A SIMULATION MODEL TO STUDY THE DYNAMICS IN A SERVICE-ORIENTED SUPPLY CHAIN

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ABSTRACT

In this paper, we investigate the dynamic behavior of a simple service-oriented supply chain in the presence of non-stationary demand using simulation. The supply chain contains four stages in series. Each stage holds no finished goods inventory. Rather, the order backlog can only be managed by adjusting capacity. These conditions reflect the reality of many service (and custom manufacturing) supply chains. The simulation model is used to compare various capacity management strategies. Measures of performance include application completion rate, backlog levels, and total cumulative costs.

1 INTRODUCTION

One of the great strengths of simulation modeling is the ability to model and analyze the dynamical behavior of a system. This makes simulation an ideal tool for analyzing supply chains because supply chains can exhibit very complex dynamical behavior. For example, simulation has been used to demonstrate and study the bullwhip effect (i.e., the amplification of demand variation as demand signals move up the supply chain from the end customer – see Forrester 1958 and Lee et al. 1997) in the MIT Beer Distribution Game (Simchi-Levi et al. 1999). The Beer Distribution Game involves the management of finished goods inventory of a single product in a serial supply chain (Senge 1990, Sterman, 1989a,b).

In this paper, we develop a simulation model to analyze the dynamic behavior of a simple service-oriented supply using simulation. The supply chain contains four stages in series. Each stage holds no finished goods inventory. Rather, the order backlog can only be managed by adjusting capacity. These conditions reflect the reality of many service (and custom manufacturing) supply chains. We use a simulation model to develop improved control strategies for dynamically managing capacity and backlog in the presence of non-stationary demand. In

particular, we will investigate the use of local control strategies such as reducing the average flow time, setting the desired target capacity, and reducing capacity adjustment time at each stage. Additionally, we consider the impact of a more global strategy in which end customer demand is shared with all stages in the supply chain. Measures of performance include application completion rate, backlog levels, and total cumulative costs.

The remainder of the paper is organized in the following manner. Section 2 contains a description of the simulation model. In section 3, we present an analysis of various capacity management strategies. Section 4 contains some concluding remarks and future research directions.

2 MODEL DESCRIPTION

Figure 1 contains a block diagram of our supply chain simulation model developed in the Vensim© Simulation Package (Ventana Systems Inc., 1998). The simulation is designed to model a simplified mortgage approval process. Each application passes through four stages: initial processing (that is filling out the application with a loan officer), credit checking (confirmation of employment and review of credit history), surveying (a survey of the proposed property to check for its value, as well as any infringements upon zoning laws or neighboring properties), and title checking (ensuring that the title to the property is uncontested and without liens).

We recognize that the simulation model is a highly simplified version of reality. Real mortgage service processes would contain more than four stages. For example, there are additional stages to perform property inspection and insurance endorsement. Additionally, some of the stages depicted in Figure 1 would not be aligned in a series but would be performed in parallel. For example, credit checks and title searches are often conducted in parallel by separate organizations. We keep the model simple in order to focus on the fundamental dynamics of service supply chain management with as few

complications as possible. Including more stages adds little to our current analysis.

Mechanically, all the stages operate in an identical manner, so we will describe here only the survey section of the model as an example of each stage's processing.
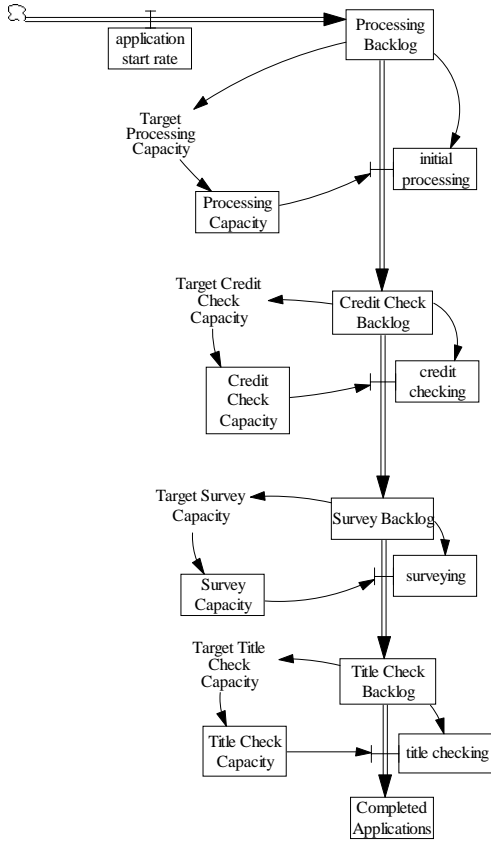

