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Application of Feedback Control Method to Workforce Management in a Service Supply Chain

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Abstract

Success of services businesses depend on how well the workforce is managed. Having the right size of workforce and the right skill set of the workforce at the right time under dynamic demand environments are challenges that many service businesses face. Demand disturbances in services businesses are typically managed by adjusting the resource levels such as acquiring additional resources from larger pool (borrowing resources from the corporate levels for departmental level needs), and releasing resources back to the larger pool for transferring and cross training of the workforce. However, the resource adjustments for changing the level of workforce are not as easy as acquiring or scraping materials as in manufacturing supply chain. The magnitudes of resource adjustment are often decided by estimating the discrepancy between the demand for services and the supply of workforce. However, naïve feedback control of the resource actions by policies that equate the discrepancy to the control action can produce undesirable effects such as oscillation between acquisition and release of workforce, and amplified oscillation through the stages of the service processes. Feedback control methods have been used very successfully in many years for controlling many engineering processes; however, they have not been applied in services supply chains. In this work, we attempt to apply control theoretic principles in managing resources to see how various feedback control schemes can improve costs, utilization and stability of workforce. Our study indicates that effective combination of multiple feedback control schemes can produce desirable policies of workforce resource management.

1 Introduction

Services supply chains can be more difficult to control than traditional manufacturing supply chains because the control variables are related the workforce rather than materials and machines. Services businesses, such as business consulting, call centers, technical services and IT outsourcing, are growing rapidly (Dietrich et al. 2006), and have become a significant portion of the U.S. and world economy. However, application of scientific methods to services businesses has been very limited partly because people (workforce) are complicated and much difficult to manage than materials and machines. Demand disturbances in services businesses occur as in other businesses, and they can produce undesirable effects for the businesses such as reduced service level, reduced utilization, and oscillation and amplification of workforce requirements. In manufacturing supply chains, and it has been observed that the business impacts arising from demand disturbance include excessive levels of inventory, poor customer service due to shortages or long backlogs, and high costs for corrections (i.e., expedited shipment and over-time of workforce, etc.). Amplification and volatility of inventory as it moves through the supply chain is known as bullwhip effect and its impacts and remedies have been studied by many researchers including Forrester (1960), Sterman (1989), and Lee at al. (1997a, 1997b). However, since the services supply chain is different than manufacturing supply chain, the demand disturbances can be manifested differently.

Services supply chains depend heavily on workforce, and unlike manufacturing supply chains, unused resources (workforce) cannot be carried over (and are thus perishable). Resource adjustment, such as acquiring, releasing and cross training from/to a larger resource pool (e.g., corporate pool), take time (lead time) and incur monetary costs such as training and administrative costs. The availability of resources also degrades over time through attrition of workforce, etc. Another unique attribute of workforce is that the skill levels and types of skill change through service engagement experience and training. Therefore, the resource management can be more complicated than material acquisition for inventory control in a typical manufacturing supply chain.

When various disturbances (e.g., surge, step, ramp, oscillatory) in demand occur in services businesses, the disturbance is typically managed by resource adjustments such as acquisition, release and cross training of the workforce. The magnitudes of resource adjustment are often decided by estimating the discrepancy between the demand of services and the supply of the workforce. However, naïve feedback control (acquiring, releasing or cross training workforce by policies that are directly proportional to the discrepancy alone) can produce undesirable effects such as oscillation between acquisition and release, and amplified oscillation through the stages of the service processes. Effective combination of multiple feedback control schemes can produce desirable policies of workforce management.

Application of control theoretic principles to manage adverse effects has been studied in manufacturing supply chains (Simon 1952, Wikner 1991, White 1999 and Dejonckheere 2004 etc.). Ortega and Lin (2004) provide an excellent review of control theory applied to the production and inventory problem. However, little study has been done in applying control theory to managing the workforce in services supply chains. Anderson and Morrice (1999, 2000) modeled a simplified services supply chain for mortgage service processing with multiple stages of application processing, credit checking, surveying and title checking, and observed oscillation and amplification through the stages. They also study the impact of resource acquiring delays and engagement execution delays, and also noticed that information sharing can reduce the amplitude of oscillation. Akkermans and Vos (2003) also ob-served amplification effects in a services supply chain for a telecommunication process, and identified that the root causes for the amplification effect are interdependence among workload, work quality and rework. They also observed that quality improvement throughout all stages of the supply chain can be an effective counter measure for the amplified oscillation of service backlog. However, no prior study has been done in applying multiple feedback control schemes by using combinations of proportional (P), derivative (D), and integral (I) control to determine effective policies of workforce resource management. Feedback control has been used widely for many years in engineering fields. For example, it is not difficult to program a feedback control in a PLC (Programmable Logic Controller) to control the temperature of a chemical reactor within a degree of the desired temperature by controlling steam or coolant into the heating/cooling coils inside the reactors. Can the similar method be applied to the services supply chain by computing effective resource management policies of controlling the level of workforce?

The purpose of this work is to model and study how disturbances of demand (e.g., surge, step, ramp, oscillatory) impact services supply chains with respect to costs, utilization and the stability of workforce, and to identify what control policies can mitigate the adverse effect by applying control theoretical principles. We attempt to characterize various control policies, PID controls, for workforce actions, i.e., the policies for acquiring, releasing and cross training resources. We also attempt to determine conditions (and timing) under which specific control actions (resource policies) are beneficial, identify conditions for stability, and explore trade-offs between responsiveness to demand and volatility of resource adjustment. Ultimately, this research work will identify good and bad polices (strategies) of resource adjustment of workforce for various demand disturbance situations, and generate useful insights for workforce management decision makers. It should be stressed that the feedback controller we describe here is not intended to replace the human decision makers by making resource adjustments on its own. The control scheme can, however, provide useful information to the workforce resource managers as a decision support tool, so that good decisions on resource actions are made. In this paper, we model a simplified IT (Information Services) service business, and two types of demand disturbances, a step increase of demand and an oscillatory demand. Then, we apply PID feedback control method to each demand disturbance scenario and compute optimal control schemes and characterize them.

The rest of paper is organized as follows. In Section 2, we present a dynamic model of a services supply chain. In Section 3, we present simulation results of two demand disturbance scenarios with a naïve feedback control. Then, we introduce feedback control system in Section 4. In Section 5, we show how the control methods are applied to the dynamic model of the service supply chain, and summarize the effectiveness of various feedback control schemes and optimal PID control schemes for the two demand disturbance scenarios. Finally in Section 6, we summarize our study and discuss future research.

2 A Services Supply Chain Model

The services supply chain we modeled here is for an IT software development service, which consists of three stages, each with a finite workforce capacity handling different tasks, as shown in Figure 1. Its structure is similar to the model described by Anderson and Morris (1999, 2000) and Akkerman and Vos (2003). In the initial stage, pre-sales service opportunities are coming to a service firm and are accumulated as potential service engagements. The first phase that involves workforce is the contracting phase, which uses sales personnel who design the contract, price and scope the work and related activities. The second stage is the consulting stage, which uses business consultants to design tools and make project plans, etc. The third stage is the development stage, which uses engineers to develop and deploy the software. Each of the stages has its own details described below and shown in Figure 2. Each stage is responsible for its own resource actions, i.e., acquiring and releasing workforce. For simplicity, we assume that there are no dropped or lost opportunities and all of the service opportunities are all eventually engaged. For this paper, we also assume that resources are not shared between the stages, although we plan to extend our research to explore the impact of sharing of resources between stages of service process.

