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SIMULATING THE IMPACT OF EXTERNAL DEMAND AND CAPACITY CONSTRAINTS IN AEROSPACE SUPPLY CHAINS

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ABSTRACT

By outsourcing major aircraft systems to Tier 1 suppliers, original equipment manufacturers depend heavily on their supply chain to meet the growing demand for aircrafts. However, capacity constraints upstream of the Tier 1 suppliers increase the risk of schedule disruption. Discrete event simulation is commonly applied to analyze capacity constraints in manufacturing systems while analytical models assess financial investment scenarios for capital equipment. This paper demonstrates a combined simulation and analytical modeling approach to simulate the operational and financial implications of capacity constraints in aerospace supply chains. A three-tier supply chain is modeled with the option of investing to remove a capacity constraint in a sub-tier supplier. The results demonstrate how a supplier's capacity investment decisions and the increasing demand for aircrafts can affect their cash flow and delivery schedule adherence.

1 INTRODUCTION

1.1 Capacity Management in Aerospace Supply Chains

The demand for air travel is expected to rise dramatically within the upcoming 15-20 years with leading aircraft manufacturers estimating demand of 36,000–41,000 new aircrafts during this period (Boeing 2017; Airbus 2018). Aircraft original equipment manufacturers (OEMs) must ensure that they and their suppliers have sufficient capacity to meet the growing demand if they are to maximize their long-term profits, leading to capacity becoming a key factor in OEMs' outsourcing decisions. This includes suppliers located upstream of Tier 1 (T1) suppliers since they are trusted to manage their upstream supply chain (SC), leading to OEMs having relatively little contact with their wider SC (Dostaler 2013; Alfalla-Luque et al. 2013). As a result, the risk of an aircraft OEM not having sufficient capacity in their upstream SC when outsourcing to a T1 supplier is increased. However, the highly strategic nature of outsourcing now requires firms to gather more information about their potential suppliers (Bayraktar et al. 2007). These suppliers are required

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to demonstrate that they currently have or will have enough capacity to support the OEM's production. If the latter, the suppliers would share their capacity management plans with the OEM, including plans to invest in additional capacity (e.g., acquiring new facilities or machines). Such decisions can have a significant impact on the wider SC (Wang et al. 2007a) due to the operational and financial consequences of capacity investments. In a similar manner to capacity constraints causing SC disruption, SC disruptions cause major operational delays in the aerospace industry due to part shortages (Treuner et al. 2012).

In addition, the financial position of SC members has become an important factor in outsourcing decisions (Bayraktar et al. 2007). Another cause of SC disruptions is suppliers becoming financially distressed and unable to meet their financial obligations (Treuner et al. 2012). Since cash is needed to sustain operations by paying for labor, overhead, etc., running out of cash places a firm's, and subsequently the SC's, operations at risk of disruption. This indicates that there is a relationship between the performance of individual firms and that of the SC that must be understood when making outsourcing decisions.

This requirement makes the resolution of capacity constraints in the SC context a particularly challenging matter. Reasons for this include the high cost to expand capacity (Wang et al. 2007b), the long lead times involved with installing the equipment (Wang et al. 2007b), and how such decisions are typically expensive and difficult to reverse (Wu et al. 2005). As a result, suppliers can be reluctant to invest in additional capacity due to the risk of demand dropping, thus making their investment redundant. One notable case of this phenomenon concerned the major expansions that Boeing and their SC made to support an increase in production of the Boeing-747 aircraft (Wang et al. 2007b). Shortly after these expansions, the Asian financial crisis occurred, causing a drop in demand for the aircraft. Boeing was forced to drop its production, and their suppliers incurred huge losses (Wang et al. 2007b). The implications of capacity constraints on the wider SC's performance are, therefore, an important matter to consider when outsourcing.

1.2 Analytical and Simulation Modeling for Supporting Supply Chain Capacity Management

Analytical models have been used to identify and analyze the financial implications of SC capacity management decisions with the aim of minimizing the total costs incurred and/or maximizing the net present value (NPV) or profit generated (Martínez-Costa et al. 2014). Analytical models are represented as a series of mathematical equations that are typically static in nature (i.e., they do not capture the dynamic behavior of the modeled system over time). The traditional approach to capacity planning (CP) is to use a spreadsheet-based tool to calculate the number of machines or workstations (WS) required by dividing the total capacity needed to meet demand by the capacity of a single WS (Geng and Jiang 2009). This approach is commonly used due to its ease of application and ability to quickly assess capacity constraints in a system.