Figure 1: Block Diagram of The Mortgage Service Simulation

As each application is checked for the credit worthiness of its applicant (*credit checking* in the diagram), the application flows from the backlog of credit checks (*Credit Check Backlog*) to join the backlog of surveys (*Survey Backlog*). Each week, based on the backlog of surveys, a target capacity is set by deciding to hire or fire employees: in this case, surveyors. However, it takes time to actually find, interview, and hire or, conversely, to give notice and fire employees; so the actual *Survey Capacity* will lag the *Target Survey Capacity* by an average of one month. Those surveyors currently in the employ of the survey company will then carry out as many surveys as they can over the next week. Finally, as each application's survey is completed (*surveying*), the application will then leave the *Survey Backlog* to join the next backlog downstream—in this case, the *Title Check Backlog*. Each of the other four stages functions analogously.

In real life, of course, the purpose of each of these checks is to eliminate those applications that are too risky. However, we will assume that each application is ultimately approved. This is reasonable because, despite the fact that a random survival rate for each stage does indeed complicate real-life management of the chain, the primary dynamic control problems derive from other sources. In particular, the largest problem results from each stage of the process generally being managed by a separate company. Each of these companies controls its own individual capacity; however, it typically only sees its own backlog when making the decision, not the new application rate (i.e., end user demand) or other stages' backlogs. This creates something akin to the bullwhip effect (Lee et al. 1997) seen in the physical goods supply chains, albeit here the inventories controlled are strictly backlogs. Also, as in many real life services, there is no way for a stage to stockpile finished goods inventory in advance as a buffer against fluctuating demand. Rather, each stage must manage its backlog strictly by managing the its capacity size, that is the number of workers it employs.

Mathematically, the structure for each stage of the process is as follows (Let stages 1, 2, 3, and 4 refer respectively to the application processing, credit checking, surveying, and title checking stages):

$$B_{i,t+1} = B_{i,t} + r_{i-1,t} - r_{i,t} \qquad (1)$$

$$r_{i,t} = \min(C_{i,t}, B_{i,t} + r_{i-1,t}) \qquad (2)$$

where $B(i,t)$, $C(i,t)$, and $r(i,t)$ refer respectively to the backlog, the capacity, and the completion rate at stage i on day t. Note that $r(0, t)$ represents new application start rate. In the simulation, this variable will remain at 20 starts per day until after week 5, when it jumps to 24 starts per day. The number of starts then remains constant at 24 per day until the end of the simulation in week 50. For simplicity, we will assume that each employee has a productivity of one application per day. This allows us to constrain the completion rate of applications at any stage to the minimum of the backlog plus any inflow from the previous stage (if material is constraining processing) or the number of employees (the more typical case). Each stage's backlog begins the simulation at $\lambda[r(i,0)]$ where λ is a constant representing the average nominal delay required to complete a backlogged application. Each stage's capacity begins at $r(i,0)$ so that the backlogging and completion rates at each stage are in balance (see Equations 3 and 4 below). Hence, if there were no change in the application start rate, there would never be a change in any backlog, capacity, or completion rate throughout the service chain.

