

# Dynamic Load Balancing in Parallel Queueing Systems: Stability and Optimal Control

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## **Abstract**

We consider a system of parallel queues with dedicated arrival streams. At each decision epoch a decision-maker can move customers from one queue to another. The cost for moving customers consists of a fixed cost and a linear, variable cost dependent on the number of customers moved. There are also linear holding costs that may depend on the queue in which customers are stored. Under very mild assumptions, we develop stability (and instability) conditions for this system via a fluid model. Under the assumption of stability, we consider minimizing the long-run average cost. In the case of two-servers the optimal control policy is shown to prefer to store customers in the lowest cost queue. When the inter-arrival and service times are assumed to be exponential, we use a Markov decision process formulation to show that for a fixed number of customers in the system, there exists a level  $S$  such that whenever customers are moved from the high cost queue to the low cost queue, the number of customers moved brings the number of customers in the low cost queue to  $S$ . These results lead to the development of a heuristic for the model with more than two servers.

## 1 Introduction

The problem of scheduling jobs in parallel processing networks has widespread use in computer, telecommunications, manufacturing, and even health systems. Given a set of processors, when a job (customer) arrives a decision-maker must decide where it should be served in order to maximize or minimize the given performance measure. In most models this decision must be made immediately and is thus, a routing decision based on the loads of each queue in the network. The customer must then wait in queue for the processor (server) to become free before receiving service. We consider a model that is quite different. Instead of a routing decision made upon arrival we allow the decision of where a customer is served to be a load balancing decision that can be made upon arrival and then adjusted at several discrete points in time. That is, suppose we again have a system of parallel queues but that each queue has a dedicated arrival stream. At some (possibly random) points in time a manager may choose to move customers in a particular queue to one of the other queues. Once this decision is made, customers move from one queue to the other with certainty and instantaneously. In this manner, a decision-maker may ensure that the load is balanced so as to avoid idleness and/or high holding costs.

The topic of load balancing in distributed systems has a vast literature, particularly in the area of multiprocessor/multicomputer systems. Two general references are the monographs of Shrazi et al. [17] and Bharandwaj et al. [1]. Wang and Morris [19] provide a survey of results for several load balancing algorithms. These basically fall into the areas of routing (Join the Shortest Queue, etc.) and server movement (analysis of the system as a polling model). The determination of optimal routing policies to balance processor loads has been studied by many authors. A representative, but by no means exhaustive, list is the work of Liu and Righter [14], Boel and van Schuppen [2], Koole [9] and Towsley et al. [18]. The additional complication of synchronization of parallel tasks is incorporated into the optimal scheduling problem examined in Xia et al. [20], where the control mechanism is also the routing of incoming arrivals.

Of particular relation to this paper is the work of Lewis [11], He and Neuts [8] and Levine and Finkel [10]. As has been alluded to, the usefulness of the current model over the routing models is in the fact that the balancing decision is made after the customers have been assigned to a particular queue. That is to say that in the routing model, if a long service time has caused the queues to become unbalanced, the decision-maker has no recourse but to wait until the long queue empties, while in the load balancing model we may immediately balance the load. Lewis [11] considers the single server case with two admission control decisions, one immediately before service, analogous to our load balancing decision. He and Neuts [8] consider the two-server case restricting attention to policies that move a fixed number of customers when the difference in the queue lengths reaches a certain level. Both works make the assumption of exponential inter-arrival and service times and therefore discuss policies that are based solely on the queue lengths. In the latter the authors use Foster's criterion to show that if the total service rate is higher than the total arrival rate, the system is stable. A simple example will show that without the exponential assumption there exists reasonable policies for which this is not sufficient. The model studied here is a generalization of that in [10]: the arrival rates are allowed to be unequal and the cost structure is more general. In addition, the focus of this paper is to find the stability region and study the structure of optimal policies, whereas in [10] there is an a priori restriction to threshold policies.

We are interested in both the design and control of the load balancing system. Since control considerations cannot be addressed without first addressing the stability question, we discuss conditions under which policies yield a stable Markov chain; one for which there exists a stationary distribution. This is done without any distributional assumptions. We then discuss the two-server case to gain insight into the structure of an optimal control policy. Unfortunately, when the number of servers increases, making the queue length information available in real-time (for every server) is undesirable. Thus, in order to extend these results to the more general case we examine a heuristic policy based on a dynamic pairing scheme. The idea is quite simple. If a server becomes idle, it chooses a queue to be paired with and uses the optimal two-server balancing decision. This reduces the overhead required and takes advantage of the insights gained from the two-server problem.

The rest of the paper is organized as follows: We give a formal description of the model in Section 2. In Section 3 we discuss conditions under which a wide class of policies are stable. Section 4 contains the analysis of the optimal control of both the two-server and  $N$ -server models. We conclude in Section 5.