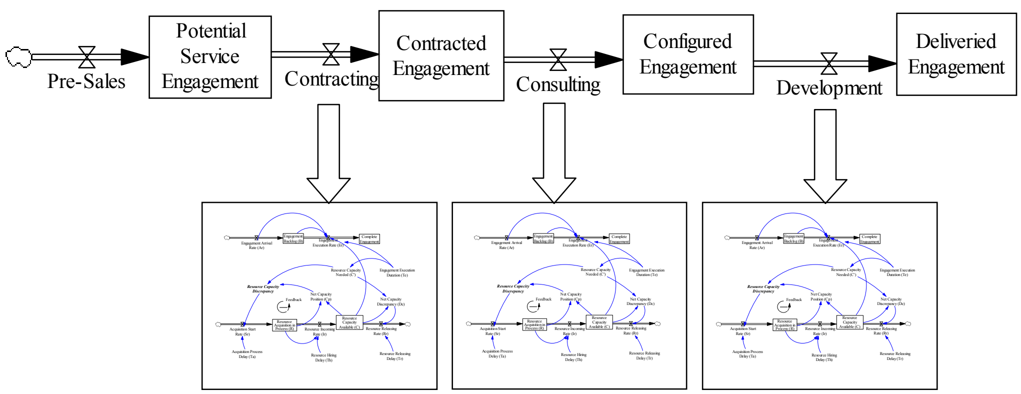

Figure 1: A Multi-Stage IT Services Business Model

We model a simplified services business using the system dynamics (SD) method (Sterman 2000). The model is developed using a system dynamics modeling tool called Vensim (Ventana Systems Inc. 1998). A simplified view of the overall multi-stage SD model is shown in Figure 1. Figure 2 is a simplified view of the SD model for each stage omitting many of the parameters.

There are two streams of activities in the model. The first one is the flow of service engagements coming into a service firm as shown in the top portion of Figure 2. The backlog of service engagements accumulates based the difference between inflow of demand arrival, R_a , and execution rate, R_e. Note that the engagement backlog (B) is actually the *engagement work-in-progress*, which is amount of engagement that is being worked on, and has different meaning as the traditional backlog in supply chain. For consistency with prior work, we will refer *engagement work-in-progress* as engagement backlog, B, throughout this manuscript. The execution of each IT service engagement requires a certain number of resources (personnel) for certain duration. In this model, we assume that all of the service engagements are ultimately executed although some engagements can be delayed as accumulated demand backlog due to capacity shortages as shown in the expression of, R_e , in Equation 1.

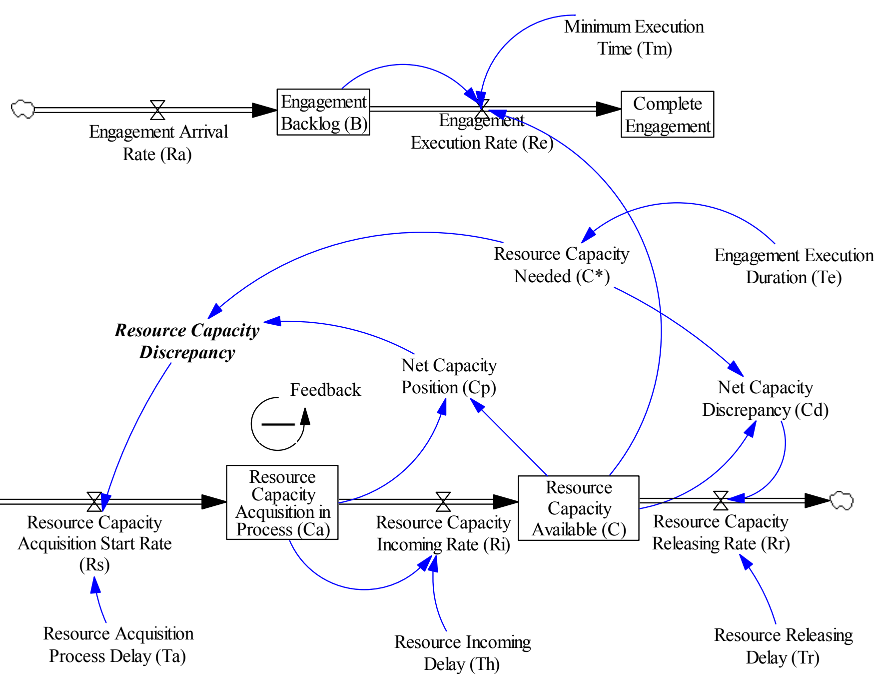

Figure 2: SD Model of Each Stage

$$B(t) = \int_0^t [(R_a(\tau) - R_e(\tau)]d\tau + B_0 \tag{1}$$

where $B(t)$ = demand backlog at t,

$R_a(t)$= arrival rate of demand at t

$R_e(t)$ = execution rate of demand at t = min[$C(t)$, $B(t)/T_m$]

$C(t)$ = resource capacity available at t

T_m = minimum engagement execution time

B_0 = initial backlog (engagement work in-progress) at $t=0$

Note that the unit of demand backlog ($B(t)$ and B_0) is expressed in units of the number of engagements, arrival rate, execution rate and resource capacity (R_a , R_e and C) are expressed in the number of engagements per day, and execution time (T_m) is expressed in the number of days. There is a minimum execution time even if unlimited resources are available. With the minimum engagement execution time, adding more resources past a certain level does not reduce the backlog but it merely reduces the resource utilization.

The second flow in the model is the flow of workforce as shown in the bottom part of the model in Figure 2. The resource capacity available, $C(t)$, accumulates based on the difference between the resource incoming (employees joining the service firm) rate, $R_i(t)$, and the resource releasing rate, $R_r(t)$ as shown in Equation 2.

$$C(t) = \int_0^t [(R_i(\tau) - R_r(\tau)]d\tau + C_0 \tag{2}$$

Where $C(t)$ = resource capacity available at t

$R_i(t)$= resource capacity incoming rate = $C_a(t)/ T_h$

$C_a(t)$ = resource capacity acquisition in-progress at t

T_h = resource incoming delay

R_r(t)= resource capacity releasing rate = $C_d(t)^+/ T_r$

$C_d(t)^+$ = net capacity discrepancy (positive part) = $[C(t) - {B(t)}/{T_e}]^+$

T_e = nominal time required to fulfill a demand engagement

T_r = delay in resource capacity releasing

C_0 = initial resource capacity at $t=0$

The resource incoming rate, $R_i(t)$, in turn, is modeled as resource acquisition in progress, $C_a(t)$, (the number of employees in the acquisition in-progress pipeline) divided by the delay in resource acquisition, T_h, (the time needed to bring in the workforce once the acquisition process is in place). The resource releasing rate, $R_r(t)$, in turn, is modeled as net capacity discrepancy, $C_d(t)^+$, divided by delay in resource releasing (the time needed to release workforce), T_r. The net capacity discrepancy, $C_d(t)$, is the resource capacity available minus the resource capacity needed.

The resource acquisition in-progress, $C_a(t)$, in turn, accumulates based on the difference between resource acquisition start rate, $R_s(t)$, and resource incoming rate, $R_i(t)$, as shown in Equation 3.

$$C_a(t) = \int_0^t [(R_s(\tau) - R_i(\tau)]d\tau + R_0 \quad (3)$$

where $R_s(t)$ = resource acquisition start rate at t

R_0 = initial resource acquisition start rate at $t=0$

The resource acquisition start rate, $R_s(t)$, is the key control variable (as explained later in the control system section of the paper) for deciding how many people to acquire, and it depends on the shortage of resource capacity, ε^{+}_{t}, (as shown in Equation 4), and control parameters such as the gain constant, K_c , which is explained below.

$$\varepsilon^{+}(t) = \left[C^{*}(t) - C_{p}(t)\right]^{+} \tag{4}$$

where C_t^{*} = resource capacity needed at $t = B(t) / T_e$

$C_p(t)$= net capacity position at $t = C_a(t) + C(t)$

Note that acquisition start rate, incoming rate and releasing rate of resource capacity (R_s , R_h , R_r) are expressed in units of the number of engagements per day per day, while the units of resource capacities, (C_a , C_t , C_d, C^{*}, C_p) are expressed in units of the number of engagements per day.

