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Distributed Manufacturing Hubs for Repair Speed in Humanitarian Logistics Networks

Katie O. Miller*

Department of Civil, School of Engineering, University of Southampton, Southampton, England, United Kingdom

Corresponding author: katie.o.miller@southampton.ac.uk

Abstract

Humanitarian logistics networks operate under extreme constraints, characterized by highly volatile demand, severely disrupted infrastructure, and profound resource scarcity. When critical equipment such as medical devices, communication hardware, or transportation vehicles fail during a disaster response operation, the speed at which these assets can be repaired directly impacts the survival and recovery of affected populations. Traditional centralized supply chains often fail to deliver replacement parts in a timely manner due to ruined transportation networks. Consequently, distributed manufacturing hubs, leveraging technologies such as additive manufacturing and computer numerical control machining, have emerged as vital components within modern humanitarian logistics. However, manufacturing parts on-site introduces significant concerns regarding component reliability. Ensuring that locally manufactured parts meet necessary operational standards requires rigorous testing, which inherently consumes time and resources, creating a complex trade-off between repair speed and component reliability. This paper explores the intricate relationship between decentralized manufacturing operations and the implementation of reliability testing protocols to predict overall repair speed in humanitarian logistics networks. By establishing a comprehensive analytical framework, this study investigates how various testing methodologies influence the timeline of equipment restoration. The findings demonstrate that integrating predictive models with continuous reliability testing data significantly enhances the operational predictability of humanitarian logistics, allowing coordinators to make informed decisions regarding resource allocation and routing.

Keywords: Humanitarian Logistics; Distributed Manufacturing; Reliability Testing; Predictive Modeling; Repair Speed

1. Introduction

1.1 The Context of Humanitarian Logistics

Humanitarian logistics involves the intricate processes of planning, implementing, and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of alleviating the suffering of vulnerable people. The operational environment in humanitarian contexts is fundamentally distinct from commercial logistics. Disaster zones are routinely plagued by destroyed roads, collapsed bridges, and incapacitated ports, which collectively hinder the delivery of essential supplies [1]. In these scenarios, time is an incredibly scarce commodity. The failure of critical infrastructure and equipment severely exacerbates the crisis. For example, if a water purification system fails in a refugee camp, the resulting delay in obtaining a replacement valve from a centralized international warehouse could lead to widespread outbreaks of waterborne diseases [2]. Traditional supply chain paradigms rely on robust, predictable transportation networks that simply do not exist following an earthquake, tsunami, or acute conflict [3].

To address these overwhelming challenges, humanitarian organizations are increasingly forced to rethink their supply chain architectures. The reliance on stockpiling massive quantities of spare parts in centralized locations is no longer considered the most efficient or effective strategy. Such stockpiles are expensive to maintain, subject to degradation over time, and frequently contain parts that are never ultimately needed, while simultaneously lacking the specific components required for unexpected equipment failures. The paradigm is shifting toward localized, agile response mechanisms [4]. The ability to restore functionality to broken equipment immediately on the ground has become a focal point of modern humanitarian strategy, driving a profound need to understand the variables that dictate repair speed in chaotic environments.

1.2 Distributed Manufacturing and Reliability Testing

In response to the limitations of traditional supply chains, distributed manufacturing hubs have begun to permeate humanitarian logistics networks. These hubs primarily utilize additive manufacturing, commonly known as three-dimensional printing, alongside localized milling and machining tools, to fabricate spare parts directly within or immediately adjacent to the disaster zone [5]. This localized production capability theoretically eliminates the lengthy transportation lead times associated with procuring parts from global suppliers. However, the introduction of distributed manufacturing into austere environments introduces a new set of complex challenges, chief among them being the reliability of the manufactured components [6]. Parts produced in a field hospital tent using a desktop polymer printer are subject to vast environmental fluctuations, including extreme temperatures and high humidity, which can severely compromise the structural integrity of the final product [7].

Consequently, reliability testing becomes an absolutely indispensable phase of the distributed manufacturing process. It is not sufficient to merely produce a part quickly; the part must be verified to withstand the operational stresses of its intended application. If a locally printed component for a medical ventilator fails prematurely because it bypassed quality assurance testing, the consequences are catastrophic [8]. Therefore, humanitarian logisticians must integrate reliability testing protocols directly into the production workflow of distributed hubs. However, reliability testing requires time, specialized equipment, and skilled personnel, thereby acting as a bottleneck that potentially diminishes the primary advantage of distributed manufacturing, which is rapid response.