## 2 Problem Description

Consider a sequence of  $N$  parallel queues. Customers arrive to queue  $i$  at times  $\{\tau_k^i, k \geq 0\}$  such that  $\tau_0^i = 0$  and  $\sigma_k^i = \tau_{k+1}^i - \tau_k^i$  are independent and identically distributed (iid) for  $i = 1, \dots, N$ . The corresponding arrival rate to queue  $i$  is  $\lambda_i = 1/\mathbb{E}\{\sigma_1^i\}$ . The service processes of each queue are independent and similarly defined. That is, the  $n^{\text{th}}$  customer that is served by server  $i$  requires  $\eta_n^i$  time units of service where  $\{\eta_n^i, n \geq 1, i = 1, 2, \dots, N\}$  are assumed to be iid. We assume that each server has the same service rate  $\mu$ , but the underlying distributions may be different.

Let  $\Pi$  be the set of all non-anticipating policies. A policy  $\pi \in \Pi$  prescribes how many customers to move from one queue to another, given the number of customers in each queue (the queue length process), perhaps the amount of time each customer has been in service, the time since the last arrival to each queue and any other information that is required to make the (policy dependent) process Markovian. In the most general case, all of this information is captured by the current *state* of the system.

The cost for moving  $j$  customers contains a fixed cost  $K$  and a variable cost  $m_j$ . Furthermore, the system continuously incurs holding cost  $h_i n_i$  per unit time that queue  $i$  contains  $n_i$  customers (including the one in service). We seek to find a strategy for load balancing under the long-run average cost optimality criterion. Note here that the term “load balancing” is used somewhat loosely since the holding costs may cause the optimal policy to leave the distribution of the number of customers at each queue unbalanced. In some sense, perhaps “load distribution” would be more appropriate, but we will continue to refer to the control as balancing without further comment in hopes that it will cause no confusion.

For a fixed policy  $\pi$ , denote the set of decision epochs by  $\mathbb{D} \equiv \{\rho_k, k \geq 0\}$  and the state at the  $i^{\text{th}}$  decision epoch by  $X_i$ . For example, if  $\pi$  depends only on the queue lengths, then  $\mathbb{D}$  is the set of arrival times and service time completions. We assume that the time between decision epochs is bounded away from zero so that only a finite number of decisions can be made in a finite amount of time. If we let  $Q^\pi(t) = \{Q_1^\pi(t), Q_2^\pi(t), \dots, Q_N^\pi(t)\}$  be the queue length process under  $\pi$ , then  $X_i = Q^\pi(\rho_i)$ . Following

the notation of Puterman [13], let

$$g^\pi(x) = \limsup_{n \rightarrow \infty} \frac{\mathbb{E}_x^\pi \left\{ \sum_{i=0}^n \left[ k(X_i, Y_i) + \int_{\rho_i}^{\rho_{i+1}} c(X_i, Y_i) dt \right] \right\}}{\mathbb{E}_x^\pi \{ \rho_n \}}, \quad (2.1)$$

where  $Y_i$  is the action taken at decision epoch  $i$ ,  $k(\cdot)$  and  $c(\cdot)$  are the lump sum cost and cost rate of said action, respectively, and the expectation is conditioned on the initial state of the system under the policy  $\pi$ . The quantity  $g^\pi(x)$  is called the long-run average expected cost starting in state  $x$  under policy  $\pi$ . The objective then is to find a policy  $\pi^*$  such that  $g^{\pi^*}(x) \leq g^\pi(x)$  for all states  $x$  and all policies  $\pi \in \Pi$ .

### 3 Stability

In this section we discuss conditions under which the system is stable. As has been alluded to, this is done in a general enough fashion so as to not require restrictive assumptions. In particular, we would like to avoid having to restrict attention to policies based solely on queue lengths or those that only redistribute customers after a fixed amount of time. The heuristic described in Section 4.3 is in fact, a hybrid of these. In order to arrive at the main results of this section, we introduce the *fluid model*. That is, we replace the (random) arrival and service processes by deterministic processes defined by their rates, at which point these processes can be thought of as fluid flows. Upon applying several classic results of Dai [3] we arrive at the conditions for the stability of the load balancing network. We then extend these results to show that under the same conditions derived for stability, we can guarantee the finiteness of the average cost.

