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CHAPTER 3

An Equilibratory Market-Based Approach for Distributed Resource Allocation and Its Applications to Communication Network Control

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1. Introduction

Resource allocation in a multi-agent system is achieved through associating agents with resources and activities. Agents associated with activities (activity agents) request agents at resources (resource agents) for the resource they require, and resource agents decide whether requests are granted. Agents are given utility functions, and each agent takes actions independently of each other to maximize its utility. Agents may not know the global state of the system, and their actions are determined based on limited information of the system.

A key research question in multi-agent resource allocation is whether a multi-agent system as a whole achieves its global objective, when agents make independent decisions to maximize their own utilities based on limited information of the system. In order to investigate this question, we introduce a market model to multi-agent resource allocation.

In our market model, resources are allocated to activities through buying and selling of resources between agents. An activity agent is considered a buyer of the resource, and a resource agent is considered a seller of the resource. A seller takes actions to maximize its earnings, and a buyer takes actions to minimize its spending*. In our model, buyers do not communicate with each other, and thus, a buyer does not know what actions the other buyers take; sellers do not communicate with each other, and thus, a seller does not know the resource prices at other sellers. The only possible communication in our model is between sellers and buyers to send resource requests (from buyers to sellers) indicating how much resource buyers require and resource price notifications (from sellers to buyers). Since agents in our model decide on their actions with limited information of the system, heuristics (or *strategies*) are introduced. A seller's strategy concerns the pricing of the resource that the seller is associated with, and the buyer's strategy concerns the amount of the resource it requests.

In this chapter, we describe the proposed market-based approach and investigate its characteristics through simulations[9]. Two case studies are presented from the domain of communication network control. Communication networks are inherently distributed in nature and involve a number of entities (such as network nodes, switching machines, and communication channels) with their own utilities (such as channel utilizations), and they provide a good platform to investigate multi-agent systems.

In case study I, we investigate a sensitivity factor, which determines how changes are to be made in the resource requests in response to price changes. In case study II, we investigate the effect of communication delay associated with disseminating the price information from sellers to buyers. Since the communication delay causes oscillation in the proposed approach, a mechanism is proposed and studied to reduce the degree of oscillations.

There have been several papers which apply a market model to resource allocation in distributed computing[2,3,5,10,11,13], where CPU time and storage space are treated as resources. Market-oriented programming was also proposed and applied to a distributed resource allocation problem in transportation planning[14,15]. The existing work assumes that the resource prices are determined through bidding. In contrast, in our market based approach, called the *equilibratory* approach, the resource prices are determined by their associated seller based on the demand for the resource[8]. This eliminates the overhead associated with the bidding process.

The behaviors of a system under a communication delay is analyzed in compu-

*Minimizing the buyer's spending is equivalent to maximizing the buyer's utility when the utility function is, for instance, a negative or an inverse of the spending.

tational ecologies[7]. When a communication delay exists, an agent is forced to rely on outdated information, and it is shown that the system oscillates[7]. A mechanism to suppress this chaotic behavior was also proposed[6]. The work in computational ecologies emphasizes behaviors of the system as a whole rather than agent strategies. In contrast, this chapter considers agent strategies in detail.

In the following, we describe the proposed approach to distributed resource allocation (section 2) and simulation results (sections 3 and 4) in detail.

2. Equilibratory Market-Based Approach

2.1. Distributed Resource Allocation

We consider a distributed resource allocation problem where resources distributed over m different locations are to be allocated to n activities. Let $R_j(t)$ denote the total amount of the resource that activity j requires at time t. Note that $R_j(t)$ dynamically changes according to time t. Among $R_j(t)$, let us assume that activity j requests $x_{i,j}(t)$ amount of the resource from location i. $x_{i,j}(t)$ represents activity j's demand for the resource at location i at time t. Since activity j's total demand for the resource is $R_j(t)$, the following equation holds:

$$\sum_{i=1}^{m} x_{i,j}(t) = R_j(t) \quad (1 \leq j \leq n). \tag{1}$$

Let N_i denote the total amount of the resource at location i. We assume that N_i is constant. Since the total demand for the resource at location i is smaller than N_i, the following equation holds:

$$\sum_{j=1}^{n} x_{i,j}(t) \leq N_i \quad (1 \leq i \leq m). \tag{2}$$

We assume that the value of N_i is large so that the above constraint is always satisfied. In other words, resource requests are always granted, and the requested amounts of the resource are always allocated. Therefore, the demand for the resource at location i, $x_{i,j}(t)$, also represents the amount actually allocated.

Let $u_i(t)$ denote the utilization of the resource at location i at time t. $u_i(t)$ is defined as follows:

$$u_i(t) = \frac{\sum_{j=1}^{n} x_{i,j}(t)}{N_i}. \tag{3}$$

We introduce a global objective of equally utilizing resources at different locations.[†] In the simulations to be presented later in this chapter, we use the variance of the

[†]In a more general case, a set of global objectives may be considered. However, we consider a single global objective in this chapter to simplify simulations.

resource utilization, $V_u(t)$, as a measure of how close resource utilizations are at different locations. $V_u(t)$ is given as follows:

$$V_u(t) = \frac{\sum_{i=1}^{m}(u_i(t) - (\sum_{i=1}^{m} u_i(t))/m)^2}{m}. \tag{4}$$

The global objective is, then, to minimize the value of $V_u(t)$.