An example of analytical modeling being used to evaluate the financial impact of capacity investments in a SC context can be found in Chauhan et al. (2004) where the authors build a strategic CP model for a three-stage SC using mixed integer programming. They modeled the cost of investing in additional production capacity within producers and/or transport capacity between SC members by modifying the capacity of each producer and transport at an aggregate level.

Strategic CP in a SC context also brings the challenge of resolving conflicts of interest between SC partners despite their interdependent relationships. One such conflict of interest regards the expense in acquiring additional capacity, since they are making a significant financial risk based on the expectation that they will experience an increase in demand from their downstream SC partners. To alleviate these risks, researchers have modeled the use of contractual agreements when developing CP strategies. In the study by Mathur and Shah (2008), suppliers are encouraged to invest by including protection against unrealized demand by adjusting the price of products in the contract. Yang et al. (2017) explore the use of cost sharing contracts to split the investment costs between suppliers and downstream SC partners upon reaching thresholds in the suppliers' capacity. Understanding the financial cash flows that suppliers experience if they invest in additional capacity can be used to identify financial risks in outsourcing decisions. However, analytical modeling is typically limited to static analysis or aggregated SC structures. To model individual machines within SC members requires increasing the size and difficulty in solving the problem modeled.

Simulation is frequently applied to process planning problems in manufacturing firms as a replacement to static analysis (Jeon and Kim 2016). In an industrially relevant example, the discrete event simulation (DES) software package QUEST is used to optimize the assembly process of the Boeing-747 to improve assembly efficiency and cycle times through use of the moving-line concept (Lu and Sundaram 2002). DES was also applied to process planning for mobile phone and ship manufacture (Jeon and Kim 2016), demonstrating its versatility. Georgiadis (2013) uses system dynamics (SD) to develop a CP model for a recycling plant that considers the impact of investment on the NPV generated over time. Hussain et al. (2016) used the SD software package iThink® to evaluate the impact of capacity constraints and safety stock on the backlog levels in a two-tier SC. Cannella et al. (2008) used the Vensim SD software to simulate the impact of various capacity constraint levels on SC performance. Their approaches focused on backlog and inventory levels in the SC although the cash-flow or financial position of SC members are not modeled.

In summary, the impact of CP decisions on the financial and operational performance of individual sites and SCs have been investigated using analytical and simulation techniques, the latter being noted for its ability to capture a SC's dynamic and complex behavior. SD in particular is frequently used for CP (Jeon and Kim 2016). DES on the other hand requires a non-trivial amount of data and time to build, run, and analyze simulation experiments (Geng and Jiang 2009). However, the flexibility of DES to model systems in high fidelity and its ability to track the movement of individual entities makes it highly applicable to modeling aircraft manufacturing SCs where production volumes are low in contrast to the problems investigated using SD in the mentioned literature. While DES is not typically used to model the financial impact of CP decisions in a SC context, it can generate high quality data to support such techniques (i.e., analytical modeling). By exporting the required data to a tool for analysis, the effort required to modify DES models to capture the financial impact of CP decisions is minimized. This creates an opportunity to leverage the strengths of DES to connect the operational implications of capacity constraints and investment strategies to the SC's financial performance to support outsourcing decisions in the aerospace industry.

This paper presents a methodology to simulate the influence of capacity constraints and available investment scenarios on aerospace SC performance to support an aircraft OEM's outsourcing decisions. Section 2 describes the methodology developed while Section 3 demonstrates its capability with experimental results. Section 4 discusses the implications of the results and their relevance to outsourcing decisions in aerospace SCs and Section 5 summarizes the main findings of this paper.

2 METHODOLOGY

2.1 Methodology Overview

Figure 1 illustrates the combined simulation and analytical modeling approach used in this paper to model the influence of external demand and CP decisions on SC performance. Since the state of each SC member's process flows changes over time due to increasing demand and the emergence of capacity constraints, DES is used to capture the SC's dynamic behavior. The simulation model described in Section 2.3 exports the timing of events that trigger the flow of cash between SC members. Additional capacity from investment in capital equipment (CE) became available after a specified time, representing their installment dates.

The arrival of a delivery initiated the time period defined by the payment terms before the supplier was paid by the recipient. This date was also used to determine how late an order was for the purposes of calculating lateness penalties. Machine-type elements with a dedicated logics file were placed in front of the raw material stores of each SC member to export the arrival date of parts entering the stores. The total manufacturing expenditure incurred and the value of inventory held by each SC member each month were exported from the simulation. Machine-type elements with a dedicated logics file were created to gather the manufacturing and inventory data of the SC member it was assigned to. The analytical model presented in Section 2.5 correlated the timing of the exported data to the appropriate time period to calculate the timing of (i) incoming revenues for delivered goods; (ii) payments to purchase raw materials and perform manufacturing processes; (iii) inventory holding cost (IHC) incurred; and (iv) late delivery penalties incurred. The analytical model linked the operational performance of each supplier to its financial performance. Inputs for the analytical model were the supplier payment terms, payment plans for capacity investment, lateness penalties, and interest rates applied when calculating the IHC.