The gain constant, K_c , is typically treated to be 1 (as in the work of Anderson and Morrice (1999, 2000)), and the effect of various values of K_c will be modeled and explained in the subsequent sections below. The overall decision of resource acquisition start rate, R_s, is delayed (divided) by the delay for resource acquisition start rate T_a.

$$R_s(t) = {K_c \cdot \varepsilon^{+}(t)} \big/ {T_a} \tag{5}$$

where $\varepsilon^{+}(t)$= resource capacity shortage

K_c = gain (sensitivity) constant

T_a = delay for resource capacity acquisition process

3 Simulation of Demand Disturbances

The system dynamics model described in the previous section is simulated for 356 days. The following parameters are used in the simulation:

- Engagement arrival rate (R_a): 20 [number of engagements/day]
- Minimum engagement execution time (T_m): 1 [day]
- Delay of fulfilling each demand engagement (T_e): 5 [day]
- Resource Incoming Delay (T_h): 30 [days]
- Resource Releasing Delay (T_r): 14 [days]
- Unit Resource Costs *(p_c):* 200 [$/day]
- Unit Acquisition Costs *(p_i)*: 10,000 [$]
- Unit Release Cost *(p_r)*: 20,000 [$]
- Unit Service Penalty Cost *(p_d)*: 1,000 [$/day]

The service penalty cost occurs when an engagement is delayed due to the shortage of workforce. Two types of demand disturbances, a step increase and oscillatory demand, are simulated. The total costs *(C_t)* consist of acquisition cost, release cost and service penalty cost as shown in Equation 6.

$$C_t(t) = \int_0^t [p_c C(\tau) + p_i R_i(\tau) + p_r R_r(\tau) + p_d C_d^{+}(\tau)] d\tau. \qquad (6)$$

3.1 Simulation of a Demand Disturbance: Step Increase

The demand disturbance modeled here is a step increase, i.e., the process starts with a steady state of demand arriving at a rate of 20 [number of engagements/day], then at day 50, the demand arrival rate increases from 20 to 25. The demand profile is shown in Figure 3. The resource acquisition start rate, $R_s(t)$, responds to this demand disturbance based on the discrepancy of resource capacity between supply and demand with the gain constant (also called proportional control constant) value of 1 ($K_c = 1$). The setting is similar to the model described by Anderson and Morrice (1999, 2000).

The multi-stage simulation includes three stages of the service business; contracting stage, consulting stage and development/deployment stage. Figure 4 shows the demand backlog changing over time for the three stages. The engagement backlog for the second stage (contracted backlog), is higher than the first stage (potential engagement backlog) and the backlog of the third stage (configured backlog) is, in turn, even higher than the second stage. The oscillation of the backlog is amplified as it moves through the stages of the services supply chain. This phenomenon is similar to the bullwhip effect observed in the supply chain (Forrester 1960, Sterman 1989, and Lee at al. 1997a, 1997b). This is also very similar to the amplification effect in a services supply chain model observed by Anderson and Morrice (1999, 2000). The costs that are computed in the simulation model to compare different scenarios and effectiveness of control schemes, and consist of unit acquisition cost of $10,000, unit releasing cost of $20,000 and unit service penalty cost of $1,000. The accumulated cost for the scenario is $10,640,000. This cost will be compared with the costs from a scenario where the optimal feedback PID control is applied in section 5 below.

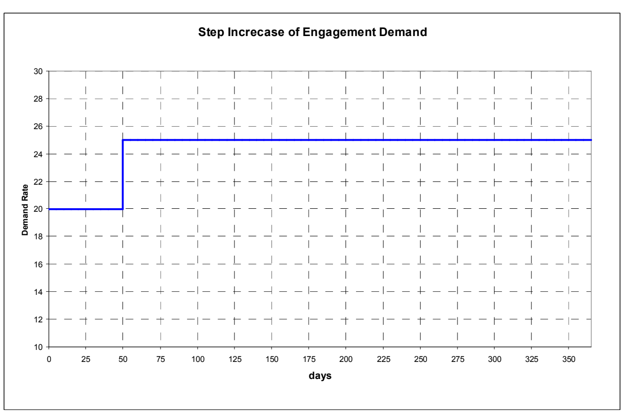

Figure 3: Step Increase of Demand

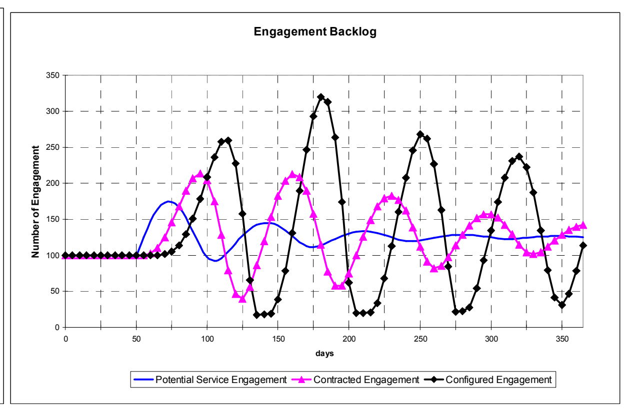

Figure 4: Engagement Backlog in Multi-Stage Service Process for a Step Increase of Demand

For simplicity, the control study first focuses on a single stage of the model. Therefore, we now separate the first stage, e.g., contracting stage, of the model and apply various control schemes. The general phenomenon observed in this stage is similar to the other stages. Figure 5 shows the simulation result of engagement backlog, which has a steady state initial value of 100 engagements, and then at day 50 it starts to jump and oscillate in response to the step increase of demand from 20 engagements per day to 25 at day 50. Figure 6 shows the resource capacity incoming rate and the resource capacity releasing rate. The resource capacity incoming rate is the rate of workforce capacity joining the firm as a result of acquisition start rate, after going through the acquiring in-progress pipeline. Once acquisition starts (with $R_s > 0$), the new resources become available according to an exponential decay model. The acquiring in-progress (in pipeline) has the resource incoming delay, T_h, and at the end of the delay, the arriving workforce gradually joins the firm as available resource. The resource releasing rate is the rate of workforce being released based on the surplus of resource capacity, ε^-_t,. Note that the resource incoming rate (R_i) and releasing rate (R_r) overlap due to the resource incoming delay. While the resource release rate (R_r) is positive (some resources are being released because the resource available is higher than the resource needed), additional resource may be joining the firm, arriving following an acquisition delay applied to resource acquisition actions that occurred in the past. Therefore, in this simulation setting as new workforce joins the firm, releasing can occur at the same time. However, the resource capacity acquisition start rate (R_s) would never overlap with the resource capacity releasing rate (R_r) because no acquisition should be initiated when workforce surplus is observed.

As it can be seen in Figure 5, the engagement backlog starts to grow, as the step increase of demand occurs at T=50 days, and the resource capacity discrepancy (shortage) also increases.

Due to the resource capacity action, R_s, additional resources start to join the firm at T=50, and gradually increase and peak at around T=70. The available resource (through acquisition) finally catches up with the needed resource, i.e., the net capacity discrepancy becomes zero at T=87 days; however, the incoming rate remains positive. At the around the same time (T=87 days), the releasing rate starts to kick in because the resource capacity available is higher than the resource capacity needed. The accumulated cost for the scenario (a single stage only) is $1,396,000. This cost will be compared with the costs for several scenarios where various PID control is applied.