2.2. Market Model

In our market model, the resource at each location has its price. Let $p_i(t)$ denote the price of a unit amount of the resource at location i at time t. A seller at location i determines the price $p_i(t)$ based on its past demand, namely $\sum_{j=1}^{n} x_{i,j}(t')$ (where $t' < t$). Buyer j determines the amount $(x_{i,j}(t))$ of the resource to request from location i at time t based on the past price, $p_i(t')$ (where $t' < t$). In our model, it is assumed that there is no communication between sellers and between buyers. Thus, sellers do not know the prices of the resources at other locations when they determine the prices. Buyers do not know the current demand for the resources when they issue resource requests.

2.2.1. Seller's Utility

The objective of a seller is to maximize its earnings. We define the utility at time t of a seller associated with the resource at location i, $U_i^s(t)$, as follows:

$$U_i^s(t) = p_i(t) \sum_{j=1}^{n} x_{i,j}(t). \tag{5}$$

2.2.2. Buyer's Utility

The objective of a buyer is to minimize its spending. Spending at time t of a buyer associated with activity j is given by $\sum_{i=1}^{m} p_i(t)\ x_{i,j}(t)$. We define the utility $U_j^b(t)$ of buyer j as a negative of the spending, namely,

$$U_j^b(t) = -\sum_{i=1}^{m} p_i(t)\ x_{i,j}(t). \tag{6}$$

Note that minimizing a buyer's spending is equivalent to maximizing the above utility of a buyer.

A seller's utility is affected by buyers' decisions, i.e., how much resource buyers request from which locations $(x_{i,j}(t))$. Similarly, a buyer's utility is affected by seller's decisions, i.e., the price $p_i(t)$ of the resource at different locations. However, since communication in our model is restricted to that between buyers and sellers for sending resource prices (from sellers to buyers) and resource requests (from buyers to sellers), agents rely on their strategies (heuristics) to maximize their utilities.

3. Case Study I – Effects of a Sensitivity Factor

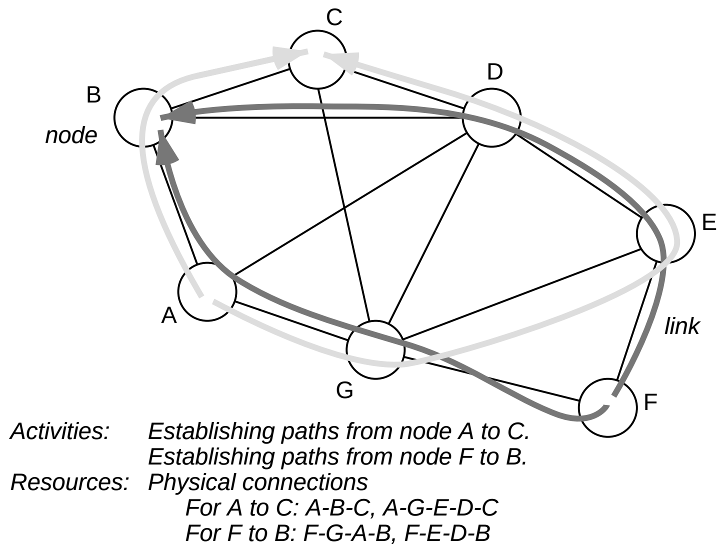


Fig. 1. Communication Path Example

In this section, we consider an example of establishing paths through a communication network. In our model, we assume that there are n source-destination pairs which require path establishment and that for the j-th source-destination pair ($j = 1, 2, \ldots, n$), there are l_j physical connections to choose from in order to establish paths. A physical connection may consist of multiple links, and some of the links making up a physical connection may be shared with physical connections for other source-destination pairs. See Fig. 1.

In this case study, activity j corresponds to establishing (one or more) paths for the j-th source-destination pair. The resource at location i corresponds to the bandwidth of physical connection i ($i = 1, 2, \ldots, m$), and its amount is denoted as N_i.

In establishing paths for the j-th source-destination pair, the sum of the bandwidths of the paths is kept constant and is denoted as R_j ($j = 1, 2, \ldots, n$). For activity j (to establish paths for the j-th source-destination pair), we use $\mathcal{S}_j$ to denote a set of l_j available physical connections ($|\mathcal{S}_j| = l_j$). Activity j issues resource requests only to these physical connections. Namely,

$$\begin{cases} x_{i,j}(t) \geq 0 & i \in \mathcal{S}_j \\ x_{i,j}(t) = 0 & i \notin \mathcal{S}_j. \end{cases} \tag{7}$$

The global objective is to equally utilize different physical connections.

In the following simulations, time is slotted. Communication between buyers and sellers (to exchange resource prices and requests) is done in each slot through separate and dedicated signaling channels and does not use any of the physical connections. Further, we assume that there is no communication delay between buyers and sellers. Sellers update resource prices in each time slot based on the demand for the resource in the previous time slot. Buyers calculate their resource requests based on the prices in the current time slot.

3.1. Agent's Strategy

3.1.1. Seller's Strategy

Since the objective of a seller is to maximize its earnings, its strategy is to raise the price when the demand for the associated resource (physical connections) is high, and lower the price when the demand is low. The demand for physical connection i in time slot t is the sum of the bandwidths of (1) paths which are already using physical connection i or part(s) of physical connection i, and (2) paths which newly request the use of physical connection i or part(s) of physical connection i. Since we assume condition eq. (2) in subsection 2.1 is always satisfied in this case study, new resource requests are always granted, and the demand for the resource becomes the same as the resource amount actually allocated to activities. Therefore, using the demand $\sum_{j=1}^{n} x_{i,j}(t)$, the resource utilization at location i is given by

$$u_i(t) = \frac{\sum_{j=1}^{n} x_{i,j}(t)}{N_i}. \tag{8}$$

In the following simulations, we use the resource utilization $u_i(t)$ as the price of the resource at location i for simplicity. Namely, we have