#### 3.1 System Dynamics

For the remainder of this section, fix an arbitrary policy  $\pi \in \Pi$ . In order to simplify notation for the quantities defined, we suppress dependence on this policy. For each  $j = 1, 2, \dots, N$ , let  $E_j(t)$  be the number of exogenous customers arriving to queue  $j$  in  $(0, t]$ . Let  $S_j(t)$  be the *potential* number of service completions by server  $j$  in  $(0, t]$ . That is to say that  $S_j(t)$  is the number of service completions that would occur if there were no idling of server  $j$ . Let  $A_j(t)$  be the residual arrival time at time  $t$  for stream  $j$  and let  $B_j(t)$  be the residual service time at server  $j$ . For convenience assume that  $A_j(t)$  and  $B_j(t)$  are right continuous for  $j = 1, \dots, N$ . Thus, we have

$$\begin{aligned} E_j(t) &= \max\{n \geq 0 : A_j(0) + \sigma_1^j + \dots + \sigma_{n-1}^j \leq t\}, \\ S_j(t) &= \max\{n \geq 0 : B_j(0) + \eta_1^j + \dots + \eta_{n-1}^j \leq t\}, \end{aligned}$$

where the maximum of an empty set is defined to be zero. Let  $T_j(t)$  be the cumulative busy time for server  $j$  in  $(0, t]$ . The evolution of the total number in the system,  $M(t)$ , is thus given by

$$M(t) = M(0) + \sum_{j=1}^N E_j(t) - \sum_{j=1}^N S_j(T_j(t)). \quad (3.1)$$

The functions  $T_j(t)$  are determined by the control policy  $\pi$ . Recall that  $\pi$  is assumed to be non-anticipating and that  $Q_j(t)$  is the number of customers in queue  $j$  at time  $t$ . Define

$$X(t) = (Q_j(t), A_j(t), B_j(t), D_k(t) : j = 1, \dots, N, k = 1, \dots, N_s),$$

where  $(D_k(t), k = 1, \dots, N_s)$  is an  $N_s$ -dimensional vector chosen such that  $X(t)$  is a Markovian state evolving on the state space  $\mathbb{X} = \mathbb{Z}_+^N \times \mathbb{R}_+^N \times \mathbb{R}_+^N \times \mathbb{R}_+^{N_s}$  and the process  $X$  has the strong Markov property. For example, if  $\pi$  is a policy such that decision epochs are spaced a constant,  $t_d$ , time units apart and decisions are made based on the queue length and residual time information, then  $N_s = 1$  and  $D_1(t)$  is the elapsed time since the last decision. If the inter-arrival and service times are exponential, residual time information is not necessary.

### 3.2 Stability of fluid models

Let  $q = M(0)$ . Suppose that the function  $(\bar{M}(\cdot), \bar{T}_j(\cdot) : j = 1, \dots, N)$  is a limit point of

$$(q^{-1}M(qt), q^{-1}T_j^q(qt) : j = 1, \dots, N)$$

when  $q \rightarrow \infty$ , where the dependence of  $T_j^q$  on  $q$  has been added for clarification. When it exists  $(\bar{M}(t), \bar{T}_j(t) : j = 1, \dots, N)$  is called a *fluid limit* of the system. Since we have been able to describe the system dynamics in the form (3.1), Dai [4, Theorem 2.3.2] yields that a fluid limit exists (it may not be unique). Furthermore, each of the fluid limits is a solution of the following set of conditions, known as the *fluid model*.

$$\bar{M}(t) = \bar{M}(0) + \sum_{j=1}^N \lambda_j t - \mu \sum_{j=1}^N \bar{T}_j(t); \quad (3.2)$$

$$\bar{M}(t) \geq 0, \quad (3.3)$$

$$\bar{T}_j(0) = 0 \text{ and } \bar{T}_j(\cdot) \text{ is non-decreasing for } j = 1, \dots, N. \quad (3.4)$$

As has previously been alluded to, (3.2) is a deterministic version of (3.1) with the arrival and service processes replaced by their rates.

The fluid model is said to be *stable* if there exists a fixed time  $t_0$  such that  $\bar{M}(t) = 0$ , for all  $t \geq t_0$ , for any fluid solution. The fluid model is said to be *unstable* if for every solution of the fluid model with  $\bar{M}(0) = 0$ , there exists a  $\delta > 0$  such that  $\bar{M}(\delta) \neq 0$ . Thus, stability of the fluid model states that eventually all queues will drain, and once drained, they remain empty.

Suppose that the following condition holds:

**P1.** For all  $t > 0$ , there exists  $\varepsilon > 0$  such that with probability one,

$$\lim_{q \rightarrow \infty} \sum_{j=1}^N T_j^q(t) \geq \left( \frac{\sum_{j=1}^N \lambda_j}{\mu} + \varepsilon \right) t - \delta$$

for some  $\delta < \infty$ .

Since a fluid limit is defined as  $q$  approaches infinity, for  $q$  sufficiently large, **P1** ensures that for all but a finite amount of time, the servers are working at a rate greater than the total arrival rate. Under **P1** the stability of the system is almost immediate (shown momentarily).

