A LEARNING CONTROL APPROACH TO DYNAMIC NETWORK RESOURCE ASSIGNMENTS

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ABSTRACT

This paper proposes a learning control approach to dynamic network resource assignment control. The proposed method uses a learning approach to approximate the characteristics of the system to be controlled. Once the function is represented, optimum control inputs can be determined by using the prespecified control criteria. The potential function method which is well-known in the area of pattern recognition is used to approximate the function under an actual operating conditions. This control method is applied to two communications system models, a multi-speed circuit switched model and a circuit/packet integrated switched model. Simulation studies are conducted in order to evaluate the method. As a result it is revealed that the method is useful for controlling network systems in which an analytical solution cannot be obtained because of the complexity of the system and the traffic characteristics.

1. INTRODUCTION

In the near future, many communications services are expected to be incorporated in one integrated communications system thanks to the digitization of communications networks. In order to utilize communications resources efficiently in light of this development, it is desirable to establish a dynamic resource assignment control strategy. However, future communications services will probably have very different traffic characteristics. For example, the introduction of video communications will necessitate wideband communications channels, while teletex service requires a narrower bandwidth than existing telephone services. The holding time of calls will change. The average holding time of conference communications services will be rather long and that of message services short. In addition the distribution of the holding time will differ from that of the conventional telephone network.

Furthermore, service grade specifications for communications services are expected to diversify into many classes. For example, in the case of packet-switched services, services will be classified according to average delay time. For circuit-switched networks, different loss probability values will be the determining factor. All the foregoing factors must be considered if a practical control method is to be found.

Another problem may entail the selection of control criteria for operating the integrated network. These criteria will differ from those used for conventional networks in the complexity of loss probabilities or delays to be controlled, and will probably combine several different evaluation measures.

One effective way to approach this problem is to apply control theory to communications networks. Control theory analytically comes up with the optimum control inputs using the state equation which represent the dynamic characteristics of the system and an objective function which represent the control criteria. However, when communications networks are seen as control objects, many problems appear. These include the nonlinearity, the saturation characteristics and limitation of the control inputs of the system.

Segall, et.al. attempted to apply control theory to communications networks [1]. They approximated the amount of traffic which is retained in each node using a continuous state variable and taking the capacities of each link connected to the specified node as control variables. They showed optimum control inputs can be obtained analytically in a feedback form for the criterion of shortest possible delay time. This approach is desirable because the feedback control is robust to system variations. However, they had to make unrealistic assumptions concerning communications networks to solve the problem. These included assuming unlimited buffer capacities, no call origination during the control due to limitations on input traffic conditions, etc. These assumptions made in the study must be rectified before actual application can be considered.

A less problematic approach is to apply learning control. In fact, this is the only approach which can be practically applied to communications network control at the moment. Narendra, et al. attempted learning control of telephone network routing [2]. They used learning automata to determine the order of routing link selection at the network nodes. A learning automaton is a kind of probabilistic automaton whose transition probability changes according to the penalty which it gets after each trial. They showed that lower loss probability could be obtained by using the learning control method than with the conventional routing scheme (far-to-near rotation routing) in unbalanced load conditions by simulation study.

In this paper, a learning control approach to communications system is studied from the different viewpoint of Narendra's approach. The problems considered here are concerning to
dynamic network resource assignment expected in the future communications systems. Section 2 describes the expected problems in network control arises from the characteristics of the communications networks. Then a learning resource assignment control method is proposed to overcome these problems. Section 3 explains the proposed method using typical communications system models expected in the future, a multi-speed circuit switched model and a circuit/packet integrated switched model. Section 4 examines the performance of the method through computer simulation.

2. COMMUNICATIONS NETWORK CONTROL

This section examines the problems specific to communications network control and proposes a learning control approach to network control.

2.1 Communications network model

(1) Problems specific to communications networks

Communications networks present the following problems when they are seen as control objects.

a. Nonlinearity coming from the nature of the system itself, such as a limited channel number and buffer capacity.

b. Complexity resulting from the large number of states of the system.

c. Limited control inputs due to topological limitations.

These factors must therefore be integrated smoothly into the model.