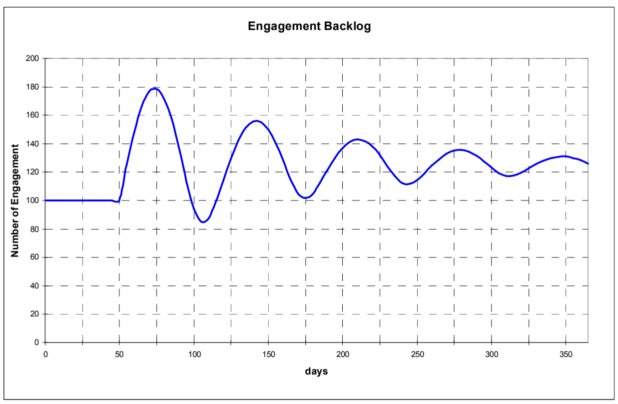

Figure 5: Engagement Backlog in a Stage for Step Increase of Demand

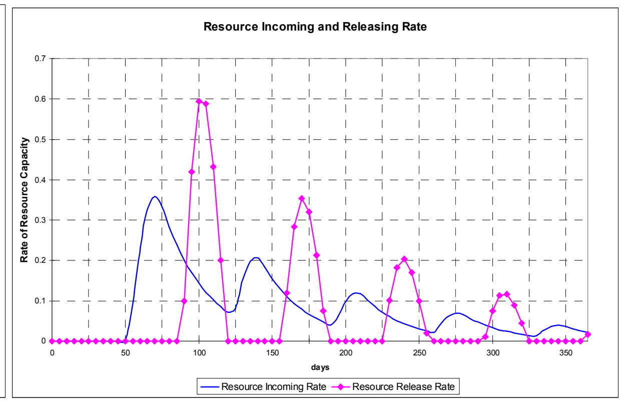

Figure 6: Resource Incoming Rate and Release Rate in a Stage for Step Increase of Demand

3.2 Simulation of a Demand Disturbance: Oscillatory Demand

The demand disturbance modeled here is an oscillatory demand, $A \cdot \sin \omega t$, with A= 5 and ω=0.05. In this setting, the overall average demand remains the same, but oscillates to simulate a simplified situation of demand seasonality. The demand profile is shown in Figure 7 below. The resource acquisition start rate, R_s, responds to this demand disturbance based on the discrepancy of resource capacity between supply and demand with the gain constant, K_c = 1.

Figure 8 shows the demand backlog changing over time for the three stages. The engagement backlog for the second stage (contracted backlog), is higher than the first stage (potential engagement backlog) and the backlog of the third stage (configured backlog) is, in turn, even higher than the second stage. As observed earlier in the scenario of step increase of demand, the oscillation of the backlog is amplified as it moves through the stages of the service supply chain. The accumulated cost for this scenario is $12,250,000.

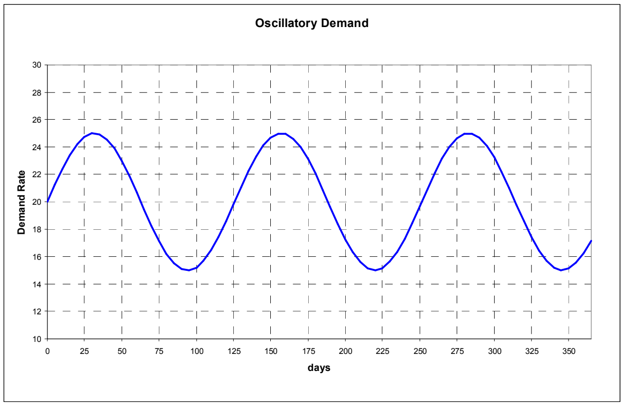

Figure 7: Oscillatory Demand

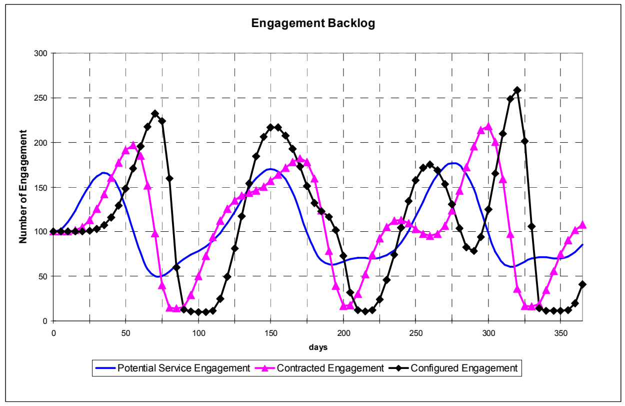

Figure 8: Demand Backlog in Multi-Stage Service Process for Oscillatory Demand

The engagement backlog of the first stage, i.e., contracting stage, is shown in Figure 9. The engagement backlog starts at 100 and oscillates between 170-180 engagement per day and 40-50 engagement per day. The oscillation is not as smooth as the demand arrival and somewhat distorted. This is because the period of the oscillatory demand cycles is not synchronized with the lead time of acquiring; therefore, there is some phase shift in downstream oscillatory pattern. As it can be seen later, our control scheme reduces the bumpiness of the backlog oscillations. Figure 10 shows the resource capacity incoming rate and resource capacity releasing rate. As in the step increase of demand case, the resource capacity incoming rate (R_i) and releasing rate (R_r) alternate and overlap due to the resource incoming delay. The profiles of engagement backlog (Figure 9) and resource capacity incoming/releasing rate for this naïve control setting with $K_c = 1$ will be later compared with more sophisticated control schemes. The accumulated cost for the scenario (a single stage only) is $2,803,000. This cost will be compared with the costs for several scenarios where various PID control is applied.

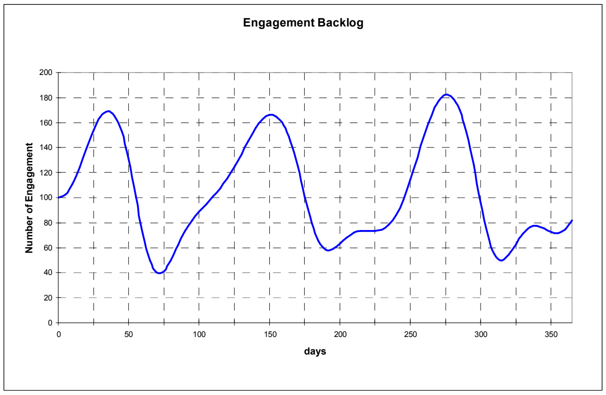

Figure 9: Engagement Backlog in a Stage For Oscillatory Demand

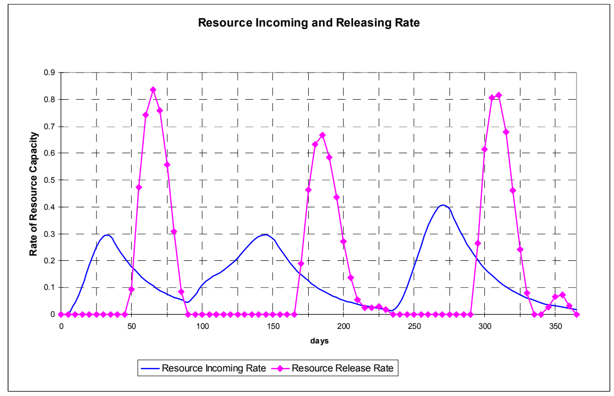

Figure 10: Resource Incoming Rate and Release Rate in a Single Stage for Oscillatory Demand

4 Feedback Control System

A feedback control system in the service supply chain can be represented by a block diagram as shown in Figure 11. (See D'Azzo and Houpis (1981) for principles of control theory and systems.) The diagram shows the flow of information around the control system and the function of each part of the system. The block diagram is a simplified view of a control system for the workforce model described in the earlier section. The needed capacity (target capacity), S^*, also called the set point, and the available capacity, S, enter the comparator, and their difference, the error, leaves the comparator and enters the controller. The set point in this case is the desired value of the systems variables, i.e., resource capacity needed. The error, ε, is split into two parts: ε^+ for shortage (as shown in Equation 4) and ε^- for excess.

Based on the size of the error, the controller computes control actions that are proportional (P), derivative (D), or integral (I) or combinations these such as PI (proportional-integral), PD (proportional-derivative) and PID (proportional-integral-derivative). Using the control action computed by the controller, the final control element determines the resource actions of acquiring or releasing. The new demand (load) and the resource action go into the process, and the available resource capacity is observed, and is again fed back to the controller as a feedback control (also called closed-loop system). The process here is the process defined in earlier section in Figure 1 and 2.