At the beginning of each week (i.e. every 5 business days), each stage can change its target capacity by deciding to hire more or fewer employees. However, it takes time to advertise for, interview, and hire employees; so the rate of capacity change is given in Equation 3.

$$C_{i,t+1} = C_{i,t} + \frac{1}{\tau}(C_{i,t}^* - C_{i,t}) \qquad (3)$$

The target capacity $C^*(i, t)$ is restricted to be nonnegative. For purposes of this simulation, τ, the capacity adjustment time, is set to one month, that is 20 business days (which is, in reality, a bit optimistic if large hiring rates are required). In essence, each stage's capacity will move one twentieth of the gap from its current value toward its target each day. On the average in a stationary system, this will translate into an average 20 business-day lag in hiring (or firing) employees.

The target capacity decision will be made as follows:

$$C_{i,t}^* = \frac{B_{i,t}}{\lambda} \text{ if } (t \text{ modulo } 5) = 0 \qquad (4)$$

$$C_{i,t}^* = C_{i,t-1}^* \text{ otherwise.}$$

Thus, each week the target capacity for each stage will be set directly proportional to the stage's current backlog $B(i,t)$ and inversely proportional to the nominal service delay time λ. This is not meant to be an optimal policy in any sense; however, it seems to reflect reasonably well how real players make decisions in capacity management simulations (Sterman 1989a). Thus, if the application start rate is unvarying, the long-run average application will take λ weeks to complete per stage. One can of course vary λ either by stage or over time to make the simulation more complex.

Based on Equation 4, each stage operates autonomously and makes its capacity decisions based on its own backlog. As an alternative, we propose another strategy called the new starts information strategy. In this strategy, each stage makes capacity decisions based on its own backlog and the new application rate. In other words, each stage gains more visibility by being able to observe end user demand in each time period. For those stages at which the computer makes the target capacity decision, Equation 4 changes to:

$$C_{i,t}^* = \alpha r(0,t) + (1-\alpha)\frac{B_{i,t}}{\lambda}, \text{ if } (t \text{ modulo } 5) = 0 \quad (5)$$

$$C_{i,t}^* = C_{i,t-1}^*, \text{ otherwise}$$

where $0 \leq \alpha \leq 1$. The degree to which each stage in the chain bases its target capacity on the new application rate

is determined by the magnitude of α. In this case, the same value for α is used for all stages that set target capacity using Equation 5. A more complicated version of the simulation could be designed to permit a different α for each stage.

We include the following costs for the mortgage service simulation. Each employee will cost $2000 to hire or terminate and $1000 per week to employ (or $200 per application processed when fully utilized). Each backlogged application costs $200 per week in potential customer alienation. The costs will be used to compare different supply chain management strategies.

3 ANALYSIS

We simulate the mortgage service applications process using the model depicted in Figure 1 for 500 days (or 100 five day weeks). We analyze several scenarios defined by the parameters λ, τ, and α. For each scenario, we examine total cumulative cost, and the dynamic behavior of applications completed per day in each stage and application backlog in each stage. For all scenarios the system is initialized in equilibrium, i.e., each stage has the capacity to process 20 applications per day and contains a backlog equal to 20λ.

We separate our analysis into two main capacity management strategies: capacity management using local backlog at each stage (i.e., Equations (1) through (4)), and capacity management based on the new application rate and local backlog (i.e., Equations (1) through (3) and Equation (5)).