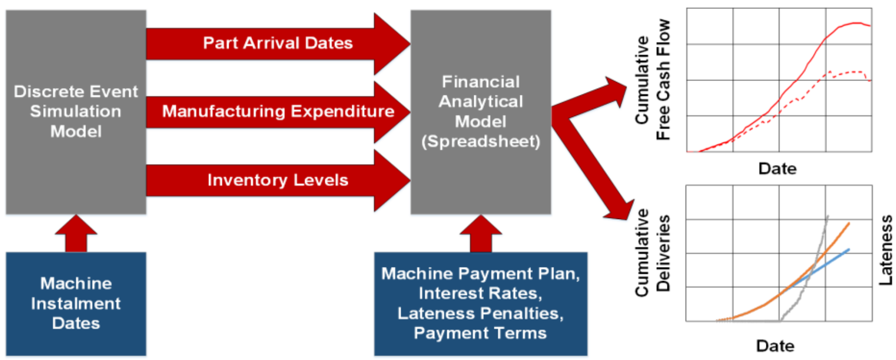

Figure 1: Overview of the combined simulation and analytical modeling methodology.

2.2 Discrete Event Simulation

This paper uses Delmia QUEST (QUeuing Event Simulation Tool), a commercial DES software package. DES concerns the modeling of dynamic systems by representing them as a series of interconnected activities and queues that are often subject to random (stochastic) variation (Robinson 2014; Law 2015). The dynamic behavior of the system is captured by updating the variables that represent their current state (the system's "status") every time an "event" occurs (a discrete point in time where the system changes in some fashion, e.g., a process begins/ends) (Law 2015). Examples of a system's state variables include the number of parts at each resource/queue and the value of attributes assigned to entities. Since the time between events can vary, the status of the system "jumps" at discrete points in time and is constant during the intervals (Robinson 2014). Examples of QUEST being used in the aerospace industry include the studies performed by Lu and Sundaram (2002) and Prado and Villani (2010). If a high level of detail is not required, a model can be simplified by aggregating parts of the system. A detailed description of DES and its underlying mechanics can be found in Robinson (2014) and Law (2015).

2.3 Supply Chain Simulation Model

Figure 2 illustrates the SC modeled, consisting of an aircraft OEM, a T1 supplier for a major aircraft structure and a Tier 2 (T2) supplier providing the structure's machined parts. Each supplier's processes were modeled to identify capacity constraints, including their inventory stores and transportation between SC partners. Discussion with the OEM's manufacturing engineers and reviews of the aircraft structure's manufacturing documents revealed that it is comprised of composite skins and stiffeners, machined parts and a variety of miscellaneous parts (fasteners, seals, etc.). The skins and stiffeners were fabricated in parallel before being taken to the final assembly jig. The skins also had a structural core attached during the ply lay-up process. All the other parts were sent directly to the assembly jig.

The OEM shared a master schedule (MS) containing their demand for aircraft structures with the T1 supplier who then used the material requirements planning (MRP) inventory management technique to schedule their manufacturing and procurement orders. These orders were generated by a Microsoft Excel VBA macro representing their MRP system.

The T1 supplier had one aircraft set's worth of assembly jigs, turnover fixtures, and composite molds to produce the skins and stiffeners. The other WS were shared with other product lines and were represented by scheduling "windows" of time where the composite parts could be served by them. The cycle time data for the T1 supplier's processes were calculated using the OEM's parametric costing guide for composite/assembly processes. The resulting data were then validated using estimates provided by the OEM's manufacturing engineers. An initial simulation run showed that an average throughput of one aircraft structure per week under a single shift pattern was established, which was validated by discussing the results with SC managers' based on their experience with the T1 supplier.

As the OEM didn't maintain direct communication with the T2 supplier, it was not possible to directly access information regarding their process flows or WS. Instead, the OEM's manufacturing expertise was used to identify the processes and WS involved in their manufacture. Cycle time estimates for each process were calculated from spreadsheet-based parametric models. Since the number of WS in the T2 supplier was unknown, it was assumed one of each type of WS was present, representing the minimum capacity the T2 supplier could be expected to have. Since all of the WS would be shared between other product lines, a "window" of time was scheduled for processing the machined parts at each WS. It was assumed the T1 supplier's procurement orders for machined parts were used as the MS for the T2 supplier's MRP system when scheduling their procurement and manufacturing orders.