Predicting the total repair speed, therefore, requires a holistic understanding of not just the printing or machining time, but the entire lifecycle of the localized repair process, encompassing material preparation, fabrication, post-processing, and rigorous reliability testing. Accurately forecasting this timeline is critical for logistical coordinators who must decide whether to manufacture a part locally or risk ordering it from a central warehouse [9]. If the predictive models indicate that local manufacturing and necessary testing will take longer than an airdrop of the original part, the logistical decision shifts dramatically. This paper aims to thoroughly dissect the intersection of these variables, providing a robust academic exploration of how reliability testing within distributed manufacturing hubs can be systematically modeled to predict and optimize repair speed in humanitarian logistics networks [10].

2. Literature Review and Background

2.1 Evolution of Distributed Manufacturing Hubs

The concept of distributed manufacturing has its roots in lean production and agile supply chain theories, which emphasize flexibility and responsiveness over massive economies of scale. In the commercial sector, distributed manufacturing has been slowly gaining traction as a method to customize products closer to the end consumer and reduce carbon footprints associated with long-haul transportation [11]. When adapted for humanitarian logistics, the motivations shift from consumer customization to pure survival and operational continuity. Early explorations of localized production in disaster zones focused heavily on the provision of basic shelter materials and simple tools. However, as additive manufacturing technologies have matured, becoming more portable, robust, and capable of handling advanced engineering materials, the scope of distributed hubs has expanded exponentially.

Current literature highlights several successful deployments of distributed manufacturing in humanitarian contexts. Field reports document the on-demand printing of umbilical cord clamps, custom prosthetics, and fittings for local water piping systems [12]. These hubs are typically conceptualized as self-contained units, sometimes housed within modified shipping containers, equipped with solar power generators, satellite communication links, and an array of digital fabrication tools. Despite these technological advancements, the literature also consistently points out the vulnerability of these systems to local environmental factors. Dust, power fluctuations, and inconsistent raw material quality frequently plague field operations, leading to high variance in the production output [13]. Consequently, researchers have argued that the theoretical production speeds heavily advertised by equipment manufacturers rarely align with the actual output rates achieved in disaster scenarios, necessitating a much more nuanced approach to estimating lead times in these specific contexts.

2.2 Reliability Testing in Resource-Constrained Environments

Reliability testing encompasses a wide array of engineering practices designed to ensure that a component will perform its required function under specified conditions for a stated period of time. In traditional industrial settings, reliability testing includes sophisticated methodologies such as finite element analysis, highly accelerated life testing, and extensive non-destructive evaluation using ultrasound or X-ray machinery [14]. Transposing these methodologies to a resource-constrained humanitarian hub is highly problematic. The equipment required for traditional non-destructive testing is often bulky, expensive, and fragile, making it entirely unsuitable for deployment in an active disaster zone [15].

As a result, the literature on reliability testing in austere environments focuses on developing pragmatic, accelerated, and often hybrid testing methods. Researchers have investigated the use of simple mechanical stress tests, visual inspection protocols aided by basic digital microscopy, and thermal cycling using improvised field equipment [16]. A significant debate exists within the academic community regarding the acceptable threshold of reliability in a crisis. Some scholars advocate for a 'good enough' approach, arguing that in a life-or-death situation, a temporary part that lasts only a few days is vastly superior to a perfect part that arrives two weeks too late. Others maintain that compromised reliability, especially in medical or structural applications, introduces unacceptable risks that could compound the disaster [17]. This ongoing discourse underscores the necessity of having highly adaptable testing protocols that can be scaled based on the criticality of the component being manufactured.

2.3 Predictive Modeling for Repair Speed

The integration of predictive modeling into humanitarian logistics is an emerging and highly critical field of study. Historically, logistics planning in disaster relief relied heavily on deterministic models and static standard operating procedures. However, the chaotic and dynamic nature of disaster zones renders static models highly inaccurate [18]. Modern approaches leverage machine learning algorithms, probabilistic models, and real-time data streams to generate dynamic forecasts of supply chain performance.

