A Method for Development of Paired Collaborative Learning in a Technical High School

Kazuhiro Shin-ike*, Hiroshi Nakamine** and Nobuo Sannomiya*

*Kyoto Institute of Technology, Faculty of Engineering and Design;
Matsugasaki, Sakyō-ku, Kyoto 606-8585, Japan.
E-mail:sanomiya@si.dj.kit.ac.jp

**Kyoto University of Education, Faculty of Education;
Fukakusa, Fushimi-ku, Kyoto 612-8522, Japan.
E-mail:nakamine@kyoko-u.ac.jp

Abstract

It is very important how to determine the optimal combination of students in order to improve the learning effect. In this paper, we improve the learning effect of collaborative learning for technical high school students who take classes in an experiment. Two neural network models are applied to predict unknown learning abilities. In order to determine the pairs of students, a local search method is applied by using the prediction results obtained from the two neural networks. From this combination of students, we investigate the learning effect of collaborative learning. The non-similarity measure is defined as the difference of the aptitude measure between two students of the pair. All pairs are classified into two types by using the non-similarity measure. We propose a pairing method to form the suboptimal pairs whose learning effect attains as high score as possible.

Key Words: Collaborative Learning, Neural Networks, Local Search Method, Group Study, Technical High School Education

Proceedings of the 2002 American Society for Engineering Education Annual Conference & Exposition
Copyright ©2002, American Society for Engineering Education
1 Introduction

It is well known that paired collaboration improves the effect of learning through interaction between students [1]. However, the learning effect is not always improved in collaborative learning situations. Moreover, paired collaborative learning is sometimes less effective than individual learning[2]. Such a phenomenon is also observed from the experiment for high school students. This implies that the combination of pairs is important[3].

In this paper, we propose a method for pairing students in order to improve the effect of the paired collaborative learning. For this purpose, two neural network (NN) models are constructed to predict the learning effect. One of NN-models (called NNs) predicts the effect of individual. The other NN-model (called NNP) predicts the effect of pairs. The input variables of the NNs are given by five aptitude abilities of a student for a learning problem. The output variable of this NNs is the correctness rate of the student. The input variables of the NNP are given by two correctness rates and two aptitude abilities of paired students. The output variable of the NNP expresses the learning effect for the problem.

By using the prediction results, a local search method[4] is applied in order to calculate the best pair groups. An improved local search method (called ILS) is proposed, and consequently student pairs are determined to improve their learning effect. As an example, a problem given to the students is to design a printed circuit board (PCB). Before solving the problem, the abilities of students for the PCB problem are examined by some aptitude tests.

Aptitude measures are defined by using the scores of aptitude test for students. The non-similarities of pairs are defined by their aptitude measures. The pairs are classified into homogeneous and heterogeneous pairs based on their non-similarities. Simulations are carried out to obtain the suboptimal combination of pairs. The method for determining pairs of students is evaluated from the results of simulation carried out for pairs with specific characteristics.

2 Prediction model of correctness rate

In this section two NN models are proposed to predict the results of individual learning and paired learning.

2.1 Prediction model for individual learning

Figure 1 shows the model NNs(i) which predicts the correctness rate of student i for learning the PCB problem. NNs(i) has five inputs and one output. The input variables

Proceedings of the 2002 American Society for Engineering Education Annual Conference & Exposition
Copyright ©2002, American Society for Engineering Education
of NN_s(i) are G_i, N_i, S_i, P_i [5] and J_i for student i. The output variable is the correctness rate C_i.

The input variables G_i, N_i, S_i and P_i are the intellectual ability, the mathematical ability, the spatial judgment ability and the form perception ability, respectively. They are determined by a vocational aptitude test. J_i is the consciousness ability related to the design problem[3]. These variables are normalized between 0 and 1. For example, G_i is given by

\[
G_i = \frac{g_i - m_g}{M_g - m_g}
\]  

(1)

where \(g_i\) is the measurement value of the intellectual ability for student i. \(M_g\) and \(m_g\) are the maximum and the minimum intellectual ability in the abilities of all students, respectively.

The correctness rate C_i is given by

\[
C_i = 1 - \frac{E_i - E_{\text{min}}}{E_{\text{max}} - E_{\text{min}}}
\]  

(2)

Figure 1: Model for predicting correctness rate of Student \(i\)

Figure 2: Variation of SSE with the number of neurons for the hidden layer of NN_s
where \( E_i \) is the number of errors of student \( i \), and \( E_{\text{max}} \) and \( E_{\text{min}} \) are the maximum and the minimum value in all students, respectively.

The back propagation method (BP) is used as the training of \( \text{NN}_i(i) \). Figure 2 shows the variation of the sum of squared errors (SSE) with the number of neurons for the hidden layer of \( \text{NN}_i(i) \). The horizontal axis in this figure represents the learning iteration of \( \text{NN}_i(i) \). From the figure, the number of neurons in the hidden layer is determined as ten.