**Proposition 3.1 (i)** *If  $\sum_{j=1}^N \lambda_j < N\mu$ , then for any control policy  $\pi$  satisfying **P1**, the fluid model is stable and, thus, an invariant probability  $\varphi$  exists for  $X$ .*

**(ii)** *If **P1** does not hold with  $\varepsilon = 0$ , then the fluid model is unstable and  $X$  is transient.*

**Proof.** (i) From **P1**,  $\sum_{j=1}^N \frac{d}{dt} \bar{T}_j(t) \geq \varepsilon + \sum_{j=1}^N \lambda_j / \mu$  for  $j = 1, \dots, N$ . Examining (3.2) we have that  $\bar{M}(t) = 0$  for all  $t \geq M(0)/\varepsilon$ . Thus the fluid model is stable, and the existence of an invariant probability for  $X$  follows from Theorem 4.2 of Dai [3].

(ii) We have  $\sum_{j=1}^N \frac{d}{dt} \bar{T}_j(t) < \sum_{j=1}^N \lambda_j / \mu$ , which implies that if  $\bar{M}(0) = 0$ ,  $\bar{M}(1) \geq \sum_{j=1}^N \lambda_j - N\mu > 0$ , so the fluid model is unstable. The transience of  $X$  follows from Theorem 2.5.1 of Dai [4]. ■

Although **P1** is intuitive, it may be a bit unwieldy to verify. One might think that instead, we could assume that all servers are busy when the number of customers reaches a certain level. This would ensure that all of the capacity is eventually used. If this capacity is greater than the arrival rate, we again arrive at stability conditions. This is captured by the following alternative to **P1**.

**P1'**. For some  $T_M > 0$ ,  $M(t) \geq T_M \geq N$  ensures that all servers are busy at time  $t$ .

It is easy to see that if **P1'** holds, **P1** holds with  $\varepsilon = N - \sum_{j=1}^N \lambda_j / \mu > 0$  and  $\delta = 0$ . That is, **P1'** is more restrictive than **P1**. The next two examples illustrate policies that satisfy **P1'**.

**Example 3.2** Suppose the holding cost rate of server  $N$  is the smallest. Consider the policy that immediately routes customers that arrive to find their respective server busy to server  $N$ . Also, if server 1 through  $N - 1$  becomes idle, a waiting customer at queue  $N$  (if any) is moved to the idle server. This satisfies **P1'** with  $T_M = N$ . Furthermore, it has the desirable properties that it reduces idling and takes advantage of the fact that queue  $N$  has the smallest holding cost.

**Example 3.3** Consider the policy that moves customers only to avoid idling. If queue  $j$  becomes idle, a waiting customer is moved from the queue where  $h_j Q_j(t)$  is maximized; ties broken arbitrarily. This satisfies **P1'** with  $T_M = N$ .

Unfortunately, in general, **P1'** may be too restrictive. That is to say, it may not be necessary to require servers to be busy for all times  $t$ . Equally perplexing is the fact that for a large number of customers in the system **P1'** requires the decision-maker to keep queue length information for each queue (or at least signal when a queue is empty). We have already discussed the pitfalls of this proposition. The next example illustrates a simple class of policies that might be useful but that do not satisfy **P1'**.

**Example 3.4** Suppose that every  $t_d$  time units, the policy equalizes the number of customers in each queue (to within one customer). Then **P1'** does not hold, but **P1** holds with  $\varepsilon = N - \sum_{j=1}^N \lambda_j / \mu$  and  $\delta = N t_d$ .

We conclude our discussion of stability with an example to dispel the conjecture that the assumption that  $\sum_{j=1}^N \lambda_j < N\mu$  is enough to guarantee stability in general. Recall, this inequality was shown to be sufficient in the exponential case in [8].

**Example 3.5** Consider a policy with periodic arrivals and deterministic service times, with  $N = 2$ ,  $\lambda_1 = 6.5$ ,  $\lambda_2 = 0.5$ , and  $\mu = 5$ . Every  $t_d = 1$  time units, one customer is moved from queue 1 to queue 2. If  $q$  is chosen such that  $Q_1(0) \rightarrow \infty$  and  $Q_2(0) = 0$ , then

$$\sum_{j=1}^N T_j^q(t) \leq 1.3t < 1.4t.$$

This violates **P1** and Proposition 3.1 part (ii) yields that the policy is unstable. To stabilize the system, either the decision epochs need to be more closely spaced, or more customers must be moved at each decision epoch.

From a design standpoint, stability is a necessary consideration. To facilitate the control question, we begin by restricting attention to policies that yield finite average cost. To this end, we make the following additional assumptions.

**M1.** The interarrival and service times have finite second moments, i.e.  $\mathbb{E}[(\sigma_j^1)^2] < \infty$  and  $\mathbb{E}[(\eta_j^1)^2] < \infty$  for  $j = 1, \dots, N$ .