$$p_i(t) = u_i(t) = \frac{\sum_{j=1}^{n} x_{i,j}(t)}{N_i}. \tag{9}$$

3.1.2. Buyer's Strategy

In time slot t, buyer j determines the value of $x_{i,j}(t)$ (the amount of physical connection i's bandwidth to request) based on $p_i(t)$. For the least expensive physical connection in $\mathcal{S}_j$, say, physical connection k, we use the following equation to calculate the bandwidth to request at time t, $x_{k,j}(t)$,

$$x_{k,j}(t) = x_{k,j}(t-1) + \alpha(R_j - x_{k,j}(t-1)). \tag{10}$$

Here, α ($0 \le \alpha \le 1$) is called a sensitivity factor. If $\alpha = 0$, the above equation reduces to $x_{k,j}(t) = x_{k,j}(t-1)$, and the requested amount in time slot t becomes same as that in the previous time slot. If $\alpha = 1$, the above equation reduces to $x_{k,j}(t) = R_j$, and all the required resource is requested from physical connection k. For the other physical connections, say, physical connection $i \in \mathcal{S}_j$ $(i \neq k)$, the resource amount to request is determined using the following equation.

$$x_{i,j}(t) = (1 - \alpha) \times x_{i,j}(t-1) \quad (i \neq k). \tag{11}$$

Note that the sum of the requested amounts ($\sum_{i=1}^{m} x_{i,j}(t)$) becomes equal to the total amount of resources an activity requires (R_j).

3.2. Simulation Parameters

Parameter values used in the following simulations are as follows. The number of resources (physical connections) is 100 ($m = 100$), and the number of activities (source-destination pairs which require paths be established) is also 100 ($n = 100$). The total amount of the resource that each activity is required to obtain is constant and is equal to 50,000 ($R_j = 50,000$). The amount of the resource at location i (the bandwidth of physical connection i), N_i, is uniformly distributed between 1 and 1,000,000. Thus, the average of N_i ($\overline{N_i}$) is approximately 500,000. The total amount of the resource that exists in a system is $\overline{N_i} \times m = 500,000 \times 100$, and the total demand for the resource is $R_j \times n = 50,000 \times 100$. Thus, the average resource utilization is around 0.1 ($= (R_j \times n)/(\overline{N_i} \times m)$). For simplicity, we assume that there are five physical connections available to establish paths for a source-destination pair ($l_j = 5$ for all j). Note that a physical connection is shared by different source-destination pairs.

3.3. Simulation Results

Figure 2 shows the variance of the resource utilization as a function of time (measured in time slots). Different values of α ($0.002 \leq \alpha \leq 0.02$) are assumed. As seen in the figure, when the value of α is larger, the variance of the resource utilization decreases more rapidly. This is because with the larger values of α, the changes in the resource allocation becomes larger, speeding up the convergence.

Figure 2 also shows that after the variance reduces to a certain level, the variance of the resource utilization starts oscillating. This is explained as follows. When the demand for cheaper resources increases, their prices also increase; this increase in the price, in turn, reduces the demand, resulting in a decrease in the price; this, then, increases the demand. This leads to the oscillation observed in Fig.2.

When the value of α is small (0.005 or smaller in Fig. 2), the oscillation is insignificant and negligible, and the variance of the resource utilization converges. This represents an equilibrium point of the resource market, where resources are equally utilized (except for the small fluctuations due to the characteristics of a problem).

Figure 3 shows U^b, the average of the buyer's utility. As seen in this figure, when α increases, U^b also increases. This indicates that large values of α are preferable for

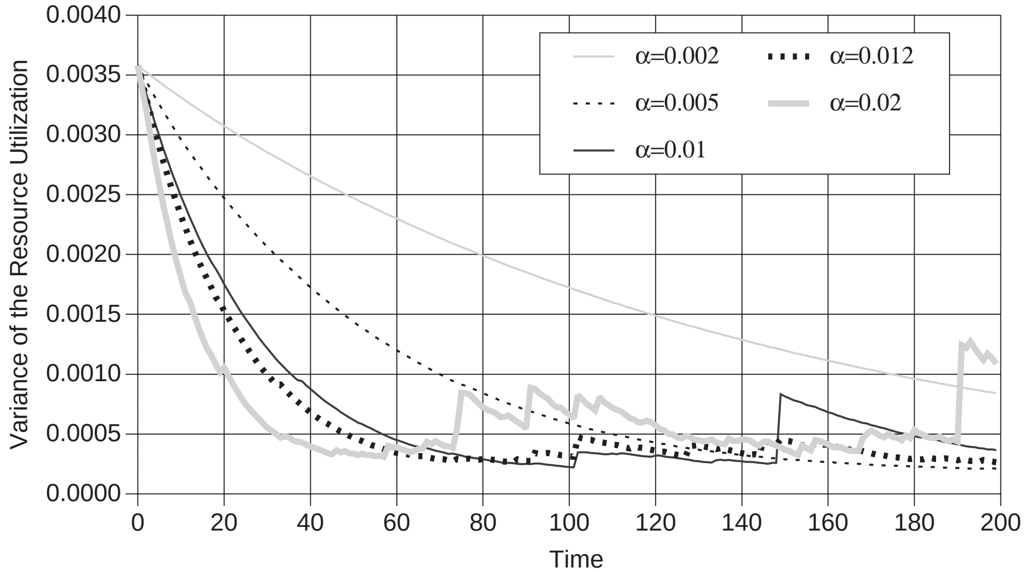


Fig. 2. Variance of the Resource Utilization (V_u) (Case Study I)