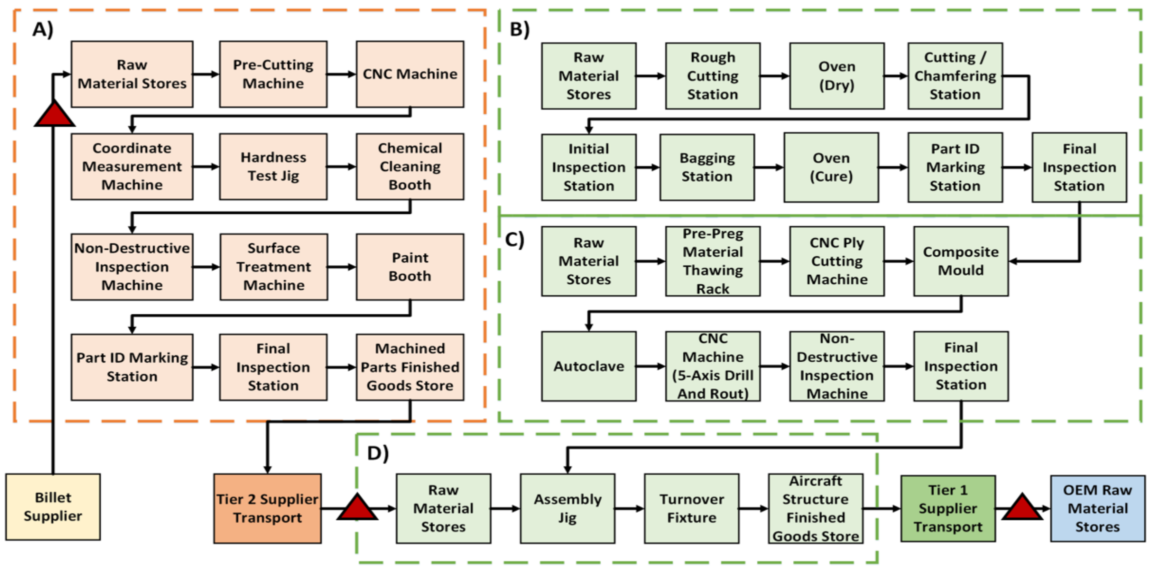

Figure 2: The SC structure showing A) the T2 supplier's machining process flow; the T1 supplier's process flow for B) structural core fabrication; C) composite skin and stiffener fabrication; and D) final assembly. The triangles show the location of elements that recorded the arrival date of parts into each SC member.

The following assumptions were applied in the simulation model:

1. Parts from suppliers not modeled arrived on time and in perfect quality.
2. There were no losses due to scrapped parts or materials.
3. Production rates steadily increased from one aircraft set per month to one aircraft set per week.
4. Unlike the T1 supplier, the T2 supplier suffered no financial penalties for late deliveries.
5. A one week safety lead-time was applied to both suppliers' raw material and finished goods stores.
6. Since both suppliers used the MRP inventory management technique, it was assumed that all lead times were constant and all of the WS in the SC model had infinite capacity when scheduling the procurement and manufacturing orders.

2.4 Capital Expenditure Model

The cost and payment plan for the CE were used to calculate the impact of the investment on each supplier's cash flow and hourly manufacturing cost rates. How expenditures related to CE are recorded and allocated to individual products depends on how the CE will be used. If the CE will be used for multiple products (e.g., a CNC machine), it is defined as non-contract-specific. The cost of the CE is depreciated over its lifecycle using the equation *Depreciation = CE Cost / CE Lifecycle* and is allocated as an overhead cost. The additional overhead cost due to depreciating the CE is included in the hourly manufacturing cost rate, which is calculated as *Machine Hourly Rate = Yearly Expenditure / Value Added Hours*. If the CE is for a bespoke product (e.g., a composite mold), the cost of the equipment is amortized over each aircraft set using the equation *Amortization Per Set = CE Cost / Number of Sets*. The number of sets the CE is amortized over requires a balance between recouping the investment as quickly as possible while minimizing the cost per aircraft set to maintain competitiveness.

2.5 Financial Model

The main long-term goal of profit-making organizations is to maximize the profits made from their activities (Dyson 2001). In a manufacturing context, making profit involves satisfying customer demand unless it is economically infeasible to do so. Investing in additional capacity implies an expected increase in demand and an opportunity to generate more profit provided there is enough demand to offset the investment. However, cash is needed to sustain operations by paying for labor, overheads, and so on; running out of cash places a firm's operational activities at risk of disruption. Making profits in the long-term is unlikely to happen unless the short-term cash position of a firm is monitored (Dyson 2001). Due to their importance to the SC's financial and operational performance, the cash flow of the T1 and T2 supplier as a result of capacity investments made are measured.

