, one can imagine 3D printing basic parts that address immediate needs during other crisis situations, such as water barriers during flooding, plumbing parts to fix leaks, or even water filters.^[12]

This observation raises the following questions: could coordinating and scaling individual efforts through a distributed network of 3D printers effectively address unexpected disruptions in the industrial supply-chain and absorb surges in product


1. Introduction

A major challenge of the existing industrial base is its limited ability to quickly respond to abrupt changes in critical product demand or to disruptions in manufacturing and supply-chain capacity, following a local or national crisis, such as a natural disaster, a major infrastructure failure, or a pandemic. For example, during the COVID-19 pandemic,^[1–3] manufacturing of medical supplies,

demand? In addition, could the network be autonomously reconfigured based on real-time information about current events to make it resilient and “crisis-proof”? Finally, what are the technical hurdles that prevent implementing such a network?

In a context beyond crisis relief, distributed networks of consumer-type 3D printers (or metal 3D printers once they become abundantly available) have broad relevance in solving supply-chain disruption and manufacturing capacity problems in different

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industries. Such networks could establish a virtual marketplace to allow individuals and businesses to exchange manufacturing capacity. For instance, businesses can buy or sell manufacturing capacity in the spot market or even engage in forward contracts to manage capital investment or hedge business risk, whereas individuals gain instantaneous access to almost unlimited manufacturing resources. Thus, this future manufacturing platform has the potential to transform how products for the masses are manufactured.

2. A “Rideshare-Like” Distributed Manufacturing Network Concept

We propose the concept of a “rideshare-like” distributed network of consumer-type 3D printers in homes and businesses across the country that autonomously reconfigures through monitoring real-time information about current events, and is supported by a cloud-based cyber-infrastructure that minimizes human involvement in managing demand and supply of manufacturing resources. The network can provide crisis relief, when it configures to prioritize reliability and speed. Alternatively, it can operate as a virtual manufacturing capacity marketplace under normal economic conditions, with focus on price and customer service. Transition between different operating priorities would be seamless and based on market needs. We define and analyze the key challenges of this concept and propose feasible solutions for its practical implementation, to promote research and spark interest at the intersection of manufacturing and intelligent systems.

Figure 1 shows the concept and the key functionalities of such a future manufacturing platform. Anyone with a 3D printer and

access to the internet (gray dots) can join the network to help manufacture products for the masses, triggered by customer demand (blue dots), and incentivized through payment, charity, or status within the network. The cloud-based cyber-infrastructure intelligently routes manufacturing orders placed by individuals, businesses, or government organizations using a smartphone application (“app”) to the available 3D printers in the network, matching their availability, production capacity, quality specification, and shipping time requirement. Physical delivery of the parts or products via traditional (e.g., user drop-off, rideshare-like delivery, and couriers) or futuristic approaches (e.g., delivery drones when they become available) fulfills the manufacturing orders (red arrows).^[13] Crucially, the network autonomously reconfigures, informed by real-time information about current events, obtained through a combination of web-scraping and analysis of local news websites and social media content, to optimally match demand and supply and avoid scenarios where manufacturing orders remain unfulfilled due to potential fallout from crises, such as flooded and blocked roads, or electricity outages. For instance, real-time information about a crisis that develops in space and time, such as a tornado or hurricane, informs the network to not route manufacturing orders to 3D printers in the path of the storm, as they may go offline due to an electricity outage, or infrastructure may be damaged, preventing delivery to the customer. Based on real-time information about the path of the storm, the network can also avoid routing manufacturing orders to 3D printers near the path of the storm to preserve local manufacturing capacity in anticipation of near-future orders to help with disaster relief once the storm has passed.

Furthermore, leveraging real-time information about current events, the distributed network can also include a predictive