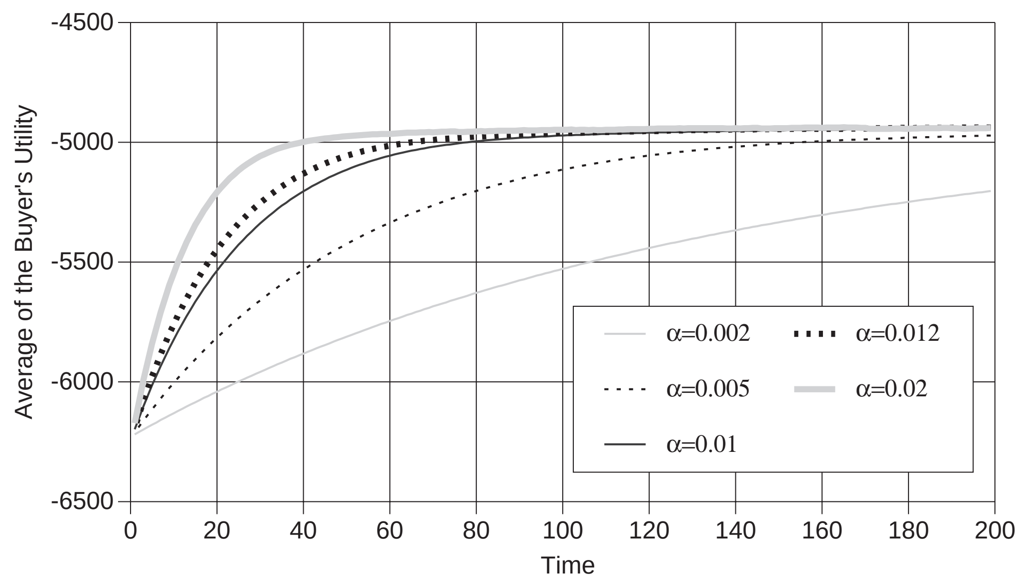


Fig. 3. Average of the Buyer's Utility (Case Study I)

buyers. This agrees with the intuition that buyers should purchase the least expensive resource as much as possible.

4. Case Study II – Effects of Communication Delay in Disseminating Price Information

In the second case study, we investigate the effects of communication delay associated with disseminating the price information to buyers. It is assumed that sellers broadcast the price information periodically with a time interval of length T and that there is a delay of D for the price information to reach buyers.

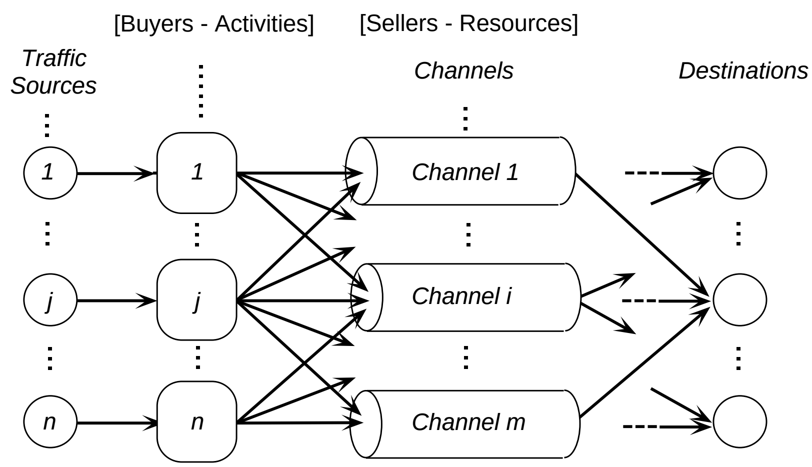


Fig. 4. Channel Allocation Model

In this case study, channels are assigned to newly arriving calls[12]. There are m channels (m resources) available for n traffic sources (n activities) to use. See Fig. 4. Calls are generated at each traffic source, and a newly generated call is assigned to a channel and uses a portion of the bandwidth of the assigned channel.

Channel i's bandwidth in this case study corresponds to the resource at location i in our market model, and the amount of channel i's bandwidth corresponds to the amount of the resource at location i, N_i. Seller i is associated with channel i ($i = 1, 2, \ldots, m$), and buyer j is associated with traffic source j ($j = 1, 2, \ldots, n$). A buyer purchases the bandwidth to accommodate a new incoming call. The amount of the bandwidth buyer j requires at time t is denoted as $R_j(t)$. $R_j(t)$ includes both the bandwidth to accommodate the existing calls (from traffic source j) and that required to accommodate a newly arriving call (also from traffic source j) at time t.

Although we assume that the bandwidth required to accommodate a call is constant, the value of R_j changes, since the number of calls generated from a traffic source varies over time.

4.1.1. Seller's Strategy

As in the case study I, the price of channel i's bandwidth is set to the utilization of channel i. Namely,

$$p_i(t) = u_i(t) = \frac{\sum_{j=1}^{n} x_{i,j}(t)}{N_i}. \tag{12}$$

4.1.2. Buyer's Strategy

Since the price information is broadcast with a constant time interval of length T, and since there is a delay D associated with the propagation of the price information, exact resource prices at a given time are not known to buyers. For a given time t, let $\langle t \rangle$ denote the most recent time that the price information was broadcast. Namely, $\langle t \rangle = \lfloor t/T \rfloor T$, where $\lfloor x \rfloor$ denotes the largest integer not exceeding x. Then, at time t, a buyer only knows the resource prices at time $\langle t - D \rangle$, namely, $p_i(\langle t - D \rangle)$ $(i = 1, 2, \ldots, m)$. Thus, we assume that buyers estimate the current resource prices from $p_i(\langle t-D \rangle)$ and determine how much resource and from which location it requests based on the estimated prices. We consider the following two estimation methods for buyers.