3.1 Local Backlog Strategy

Figures 2 and 3 contain results for daily application completions and backlog for all stages in the mortgage service supply chain over a 500-day period. (Note: Comp Rate stands for completion rate and App Start Rate stands for new applications start rate; P, C, S, and T stands for Processing, Credit Check, Surveying, and Title Check). The graphs in Figures 2 and 3 are generated by simulating Equations (1) through (4) for managing capacity or backlog with $\lambda = 5$ and $\tau = 20$, i.e., capacity decisions are completely based on the local backlog at each stage. Notice the erratic behavior that results in all stages of the supply chain resulting from a change in the new application rate from 20 to 24 after week five. Each stage transfers its variation to subsequent stages. Consequently, demand variation is magnified as it moves through the stages of the supply chain. This is an illustration of something akin to the bullwhip effect in managing backlog with capacity adjustments. The total cumulative costs are $20,405,338.
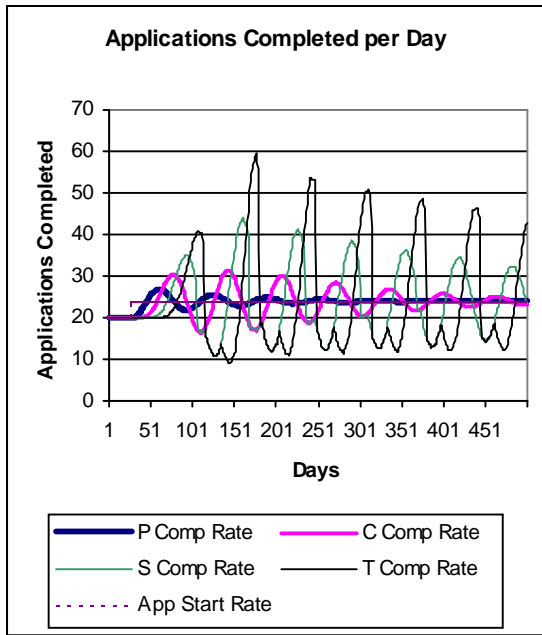
Applications Completed per Day

Figure 2: Completions per Day for $\lambda = 5$ and $\tau = 20$
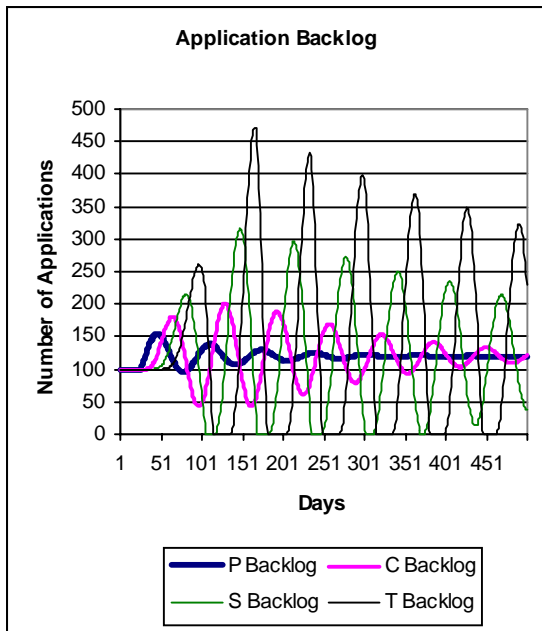
Application Backlog

Figure 3: Backlog for $\lambda = 5$ and $\tau = 20$

Figures 4 and 5 contain applications completed per day and application backlog for all stages when $\lambda = 10$ and

$\tau = 20$. With more backlog at each station, the total cumulative costs in the supply chain increases to $28,527,483 due to the increase in backlog costs. However, cost does not tell the whole story. Comparing Figures 2 and 3 with Figures 4 and 5, respectively, reveals that the longer processing delay leads to less erratic changes in the performance measures. If fact, under a different costing structure, either increased capacity adjustment costs or reduced backlog costs, a different ranking of the two scenarios based on cost can result. For example, if backlog costs drop to zero, the total cumulative costs for the scenario with $\lambda = 5$ and $\tau = 20$ is 10,322,990 and with $\lambda = 10$ and $\tau = 20$ is $9,507,091.