(2) Network modeling

The following items must be decided upon when determining the modeling procedure.

a. Modeling technique

There are two modeling approaches to choose from, one in which the model is constructed in keeping with structural knowledge of the control object and the other in which it does not incorporate such knowledge but rather it identifies the system using its inputs and outputs.

b. Selection of state variables

The number of simultaneous calls, waiting calls, loss probabilities, waiting time, etc., must be determined.

c. Selection of control inputs

The method of assigning resources restricting input calls, routing, etc., must be decided upon.

2.2 Learning approach to network control

Let us consider problem shared common resources in communications networks present to resource assignment control. The dynamic characteristics of the system are difficult to assess because of the complexity of the system. Static characteristics such as the relation between offered traffic and loss probabilities can be assessed for simple systems, for example, those for which Poissonian call origination and the exponential distribution of holding time can be assumed. However, in systems where these assumptions can not be made safely even static characteristics become difficult to assess easily.

In order to overcome these problems, a learning control approach is proposed. The method involves using the potential function method to approximate the functions in a learning procedure. This method consists of the two following algorithmic steps;

(i) Approximating the system function which is to represent the system characteristics using the potential function method with state variables, applied control and the observed system outputs by learning.

(ii) Determining the control input to be applied to the system using the approximated function and the objective function to represent the control criteria.

The learning control method does not require detailed knowledge of the system because it only uses input and output pairs of the system, regarding the system as a black box. Using the potential function method to approximate functions has the advantage of being effectively applicable to systems under normal operating conditions without the use of much data.

3. LEARNING RESOURCE ASSIGNMENT CONTROL

This section explains the proposed network control method using sample communications system models.

3.1 Network model

We will consider the resource assignment problem of a multi-speed circuit-switched traffic system with two different call speeds sharing one common resource (a group of channels). Low-speed calls use a single channel of the common channel group and high-speed calls use multiple channels to form a high-speed transmission channel. This kind of system is expected to be used in the multi-service environment of the future. For example, the system has the potential to handle a wide range from high-speed telephone service traffic to low-speed teletex service traffic.

Let us consider the problem of operating this system according to prespecified control criteria. The following criteria, for example, will probably be used in such systems.

a. Minimizing the loss probability of one class of services while keeping the loss probability of another service class to a certain level.

b. Maintaining two loss probabilities of services to a same value.

The former criterion, for example, can be used in the environment in which human-human and machine-machine communications services are mixed in a system. It is in general desirable to give a priority to the services in which human is involved. If the system can be operated according to the criterion, the quality of the human-human communications system is kept to a constant level by worsening the quality of machine-machine communications service.

In the case of multi-speed traffic systems, the loss probabilities of high-speed calls are larger than those of low-speed calls due to the odd number line effects. The trunk reservation method can be used to balance the loss probabilities. However this method can only be used in static, non-varying traffic conditions. Our objective here is to obtain an effective control law even in conditions where traffic
varies dynamically.

The model examined here is shown in Fig. 1. In the figure, call 1 is a high-speed call and call 2 is a low-speed call. A learning control mechanism consists of a random switch which restricts the low-speed traffic inputs and a control system which calculates the suitable control inputs from the value of state variables. The measurement system measures state variables such as the amount of offered traffic and the loss probabilities of both calls.

The control procedure can be explained as follows:

(i) The learning part of the control system approximates the function \( f(x) \) that represents the characteristics (the relation between the offered traffic and the loss probability) of the system using state variables \( x \) and \( y \), observed value of \( f(x) \).

(ii) The control system determines the suitable control input \( \beta \) (the passing rate of the random switch) to satisfy the control criterion based on the approximated function and the object function.

Let us take a function \( f(x) \), which represents the relation among the loss the probabilities, the offered traffic and the passing rate of the random switch, as an approximated function here.

\[
\begin{align*}
\beta &= f(x_1, x_2, x_3) \\
&= \text{g}(f(x_1, x_2, x_3), x_1, x_2, h)
\end{align*}
\]  

where \( x=(x_1, x_2, x_3) \); 
\( x_1 \) : offered traffic 1 (high-speed call) 
\( x_2 \) : offered traffic 2 (low-speed call) 
\( x_3 \) : passing rate of the random switch \( \beta \) 
\( b_j \) : loss probability of call \( j \).