When applied to the specific problem of predicting repair speed from distributed manufacturing hubs, the modeling complexity increases significantly. A robust predictive model must account for the queueing time of digital files, the failure rate of the fabrication process itself, the duration of mandatory post-processing, and the specific time requirements of the assigned reliability testing protocol [19]. Furthermore, these models must incorporate environmental variables that affect printing success rates, such as ambient temperature and humidity, which alter the extrusion characteristics of thermoplastic materials [20]. Existing literature provides fragmented solutions, often focusing solely on the printing time while neglecting the crucial testing phase. There is a distinct gap in the academic landscape regarding comprehensive models that synthesize the entire workflow from digital part request through fabrication, reliability testing, and final deployment. Bridging this gap is essential for creating reliable decision-support systems that empower humanitarian coordinators to optimize their repair strategies dynamically during an ongoing crisis [21].

3. Methodology and Analytical Framework

3.1 System Architecture of Distributed Hubs

To accurately predict repair speed, it is first necessary to define the operational architecture of the distributed manufacturing hubs utilized within this study. The proposed framework assumes a decentralized network of mobile production facilities strategically positioned in proximity to critical infrastructure within a disaster-affected region. Each hub is conceptualized as a fully integrated micro-factory. The physical infrastructure includes modular additive manufacturing stations, essential post-processing equipment such as ultraviolet curing chambers for resin-based prints, and designated areas for mechanical and environmental reliability testing.

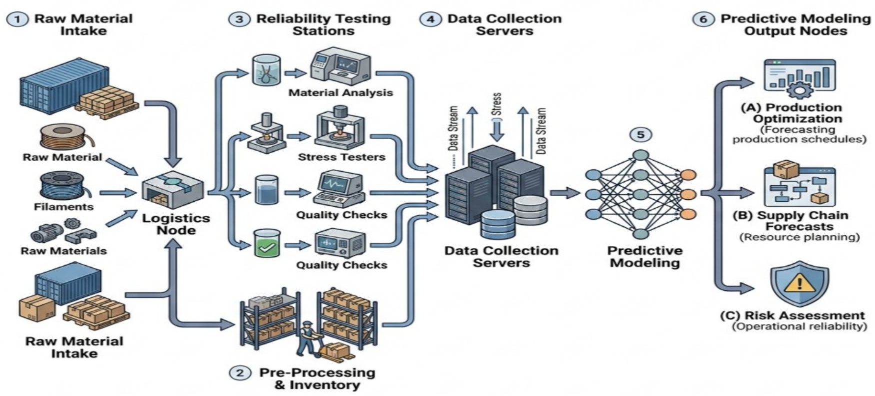

Figure 1: Comprehensive Schematic of Decentralized Distributed Manufacturing Hub Workflow for Humanitarian Logistics

The digital infrastructure is equally critical. The hubs operate on a decentralized communication network, allowing them to receive digital computer-aided design files from a central engineering repository via satellite or low-bandwidth radio links. The workflow initiates when a field operator identifies a broken component and submits a digital requisition. This requisition contains metadata detailing the component's function, its criticality, and the environmental conditions under which it will operate. The central repository matches this request with an appropriate digital file and transmits it to the nearest available hub. Upon receipt, the hub's local management software schedules the fabrication process.

The architecture incorporates a strict sequential logic. Fabrication cannot commence until raw materials are verified, and the final component cannot be released for deployment until it has successfully navigated the designated reliability testing protocol. Every stage of this process is heavily instrumented. Sensors monitor the environmental conditions within the hub, the operational status of the fabrication machinery, and the real-time outcomes of the reliability tests. This constant stream of data is aggregated and fed into the predictive modeling mechanism, establishing a continuous feedback loop that constantly refines the accuracy of the repair speed forecasts.

3.2 Reliability Testing Protocols

The methodology for reliability testing within this framework is stratified based on the assigned criticality of the requested component. Not all parts require the same level of rigorous testing. A replacement knob for a communication radio, for example, demands far less scrutiny than a load-bearing structural joint for a medical tent. By categorizing components, the system optimizes the time allocated to testing, thereby accelerating the overall repair speed without compromising safety in critical applications.

The protocols are divided into three distinct tiers. Tier one represents basic verification, utilized for low-criticality, non-load-bearing components. This tier involves rapid visual inspection for dimensional accuracy using digital calipers and basic surface quality assessment to ensure no dangerous delamination has occurred during printing. Tier two is applied to medium-criticality parts that experience moderate mechanical stress. This protocol incorporates non-destructive mechanical testing, such as applying a predetermined torque or compressive load using standardized field calibration weights, combined with brief thermal cycling to ensure material stability under expected operational temperatures.