In our earlier paper[3] we examined that the absolute values of the difference between the prediction values and the measurement values are less than 0.1. The correlation coefficient between the measurement values and the prediction values is 0.98. Therefore, it is effective to predict the correctness rate for student \( i \) by using \( \text{NN}_i(i) \).

### 2.2 Prediction model for paired learning

Figure 3 shows the model \( \text{NN}_p(i, j) \) which predicts the correctness rate \( C_{ij} \) for the paired collaborative learning of students \( i \) and \( j \). In this figure, \( C_i \) and \( C_j \) are the outputs of \( \text{NN}_i(i) \) and \( \text{NN}_i(j) \), respectively. It is assumed that \( C_j \) is larger than \( C_i \). \( K_i \) and \( K_j \) are the cooperative abilities obtained from the Yatabe-Guilford test[6] for students \( i \) and \( j \), respectively. They are normalized between 0 and 1. For example, \( K_i \) is given by

\[
K_i = \frac{k_i - m_k}{M_k - m_k}
\]  

where \( k_i \) is the measurement value of the cooperative ability for student \( i \). \( M_k \) and \( m_k \) are the maximum and the minimum cooperative ability in the abilities of all students. \( C_{ij} \) is also normalized between 0 and 1.

BP is also used as the training of \( \text{NN}_p(i, j) \). Figure 4 shows the variation of SSE with the number of neurons for the hidden layer of \( \text{NN}_p(i, j) \). The horizontal axis in this figure

![Diagram of NN_p(i, j)](image)

Figure 3: Model for predicting the correctness rate of two students \( i \) and \( j \)

---

*Proceedings of the 2002 American Society for Engineering Education Annual Conference & Exposition
Copyright ©2002, American Society for Engineering Education*
Figure 4: Variation of $SSE$ with the number of neurons for the hidden layer of $NN_p$.

Figure 5: Prediction result by $NN_p$.

represents the learning iteration of $NN_p(i, j)$. From Figure 4, the number of neurons in the hidden layer is determined as thirty.

Figure 5 shows the correctness rates predicted for the sixteen pairs and the experimental results for them. In the figure, the error bar shows the range in which the absolute value of the difference from the experimental result is less than 0.1. Consequently the absolute values of the difference between the prediction values and the experimental results are less than 0.1. The correlation coefficient between the measurement values and the prediction values is 0.99. Therefore, the prediction by using $NN_p(i, j)$ is effective.

3 Method for determining suboptimal pair

In this section, an ILS is proposed by using the results of NN-models to determine the suboptimal pairs of students.

We have $2p$ students \( \{M_i; i = 1, 2, \cdots, 2p\} \) two of which form a pair. Consequently the number of pairs is $p$. The objective of the problem is to maximize the minimum value
in the correctness rates predicted for all pairs.

The solution \( y \) for this problem is described by
\[
y = \{ x^h = (M_i, M_j); h = 1, 2, \ldots, p; \\
i, j \in \{1, 2, \ldots, 2p\}; i \neq j \}
\] (4)

The objective function is defined by
\[
f(y) = \min_h C_{ij}^h = C_{ij}^h
\] (5)

where \( C_{ij}^h \) is the prediction value of the correctness rate of a pair \( x^h \). Then the problem is
\[
\max_y f(y)
\] (6)

In this paper, an ILS is proposed to solve this pairing problem. ILS is a similar method to simulated annealing method (SA). But they differ in the function which permits deterioration of a solution. SA can escape from a local minimum, but the probability for doing so decreases after a large number of iterations. On the other hand, the proposed ILS can adjust the probability of escape from a local minimum by setting a parameter.

The present solution and a new solution are denoted as \( y_{\text{now}} \) and \( y_{\text{new}} \), respectively. Then the condition to update \( y_{\text{now}} \) with \( y_{\text{new}} \) is given as follows.
\[
f(y_{\text{new}}) > g(n)f(y_{\text{now}})
\] (7)

where \( g(n) \) is given by
\[
g(n) = \exp \left( \frac{-\alpha^{m-1} \beta}{n} \right)
\] (8)

In (8), \( n \) is the number of iterations, \( m \) is a parameter and \( \alpha (> 1) \) and \( \beta (> 0) \) are constants. We set \( \alpha = 1.04 \) and \( \beta = 1000 \) in our algorithm. The initial value of \( m \) is 1. When the solution \( y \) is invariant during \( m_c \) iterations, we add 1 to \( m \). By varying \( n \) and \( m \), the value of \( g(n) \) becomes either smaller or larger.

The outline of ILS is described as follows.

**ILS:**

**Step 1**  Set \( m \leftarrow 1 \), \( n \leftarrow 1 \), \( n_{\text{end}} \leftarrow 40000 \), \( m^* \leftarrow 0 \) and \( m_c \leftarrow 200 \).