The control input \( \beta \) can be determined using the function \( f(x) \), measured variables \( x_1, x_2 \) and the control criteria \( H \), in the following equation;

\[
\beta = g(f(x), x_1, x_2, h)
\]

Let us assume that \( f(x) \) is the unknown function which is going to be approximated. Where \( x \) is a \( m \)-dimensional variable vector,

\[
x=(x_1, x_2, x_3, \ldots, x_m).
\]

Let us approximate \( f(x) \) with the finite number of vector \( x \) and \( y \), the observed value of \( f(x) \).

If we assume that \( f(x) \) can be expanded into a sequence of functions \( \psi(x) \),

\[
f(x) = \sum \psi_i(x).
\]

Let us then introduce the potential function which is expressed as follows,

\[
K(u,v) = \sum \psi_i(u)\psi_i(v).
\]

With this function and the values of input and output variables the function \( f(x) \) can be approximated using the following repetition algorithm.

\[
f_{n+1}(x) = f_n(x) + \gamma_n s(f_n(x_{n+1}), f^{*}(x_{n+1}))k(x_{n+1}, x),
\]

where \( f(x) \) is the \( n \)-th approximation of the function, \( x_1 \) is the realized value of \( n \)-th occurrence, \( \gamma_n \) is a convergence coefficient, \( s(f, f) \) is a function evaluating the degree of approximation and \( K(u,v) \) is a potential function.

The approximation can be obtained with this algorithm using an initial approximation such as \( f_0(x) = 0 \).

There are some conditions which assure the convergence of the algorithm (6). Especially, we must consider cases in which the function to be approximated is probabilistic as these will inevitably occur when this method is applied to communications networks. The observed value \( y \) is expressed by true value of the function \( f(x) \) and noise term \( \xi \) as follows;

\[
y_n = f(x_n) + \xi_n
\]

where \( \xi \) satisfies the condition listed below,

(1) random variable \( \xi \) is independent of the observation time \( n \),
(2) conditional probability distribution of \( \xi \) under condition \( x \) is independent of the observation time \( n \),
(3) the conditional expected value of the random variable is \( M(\xi | x) \) and variance \( M(\xi^2 | x) \) is finite for all \( x \).

It can be readily shown that these conditions are satisfied for the function described in Section 3.1. The function \( f(x) \) converges with \( f(x) \) when these conditions are satisfied and function \( s(f_n, f^{*}) \) is the form,

\[
s(f_n, f^{*}) = f_n(x) - f^{*}(x)
\]

and \( \gamma_n \) satisfies the condition below.

\[
\sum_{n=1}^{\infty} \gamma_n = \infty
\]

One of the advantages of this method is that it can accurately approximate most types of...
functions even when the function cannot be expanded by the sequence of functions composing the potential function \([3J\]. The other advantage of the method is that the data used for the algorithm need not be regularly organized but can be distributed at random. Therefore this method is suitable for approximation problems where systematic experiments to obtain the statistical characteristics are impossible. This method is ideal for communications network control because it can use data obtained during the normal operation process of the communications system.

4. SIMULATION STUDY

This section examines the method's convergence and the effects of parameters, traffic variation and control period on its accuracy and speed.

4.1 Simulation study conditions

(1) Communications network model

The validity of the method is verified using the multi-speed circuit-switched traffic model described in the preceding section. The following assumptions are made.

(i) The distributions of call origination conform to the interrupted Poisson process (IPP) for both calls.
(ii) The offered traffic varies sinusoidally with the \(T_1\) and \(T_2\) periods and the ratio of \(v\).
(iii) The holding times of the calls conform to the same negative exponential distribution with the mean value of \(1/h\).
(iv) The amount of traffic is measured accurately.
(v) The random switch passes the call with the probability equal to passing rate on a call-by-call basis.
(vi) Measurement and control is carried out in each control cycle \(t\).
(vii) No trunk reservation is done.

The following numerical conditions are used.