**Theorem 3.6** *If  $\pi$  satisfies **P1**, the system satisfies **M1** and  $\sum_{j=1}^N \lambda_j < N\mu$ , then  $g^\pi(x) < \infty$  for all  $x \in \mathbb{X}$ .*

**Proof.** From Proposition 3.1 (i) and Theorem 4.1 of Dai and Meyn [5], we have

$$\lim_{t \rightarrow \infty} \mathbb{E}_x[Q_j(t)] = \mathbb{E}_\varphi[Q_j(0)] < \infty.$$

From this, we also conclude that the mean time spent in the system by a customer from any stream  $j$ ,  $\lim_{t \rightarrow \infty} \mathbb{E}[W_j(t)]$ , is finite. The average cost can be broken into two parts; that due to the holding costs and that due to the switching costs. The portion due to the holding costs can be written,

$$\lim_{t \rightarrow \infty} \sum_{j=1}^N h_j \mathbb{E}_x[Q_j(t)] < \infty.$$

By assumption, the expected number of decision epochs that occur while a customer is in the system is also finite. Thus, the part of the average cost due to switching costs per unit time is finite and the result is proven.

■

## 4 Optimal Control

In this section we discuss the optimal control of the load balancing network. It should be clear that as the number of servers grows the size of the state space becomes intractable. In fact, even in the case with  $N = 2$ , without any distributional assumptions the state space is uncountable since (at the very least) the residual arrival and service times must be included. Our approach is thus to consider the two-server model and prove what we can about the structure of an optimal control policy in this case. We then take the insights gained from this model and develop a heuristic for control of the general  $N$ -server model. Unless otherwise stated for the remainder of the paper we assume **P1** and **M1** hold and that  $\sum_{j=1}^N \lambda_j < N\mu$ .

### 4.1 The Two-server model

In this section we study the model when  $N = 2$  in an attempt to understand more fully motivations for optimal control in the more general case. Under various assumptions we discuss the structure of an optimal control policy. The main point that should become obvious in this section is that the load balancing decision

should incorporate the desire to empty the system as quickly as possible and the need to do so at minimal cost. Without loss of generality we assume (unless otherwise stated) that  $h_1 \geq h_2$ . The first result states that one should not move customers to a higher cost queue except possibly to avoid idling.

**Theorem 4.1** *Suppose  $h_1 \geq h_2$ , then there exists an optimal policy that moves customers from queue 2 to queue 1 only when queue 1 is empty.*

**Proof.** The result is proved by a sample path argument. Consider two processes defined on the same probability space so that each sees the same sequence of inter-arrival times and service times. Denote process 1 by  $\{Y(t) = (Q_1(t), Q_2(t)), t \geq 0\}$ . This process uses a policy  $\pi$  that calls for moving  $k > 0$  customers from queue 2 to queue 1 when  $Y(t) = (i^*, j^*)$ ,  $i^* > 0$  where  $(i^*, j^*)$  is assumed to have positive probability of being reached during the cycle. Process 2,  $\{Y'(t) = (Q'_1(t), Q'_2(t)), t \geq 0\}$  uses the same policy as  $\pi$  with the exceptions detailed below. Each process begins at  $(0, 0)$ . For simplicity, if  $t'$  is a decision epoch we let  $\pi(t') = \kappa > 0$  when the policy calls for moving  $\kappa$  customers from queue 1 to queue 2. Similarly, let  $\pi(t') = \kappa < 0$  when the policy calls for moving  $\kappa$  customers from queue 2 to queue 1. Let

$$\begin{aligned}\alpha &= \inf\{t \geq 0 \mid Y(t) = Y'(t) = (i^*, j^*), \pi(t) > 0\} \\ \beta &= \inf\{t \geq \alpha \mid Y'(t) = (0, j) \text{ for some } j \geq 0\} \\ \gamma &= \inf\{t \geq \alpha \mid \pi(t) > 0\} \\ \delta &= \inf\{t \geq \alpha \mid Y(t) = (i, 0), \pi(t) = 0 \text{ for some } i \geq 0\}\end{aligned}$$

where the infimum of the empty set is taken to be infinite.

We now complete the description of  $\pi'$ . At time  $\alpha$ ,  $\pi'$  does not move any customers from queue 2 to queue 1. Thus,  $Y(\alpha) = (i^* + k, j^* - k)$  and  $Y'(\alpha) = (i^*, j^*)$ . Suppose first that  $\delta < \gamma \leq \beta$  so that  $Y(t) = (i, 0)$  while there are  $k$  customers in queue 2 of process 2. Then  $\pi'(\delta)$  moves  $k$  customers from queue 2 to queue 1 in process 2. The processes couple and the costs after  $\delta$  are the same. The difference in the total costs on the cycle is