**Step 2**  Generate an initial solution \( y_0 \) randomly and calculate \( f(y_0) \) given by (5).

**Step 3**  Choose a pair \( x^r \) from solution \( y_0 \) randomly, and choose a student \( M_a \) from \( x^r \) randomly.

**Step 4**  Choose a pair \( x^q (q \neq r) \) from solution \( y_0 \) randomly, and choose a student \( M_b \) from \( x^q \) randomly.

**Step 5**  Construct a new solution \( y \) by exchanging \( M_a \) and \( M_b \).

**Step 6**  Calculate \( f(y) \).

**Step 7**  If \( f(y) > g(n)f(y_0) \), set \( y \rightarrow y_0 \), \( f(y) \rightarrow f(y_0) \) and go to step 9.

**Step 8**  If \( m^* = m_c \), set \( m + 1 \rightarrow m \) and \( 0 \rightarrow m^* \). Otherwise, set \( m^* + 1 \rightarrow m^* \).

**Step 9**  If \( n = n_{\text{end}} \), terminate the computation. If not, set \( n + 1 \rightarrow n \) and go to step 3.
4 Application of the proposed method to a circuit design problem

4.1 Statement of PCB design problem

The problem is to design a PCB by using CAD softwares. Sixty-one male and three female students participate in the experiment of the electronics course of a technical high school in Japan. They are classmates and have similar educational backgrounds.

First, students take the vocational aptitude test and the Yatabe-Guilford test. Secondly, students are randomly assigned to one of two groups. In group I(individual learning group), 32 students design the PCB individually. In group II(collaborative learning group), 32 students are assigned to 16 pairs randomly. Each pair designs the PCB, collaboratively. Figure 6 shows the PCB design problem. It is an electric circuit to turn on or off a lamp. After the design of PCBs, students take the consciousness test related to the design problem.

PCBs designed by students are printed out. A teacher grades the correctness rates by counting the number of errors in the design works. For students of group I, the maximum number of errors was 8 and the minimum number of errors was 0. On the other hand,

![Figure 6: A design problem of PCB](image1)

![Figure 7: An example of result designed by a student](image2)
for pairs of students in group II, the maximum number of errors was 5 and the minimum number of errors was 0. Figure 7 shows an example designed by a student. In this work, the number of errors is 4 and the correctness rate is 0.5.

4.2 Aptitude measure and non-similarity measure

In this paper, the aptitude value for each student is evaluated by using a vocational aptitude test and a consciousness test. The aptitude measure of student \( i \) is defined, by summing up the respective values, as

\[
d_i = (G_i - G_{\text{min}})^2 + (N_i - N_{\text{min}})^2 + (S_i - S_{\text{min}})^2 + (P_i - P_{\text{min}})^2 + (J_i - J_{\text{min}})^2
\]

where \( G_{\text{min}}, N_{\text{min}}, S_{\text{min}}, P_{\text{min}} \) and \( J_{\text{min}} \) are the minima of the respective aptitude values in all students. The value of \( d_i \) expresses an ability for student \( i \) to solve the design problem correctly.

The non-similarity measure \( r_{ij} \) of ability between students \( i \) and \( j \) is defined as the difference of aptitude measure, i.e.

\[
r_{ij} = |d_i - d_j|
\]

Table 1 shows the average aptitude values \( G \) to \( K \) and the numbers \( E \) of errors for group I and group II. Table 1 also shows the result of \( t \)-test. As the result of \( t \)-test, the aptitude \( N \) of group I is higher than that of group II. But, there is no significant difference in the other aptitude abilities.

4.3 Classification of pairs by using the non-similarity measure

Table 2 shows the measure of the non-similarity \( r_{ij} \) for four kinds of pair groups. In the table, group A is formed according to the order of student ID numbers in all students. Group B is formed according to the order of student ID numbers in each class. Group C is formed according to the intention of students such as the group formed in the experiment. Group D consists of the suboptimal pairs obtained by ILS.

<table>
<thead>
<tr>
<th>Group</th>
<th>( G )</th>
<th>( N )</th>
<th>( S )</th>
<th>( P )</th>
<th>( J )</th>
<th>( K )</th>
<th>( E )</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.527</td>
<td>0.746</td>
<td>0.578</td>
<td>0.436</td>
<td>0.690</td>
<td>0.500</td>
<td>2.879</td>
</tr>
<tr>
<td>II</td>
<td>0.439</td>
<td>0.537</td>
<td>0.540</td>
<td>0.530</td>
<td>0.666</td>
<td>0.500</td>
<td>2.500</td>
</tr>
<tr>
<td>( t )</td>
<td>1.561</td>
<td>3.685</td>
<td>0.600</td>
<td>1.555</td>
<td>0.426</td>
<td>0.000</td>
<td>0.771</td>
</tr>
<tr>
<td>( t_{df}(\alpha) )</td>
<td>2.000</td>
<td>2.000</td>
<td>2.000</td>
<td>2.000</td>
<td>2.000</td>
<td>2.000</td>
<td>2.000</td>
</tr>
</tbody>
</table>