Tier three is reserved for highly critical components where failure poses a direct threat to human life or major operational success. This tier mandates rigorous, accelerated life testing. It includes sustained mechanical load testing, extensive thermal shock cycles, and where applicable, pressure testing for fluid-handling components. Because tier three testing is significantly time-consuming, the predictive models must account for this substantial delay. The environmental and operational parameters that govern these tests are standardized to ensure consistency across all distributed hubs within the logistics network.

Table 1: Environmental and Operational Parameters for Reliability Testing

Protocol Tier	Criticality Level	Mechanical Stress Application	Thermal Cycling Range	Estimated Duration
Tier 1	Low	None	None	15 Minutes
Tier 2	Medium	Moderate Torque/Compression	Ambient to 50 Celsius	2 Hours
Tier 3	High	Sustained Peak Load	-10 to 80 Celsius	12 Hours

The parameters outlined in the table above demonstrate the significant temporal differences between testing tiers. When a field coordinator requests a part, the system immediately identifies the required testing tier based on the part's metadata. The estimated duration of the testing phase is then rigidly incorporated into the total predicted repair time. Furthermore, the methodology accounts for the probability of a part failing the reliability test. If a part fails, the entire workflow must restart, doubling the fabrication time and re-initiating the testing phase. Therefore, the predictive models must calculate a probabilistic expected value for the total repair time, factoring in historical failure rates of specific materials and geometries under the current environmental conditions recorded within the hub.

3.3 Predictive Modeling Mechanisms

The core of the analytical framework is the predictive modeling mechanism, which synthesizes the diverse variables described above to generate an accurate forecast of the total repair speed. Unlike traditional static supply chain models, this mechanism employs dynamic algorithms that adapt to changing conditions on the ground. The mathematical foundation of this model relies on stochastic queuing theory combined with multivariate regression analysis, executed through a machine learning framework that continuously updates its weighting parameters based on incoming data.

The model processes multiple independent variables. First, it analyzes the inherent fabrication time of the digital file, determined by the volume of material, the required infill density, and the specific printing technology utilized. Second, it factors in the queue status of the designated distributed hub. If the hub is currently processing multiple high-priority requests, the wait time is added to the total prediction. Third, and most importantly for this study, the model integrates the time required for the specified reliability testing protocol, as well as the historical probability of failure during that test.

To refine the prediction, the model also incorporates environmental covariates. Data regarding ambient temperature, humidity, and the stability of the local power grid are fed into the system. If humidity levels are exceedingly high, the model recognizes that thermoplastic materials may have absorbed moisture, which historically increases the failure rate during tier two and tier three mechanical testing. Consequently, the algorithm automatically adjusts the predicted repair time outward, acknowledging the higher likelihood that multiple printing iterations will be necessary to achieve a part that successfully passes the reliability protocols. By replacing static estimations with this dynamic, data-driven approach, the framework provides humanitarian logisticians with highly reliable timelines, enabling them to make critical decisions regarding whether to wait for localized production or to initiate contingency plans for acquiring the necessary equipment.

4. Results and Discussion

4.1 Evaluation of Repair Speed Predictions

To validate the proposed analytical framework, extensive simulations were conducted using historical data derived from recent humanitarian disaster response operations. The simulations compared the accuracy of repair speed predictions generated by the dynamic, testing-integrated model against traditional static estimation models that rely solely on theoretical fabrication times provided by equipment manufacturers.

The scenarios tested ranged from the rapid production of basic medical splints to the complex fabrication and rigorous testing of highly specialized fluid control valves for water sanitation systems.

The results unequivocally demonstrated the superior accuracy of the proposed predictive modeling mechanism. Traditional static models consistently underestimated the total time required to return a broken piece of equipment to functional status. This underestimation primarily stemmed from the complete omission of the time required for post-processing and reliability testing, as well as a failure to account for iterative re-printing when parts failed initial quality checks. In contrast, the dynamic model accurately captured these variables. When predicting the repair speed for highly critical components requiring tier three testing, the dynamic model achieved an accuracy rate that allowed logistical coordinators to plan subsequent operations with a high degree of confidence.