The capital expenditure model incorporated any capacity investment payments made (defined by the payment plan for the WS). The date and value of these payments were correlated to the appropriate month to calculate the net cash flow (NCF) into the firm after expenses for manufacturing activities, raw material purchases, lateness penalties, and payments for capacity investments. The total manufacturing expenditure incurred by each supplier was calculated by summing the product of the cycle time for each process performed each month and its hourly cost rate. The NCF of each month, t_m, was summed to calculate the cumulative cash flow (CCF) of each supplier at a given month, T_m:

$$NCF_{t_m} = Gross\ Income_{t_m} - Manufacturing\ Expenditure_{t_m} - Raw\ Material\ Purchases_{t_m}$$
$$- Lateness\ Penalties_{t_m} - Machine\ Investment\ Payments_{t_m}$$

$$CCF_{T_m} = \sum_{t_m=1}^{T_m} NCF_{t_m}$$

As OEMs can suffer significant financial consequences because of schedule disruptions, financial penalties were applied to the T1 supplier when they delivered aircraft structures late to the OEM. The penalty applied was calculated by multiplying the lateness of the product by a constant. The lateness of the product was equal to the number of days a delivery was late according to the MS. The IHC was modeled by measuring the average total value of raw materials, work in progress (WIP) and finished goods held by each supplier and multiplying it by their interest rate. Any parts or products in transit to a customer were included in the supplier's finished goods inventory. The value of inventory of each supplier was measured by summing the value of each part's raw material and manufacturing cost in their stores and process flows. The raw material cost is the price paid to acquire the part while the manufacturing cost represents the work performed on it to create a saleable product. Both costs were modeled as part attributes. When a process was completed on a part, the cost to perform the process was added to the part's manufacturing cost.

Since outsourcing decisions for large aircraft systems and structures in the aerospace industry are strategic in nature, a long-term perspective is required. Having cash available today is more valuable than having it later. To represent this, the NPV of cash was calculated to adjust the value of cash flows, C, in each year, t, after the start date up to the year of interest, T. A rate of return, r, of 10% was assumed when calculating the NPV. More details regarding the NPV of cash can be found in Dyson (2001).

$$NPV = \sum_{t=0}^{T} \frac{C_t}{(1+r)^t}$$

3 RESULTS

3.1 Supply Chain Scenarios and Capacity Analysis

The capacity constraint in the SC model was initially identified using a spreadsheet-based capacity planner (Figure 3). The capacity constraint in the SC was found to be the non-destructive inspection (NDI) machine at the T2 supplier. As it was a non-contract-specific machine, the cost to acquire a NDI machine is depreciated as an overhead, thus increasing the hourly manufacturing cost rate.

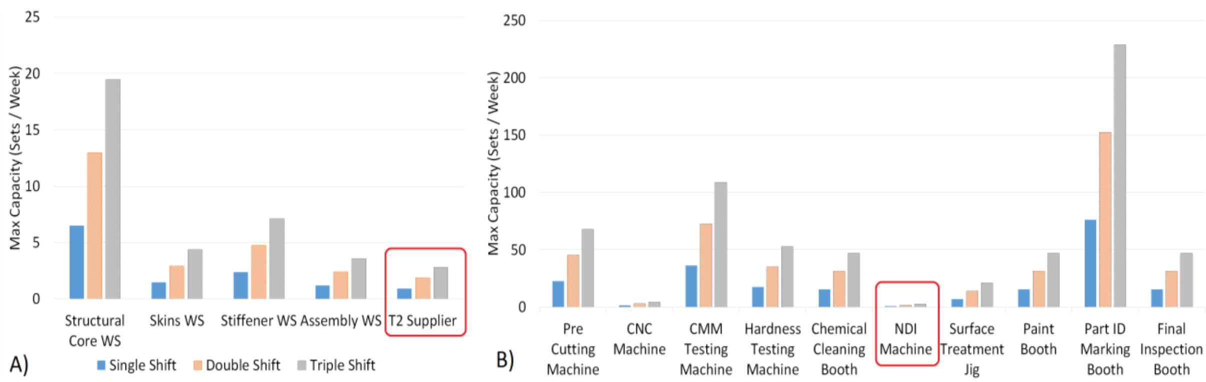

Figure 3: Location of the capacity constraint in A) the SC; and B) the T2 supplier (indicated by the boxes).