0th Order Estimation Let $\hat{p}_i(t)$ denote the estimated price of the resource at location i at time t. In the 0th order estimation, it is assumed that the price of the resource at location i at time t is same as that at time $\langle t - D \rangle$. Namely,

$$\hat{p}_i(t) = p_i(\langle t - D \rangle). \tag{13}$$

1st Order Estimation In the 1st order estimation, it is assumed that the rate of the price change (increase or decrease) during the time interval of $(\langle t - D \rangle, t)$ is same as that of $(\langle t - 2D \rangle, \langle t - D \rangle)$. In other words, the estimated price, $\hat{p}_i(t)$, is given by the following equation:

$$\hat{p}_i(t) = p_i(\langle t - D \rangle) + \{p_i(\langle t - D \rangle) - p_i(\langle t - 2D \rangle)\} \frac{t - \langle t - D \rangle}{\langle t - D \rangle - \langle t - 2D \rangle}. \tag{14}$$

When a new call is generated, channel bandwidth is allocated to this call. Let $\Delta R_j^+(t)$ denote the amount of the bandwidth required for a new call arriving from traffic source j at time t. Similarly, when a call ends, it releases the allocated bandwidth. The amount of the bandwidth released by a call terminating at time t is denoted as $\Delta x_{i,j}^-(t)$. The suffix i in this notation indicates where the allocated bandwidth originally came from.

Assume that a call from traffic source j ended at time t. Assume further that the resource allocated to this call was from i. The amount of resource that this call frees at time t is $\Delta x^-_{i,j}(t)$. Assume also that a new call arrives from traffic source j at time t. Assume that we allocate the resource at location i to this call. Then, the demand for the resource at location i at time t, $x_{i,j}(t)$, becomes

$$x_{i,j}(t) = x_{i,j}(t^-) + \Delta R^+_j(t) - \Delta x^-_{i,j}(t). \tag{15}$$

Note that t^- represents the time immediately before t.

Since the buyer's strategy is to minimize its expense, buyer j estimates the current resource prices and acquires the required resource for a new call ($\Delta R^+_j(t)$) from the one which it thinks the least expensive. Let us assume that buyer j estimates that the resource at location k is the least expensive at time t. Then, the amount of the resource that buyer j requests from location k is given by

$$x_{k,j}(t) = x_{k,j}(t^-) + \Delta R^+_j(t) - \Delta x^-_{k,j}(t). \tag{16}$$

For the resource at location i ($i \neq k$), its demand at time t is given by

$$x_{i,j}(t) = x_{i,j}(t^-) - \Delta x^-_{i,j}(t) \quad (i \neq k). \tag{17}$$

This is because $\Delta R^+_j(t)$ becomes zero for i ($i \neq k$), since a buyer acquires the resource for a new call only from the one which the buyer thinks is the least expensive (k).

4.2. Simulation Parameters

In the following simulations, we consider two traffic sources ($n = 2$) and two communication channels ($m = 2$), for simplicity. The bandwidth of each channel is assumed to be 156 M bits/sec, a typical ATM (Asynchronous Transfer Mode) channel bandwidth. The unit of the resource is assumed to be 1 kbits/sec, and thus, the 156 Mbits/sec represents 156,000 units of the resource (i.e., $N_i = 156,000$). Calls arrive from each traffic source according to a Poisson process with a rate of 1 call per 0.14 seconds, and call holding times follow an exponential distribution with an average of 60 seconds. These values represent typical phone calls. Each call requires a bandwidth of 64 kbits/sec or 64 units of resource, which corresponds to a PCM (Pulse Code Modulation) encoded voice.

4.3. Simulation Results

In the following two figures (Figs. 5 and 6) we assume that the time interval for price information broadcast, T, is negligibly small. Fig. 5 shows the variance of the resource utilization, V_u. This figure includes the results for the 0th order estimation and the 1st order estimation. Simulation results for the first 10 seconds are not shown in order to exclude the transient behavior of the system. As shown in this figure, when the communication delay D is 0 sec, V_u is almost zero. This is because buyers correctly

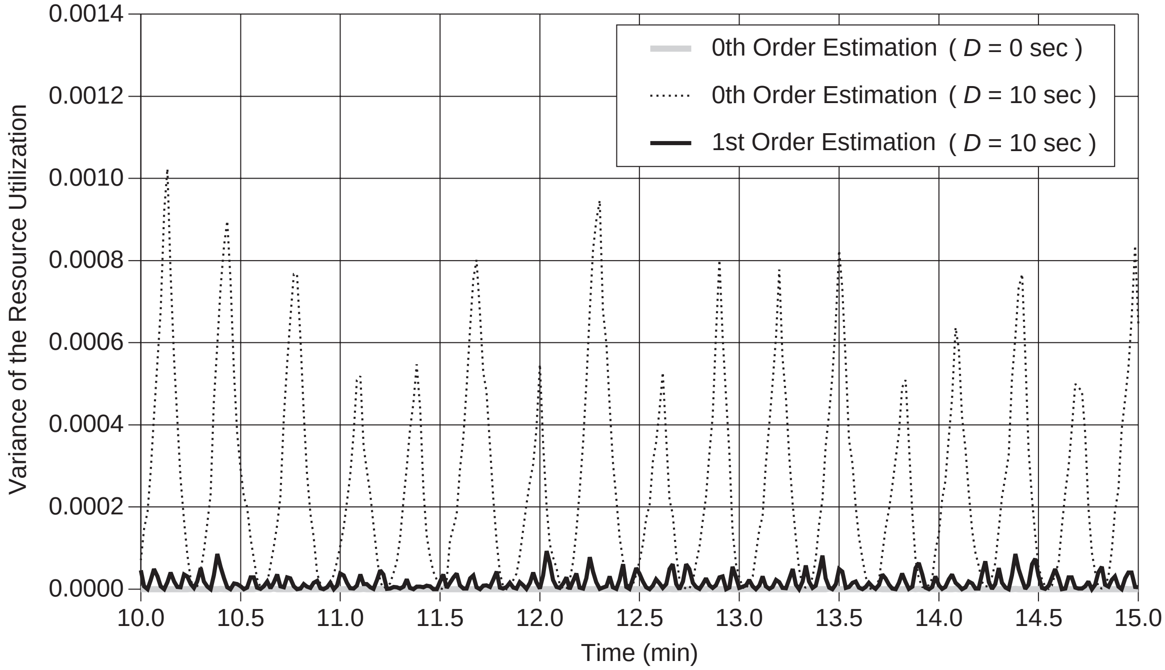


Fig. 5. Variance of the Resource Utilization (V_u) (Case Study II)