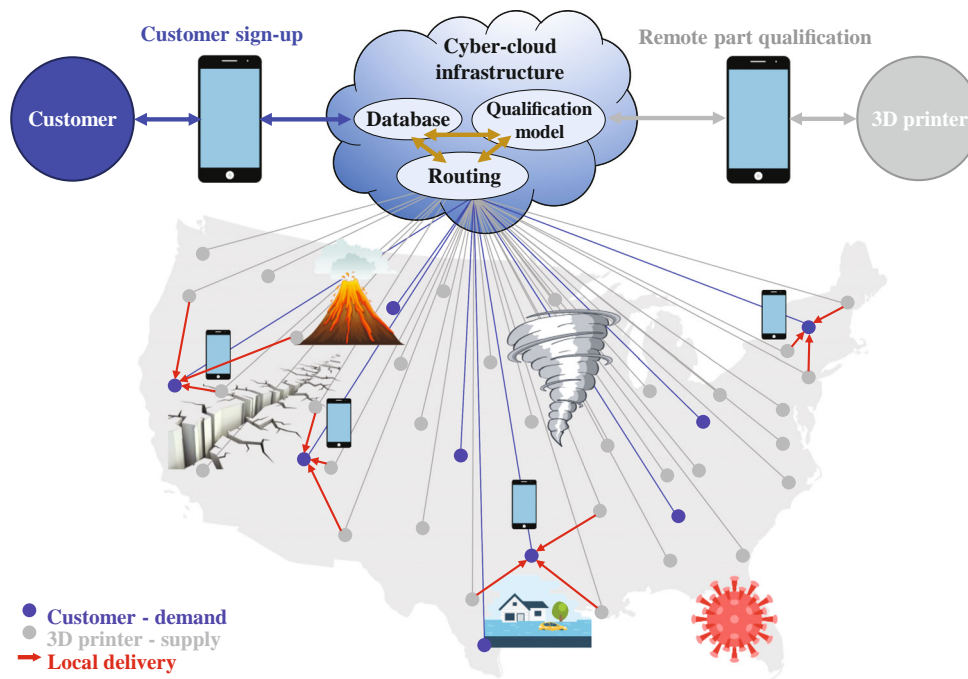


Figure 1. Concept of a distributed additive manufacturing network to manufacture critical supplies during a crisis. It leverages consumer-type 3D printers in homes and small businesses (gray dots) and matches demand (blue dots) and supply (red), driven by an artificial intelligence, cloud-based infrastructure. The network autonomously reconfigures based on monitoring constantly evolving current events in real time, to handle potential disruptions.

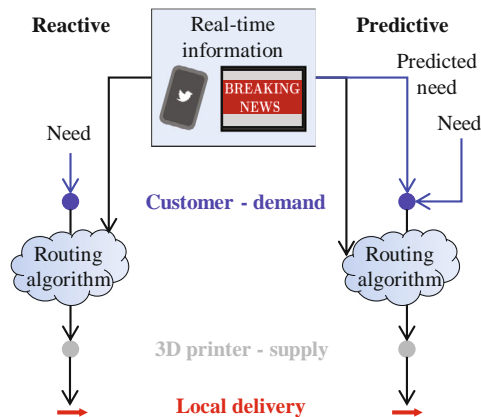


Figure 2. Reactive versus predictive routing of manufacturing orders, showing customer demand, 3D printer supply, and local delivery. The routing algorithm leverages real-time information. Reactive routing is based on customer demand informed by need, whereas predictive routing is based on both need and predicted need depending on real-time information about current events.

component together with its reactive component. **Figure 2** conceptually illustrates the difference between the reactive and predictive component of the manufacturing platform. The predictive component bases customer demand on both need (customers submitting manufacturing orders) and knowledge about where near-future need may exist (e.g., a storm is about to make landfall), whereas the traditional reactive component bases customer demand only on need. In this vein, the network could predict demand for parts based on historical information about disaster relief, geographical information, and county tax assessor data about the type of houses in the path of the storm, and autonomously submit manufacturing orders based on that predicted demand.

3. Major Roadblocks

Three major roadblocks must be addressed to implement the rideshare-like distributed network of consumer-type 3D printers: 1) ensuring consistent part-to-part quality despite printer-to-printer variability across a network of different consumer-type 3D printers without central quality control and subject to variable user-skill and printer maintenance; 2) dynamic routing of manufacturing orders during a crisis that evolves in both space and time while taking advantage of real-time information about infrastructure damage brought about by that crisis (such as, floods, road blocks, and rolling blackouts); and 3) measuring and evaluating the performance of the platform to inform dynamic routing.

These challenges are specific to the concept of a distributed network of consumer-type 3D printers, and contrast those of centralized manufacturing systems where, for instance, trained personnel uses quality control methods to assess part-to-part quality in a controlled environment of a single or small number of manufacturing facilities. In fact, a recent article also notes that ensuring consistent part-to-part quality is one of the challenges that prevents the implementation of a distributed network of manufacturing machines,^[14] and other articles report progress

in self-calibrating 3D printers^[15] and systems with automated mechanical testing.^[16] It is evident that the success of such a network hinges on the ability to produce identical parts in different locations, potentially using different machines and feedstock, yet ultimately meeting a single set of design specifications and quality standards with regard to dimensional accuracy, surface quality, and bulk properties, among other properties, defined by the customer. This requirement contrasts rideshare networks that try to ensure consistent (or minimum) driver and rider quality through peer-evaluation scores after the transaction (postperformance), instead of before the transaction (preperformance).