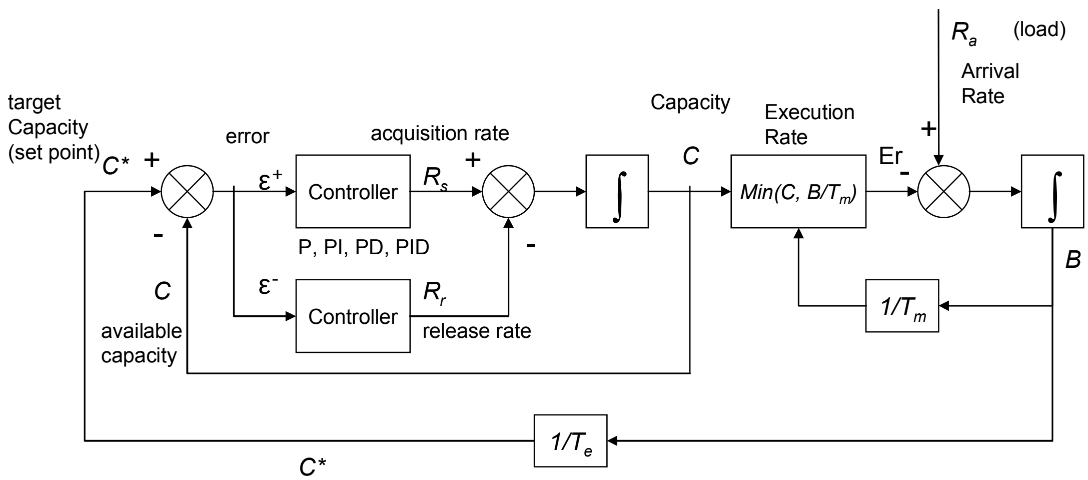

Figure 11: Block Diagram for the Control System

There are two control variables here: resource acquisition start rate (R_s) and resource release rate (R_r). For simplicity, we focus our PID feedback control study only on acquisition start rate (R_s) and use a very simplistic controller for the resource release rate (R_r). For the resource capacity acquisition start rate, R_s , and the controller can use a combination of P, D, or I controls as shown in Equation 7 below. The proportional controller produces a resource action which is proportional to the error ε^+ (shortage of resource) as shown in the first term in 7. The second term is the derivative control which is derivative of the error, which can be used to reduce the change of error from time to time. And the third term is the integral control which is based on the integral of the error, which can be used to reduce the accumulated error over time. The controller can be combinations of PI, PD or PID.

$$R_s = \left(K_c \varepsilon^+ + K_c \tau_D \frac{d\varepsilon^+}{dt} + \frac{K_c}{\tau_I} \int_0^t \varepsilon^+ \cdot dt \right) \Big/ T_a \tag{7}$$

Where ε^+_t = resource capacity shortage

K_c = gain (sensitivity) constant

T_d = derivative time constant

T_i = integral time constant

T_a = delay for resource acquisition process

For the services supply chain models (in both single-stage and multiple-stage) used in the simulation analysis in Section 3, the control variable (the resource capacity acquisition start rate, R_s) uses a simplistic, naïve control (using only the first term of Equation 7), i.e., a proportional control with the gain constant (also called proportional control constant) value of 1 (K_c = 1). The service supply chain modeled by Anderson and Morrice (1999, 2000) also used a special case (K_c = 1) of proportional control. In our work, we explore more sophisticated control schemes (P, I, D controls) for the service supply chain. Although we apply the control scheme only to acquiring (i.e., resource capacity acquisition start rate, R_s) but not to releasing (i.e, resource capacity releasing rate, R_r) for the sake of simplicity for this paper, we plan to apply control scheme to both acquiring and releasing in our subsequent paper.

5 Application of Feedback Control Schemes

The control variable in this services supply chain process is the resource capacity acquisition start rate, R_s . Therefore, the controller adjusts R_s to eliminate the error, which, in this case, is the resource capacity shortage. It seems natural to think that the controller should change the resource capacity acquisition start rate by an amount proportional to the error as done by Anderson and Morrice (1999, 2000); however, that is not always effective as we shall see below. Since the controller uses information about the deviation of the system from its desired state (zero error) to control the system, the system is a feedback control system.

5.1 Feedback Control for Step Increase of Demand

In this section, we apply PID feedback control schemes to the step increase demand disturbance shown earlier in Figure 3. We first study various magnitudes and effects of proportional control, derivative control and integral control. Then, the optimal PID control scheme is computed. For each scenario we compare the benefit of various control schemes with the naïve control shown in section 3.

5.1.1 Effect of Proportional Control: Step Increase of Demand

We use various settings for the proportional control, i.e., starting with $K_c = 1$, then increasing K_c gradually to 50. Figure 12 shows the profiles of backlog for $K_c = 1$, 10, 30 and 50, and Table 1 shows the total costs corresponding to the four K_c values. At first glance, it seems that the larger the value of K_c , the better the control. From $K_c =1$ to $K_c=10$, the magnitude of the backlog oscillation becomes smaller, and the total cost decreases to \$835,000 from \$1,396,000. However, as K_c increases beyond 10, a problem starts to appear. At $K_c = 30$ and 50, as shown in Figure 12, the oscillation of backlog fluctuates more (in reverse shape, though), and the resulting total cost increases to \$1,601,00 for $K_c =30$ and \$2,274,000 for $K_c = 50$ due to the oscillation of acquiring and releasing of workforce and the penalty of delayed execution of engagements. High values of K_c can introduce instabilities for step response demand disturbances. This causes an undesirable effect of the backlog fluctuating. Therefore, as K_c is increased beyond a certain value, the system becomes over-sensitive causing fluctuation of systems variables.

5.1.2 Effect of Derivative Control: Step Increase of Demand

In this section, we add a derivative control term, which is proportional to the derivative of the error, to the proportional control. Therefore, the control system becomes a PD (Proportional-Derivative) control, and the control equation would include only the first two terms in Equation 7. We use a constant proportional control (K_c =1), but increase the derivative term, T_d , from 0 to 5, 10 and 30. Derivative control typically stabilizes the response of the system by reducing the rate of change of system variables. As it can be seen in Figure 13, as T_d increases from 0 to 5 and 10, the amplitude of the oscillations reduces, and the total costs also reduce from $1,396,000 to $833,000 and to $593,000 (see Table 2), which is much better than the minimum costs we observed from the proportional control. However, as T_d becomes very large (e.g., T_d=30), although the stability is improved, the total cost increases to $1,592,000 as the control system now incurs large resource releasing costs.

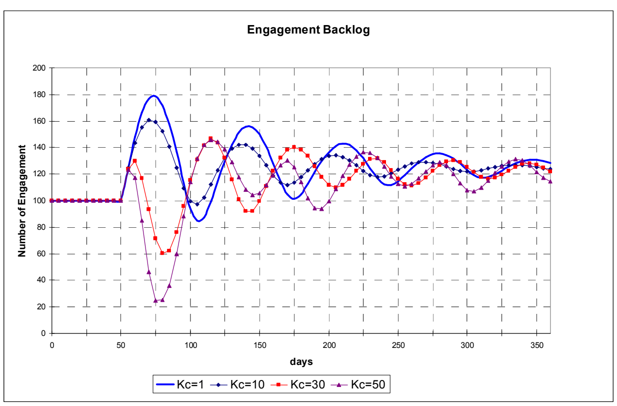

Figure 12: Effect of Proportional Control in a Single Stage For Step Increase of Demand

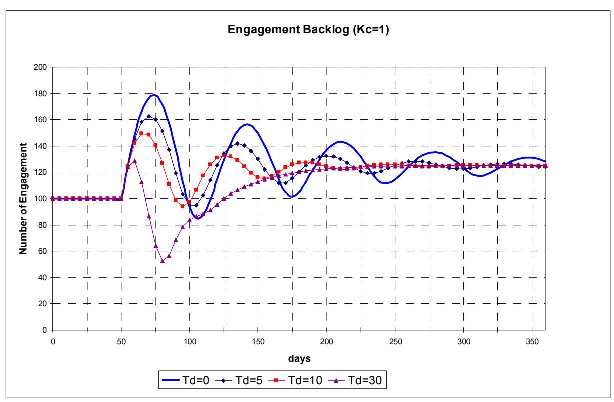

Figure 13. Effect of Derivative Control in a Single Stage for Step Increase of Demand