choose the least expensive resource (i.e., the least utilized channel), and the channel utilization imbalance is immediately corrected. However, when the communication delay exists ($D = 10$ sec), the values of V_u oscillate when the 0th order estimation is used. This is because buyers select resources (channels) based on outdated price information. On the contrary, when the 1st order estimation is employed, simulation results show that the degree of oscillation is reduced significantly, even when there is a communication delay of 10 sec. This indicates that the 1st order estimation effectively reduces the degree of oscillations, when changes in $R_j(t)$ during the interval of D are small.

Figure 6 shows the average of the buyer's utility, U^b $(= \frac{1}{2} \sum_{j=1}^{2} U_j^b)$. There is not a significant difference in U^b between the two estimation methods. This indicates that the different estimation methods only impact balancing the resource utilization.

4.4. Effects on the Cell Loss Rate[12]

In this subsection, we apply the proposed estimation methods to an ATM network, in which each call generates cells at a variable rate. In the ATM network, cell size is fixed, and the channel bandwidth actually used by a call is determined by the rate of cell generation of the call. Note that a channel is selected on a call-by-call basis, not on a cell-by-cell basis. Thus, once a channel is assigned to a call, all the cells belonging to the same call are transmitted on the same channel. This complicates the channel selection because the statistics of the cell generation are not known beforehand.

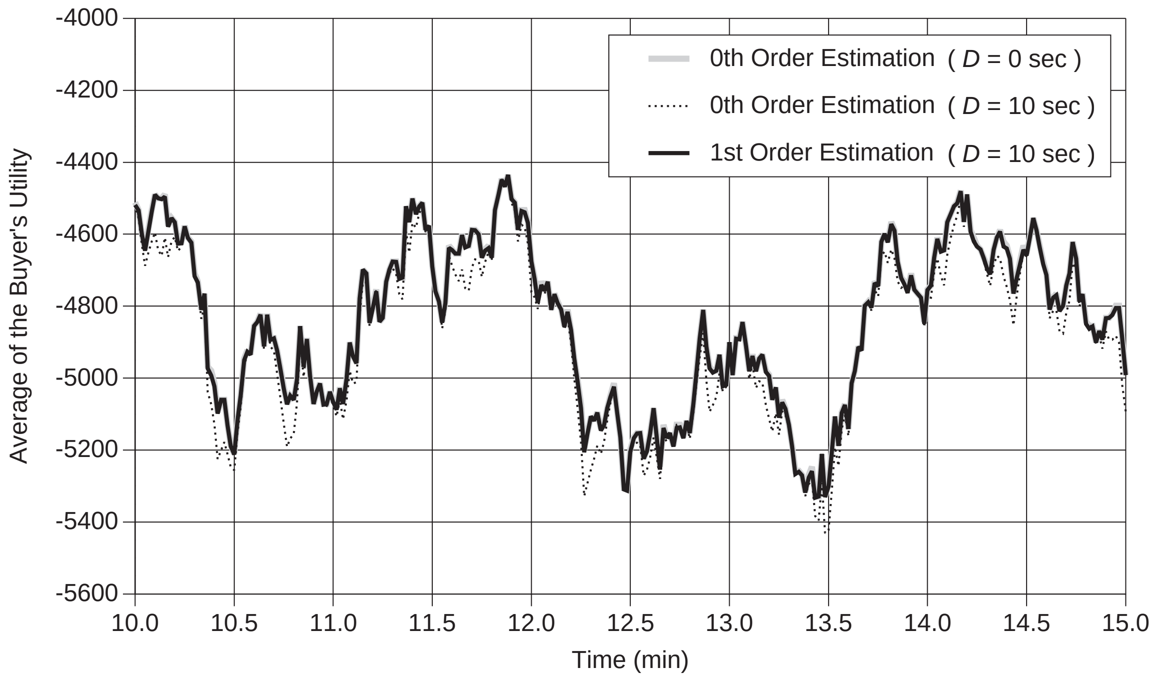
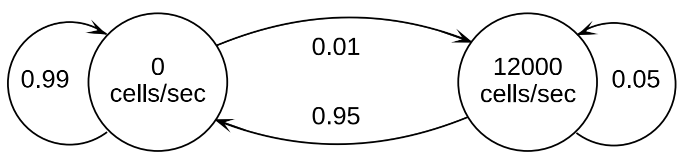
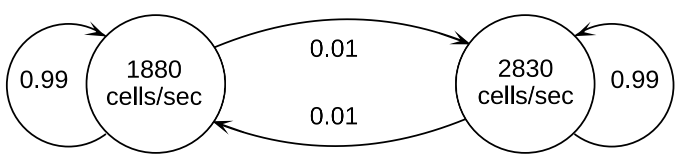


Fig. 6. Average of the Buyer's Utility (Case Study II)



(a) Bursty Cell Arrivals



(b) Non-Bursty Cell Arrivals

Fig. 7. Traffic Source Model

In order to examine the effectiveness of the proposed estimation methods, we conducted simulations. In the simulations in this subsection, we remove the assumption that all the resource requests are granted. Namely, condition eq. (2) in subsection 2.1 may not always hold. Rejected requests result in cell loss.