The impact of this capacity constraint on the SC's operational and financial performance was investigated in three scenarios (Table 1). The MS for aircraft structures, the daily lateness penalty applied to the T1 supplier, the T1 supplier's manufacturing cost rate, capacity, and price for the aircraft structure were constant across all three scenarios.

Table 1: The experimental scenarios.

Scenario	Investment Made?	Hourly Rate	Price
1	No (Required)	100%	100%
2	Yes (Required)	105%	105%
3	No (Not Required)	110%	110%

In the first scenario, the T2 supplier decides not to invest in another NDI machine due to the cost involved despite the anticipated increase in demand, since they do not incur any penalties for late deliveries. In the second scenario, the T2 supplier decides to invest in another NDI machine in order to generate more profit once demand increases. The price of the NDI machine was paid in three installments; the first and second payments were valued at 25% of the machine's price and were paid two years and one year prior to the installment date respectively. The remaining 50% was paid on the date the machine was installed. The investment causes the T2 supplier's overheads to rise as the machine is depreciated, increasing their hourly manufacturing cost rate by 5% compared to scenario 1. To compensate, the T1 supplier agrees to a price increase of 5% for all the machined parts delivered. In the third scenario, another T2 supplier is identified by the T1 supplier. The T2 supplier already has enough capacity to support the T1 supplier's production and does not need to invest. However, they are more expensive; their hourly cost rate and prices for machined parts is 10% higher compared to scenario 1.

Each scenario was run for a simulated period of 5 years with an additional warmup time of 5 months to accommodate for the materials' long lead times and safety lead time buffers. Each simulation run took about 15½ minutes to execute on a Dell Inc. Precision 7710 with an Intel(R) Core(TM) i7-6820HQ CPU @ 2.70GHz, 16GB RAM, 4 Core(s), 8 Logical Processor(s) and a 64-bit operating system. The primary aim of using simulation in this paper was to capture the dynamic build-up of WIP in the system, and identify the key trends in the system as a result of investing in capacity (or not). As a result, the simulation models were deterministic and thus only required one replication per scenario.

3.2 Tier 2 Supplier Performance

The first set of results explore the impact of the increasing demand on the T2 supplier's IHC and CCF (Figure 4). In scenario 1, the T2 supplier quickly becomes unstable due to the buildup of inventory in front of the NDI machine. The date when this behavior began was used to determine when an additional NDI machine was needed in scenario 2. While the T2 supplier's inventory levels in scenarios 2 and 3 rise due to the increasing production rate, the additional capacity stabilizes the inventory in both scenarios at a new level. Interestingly, the inventory levels in scenarios 2 and 3 are the same. This could be explained by the MRP system outputting the same procurement and production schedules in both scenarios.

In all three scenarios, the CCF was initially less than zero due to paying for raw materials before they can be sold. In scenario 1, the CCF steadily increased alongside demand until the T2 supplier's maximum capacity was exceeded, at which point the rate levelled out. In scenario 2, the additional NDI machine was purchased and installed in time to meet the increasing demand, represented by the steeper gradient of the CCF after the installation date. The T2 supplier in scenario 3 experienced the greatest CCF. This was due to the extra profit on the products despite their higher manufacturing costs by meeting the rising demand without needing to invest in another NDI machine.

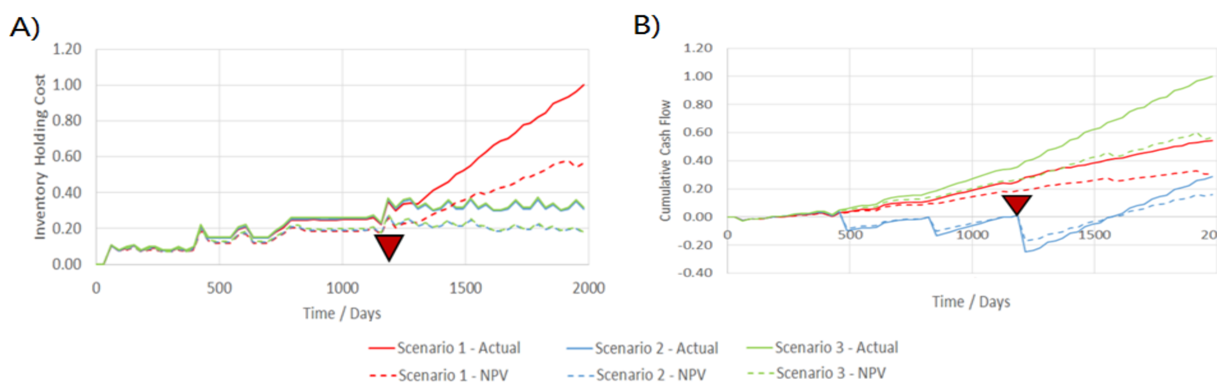

Figure 4: T2 supplier's A) IHC and; B) CCF. The triangle marks when the effect due to increasing demand sets in and the extra capacity is available in scenario 2. The data are normalized.