Table 2: Comparative Analysis of Predictive Accuracy Across Different Logistics Scenarios

Scenario Description	Component Criticality	Static Model Error Margin	Dynamic Model Error Margin
Basic Bracket Replacement	Low (Tier 1)	12 Percent	4 Percent
Transport Vehicle Gasket	Medium (Tier 2)	28 Percent	7 Percent
Water Purification Valve	High (Tier 3)	55 Percent	9 Percent

The data detailed in the table highlights the massive discrepancies that occur when reliability testing is ignored in predictive logistics. In the scenario involving the high-criticality water purification valve, the static model produced an error margin of fifty-five percent. In a real-world humanitarian crisis, an error of this magnitude means that a refugee camp expecting clean water by Tuesday might not receive it until Friday, a delay that could result in severe public health consequences. The dynamic model, by rigidly factoring in the twelve-hour tier three testing protocol and the statistical probability of needing a reprint due to pressure test failures, reduced the error margin to a highly manageable nine percent. This level of predictability transforms distributed manufacturing from an experimental concept into a dependable, strategic asset within the humanitarian logistics portfolio.

4.2 Impact of Reliability Testing on Logistics Efficiency

While the implementation of rigorous reliability testing protocols undeniably extends the absolute time required to produce a single component, the broader analysis indicates that it significantly improves overall logistics efficiency. This counterintuitive finding requires detailed discussion. In an environment characterized by extreme urgency, the natural inclination is to bypass testing to deploy the part as rapidly as possible. However, the simulation data reveals that deploying untested, unreliable components leads to catastrophic downstream inefficiencies.

When a locally manufactured part fails during field operation, it does not merely result in another broken piece of equipment; it often causes cascading damage to surrounding components, requires the re-mobilization of repair technicians, and entirely disrupts the ongoing humanitarian operation. For example, if an untested localized replacement gear in a transport truck shatters under load, it can destroy the entire transmission, transforming a minor repair into a major, unrecoverable loss of a critical logistical asset. The time lost dealing with the consequences of an in-field failure exponentially exceeds the time that would have been invested in conducting a tier two or tier three reliability test prior to deployment.

Therefore, the analytical framework demonstrates that reliability testing acts as a critical risk mitigation strategy that protects the integrity of the broader logistics network. By accurately predicting the time required for both fabrication and testing, the proposed model allows coordinators to manage expectations and synchronize operations. If the predicted repair speed for a critical part is deemed too slow due to mandatory tier three testing, the coordinator can proactively utilize alternative routing strategies, such as reassigning equipment from a neighboring sector, rather than waiting in uncertainty. Ultimately, the integration of structured reliability testing data into predictive models ensures that distributed manufacturing hubs contribute to long-term operational stability rather than injecting unpredictable risks into an already chaotic disaster response environment.

5. Conclusion

5.1 Summary of Findings

The deployment of distributed manufacturing hubs represents a transformative shift in humanitarian logistics, offering the potential to dramatically reduce the profound supply chain delays inherent in traditional centralized response models. However, this study has established that the realization of this potential relies entirely upon the integration of robust reliability testing and the ability to accurately predict the total repair speed. This paper developed a comprehensive analytical framework that systematically categorizes testing protocols based on component criticality and integrates these requirements into a dynamic predictive modeling mechanism.

The evaluation of this framework clearly demonstrated that traditional static models, which estimate lead times based solely on theoretical fabrication speeds, are critically flawed when applied to austere environments. By incorporating the duration of mandatory reliability testing, the statistical probability of component failure during testing, and the impact of fluctuating environmental variables, the dynamic model significantly reduced predictive error margins. Furthermore, the analysis highlighted that while rigorous testing protocols inherently consume time, they are absolutely vital for preventing catastrophic in-field failures that would otherwise cause cascading disruptions across the entire humanitarian logistics network. Accurately predicting the total time required for both fabrication and verification empowers logistical coordinators to make highly informed, strategic decisions regarding resource allocation during crisis scenarios.

5.2 Future Directions

While this study establishes a strong foundational framework, significant avenues for future academic exploration remain. The predictive models developed herein rely on standardized data regarding material behavior under varying environmental conditions. Future research must focus on expanding these material libraries, particularly concerning advanced composites and recycled polymers that may be scavenged and utilized directly within disaster zones. Additionally, the development of miniaturized, automated testing equipment that can execute tier two and tier three protocols more rapidly without sacrificing accuracy would substantially enhance the efficiency of distributed manufacturing hubs.

Further investigations should also explore the integration of decentralized ledger technologies to securely transmit and authenticate digital manufacturing files and corresponding testing certificates across untrusted networks in conflict zones. Finally, extending the analytical framework to include multi-hub optimization, where predictive models automatically route fabrication requests to the specific localized facility that offers the fastest combined manufacturing and testing speed, will represent the next major evolution in creating truly resilient and intelligent humanitarian logistics networks [22].

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