In our simulations, the cell generation process is modeled as an aggregation of two 2-state Markov Modulate Bernoulli Processes (MMBPs)[1] (See Fig. 7). The MMBP process in Fig. 7 (a) represents *bursty* cell arrivals (such as cell arrivals due to a scene change in a video sequence), and that in Fig. 7 (b) represents *non-bursty* cell arrivals (such as cell arrivals due to fluctuations between scene changes). The process in Fig. 7 (a) moves from an idle state (where the cell generation rate is zero) to a *burst* state (where cells are generated with Bernoulli intervals at the rate of 12,000 cells/sec, or equivalently, 5.08 M bits/sec with the standard 48 byte cell payload). The state transition probabilities are 0.01 (from the idle state to the burst state) and 0.95 (from the burst state to the idle state). The average time that the process stays in the idle state and in the burst state are 3 seconds and 1/30 seconds, respectively.

The process in Fig. 7 (b) generates cells in a similar manner. In one state, the cell arrival rate is 1,880 cells/sec (approximately 0.8 M bits/sec), while in the other state, the cell arrival rate is 2,830 cells/sec (approximately 1.2 M bits/sec). Cells are generated with geometrically distributed interarrival times. Note that this process generates cells at the average rate of 2,355 cells/sec (approximately 1 M bits/sec). Thus, the peak rate of the process in Fig. 7 (a) (i.e., 12,000 cells/sec) is approximately 5 times greater than the average bit rate of process in Fig. 7 (b).

The bandwidth of each of the two channels is assumed to be 1244.16 Mbits/sec, which corresponds to the standard OC-24 digital interface rate for SONET (Synchronous Optical Network). Calls are generated according to a Poisson process with the rate of 1 call per 0.41 seconds, and the average call holding time is 180 seconds.

Figure 8 shows the average utilization of the two channels. This figure shows the characteristics of the cell generation from the traffic sources. Fig. 9 shows the changes in the variance of the resource (channel) utilization as a function of time. In this figure, we assume the zero communication delay ($D = 0$) in order to examine the effects of the time interval T of the price information broadcast. Fig. 9 shows the results for the 0th order estimation with $T = 1/30$ sec and with $T = 30$ sec, along with the results for the 1st order estimation with $T = 30$ sec. When the 0th order estimation is used, the variance of the resource utilization is smaller for the $T = 1/30$ case than for the $T = 30$ case. This is because when T is smaller, buyers know more accurate (up-to-date) resource prices. Note that fluctuations seen in Fig. 9 are due to the changes in the cell generation rate of the traffic sources (shown in Fig. 8), not because the proposed estimation methods oscillate. When the 1st order estimation is used, the variance of the resource utilization becomes smaller, showing the effectiveness of the 1st order estimation.

If a burst cell arrival occurs during the period when the channel utilization is high, cell loss is likely to occur, since the channel bandwidth is limited. Thus, by suppressing the oscillation, and making the utilization of the two channels balanced, it is possible to reduce the cell loss. Fig. 10 shows the relationship between the cell