Participants who join the manufacturing platform and network (see Figure 1) must first remotely qualify their 3D printers through, for example, a DIY smartphone-based process that exploits the embedded sensors and actuators in the phone, and links to a cloud-based data-driven qualification model. Remote qualification is crucial because no central ownership or quality control exists in the network. Furthermore, it is the key to enabling scalability, as any user can perform the qualification themselves, independent of their skill, assisted by a smartphone app.

Second, manufacturing orders are optimally routed to match supply in reaction to demand, and the network autonomously reconfigures based on real-time information about current events that might affect the fulfillment of manufacturing orders (see Figure 2). Contrary to traditional network optimization problems, routing in crisis situations relies on evolving information. For instance, while rideshare network algorithms use a fixed connectivity map, crisis algorithms must continuously update their connectivity maps to reflect 3D printers that have become unavailable, or to account for impediments to part delivery because of the unfolding crisis. To increase resilience of the dynamic routing algorithm, one can supplement reactive routing with predictive routing, which uses artificial intelligence (AI) to project future demand and manage supply, based on real-time information about current events and about the status and capacity of each 3D printer in the network. The combination of reactive and predictive routing of manufacturing orders is paramount to quickly respond to abrupt demand surges, or to disruptions in manufacturing and supply-chain capacity.

4. Pathway to Implementation

4.1. DIY Qualification

A DIY framework for remote qualification of 3D-printed parts and printers by the 3D printer owner can be leveraged. This process requires the evaluation of different characteristics of a 3D-printed part, namely, 1) geometry and dimensions, 2) surface topography or surface quality, and 3) bulk properties. To accomplish this, one possible approach involves instructing the 3D printer owner through a smartphone app to 3D print a specific test specimen using the printer they seek to qualify. Then, the embedded sensors and actuators of the smartphone can be used to measure the characteristics of the 3D-printed part. A data-driven qualification model^[17] qualifies the test specimen, by benchmarking the measurements against model predictions that account for the process parameters used to 3D print the test

specimen. The data-driven qualification model captures the relationship between the 3D printing process parameters and the different qualification metrics, and it is trained using machine learning (ML) algorithms and large datasets of 3D-printed test specimens. The magnitude of the deviation between the measurements resulting from the 3D-printed test specimen and those predicted by the data-driven qualification model allows categorizing 3D printers in terms of the accuracy and quality of the parts they produce. The dynamic routing algorithm that assigns manufacturing orders to different 3D printers in the network can use this information to improve its decision-making.

Figure 3 shows different possible concepts to use smartphone sensors and actuators to measure dimensions, surface topography, and bulk properties such as stiffness, damping, and energy storage of a 3D-printed test specimen.

First, the dimensions of the 3D-printed test specimen can be measured using a smartphone's camera, inertia measurement unit (IMU) sensor, and a low-cost laser line generator, in addition to a printed calibration pattern, as illustrated in the 3D reconstruction and height estimation concept of **Figure 3a**. Specifically, the smartphone is oriented at a known pose inferred from its IMU sensor, in a fixture that is part of the 3D-printed test specimen, and rests on the printed calibration pattern. The calibration pattern allows to determine intrinsic and extrinsic parameters, as well as distortion coefficients, of the camera using computer vision and triangulation, such that the height information can be calculated for image pixels in the projected laser line. In the absence of an object, the laser line is straight and does not distort. The presence of an object distorts the laser line, which is detected by the camera, and the image pixel information in conjunction with the camera's pose enables estimation of height h . Comparing similar triangles ΔAPB and ΔLPC in **Figure 2a**, the height can be calculated as $h = (D\beta)/\alpha$, assuming that $D \gg h$, which can be controlled through the design of the 3D-printed test specimen and test fixture, respectively. Using this approach, a 3D model of the part can be reconstructed along with its dimensions, by scanning the phone and laser line projector around the part, while keeping track of the pose of the phone. Subsequently, the volume can be determined from the 3D model reconstruction, and the density from the weight of the test specimen.

Second, the surface topography of the 3D-printed test specimen can be estimated by using the ambient light sensor of

the phone, in combination with its on-board LED light source and its camera. The surface topography affects the reflectivity of the surface. Thus, extracting information from the phone's ambient light sensor under a known pose (through a 3D-printed smartphone stand with preset stand angles) that captures the light reflecting off the test specimen's surface, illuminated by the phone's light source (or additional integrated light source), yields information about the surface topography (**Figure 3b**). Comparing those results with images of the specimen under multiple angles further enhances the information that can be extracted from the surface. ML algorithms can establish a data-driven model that relates reflectivity and image pixel intensity to known surface topography benchmarks. Similar to surface topography, in-fill pattern consistency can be measured by analyzing photographs under different angles and exposure settings, in combination with ML algorithms that relate the observations to known in-fill patterns.