The above result is somewhat surprising because it differs from that seen in the classic bullwhip effect in which shorter lead times generally reduce oscillatory behavior (Anderson and Fine, 1998). However, as Anderson and Morrice (1999) point out, the behavior is a natural consequence of the shorter lead-time coupled with the relatively long capacity adjustment lag time. When the two are more closely matched less erratic behavior results. As further support, consider the results in Figures 6 and 7 for the case when $\lambda = 5$ and $\tau = 10$ (i.e., compare Figures 2 and 3 with Figures 6 and 7, respectively).
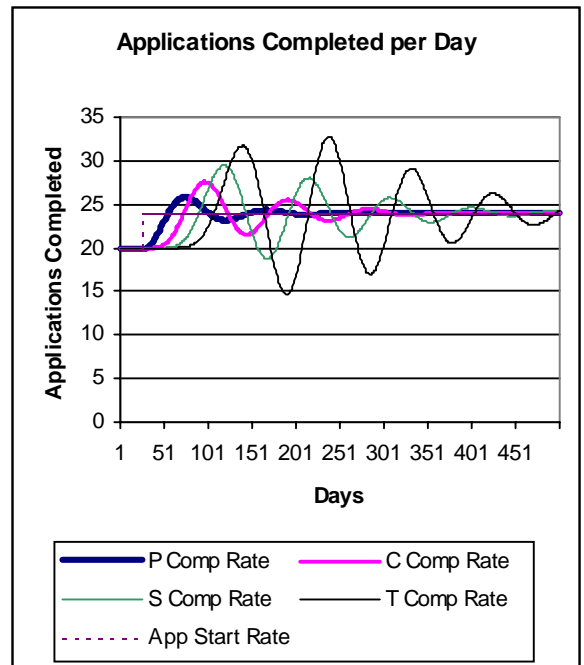
Applications Completed per Day

Figure 4: Completions per Day for $\lambda = 10$ and $\tau = 20$

Application Backlog
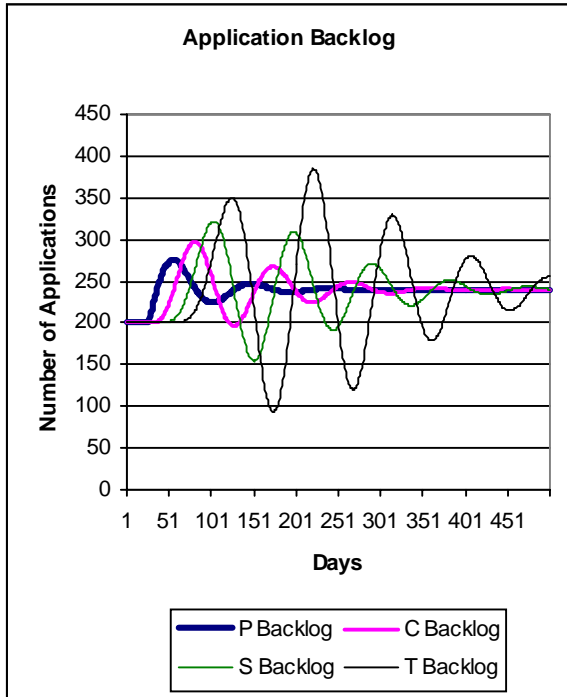
Figure 5: Backlog for λ = 10 and τ = 20

Application Backlog
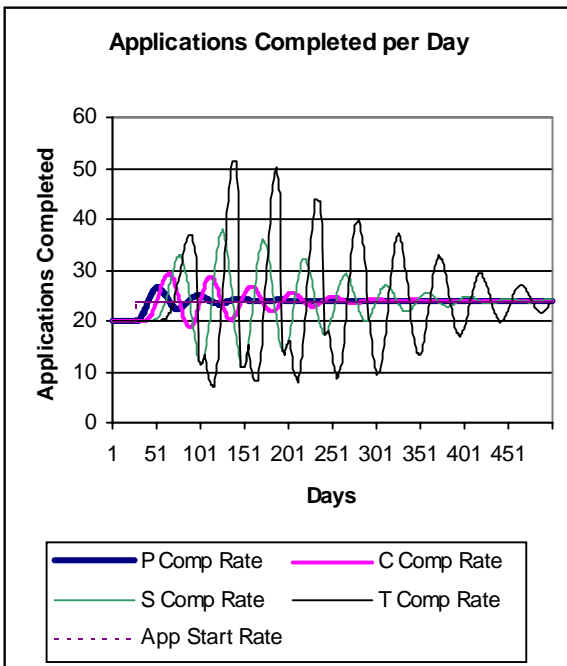
Figure 7: Backlog for λ = 5 and τ = 10