Table 1: Total Costs for Various P-Control Parameters

P-Control	D-Control	I-Control	Costs
$K_c = 1$	None	None	$1,396,000
$K_c = 10$	None	None	$835,000
$K_c = 30$	None	None	$1,601,000
$K_c = 50$	None	None	$2,274,000

Table 2: Total Costs for Various D-Control Parameters

P-Control	D-Control	I-Control	Costs
$K_c = 1$	$T_d = 0$	None	$1,396,000
$K_c = 1$	$T_d = 5$	None	$833,000
$K_c = 1$	$T_d = 10$	None	$593,000
$K_c = 1$	$T_d = 30$	None	$1,592,000

5.1.3 Effect of Integral Control: Step Increase of Demand

With proportional action only, the control system is able to change the control variable and modify the steady state value of the backlog. The difference between this new steady state value and the original value is called offset. The integral control is known to be effective in eliminating the offset. In our model, the proportional control eventually brings the state variable, net capacity discrepancy, to the steady-state value, $C_d = 0$, i.e., to the original value before the demand disturbance, after some fluctuations. Therefore, the P-control does not introduce an offset, and the integral control doesn't need to reduce the offset as in other systems where a steady state offset occurs. However, in order to show benefits of integral control, we start with a PD control (with K_c=1, and T_d=30), and increase the I-control (by reducing the T_i from very high number to smaller values, i.e., T_i of 300, 100 and 30) as shown in Figure 14. As the T_i value decreases to 100 from the very high value, the total costs actually improve from $1,592,000 to $1,273,000 as shown in Table 3. However, as T_i decreases further to 30, the oscillation of the backlog increases, and the total costs go to $2,376,000. Therefore, as seen in previous sections for P-control and D-control, though I-control can improve overall control of system in certain situations, too much I-control will produce negative effects.

5.1.4 Effect of PID Control: Step Increase of Demand

In this section, we attempt to find optimal PID control schemes by using an optimization capability available in Vensim, which uses the Powell optimizer (Ventana Systems Inc 1998). The optimization result indicates that for this services business model, the optimal control is a PD control with K_c=1.28 and T_d=9.88 with no integral control as summarized in Table 4. The total costs for this optimal control scheme is $558,000, which is lower than any other combination of P, D, or I control described earlier. Comparing with the simple proportional control (K_c =1) described in section 3.1, the total costs was reduced by 60% from $1,394,000 to $558,000.

Table 3: Total Costs for Various I-Control Parameters

P-Control	D-Control	I-Control	Costs
$K_c = 1$	$T_d = 30$	None	$1,592,000
$K_c = 1$	$T_d = 30$	$T_i = 300$	$1,407,000
$K_c = 1$	$T_d = 30$	$T_i = 100$	$1,273,000
$K_c = 1$	$T_d = 30$	$T_i = 30$	$2,376,000

Table 4: Total Costs for Optimal PID Control for a Single Stage

P-Control	D-Control	I-Control	Costs
$K_c = 1.28$	$T_d = 9.88$	None	$558,000

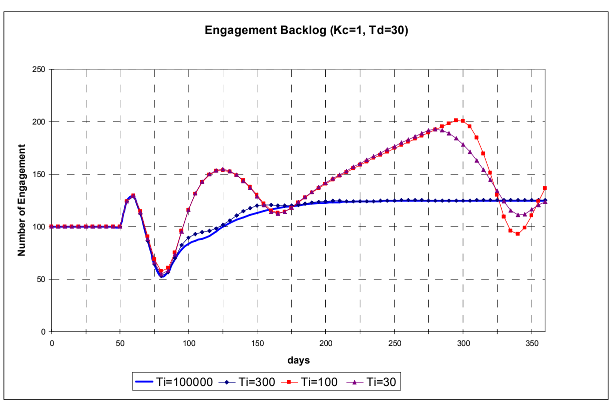

Figure 14: Effect of Integral Control in a Single Stage For Step Increase of Demand

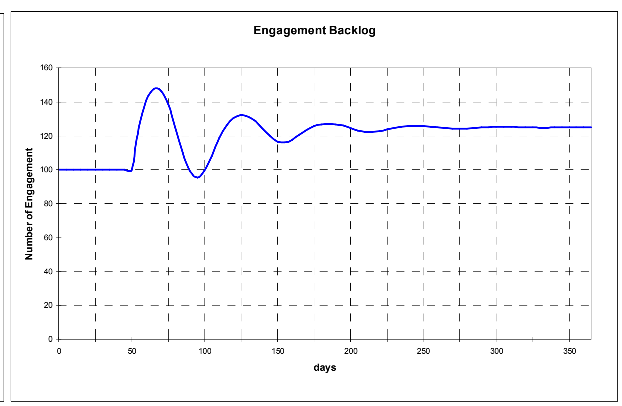

Figure 15: Effect of Optimal PID Control in a Single Stage for Step Increase of Demand

The profile of engagement backlog for the optimal control (Figure 15), having fewer oscillations and smaller amplitudes, looks much better controlled than one with simple proportional control (Figure 5). Similar improvement is also observed for the resource capacity discrepancy (ε^+) and the net capacity discrepancy (C_d), which also have fewer oscillations and smaller amplitudes than the ones for simple proportional control. For the optimal control, the acquiring and releasing is much better balanced (Figure 16) than the one for simple proportional control (Figure 6). Especially, the peaks for resource releasing rate are much less than the case of simple proportional control. This is significant improvement because unnecessarily releasing workforce in large numbers and acquiring back some would be a bad of workforce management practice.

Figure 17 shows engagement backlogs of the three stages when an optimal PID control is applied to all three stages. When compared with the scenario from the same model but without PID control (Figure 4 in section 3.1), there are substantial improvements in two aspects. First, the oscillations of engagement backlog in each of three stages seen here in this case with optimal PID control (Figure 17) are much less than the ones we saw in the case of naïve control in Figure 4. The amplitudes of the oscillations are much smaller and the oscillations diminish quickly. Secondly, the amplification of oscillations through the stages of the services business seen in the case of naïve control (Figure 4) completely disappeared. In fact, the oscillations of the backlogs are reduced as it moves through the stages of supply chain. Therefore, the bullwhip effect can be reduced through effective usage of PID control. The accumulated total cost for the optimal PID control scenario is $1,841,000, which is much lower than the naïve control case ($11,170,000). The value of control parameters and the total costs are summarized in table 5.

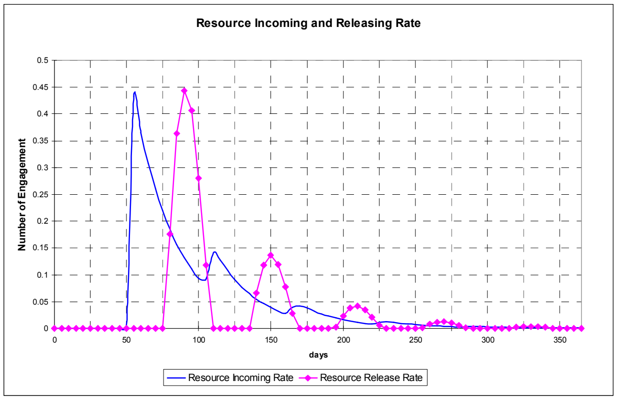

Figure 16: Resource Incoming Rate and Release Rate with optimal PID Control for s Step Increase of Demand