Numerical conditions

<table>
<thead>
<tr>
<th>The number of circuits</th>
<th>100 channels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input traffic</td>
<td></td>
</tr>
<tr>
<td>average traffic</td>
<td>(a_1, a_2: 50\text{erl} )</td>
</tr>
<tr>
<td>the variation ratio</td>
<td>(v: 0 \sim 0.4)</td>
</tr>
<tr>
<td>the variation period</td>
<td>(T_1: 3.1\text{ hours} )</td>
</tr>
<tr>
<td>class 1 call</td>
<td>(T_2: 2.2\text{ hours} )</td>
</tr>
<tr>
<td>class 2 call</td>
<td></td>
</tr>
<tr>
<td>Holding time of the calls</td>
<td>(h: 100\text{ seconds} )</td>
</tr>
<tr>
<td>Period of the control cycle</td>
<td>(t: 7.5\text{ minutes} )</td>
</tr>
<tr>
<td>Speed ratio of calls</td>
<td>(u_1/u_2: 4)</td>
</tr>
</tbody>
</table>

(2) Control criteria

The following two control criteria are considered;

- criterion 1
  - maintaining the loss probability of call 1 to 0.05,
- criterion 2
  - maintaining the loss probability of call 1 and call 2 to the same level.

(3) Selection of potential function

Potential function is expressed as an infinite sum of the sequence of functions, as described in the preceding section. However, a function should be used which can be written in a closed form for a practical usage. In addition, the function which can be expressed as a function of distance between the points \(u\) and \(v\) are suitable for implementing the algorithms from the viewpoint of the calculation needed \([3J\]. The function below satisfies all these conditions.

\[
K(u,v) = e^{-\alpha \sum_{k=1}^{2} (u_k-v_k)^2}
\]

where \(\alpha\) is a constant coefficient.

4.2 Results

(1) Convergence evaluation of the method

The convergence is quantitatively analyzed. As an evaluation value, the square norm of the approximated function and true function, \(J\), is used.

\[
J = \int c_1 \int c_2 (f(x_1, x_2) - f(x_1, x_2))^2 dx_1 dx_2
\]

where \(f(x)\) is the true function, \(f(x)\) is the approximated function and \(c_1\) and \(c_2\) are the function's domain. In order to obtain the true function, a Poisson origination call is applied to the model described in the preceding section instead of the IPP call \([4J\). The values obtained for \(J\) after 1000 control cycles are shown in Table 1. The numerical conditions used for this evaluation are listed below.

Numerical conditions

<table>
<thead>
<tr>
<th>The number of circuits</th>
<th>100 channels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input traffic</td>
<td></td>
</tr>
<tr>
<td>average traffic</td>
<td>50\text{erl}</td>
</tr>
<tr>
<td>variation ratio</td>
<td>(v: 0.8)</td>
</tr>
<tr>
<td>Speed ratio of calls</td>
<td>(u_1/u_2: 4)</td>
</tr>
<tr>
<td>Range of integration</td>
<td>(c_1: 30 \sim 70\text{ erlang} )</td>
</tr>
<tr>
<td>Range of integration</td>
<td>(c_2: 30 \sim 70\text{ erlang} )</td>
</tr>
</tbody>
</table>

Table 1. Discrepancies with actual blocking rates using the approximation method

<table>
<thead>
<tr>
<th>Actual figures</th>
<th>0.2070</th>
<th>0.0547</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average discrepancy</td>
<td>0.0094</td>
<td>0.0042</td>
</tr>
</tbody>
</table>

Fig. 2 shows the relation between residual error rate and control cycle. These results show that the residual error rate is under 1% as an
absolute value. Relative errors in the low traffic region are large compared to the high traffic region. However, this does not become a serious problem when the method is actually applied since it is the high traffic region which is the main control object.

(2) Control results

Fig. 2 and Fig. 4 show the results obtained from applying criterion 1 criterion 2. The horizontal axis shows the number of control cycles and the vertical axis shows the control results $b_1$, $b_2$ (loss probabilities of call 1 and call 2), $b_1/b_2$ (the ratio of loss probabilities) and $\beta$ (passing rate of the random switch). The traffic variation ratio is 0.3. The broken lines represent the control target. In the case of criterion 1, the loss probability of call 1 (high-speed calls) is found to maintain a prespecified level (0.05) irrespective of the traffic variation. The loss probability of call 2 (low-speed calls) varies widely because of the restriction placed on the call in order to keep the loss probability of call 1 to a specified value in the high traffic region. In the case of criterion 2, the ratio of loss probabilities of call 1 and call 2 maintained a prespecified level (1.0). In both cases, it can be concluded that control was carried out quite effectively according to the control criteria.