3.3 Tier 1 Supplier Performance

Figure 5 shows the financial penalties paid by the T1 supplier at each point in time. Since the T2 supplier fails to support the T1 supplier's production once demand exceeded capacity in scenario 1, this causes a backlog of late deliveries to accumulate at the T1 supplier. As a result, the lateness penalties paid to the OEM increase. However, this only began several months after the T2 supplier exceeded their capacity. The use of safety lead time buffers absorbed the disruptions for a significant period of time before the OEM experienced late deliveries. This did not occur in scenarios 2 and 3, since the T2 supplier had sufficient capacity to support the T1 supplier's production and ultimately meet the OEM's demand.

The T1 supplier's IHC mirror those of the T2 supplier (Figure 4). Late deliveries from the T2 supplier delayed the assembly and delivery of aircraft structures to the OEM, thus causing an increase of WIP around the T1 supplier's assembly jig. By pushing material onto the shop floor, the MRP system escalated this behavior. In scenarios 2 and 3, the IHCs are identical despite the increased prices for the machined parts; the price increase for the machined parts was minor compared to the price for an aircraft structure, making their effect unnoticeable. The IHC increase in distinct steps as the production increases before stabilizing, suggesting a steady flow of material through the T1 supplier. The impact of the T2 supplier's capacity on the T1 supplier's CCF is clear. In scenario 1, the T2 supplier's inability to support the T1 supplier's increasing production limited the maximum CCF that the T1 supplier could achieve. The CCF in scenario 1 starts diverging from that of scenarios 2 and 3 when the lateness penalties are incurred. These lateness penalties eventually caused the T1 supplier's CCF to peak as they began to outweigh the revenue from deliveries. The CCF in scenarios 2 and 3 are identical due to the timely deliveries from the T2 supplier enabling the T1 supplier to benefit from the additional revenue by meeting the OEM's increased demand.

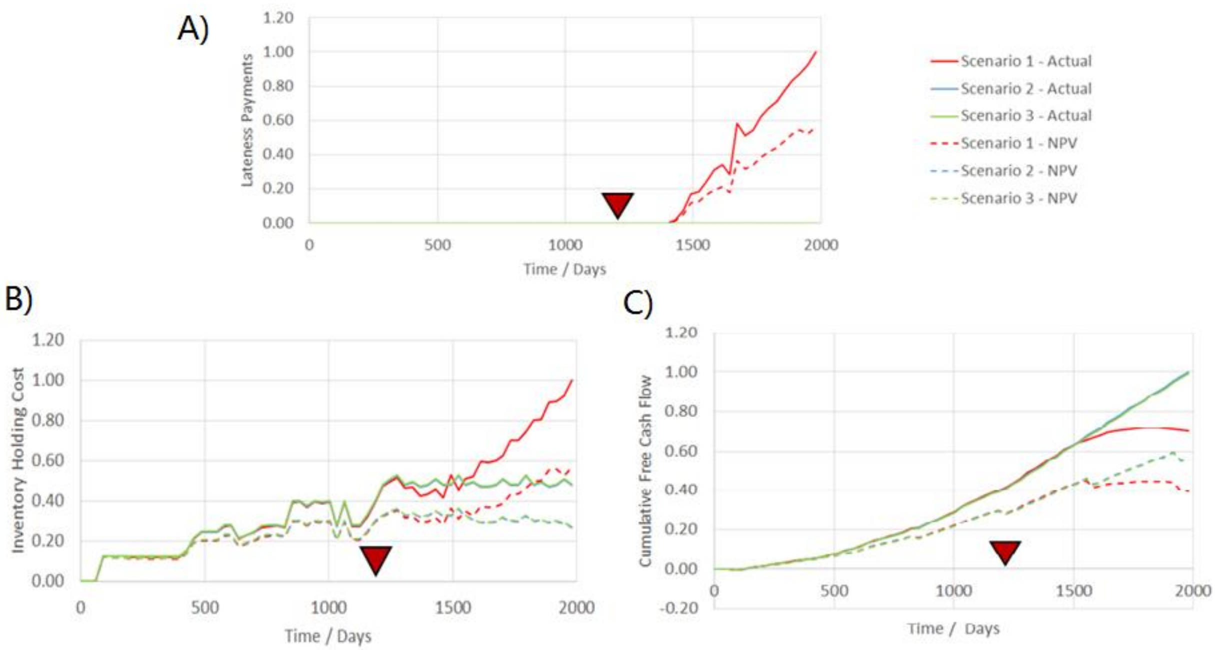

Figure 5: T1 supplier's A) lateness penalties; B) IHC; and C) CCF. The triangle marks when the effect due to increasing demand sets in and the extra capacity is available in scenario 2. The data are normalized.