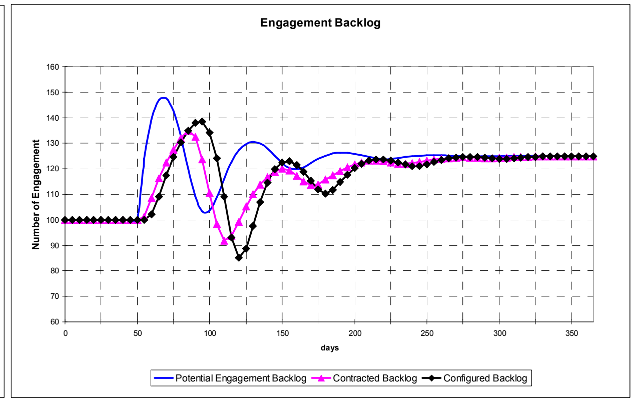

Figure 17: Engagement Backlog in Multiple-Stage with Optimal PID Control for a Step Increase of Demand

Table 5: Total Costs for Naïve Control and Optimal PID Control for Multiple Stages, Step Increase of Demand

	P-Control	D-Control	I-Control	Costs
Naïve Control	K_c (stage 1) = 1 K_c (stage 2) = 1 K_c (stage 3) = 1	None	None	\$11,170,000
Optimal PID Control	K_c (stage 1) = 1.26 K_c (stage 2) = 2.95 K_c (stage 3) = 4.58	T_d (stage 1) = 8.67 T_d (stage 1) = 26.6 T_d (stage 1) = 19.8	None	\$1,841,000

5.2 Feedback Control for Oscillatory Demand

In this section, we apply PID feedback control schemes to the demand disturbance of oscillatory demand shown in Figure 7 earlier. We first study various magnitudes and effects of proportional control, derivative control and integral control. Then, the optimal PID control scheme is computed. For each scenario, we compare the benefit of various control schemes with the naïve control shown in section 3. For the oscillatory demand, if the oscillation is known advance, a simple feedforward control could reduce the oscillation. In fact, if the lead time for acquiring or releasing matches the period of oscillation, the oscillation of backlog can be eliminated completely with a simple feedforward control. In this paper, we assume that the demand oscillation is not known in advance, and we focus our study only on feedback control.

5.2.1 Effect of Proportional Control: Oscillatory Demand

We use various settings for the proportional control, i.e., starting with $K_c = 1$, then increasing K_c gradually to 100. Figure 18 shows the profile of backlog for $K_c = 1$, 20, 70 and 100, and Table 6 shows the total costs for the four K_c values. At first glance, it seems that the larger the value of K_c, the better the control. From $K_c = 1$ to $K_c = 20$, the magnitude of the backlog oscillation becomes smaller, and the total cost decrease to \$2,206,000 from \$2,803,000. However, as K_c increases beyond 20, a problem starts to appear. At $K_c = 70$ and $K_c = 100$, as shown in Figure 18, the oscillation of backlog fluctuates more, especially in the bottom part, and the resulting total cost increases to \$3,081,000 for $K_c = 70$ and \$5,961,000 for $K_c = 100$ due to the oscillation of acquiring and releasing of workforce and the penalty of delayed execution of engagements. As seen in the case of step increase of demand, high values of K_c have the tendency of over-adjusting. That is, it is too sensitive to demand disturbances which would tend to disappear in time even with smaller K_c. This causes an undesirable effect of the backlog fluctuating. Therefore, as K_c is increased beyond a certain value, the system becomes over-sensitive causing fluctuation of systems variables.

5.2.2 Effect of Derivative Control: Oscillatory Demand

In this section, we add derivative control term, which is proportional to the derivative of the error, to the proportional control. Therefore, the control system becomes a PD (Proportional-Derivative) control, and the control equation includes only the first two terms in Equation 7. We use a constant proportional control (K_c =1), but increase the derivative term, T_d , from 0 to 10, 20 and 45. Derivative control typically stabilizes the response of the system by reducing the rate of change of system variables. As it can be seen in Figure 19, as T_d increases from 0 to 10 and 20, the amplitude of the oscillations reduces, and the total costs also reduce from $2,803,000 to $1,926,000 and to $1,551,000 (see Table 7), which is much better than the minimum costs we observed from the proportional control. However, as T_d becomes very large (e.g., T_d= 45), although the stability is improved, the total cost increases to $3,419,000 as the control system now incurs large resource releasing costs.

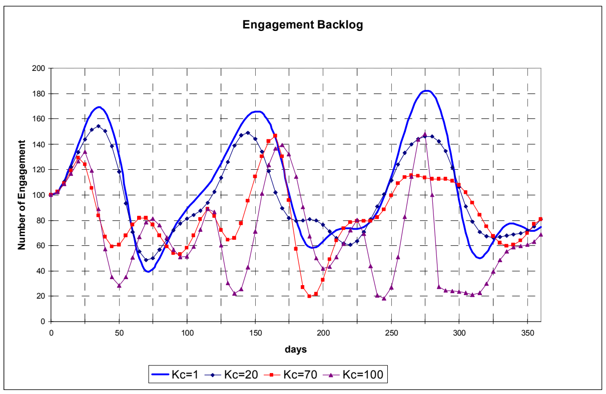

Figure 18: Effect of Proportional Control

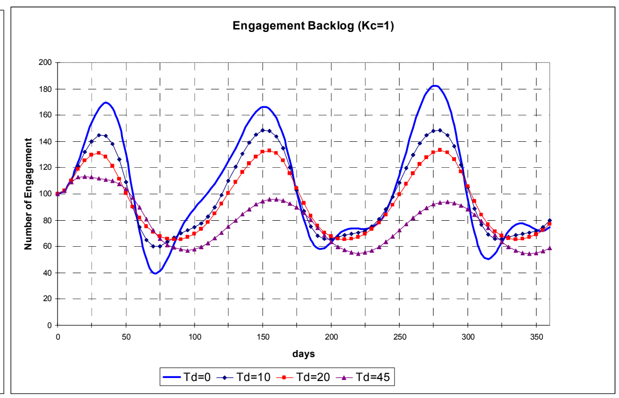

Figure 19: Effect of Derivative Control

Table 6: Total Costs for Various P-Control Parameters

P-Control	D-Control	I-Control	Costs
$K_c = 1$	None	None	$2,803,000
$K_c = 20$	None	None	$2,206,000
$K_c = 70$	None	None	$3,018,000
$K_c = 100$	None	None	$5,961,000

Table 7: Total Costs for Various D-Control Parameters

P-Control	D-Control	I-Control	Costs
$K_c = 1$	$T_d = 0$	None	$2,803,000
$K_c = 1$	$T_d = 10$	None	$1,926,000
$K_c = 1$	$T_d = 20$	None	$1,551,000
$K_c = 1$	$T_d = 45$	None	$3,419,000

5.2.3 Effect of Integral Control: Oscillatory Demand

In our model, the proportional control makes the state variable, net capacity discrepancy, oscillate around 0, i.e., $C_d = 0$, i.e., but with smaller amplitudes. The P-control does not introduce an offset; therefore, the integral control is not as useful as in other systems where a steady state offset occurs. However, in order to show benefits of integral control, we start with a PD control (with K_c=1, and T_d=30), and increase the I-control (by reducing the T_i from very high number to smaller values, i.e., T_i of 300, 100 and 5) as shown in Figure 20. As the T_i value decreases to 300 from the very high value, the total costs decrease from \$3,419,000 to \$1,789,000 as shown in Table 8. However, as T_i decreases further to 100, the oscillation of the backlog increases, and the total costs go to \$1,839,000, and then go to \$4,616,000 when $T_i = 5$. Therefore, as seen in previous sections for P-control and D-control, though I-control can improve overall control of system in certain situation, too much I-control will produce negative effects.