(3) Traffic variation and residual error

Fig. 5 and Fig. 6 show the effect of the control cycle on convergence for criteria 1 and 2. The values given were obtained after 120 control cycles. It was expected that the convergence speed would drop when traffic variation is large since the probability density
of originating data decreases for each point in
the function domain. However, the results show
that residual errors do not depend on traffic
variation. This can be explained by assuming
that the number of control cycles applied was
sufficient to come up with the function. The
residual error rate for the criterion 1 is 3 %
and that for criterion 2, 0.3. It can
accordingly be concluded that traffic variation
does not affect convergence nor the control
performance.

4) Control period and residual errors
The optimum control period depends on the
variance of approximated function. Fig. 7 shows
the relation between control periods and the
residual error rate in the case of criterion 1.
The horizontal axis gives time in hours. The
plotted lines graph data for control periods of
7.5, 15 and 30 minutes. The figure shows that if
the control period can be shortened to include a
greater number of control cycles the convergence
speed can be improved under the conditions
assumed here. This can be interpreted to mean
that the number of the control cycles has a
greater impact than the loss probability
variance. However when the control cycle is too
short, it can be expected that convergence speed
will be slow due to the variance in measured
values.

The above results show that this control
method takes a few hours to become effective
after operation commences. The residual error
rate is small enough to satisfy the control
criteria irrespective of the traffic variation.

4.3 Circuit/Packet switched model

To investigate the general applicability of
this learning control scheme, we applied it to
another type of communications system. In this
discussion, learning control method has been
applied to the channel allocation control model
of the integrated circuit/packet switched system.
This model is shown in Fig.8. As a control
criterion, "keep the loss probability of
circuit-switched call to constant (0.1)" is used.
The numerical conditions used for computer
simulation are listed below.

![Fig. 8 Circuit/Packet integrated switched traffic model](image)

**Numerical conditions**

- The number of circuits: N: 5 channels
- Input traffic
  - CS (circuit-switched): a: traffic 0.4sin{(m-0.5)/5}+1.2 erlang
  - PS (packet-switched): a: 3 erlang
- Holding time of CS call: h: 10 seconds (negative exponential distribution)
- Holding time of PS call: h: 0.1 seconds (unit distribution)
- Maximum number of packets in the system: M: 100 packets
- Period of control cycle: t: 30 minutes

Simulation results from 30 control cycles are shown in Fig.9 (a) and (b) for the loss probability of circuit-switched call and average number of waiting packets of packet-switched call, respectively. In Fig.9(a), the loss probability changes according to traffic fluctuations in the circuit-switched call in the case (i) of fixed channel allocation (with no learning control). But in the case (ii) of learning control, the loss probability converges with the target value of 0.1 after about 10 control cycles.

In Fig. 9 (b), the average number of packets in the case (ii) of learning control increases by at least over 70 (value over 100 are overflow because of the system's restriction on maximum number of calls). This is due to the fact that the loss probability for case (ii) is better than case (i). For both cases, the Fixed Boundary scheme (FB) (neither packet nor circuit traffic can use each other's empty channels) is applied. Increase in the average number of waiting packets can be kept below 13 packets by applying the Movable Boundary scheme (MB) [5] (packet traffic can use empty channels for circuit traffic) instead of FB. These results are shown by (i)' and (ii)' in Fig. 9 (b).

The foregoing discussion demonstrates the effectiveness of this learning control scheme in the integrated switching system which handles a mixture of circuit and packet traffic with different characteristics and required quality, as well as in the multi-speed circuit-switched system.

5. CONCLUSIONS

A learning control approach to communications networks has been studied. A control method suitable for resource assignment

![Fig. 7 Control cycle vs. residual error rate (Criterion 1)](image)
problems expected in future communications networks has been proposed. The concept of the control method was explained using the multi-speed circuit-switched traffic system model. Then this method was evaluated through the simulation studies. Results revealed the convergence of the method, the effects of traffic variation length of control period on the residual error rate and the convergence speed, etc. Furthermore, its general applicability was demonstrated by its successful use in a circuit/packet integrated switched traffic system. In conclusion, the method showed good control performance for models where control laws cannot be obtained analytically. It can be assumed to be effective not only for the systems studied here, but for all communications systems whose complexity make it difficult to determine control laws. The performance of the method can no doubt be further improved in the future by incorporating dynamic characteristics into the model.

ACKNOWLEDGMENT

The authors wish to thank Dr. Keiji Okada and Mr. Masaichi Kajiwara for their invaluable advice.

REFERENCES