$$D_0 \equiv k(\delta - \alpha)(h_1 - h_2) \geq 0.$$

Suppose  $\gamma < \delta \leq \beta$  or  $\gamma \leq \beta < \delta$ . That is,  $\pi$  calls for moving customers from queue 1 to queue 2 before queue 1 for process 2 empties or queue 2 for process 1 idles. Then  $\pi'$  moves only enough customers to queue 1 in process 2 so that the two processes coincide, after which,  $\pi'(t) = \pi(t)$  for all  $t > \gamma$ . The processes are then coupled and the costs thereafter on the cycle are the same. For example, if  $\pi(\gamma) = \ell$  (move  $\ell$  customers from queue 1 to queue 2), then  $\pi'(\gamma) = k - \ell$ . The difference in the total cost on the cycle is

$$D_1 \equiv k(\gamma - \alpha)(h_1 - h_2) + (2K + mk + m\ell) - (K + m|\ell - k|) > 0,$$

where the first term defines the difference in the holding costs for having held  $k$  more customers in queue 1 under  $\pi$  than  $\pi'$ . The remaining terms represent the difference in having to make 2 load balancing decisions under policy  $\pi$  and only 1 under  $\pi'$ .

If  $\beta \leq \gamma < \delta$  or  $\beta \leq \delta < \gamma$ , then  $Q'_1(\beta) = 0$ ,  $Q'_2(\beta) \geq k$  and  $Q_1(\beta) = k$ . At this point,  $\pi'$  calls for moving  $k$  customers from queue 2 to queue 1;  $\pi'(\beta) = k$ . The processes again are coupled and the costs thereafter are the same. The difference in total cost on the cycle in this case is

$$D_2 \equiv k(\beta - \tau)(h_1 - h_2) \geq 0.$$

In each case the total cost under  $\pi'$  is less than that under  $\pi$ . Furthermore, since the cycle times are the same, the average cost under policy  $\pi'$  is less than that under  $\pi$ . Since  $\pi$  was an arbitrary policy that moves work from queue 2 to queue 1 when  $i^* > 0$  the proof is complete. ■

We make several remarks that are apparent from the previous theorem. Notice that the proof of Theorem 4.1 does not depend on the arrival processes. Thus, using symmetry, if  $h_1 = h_2$  then there is no need to move customers from one queue to another unless one is empty. Consider now the case when  $h_1 > h_2$  and  $m = K = 0$ . Theorem 4.1 implies that we need not move customers from queue 2 to queue 1 unless queue 1 is empty. It is simple to see that if we move more than one customer, the holding cost is higher than if we had only moved one, yet the system is still working at the same rate ( $2\mu$ ). Since moving customers does not cost anything, the average cost on any sample path is higher. Similarly, arriving customers to queue 1 can be “stored” in queue 2 at a lower cost so that (at least) all but one of these customers should be moved to queue 2. That is, when there are no switching costs, the high cost queue is only used to avoid idling. If in addition to zero switching costs there is no high cost queue ( $h_1 = h_2$ ), then any non-idling policy is optimal.

Finally consider the symmetric case with zero variable switching costs;  $h_1 = h_2$ ,  $\lambda_1 = \lambda_2$  and  $m = 0$ . The previous remarks yield that we need not move customers unless one of the queues is empty. Furthermore, since the arrival rates are the same, when they are non-empty, both queues drain at the same rate  $\mu$ . If the decision is made to move customers, to avoid having to balance the load frequently, one should move precisely half of the customers.

We collect all of the ideas of the previous discussion in the next proposition. Since the methods of proof have already been outlined we omit proofs, but they follow from sample path arguments similar to that in Theorem 4.1.

**Proposition 4.2** *In the two-server problem if*

1.  $h_1 = h_2$  (equal holding costs), then there exists an optimal policy such that customers are moved from one queue to another only to avoid idling.
2.  $m = K = 0$  (no switching costs), then there exists an optimal policy such that there is never more than one customer in the queue with the highest holding cost.
3.  $m = K = 0$  and  $h_1 = h_2$ , then any non-idling policy is optimal.
4.  $m = 0$ ,  $h_1 = h_2$  and  $\lambda_1 = \lambda_2$ , then there exists an optimal policy that when customers are moved from one queue to the other, half (or the integer part of half) of the customers are moved.

## 4.2 The Exponential Case

In this section we assume that the inter-arrival and service times are exponential. We note that this assumption allows the interpretation that customers actually arrive to a router in accordance with a Poisson process of rate  $\alpha$  say, and that a customer is routed to queue  $i$  with probability  $\lambda_i/\alpha$  for  $i = 1, 2$ . The system dynamics for this model are the same as that in He and Neuts [8], the difference in our model is that the optimality criterion is quite different and we make no a priori restrictions to a particular class of policies. Of course, since the exponential assumption has been made, the stability conditions only require that  $\lambda_1 + \lambda_2 < 2\mu$ . For the remainder of this section assume that *uniformization* has been applied in the spirit of Lippman [12] with uniformization constant  $\Psi \equiv \lambda_1 + \lambda_2 + 2\mu$ . Without loss of generality we assume  $\Psi = 1$  so that the arrival and service rates can be interpreted as probabilities. Thus, instead of considering the continuous-time load balancing problem, we consider a discrete-time equivalent.