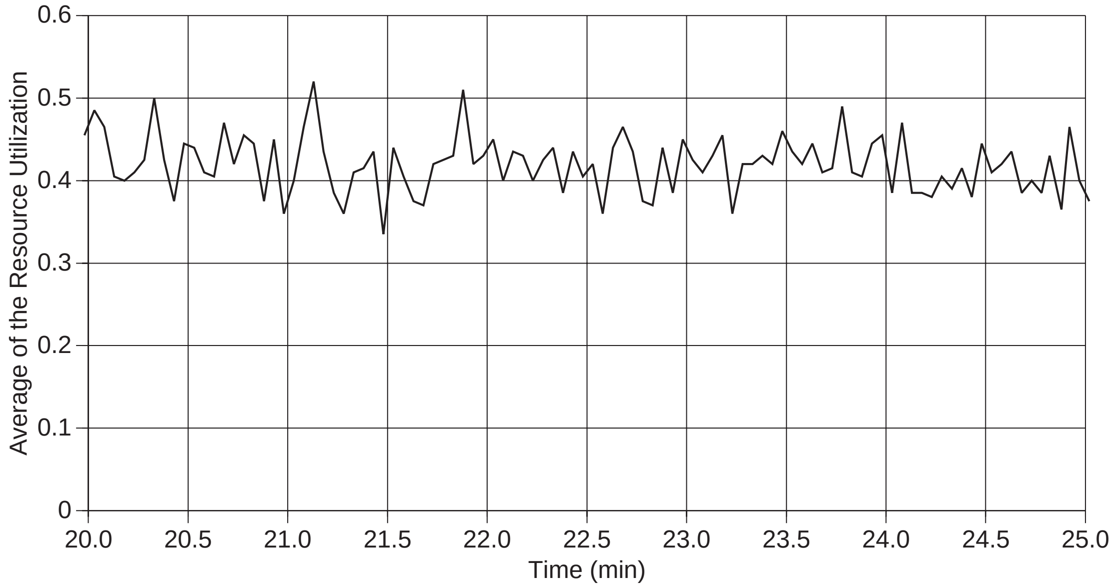


Fig. 8. Average of the Resource (Channel) Utilization

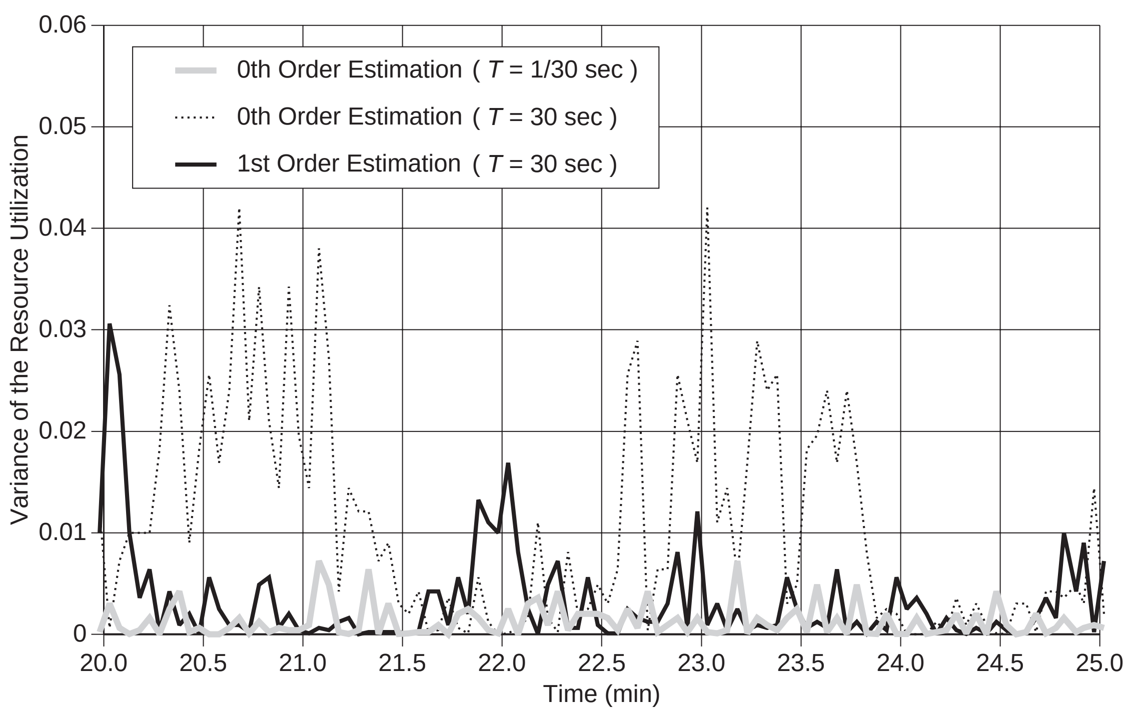


Fig. 9. Variance of the Resource (Channel) Utilization

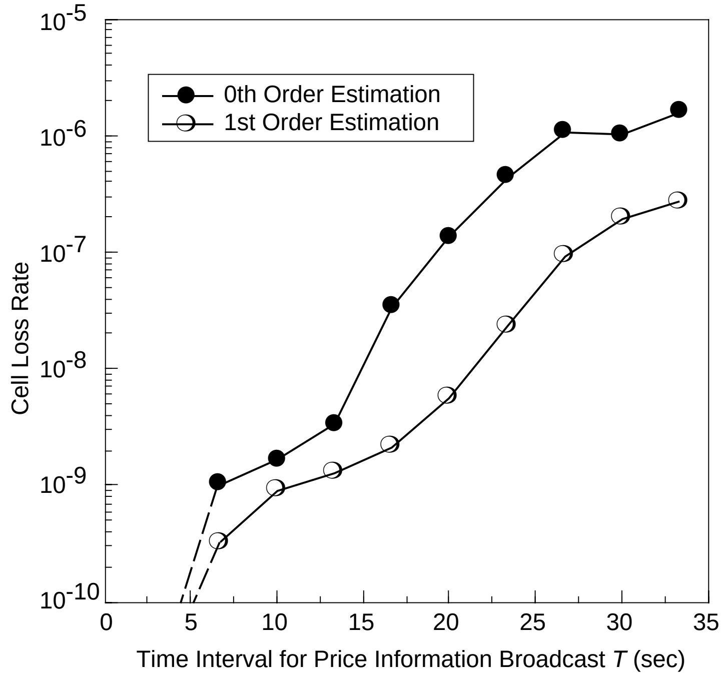


Fig. 10. Cell Loss Rate

loss rate and T, the time interval for the price information broadcast. It is seen that the 1st order estimation reduces the cell loss rate to approximately the 1/10-th. The proposed market-based approach with the 1st order estimation achieves low cell loss by reducing the degree of the oscillation.

5. Conclusion

In this chapter, the equilibratory market-based approach for distributed resource allocation was described, and its characteristics were shown through simulations. Two case studies from the communication network control domain were investigated through simulations. Simulation results showed that the proposed approach exhibits oscillation in the variance of the resource utilization.

Oscillation was caused by a large sensitivity value (case study I) and by the communication delay associated with disseminating price information (case study II). It was shown that small values of the sensitivity (case study I) and the 1st order estimation (case study II) reduce the degree of oscillation.

The proposed approach requires thorough investigation under more realistic parameter settings. Incorporating a learning mechanism in the agent's strategy also presents a challenging problem. A learning mechanism may be incorporated with or without a reward/penalty scheme (such as that seen in a co-adaptation system[4]).

Extending the proposed approach to accommodate different pricing structure is also important. For instance, the resource utilization was used as the price in our simulations. However, a number of different pricing structures are possible[8], leading to different overall system behaviors. In the domain of communication networks, not only the quantity of the channel bandwidth, but also its quality may be incorporated in the pricing structure. Users' preference may also be incorporated into the pricing structure. By incorporating users' preference to certain resources into the model, the proposed equilibratory market-based approach may be expanded to include economic activities of the user. The authors hope that the work presented in this chapter presents a first step toward this direction.

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