3.1 New Starts Information Strategy

Under this strategy, Equation (5) is used to establish target capacity rather than Equation (4). Figures 8 and 9 contain results for the case when λ = 5, τ = 20, and α = 0.5. Including new starts information into the target capacity decisions improves both performance measures by smoothing out oscillations (compare Figures 2 and 3 with Figures 8 and 9, respectively). Furthermore it also reduces total cumulative cost to $19,111,716.
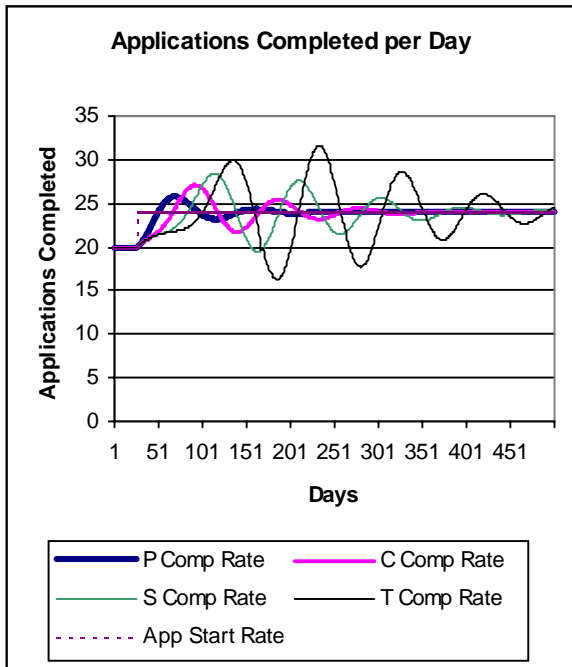
Applications Completed per Day

Figure 6: Completions per Day for λ = 5 and τ = 10

Applications Completed per Day

Figure 8: Completions per Day for $\lambda = 5$, $\tau = 20$, $\alpha = 0.5$
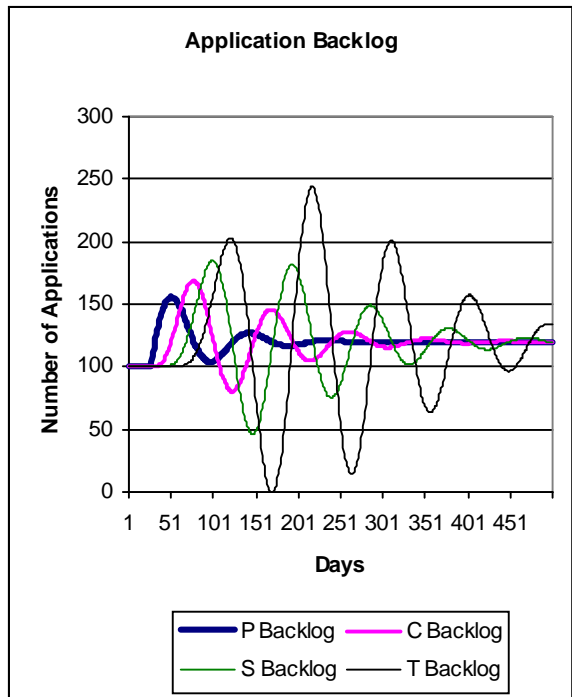
Application Backlog