Finally, by leveraging the smartphone's camera to capture a video of the 3D-printed test specimen's transient response, driven by the phone's vibration actuator, the bulk properties of the test specimen, including stiffness and damping, can be measured. **Figure 3c** shows this process, for example, 3D-printed nasal swab, while capturing a video with pixel tracking to record the transient response. ML in combination with a Gaussian process can enable modeling the dynamics of the test specimen. Furthermore, combining the 3D CAD model (or its reconstruction) and finite element analysis can determine the frequency response function of the test specimen and compare it with a benchmark. Similarly, it is conceivable to measure energy storage of the test specimen by performing simple drop tests (**Figure 3c**). The phone and test specimen are affixed to each other and dropped from a short height (a few inches) while measuring the acceleration during impact using the phone's IMU sensor. The energy absorption of the specimen relates to the acceleration during and after impact. State-of-the-art smartphones can tolerate drops up to 6 ft.^[18]

4.2. Dynamic Routing of Manufacturing Orders, Accounting for Real-Time Information

Contrary to classical optimization problems, routing in crisis situations relies on dynamic information. Thus, timely access to

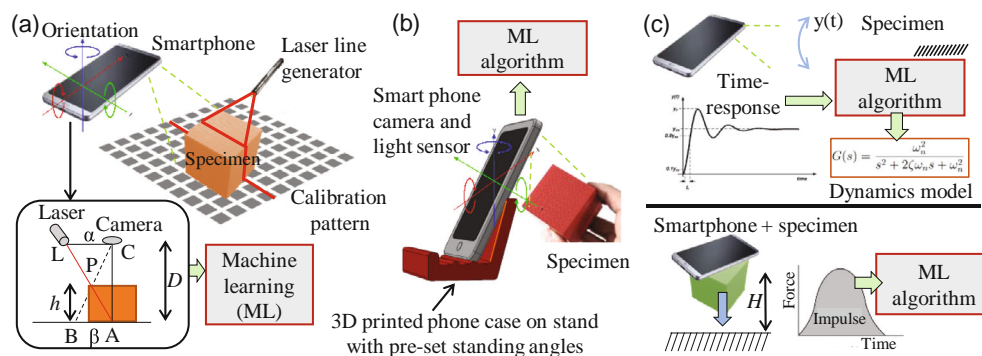


Figure 3. Schematic of potential concepts to remotely qualify a 3D-printed test specimen through a smartphone with embedded sensors/actuators combined with ML algorithms: a) vision and IMU-based dimensional characterization, b) camera and light-intensity-based surface topography characterization, and c) vision-based dynamic response characterization and IMU-based energy storage and structural testing.

information, such as through web-scraping, is important to optimally route manufacturing orders to different 3D printers. Relying on individual information channels may not provide thorough and timely access to information. News outlets and government reports are typically reliable but often broadcast with a delay. In contrast, social media updates from individuals are swiftly available, but they are not indexed and well organized, and they could be prone to individual misinterpretations. Thus, it is necessary to integrate information from both official and unofficial sources to provide reliable and information-rich, real-time input for the routing algorithm.^[19,20]

The theory of temporal networks^[21–23] constitutes a powerful lens through which one can analyze the problem of routing during crises. **Figure 4** shows a bivariate network in which demand (manufacturing orders submitted by customers) and supply (3D printers in the network) represent two distinct sets of nodes. Demand nodes encode the manufacturing order that must be fulfilled and a geographical destination where the parts are needed. Similarly, supply nodes are characterized by their production capacity, production efficiency, and the quality of the parts they produce, which is known from the smartphone-based remote qualification. The demand and supply network could vary in time due to the concurrent evolution of a crisis. For instance, in the case of an electricity outage, a portion of the supply nodes may become unavailable and road closures may prohibit connections between demand and supply even though they are geographically proximal. Along with temporal patterning, spatial heterogeneities exist, whereby quality of the printed parts, production capacity, and geographical location of supply nodes jointly vary with respect to demand nodes. Indeed, a specific demand node may be geographically close to several supply nodes, but none of them prints parts with the desired quality or provides the required production capacity.