We develop a Markov decision process describing the average cost problem. We then further characterize the optimal policies by considering the structure of policies that achieve the minimum in the *average cost optimality equations* (ACOE), and are thereby average cost optimal. We first state the ACOE for our model. Let  $(I, i) \in \{(k, \ell) \in \mathbb{Z}^+ \times \mathbb{Z}^+ | k \geq \ell\} \equiv \mathbb{X}$ , where the first element represents the **total** number of customers in the system and the second element represents the number of customers in queue 2 (the low-cost queue). The ACOE for  $i \leq I$  are

$$g + h(I, i) = \min_{a \in \{-i, \dots, I-i\}} \{K 1_{\{a \neq 0\}} + m|a| + (I - i - a)h_1 + (i + a)h_2 + U(I, i + a)\}, \quad (4.1)$$

where

$$U(I, i) = \lambda_1 h(I + 1, i) + \lambda_2 h(I + 1, i + 1) + \mu h((I - 1)^+, i) + \mu h((I - 1)^+, (i - 1)^+).$$

It is well-known that if  $(g, h)$  satisfies (4.1) then  $g = g^* \equiv \inf_{\psi \in \Pi} g_\psi$  and  $h$  (often called a *relative value function*) is unique up to a constant. The fact that a solution to the ACOE exists follows from Theorem 3.6 and results in Meyn [15, Theorems 3.1, 5.1-2]. For brevity we simply note that the proof requires that the policy improvement algorithm be initialized with a policy with finite average cost. Since existence of such a policy is guaranteed by Theorem 3.6 the algorithm converges to a solution to the ACOE. The next result follows directly from the ACOE, but simplifies the search for an optimal policy considerably.

**Proposition 4.3** *Suppose that there are  $I$  customers in the system. There exists an  $S \leq I$  (dependent on  $I$ ) such that*

1. *the optimal policy does not move customers for  $i > S$  and*
2. *when customers are moved from the high to the low cost queue the number of customers in the low cost queue is  $S$ .*

The conspicuous use of “ $S$ ” in Proposition 4.3 is not accidental. The result states that the optimal policy is an *order-up-to* policy analogous to  $(s, S)$  policies in inventory control models. That is to say that if  $i < S$ , and it is optimal to move customers, then it is optimal to bring the number of customers in queue 1 up to  $S$ .

**Proof.** For  $0 \leq i \leq I$  let

$$G(I, i) \equiv mi + (I - i)h_1 + ih_2 + U(I, i).$$

The ACOE can be rewritten for  $i < I$

$$g + h(I, i) = \min\{G(I, i), \min_{a \in \{-i, \dots, I-i\}/\{0\}} \{K + 2ma^- + G(I, i + a)\}\} - mi, \quad (4.2)$$

where the superscript “ $-$ ” represents the negative part of  $a$ . Using the change of variables  $b = i + a$ , (4.2) becomes

$$g + h(I, i) = \min\{G(I, i), \min_{b \in \{0, \dots, I\}/\{i\}} \{K + 2m(b - i)^- + G(I, b)\}\} - mi.$$

Let

$$S \in \operatorname{argmin}\{b \in \{0, \dots, I\}/\{i\} \mid 2m(b - i)^- + G(I, b)\}.$$

Then directly from the ACOE we note that the optimal policy moves customers to make the number of customers in the low cost queue  $S$  when  $K + 2m(S - i)^- + G(I, S) < G(I, i)$ , moves no customers when the reverse inequality holds and is indifferent when equality holds. Furthermore, the results of Theorem 4.1 state that we need not move customers when  $I > i > S$  since that would entail moving customers from the low cost queue to the high cost queue when the high cost queue is not empty. Thus, the result is proven. ■

One might note that Proposition 4.3 does not eliminate from consideration the policy that does not move customers in state  $(I, i)$ , yet moves customers in state  $(I, i + 1)$ , where  $(i + 1 < I)$ . We conjecture that there exists an optimal policy that does not have this property. Indeed our numerical studies have confirmed this conjecture, but we have not been able to prove it to date.

This section has yielded several insights. There are in essence two questions that we have tried to answer:

- When should we move customers?
- When customers are to be moved, how many customers should be moved?

The first question is addressed in Theorem 4.1 and Proposition 4.2. The intuition is simple, we should move customers to avoid idling with the restriction that we would also like to have most of the customers in the lower cost queue. When these concerns are alleviated, several special cases arise.

The second question above is discussed in the context of the exponential assumptions. Under these assumptions the existence of an optimal policy that is analogous to the order-up-to policies found in inventory control is shown. That is, for each fixed number of customers in the system, when customers are to be moved, there is a number of customers in the low cost queue that it is optimal to meet. This of course is tempered by the fact that we do not move customers from the low cost to the high cost queue unless the low cost queue is empty. In the next section we attempt to apply these insights to the more general case with any finite number of servers.