Figure 9: Backlog for $\lambda = 5$, $\tau = 20$, $\alpha = 0.5$

Under the current costing structure, Figure 10 indicates how much new starts information to include (i.e., how to select α) in setting target capacity if the objective is to minimize total cumulative costs. The current cost structure dictates that it would be optimal to set $\alpha = 1$ and use only new starts information for setting the target capacity.
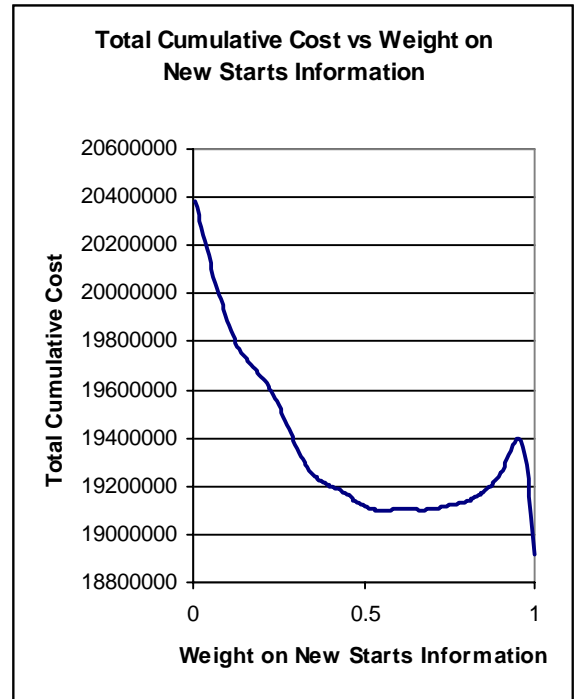
Total Cumulative Cost vs Weight on New Starts Information

Figure 10: Cumulative Cost versus α for $\lambda = 5$, $\tau = 20$
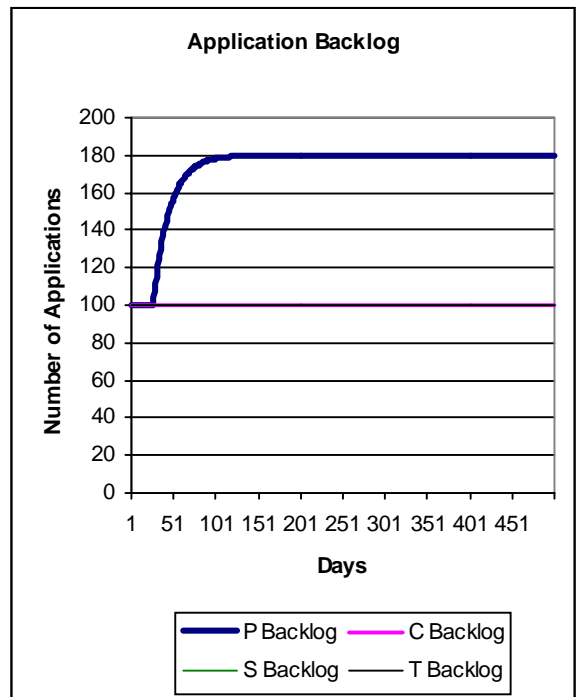
Application Backlog

Figure 11: Backlog for $\lambda = 5$, $\tau = 20$, $\alpha = 1$

Once again total cumulative costs do not provide a complete picture. Figure 11 indicates that with $\alpha = 1$ the erratic oscillations in backlog are eliminated. However, the backlog remains unbalanced with the first stage holding the most and never being able to work it off after the change in demand. For the organization controlling the first stage of the supply chain, this may be considered an inequitable solution to adjusting to the changes in demand. Perhaps the costing structure could be revised to more accurately reflect the costs associated with inequitable solutions in the supply chain.

4 CONCLUSION

We have presented a simple framework in which to study capacity management strategies in a serial supply chain. We have demonstrated that even this simple supply chain model exhibits fairly complex dynamic behavior. Therefore, simulation is an excellent tool for conducting this type of analysis.

As part of future research, we will investigate the impact of uncertainty in demand and process yield. Additionally, we will embellish the current model to include such things as reentrant flow and parallel activities. New management strategies and decision rules will be investigated such as cooperation and coordination between the various stages. Finally, we will explore different costing structures in order to represent all the costs involved more accurately.

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