4 DISCUSSION

Whether the T2 supplier had sufficient capacity to meet the increasing demand was the most influential factor on the T1 supplier's financial and operational performance. This was expected since the financial penalties for late deliveries on the T1 supplier began to outweigh incoming revenue as observed in scenario 1. The T1 supplier's performance was identical in scenarios 2 and 3; having additional capacity available earlier than required made no difference and the price increase for the machined parts was marginal compared to the price of the T1 supplier's end product.

The practical significance of this in decision making is twofold. First, having a T2 supplier who can support the MS led to generating a greater CCF compared to using a slightly cheaper alternative who increases the risk of late deliveries and causes the T1 supplier to incur lateness penalties. The reason for this is due to the effects of the price increase for the machined parts, which was outweighed by the value of the aircraft structure and the lateness penalties. Increasing the price for the machined parts may have had a greater effect if they accounted for a greater portion of the total aircraft structure's value. The second point is more subtle; having the additional capacity available in the T2 supplier before it is required is irrelevant unless there is a possibility of demand from the OEM increasing earlier than forecasted. Having the available capacity would only be advantageous if there was sufficient risk of disruption due to uncertainty in the OEM's aircraft demand forecasts to justify even a marginal price increase.

With that said, the above points fail to consider the T2 supplier's financial performance. While the T2 supplier in scenario 1 doesn't yield the potential revenue available by supporting the increasing production rate, their CCF is still higher compared to scenario 2, as they needed to pay for the CE (Figure 4). The T2 supplier could either choose to invest in additional capacity and risk financial instability from having cash tied up in capital, or they can choose not to invest and risk disrupting the Tier 1 supplier's material and financial cash flows instead (Figure 5).To compensate for their losses due to the lateness penalties in scenario 1, the T1 supplier could apply a lateness penalty to the T2 supplier. Such an action is likely to be a short-term solution as their financial performance would quickly deteriorate, thus increasing the risk of the T2 supplier becoming unable to support future production. From considering the T2 supplier's financial position, the methodology in this paper suggests that an OEM would prefer scenario 3 as it holds the least risk of disruption through exceeding capacity or financial instability in the SC. This is despite the increase in price due to the lack of practical difference to the T1 supplier's performance. With this methodology it is possible to reveal such risks in the wider SC to the OEM to support their outsourcing decisions.

5 CONCLUSION

Due to the disruption capacity constraints can cause to an aerospace SC's material and financial cash flows, whether the SC has enough capacity to support the OEM's production is a critical factor in their outsourcing decisions. If a capacity constraint is identified, the decision to invest in additional capacity is risky due to the expense and difficulty in reversing such decisions. If it is identified upstream of a T1 supplier, these decisions are beyond the OEM's control due to their lack of direct communication with the wider SC beyond their T1 suppliers. Analytical and simulation modeling techniques have typically been applied to resolve the financial and operational implications of CP decisions respectively. This paper presents a hybrid simulation and analytical modeling approach to capture the impact of increasing demand and capacity constraints on the operational and financial performance of aerospace SCs.

The results show how the increased productivity due to investment can enable firms to improve SC performance. Despite this, the cost of investment can force a firm to operate with cash tied up in capital for prolonged periods of time. This may force a sub-tier supplier to choose between not investing in additional capacity or risk financial instability. Such actions can have serious consequences for downstream suppliers due to financial penalties for late deliveries. While applying lateness penalties to upstream suppliers could provide an incentive to support downstream production, this option should be exercised with caution as it may threaten financial instability in sub-tier suppliers. Instead, the methodology could be used to identify such risks and possible solutions by having a greater understanding of the implications of CP decisions on the wider SC. One example of this was the financial risk that the T2 supplier took by investing in an additional NDI machine; making payments for the machine in advance caused the T2 supplier to operate with a large amount of cash tied up in capital, which could threaten their financial stability. From the OEM's perspective, it may be preferable for a T1 supplier to have a more expensive T2 supplier that has or will have the capacity to minimize the risk of disrupting the physical flow and materials and financial cash flow.

The model in this paper was deterministic to demonstrate how simulation can be used to capture the dynamic build-up of WIP the system and identify the defining trends. Future work could introduce stochastic behavior such as uncertain process cycle times, scrap, and rework. The developed methodology could also be applied to more complex SCs by including more SC members and connections between them.

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