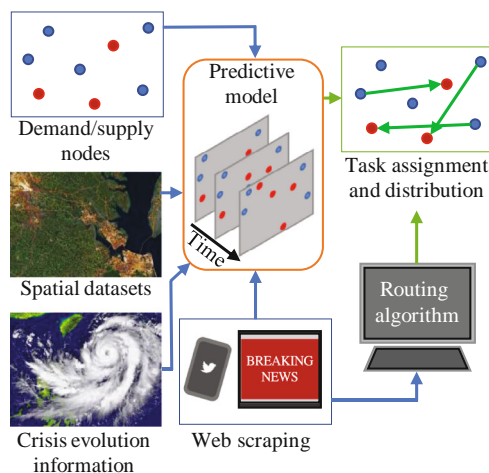


Figure 4. Schematic of the demand and supply network optimization algorithm. Demand and supply nodes with individual orders and production capacities represent the input of the predictive model, along with spatial datasets and information about the crisis evolution. The predictive model informs the routing algorithm that assigns tasks to supply nodes and distribution to demand nodes. Web-scraping informs the parameters of the predictive model and routing algorithm from real-time information.

Spatiotemporal features of the demand and supply network contribute to the complexity of the routing that must be undertaken in real time with granular feedback about the topology of the network and the attributes of its nodes. As spatial and temporal scales of the demand and supply network are on the same order as those of the unfolding crisis, the solution of the routing problem at the time a manufacturing order is placed should leverage predictive tools to forecast potential disruptions that may occur during 3D printing and delivery. In addition, digital media may add predictive power to the algorithm in forecasting the true demand for the product requested and the geographic distribution of that demand. As such, the algorithm could strategically withhold tasks from certain supply nodes in anticipation of a large volume of near-future tasks.

4.3. Network Performance

The physical structure of a traditional supply-chain, together with managerial decision making, determines its performance. As opposed to traditional centralized supply-chain networks, the distributed network of 3D printers is dynamic, and its structure autonomously reconfigures based on demand and supply, as well as real-time information about current events. Furthermore, the effect of information sharing within the network is of critical importance for the predictive routing algorithm. A set of performance metrics is needed that captures the specifics of this type of network, which is unlike traditional, centralized networks, or even static distributed networks. Using such metrics, analysis and evaluation can be performed on distributed 3D printer networks under distinct operating conditions (such as normal, distressed, demand surges, excess supply) and specific possible configurations (including single product versus multiple product mix, and centralized decision-making versus decentralized decision-making). Ultimately, this information can further enhance the dynamic routing algorithm.

5. What Are the Benefits?

Implementing distributed networks of 3D printers has been attempted before^[24] in the forms of cloud-based manufacturing of dental parts^[25] and a marketplace to sell and buy excess manufacturing capacity to mitigate production risk,^[26] among other examples.^[27] A recent perspective^[14] also put forward the idea of massively distributed manufacturing, which combines geographically distributing and democratizing manufacturing. Therefore, this perspective shares some of these high-level ideas,^[14] but specifically focuses on identifying the key challenges that must be solved to implement such a network and, additionally, proposes feasible solutions that are specific to crisis relief, as discussed in Section 4.

Companies such as 3DHUB and GEOMIQ offer manufacturing services, including additive manufacturing services, through a distributed network of contract manufacturers, and they have implemented the idea of a cyber-like manufacturing marketplace with fixed nodes. However, these implementations do not consider dynamic routing, do not operate autonomously, and are difficult to scale because they rely on professional-type contractors in the network. They also do not reconfigure, in part, because the

network does not have a sufficiently large number of nodes. Thus, a distributed manufacturing network that allows consumers and small businesses to contribute their own 3D printing resources, such as the rideshare model for transportation (such as Uber and Lyft), has not been implemented before. The idea of remote 3D printer qualification allows quality control across the network and optimally routing manufacturing orders minimizes logistical expense, thus powering a virtual marketplace for trading manufacturing capacity.

6. Conclusion

Coordinating and scaling local or regional efforts through a distributed network of 3D printers presents a promising route to absorb surges in product demand and address unexpected disruptions in the industrial supply-chain. The key technical hurdle that prevents implementing such a network is the ability to reliably and repeatably perform remote qualification of 3D-printed parts and printers. In addition, taking advantage of real-time information about current events could enable the network to reconfigure, and effectively route manufacturing orders both in crisis (prioritize speed and reliability) and normal operating conditions (prioritize price and customer service). It could even enable predictive routing of manufacturing orders based on anticipated demand. Beyond crisis relief, distributed networks of manufacturing assets could establish a virtual marketplace to exchange manufacturing capacity. Thus, this future manufacturing platform has the potential to transform how to manufacture for the masses.

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Conflict of Interest

The authors declare no conflict of interest.

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