5.2.4 Effect of PID Control: Oscillatory Demand

In this section, we compute the optimal PID control schemes. The optimization result indicates that for the services business modeled here, the optimal control is a PD control with K_c=2.77 and T_d=24.7 with no integral control as summarized in Table 9. The total costs for this optimal control scheme is \$1,443,000, which is lower than any other combination of P, D, or I control described earlier. Comparing with the simple proportional control (K_c =1) described in section 3.1, the total costs was reduced by 48% from \$2,803,000 to \$1,443,000. The profile of engagement backlog for the optimal control (Figure 21), having smother oscillations and smaller amplitudes, looks much better controlled than one with simple proportional control (Figure 9). The optimal control scheme removed the bumpiness of engagement backlog that is observed in the naïve control (Figure 9). Similar improvement is also observed for the resource capacity discrepancy (ε^+) and the net capacity discrepancy (C_d). For the optimal control, the acquiring and releasing is much better balanced (Figure 22) than the one for simple proportional control (Figure 10). Especially, the peaks for resource releasing rate are much less than those occurring under the simple proportional control. This is a significant improvement because unnecessarily releasing workforce in large numbers and acquiring back some would be a bad of workforce management practice.

Table 8: Total Costs for Various I-Control Parameters

$K_c = 1$	$T_d = 45$	None	\$3,419,000
$K_c = 1$	$T_d = 45$	$T_i = 300$	\$1,789,000
$K_c = 1$	$T_d = 45$	$T_i = 100$	\$1,839,000
$K_c = 1$	$T_d = 45$	$T_i = 5$	\$4,616,000

Table 9: Total Costs for Optimal PID Control

P-Control	D-Control	I-Control	Costs
$K_c = 2.77$	$T_d = 24.7$	None	\$1,443,000

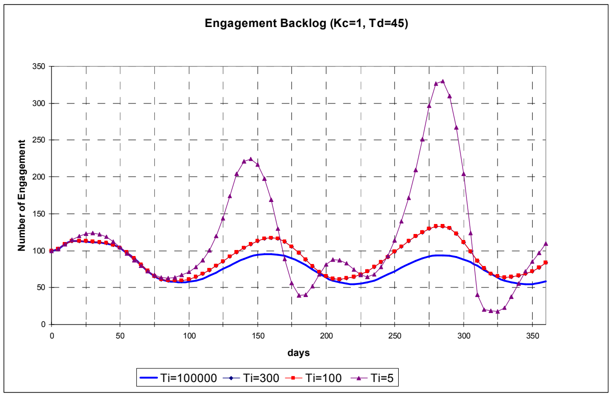

Figure 20: Effect of Integral Control

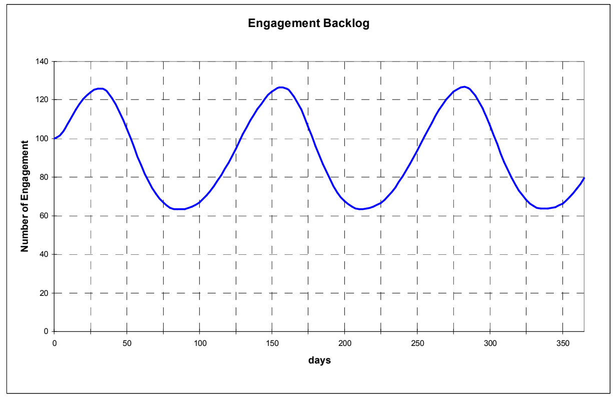

Figure 21: Effect of Optimal PID Control

Figure 23 shows engagement backlogs of the three stages when an optimal PID control is applied to all three stages. When compared with the scenario from the same model but without PID control (Figure 8 in section 3.2), there are substantial improvements in two aspects. First, the oscillations of engagement backlog in each of three stages seen here in this case with optimal PID control (Figure 23) are much less than the ones we saw in the case of naïve control in Figure 8. Amplitudes of the oscillations are much smaller and the oscillations diminish quickly. Secondly, the amplification of oscillations through the stages of the service business seen in the case of naïve control (Figure 8) almost disappear. The accumulated total cost for the optimal PID control scenario is \$4,780,000, which is much lower than the naïve control case (\$12,250,000). The value of control parameters and the total costs are summarized in table 10.

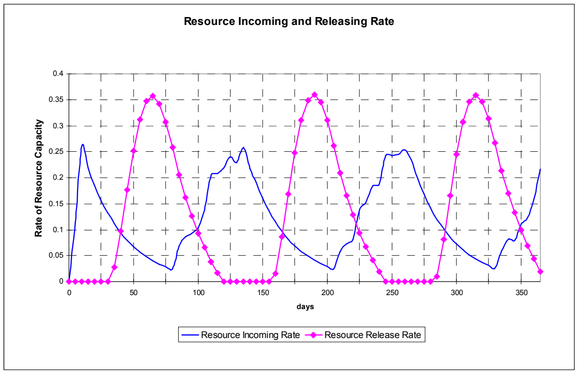

Figure 22: Resource Incoming Rate and Release Rate with optimal PID Control for an Oscillatory Demand

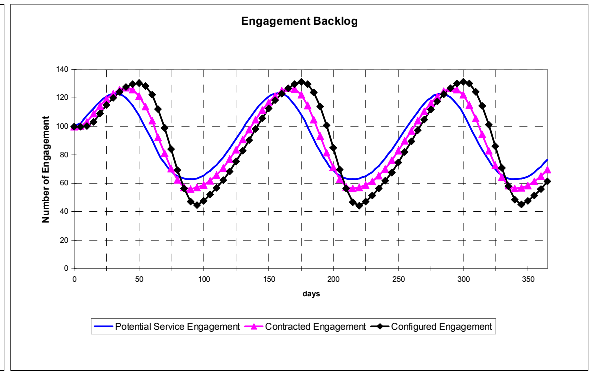

Figure 23: Engagement Backlog in Multiple-Stage with Optimal PID Control for an Oscillatory Demand

Table 10: Total Costs for Naïve Control and Optimal PID Control for Multiple Stages, Oscillatory Demand

Naïve Control	K_c (stage 1) = 1 K_c (stage 2) = 1 K_c (stage 3) = 1	None	None	\$12,250,000
Optimal PID Control	K_c (stage 1) = 3.03 K_c (stage 2) = 1.43 K_c (stage 3) = 1.07	T_d (stage 1) = 27.1 T_d (stage 1) = 26.9 T_d (stage 1) = 15.3	None	\$4,780,000

6 Conclusion and Future Research

Control theory has been used for many years in chemical and electrical engineering problem of controlling various processes, and recently in supply chain management problems. The analysis and design of feedback control systems that incorporate PID controllers is well-established; however, they have not been applied to the new area of services supply chains. Demand disturbances in a services business can be managed effectively by applying control theory to the resource adjustment such as acquisition, release and cross training of workforce.

The oscillation of service backlog and discrepancy between demand and workforce can occur when simplistic feedback control method is used, and amplification of the oscillation can be propagated through the stages of the service supply chains. In this paper, we describe an exploratory study evaluating the applicability of classical control theory to managing workforce in service supply chain. Our study indicates that each of proportional, integral and derivative control can have some effect of reducing the oscillation of service backlog or resource. However, excessive usage of the control methods can bring even more oscillation. The best control schemes are different for different processes. Optimal control schemes can be computed to determine the best combination of PID control for various services supply chains. Our study indicates that effective use of feedback control schemes can substantially reduce oscillation between acquisition and release, and amplified oscillation through the stages of the service processes in management of workforce. The PID feedback control can improve costs, utilization and stability of workforce in services businesses. The benefits of PID control is evident for two situations of demand disturbances; when there is a step increase of demand and when there is oscillation of demand without any average net increase.

It should be stressed that the feedback controller we described here is never meant to make decisions by itself on resource adjustment by replacing human decision makers. The control scheme can, however, provide useful information to the workforce resource managers as a decision support tool, so that good decisions, which minimize undesirable effects such as oscillation and its amplification of workforce resource adjustment, are made. The feedback control is also an effective way to handle impact of noises coming into the process. We plan to extend our research by analyzing various demand disturbances in many services business environments, and generate useful insights that can lead to effective management of workforce. Managing workforce resource action for services businesses with a PID feedback control scheme is a good example of applying science to services, which have long been considered an art rather than a science.

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