### 4.3 The $N$ –server model

The results of the previous two sections give insight into how to design policies for systems with more than two servers. Unfortunately, implementing some of these ideas on a general network is undesirable due to the amount of information that must be provided to each processor. On the other hand, since we are able to construct simple optimal policies for two-server systems, we suggest a set of policies in which an idle server probes others until it finds a suitable match. The optimal two-server policy is then used to decide the number of customers to move. The advantage to this simple, scalable set of policies is that there is a minimal amount of communication overhead, while maintaining a connection to our previous results.

The set of policies we propose are similar to that suggested in Eager, Lazowska and Zahorjan [7] for a routing problem. For simplicity, assume equal holding costs, i.e.  $h_i = 1$ ,  $i = 1, \dots, N$ . The policy is (informally) described as follows:

1. When queue  $i$  empties, (randomly) choose another queue  $j$ .
2. Perform a transfer from queue  $j$  to queue  $i$  according to the optimal policy for the corresponding two-server system.
3. If no transfer takes place, choose another queue  $j$  that has not previously been selected. Repeat steps two and three until either a transfer is made or until all queues have been examined.
4. If queue  $i$  remains empty after this procedure, wait until a customer arrives to queue  $i$  or until some fixed time  $T$  elapses. Return to step one.

This set of policies has several desirable properties. First, decisions are made only at emptying times, which from Part 1 of Proposition 4.2 appears to be a reasonable choice. Second, a queue only needs to gather information from queues until a transfer is made. These first two properties result in low communication overhead. Once this communication is made, guidelines on how many customers should be moved, can be obtained from the results of Section 4.2 and in special cases, the remaining results of Propositions 4.2. In the exponential case, the order-to-levels can be stored in a one-dimensional array for easy look up. Finally, the policy is stable as **P1'** is satisfied for all  $t \geq T$ . This of course is crucial as a priori there is no need to believe a non-idling policy is stable.

To illustrate how this policy performs, we simulated a system with six servers, with arrival rates  $\lambda_1 = .75$ ,  $\lambda_2 = .9$ ,  $\lambda_3 = .85$ ,  $\lambda_4 = 1.10$ ,  $\lambda_5 = \lambda_6 = .8$ . The service rate  $\mu$  was set to one and we varied the switching costs. All inter-arrival and service times were assumed exponential. In implementing the policy, the choice of which server to examine made by an idle server was done so randomly (uniform). The time an idle server would wait before probing again was  $T = 100,000$ . The simulations were run using 30 replications of length 10,000. The resulting 95 percent confidence intervals for the mean cost are given in Table 1.

The results are quite promising, indicating that policies of this form merit further detailed study. Note that the original system would be unstable if no control were used. For the  $m = K = 0$  case, a benchmark would be an M/M/6 system, which yields an average cost of 9.50. The difference is due to the large value of  $T$ . It is not difficult to see that as  $T$  decreases, the behaviour would approach that of an M/M/6 system. The

$m$	$K$	Average cost
0	0	$11.25 \pm .94$
1	0	$13.31 \pm .90$
0	1	$13.18 \pm .85$
1	1	$15.31 \pm .80$
10	10	$33.63 \pm .83$

Table 1: Simulation results for a six-server system

choice of  $T$  thus involves a tradeoff between performance and overhead. Finally, when the costs increase by a factor of 10, the resulting overall cost roughly doubles, indicating that the proposed policy may be particularly useful in the face of high switching costs.

## 5 Conclusions

In this paper we have examined a method for dynamically balancing the load in parallel processing networks. We showed that in order to cover a larger class of policies, the assumptions implied by the exponential case are not sufficient. The fluid model opens the door to policies that are based on queue length, time since the last decision and/or those that are some hybrid of the two.

For control, we used a “divide and conquer” approach that is usual in operations research practice. By examining the model with only two servers, we gain valuable insights into the structure of an optimal policy in the  $N$ -server system. In particular, we note that when the switching costs are small, and the holding costs equivalent, the main concern is to avoid idling. In this case, a non-idling policy seems sufficient, but at the cost of an inordinate amount of overhead. In order to alleviate this difficulty, we discuss a simple policy that attempts to minimize idleness, but does so in a “smart” way. We use the optimal two-server policy and only probe a single server at a time. This is quite simple when we have equal holding costs. In a more complicated system, we expect to begin probing before the low-cost queue becomes empty. This complicates our heuristic somewhat, and provides an interesting challenge for future research.

In our numerical results, an idle server chose the next server to pair with uniformly. One extension may be that each server keeps information about the last state of the queues probed and uses this information to decide which queue to pair with next. This and other extensions will be undertaken in subsequent research.

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