Proceedings of the 2002 American Society for Engineering Education Annual Conference & Exposition
Copyright © 2002, American Society for Engineering Education
Table 2: Non-similarity measure for four kinds of pairs

<table>
<thead>
<tr>
<th>Kind of pairs</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of pairs</td>
<td>31</td>
<td>31</td>
<td>16</td>
<td>31</td>
</tr>
<tr>
<td>Maximum value</td>
<td>1.829</td>
<td>1.829</td>
<td>1.479</td>
<td>1.778</td>
</tr>
<tr>
<td>Minimum value</td>
<td>0.000</td>
<td>0.109</td>
<td>0.153</td>
<td>0.005</td>
</tr>
<tr>
<td>Average value</td>
<td>0.514</td>
<td>0.533</td>
<td>0.611</td>
<td>0.619</td>
</tr>
</tbody>
</table>

The average of non-similarity measure for four kinds of pair groups is 0.574. We propose to divide all pairs into homogeneous pairs and heterogeneous pairs based on the concept of non-similarity. This idea is stimulated by the research of behavior of an ecological system[7]. If the non-similarity measure for a pair is greater than 0.6, the pair is called a heterogeneous pair. If the non-similarity measure is equal to or less than 0.6, the pair is called a homogeneous pair.

4.4 Comparison of suboptimal combination of pairs for various characteristics

In this section, we compare the performance of the suboptimal combination of pairs with specific characteristics which is defined by the non-similarity measure.

First, we consider the case where 62 students are divided into 31 homogeneous pairs. For this propose, “Step5” in the ILS algorithm is replaced by the following step:

Step5’ Construct a new solution $y$ in such a way that the non-similarity measure of each pair is equal to or less than 0.6. If such a solution $y$ does not exist, go to step 9.

Fifty initial solutions are set and ILS algorithm is applied repeatedly fifty times.

Secondly, we consider the case where 62 students are divided into 31 heterogeneous pairs. For this propose, “Step5” in the ILS algorithm is replaced by the following step:

Step5” Construct a new solution $y$ in such a way that the non-similarity measure of each pair is greater than 0.6. If such a solution $y$ does not exist, go to step 9.

Fifty initial solutions are set and ILS algorithm is applied.

Finally, we consider the pairs including both homogeneous pair and heterogeneous pair(called mixed pairs). Fifty initial solutions are set in the ILS algorithm.

Table 3 shows the average value and the worst value of correctness rates for three kinds of pair groups. As shown in the table, the average value of mixed pair is the highest correctness rate among three kinds of pair groups and the standard deviation of average value is the smallest among them. The worst value of mixed pair is the highest and
Table 3: Comparison of correctness rate among three kinds of pair groups

<table>
<thead>
<tr>
<th>Kind of pair groups</th>
<th>Average value</th>
<th>$\sigma_{\text{average}}$</th>
<th>Worst value</th>
<th>$\sigma_{\text{worst}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homogeneous</td>
<td>0.576</td>
<td>0.056</td>
<td>0.150</td>
<td>0.045</td>
</tr>
<tr>
<td>Heterogeneous</td>
<td>0.608</td>
<td>0.060</td>
<td>0.236</td>
<td>0.066</td>
</tr>
<tr>
<td>Mixed</td>
<td>0.950</td>
<td>0.000</td>
<td>0.624</td>
<td>0.063</td>
</tr>
</tbody>
</table>

the standard deviation of average value is the smallest. The mixed pairs also show that the correctness rate of all 31 pairs in solving the PCB problem becomes more than 90%. Consequently, the mixed pairs are expected to attain as high correctness rates as possible.

4.5 Pairing method based on cooperativeness ability and aptitude measure

Figure 8 (a) and (b) show, respectively, the distributions of $(K_i, K_j)$ and $(d_i, d_j)$ for the homogeneous pairs $i$ and $j$ obtained by mixed pair. These pairs are obtained from twenty initial solutions by using ILS algorithm.

In Figure 8 (a), the average value of correctness rate is 0.804 for 334 homogeneous pairs. The pairs, whose values of both $K_i$ and $K_j$ are equal to or more than 0.800, show less correctness rate than the average value. We call these pairs over-cooperation pairs. There are no pairs whose values of both $K_i$ and $K_j$ are less than 0.300. In Figure 8 (b), most of $d_i$ and $d_j$ are equal to or more than 1.000. Therefore, the pairing method for the homogeneous pairs is effective when the following condition is satisfied:

$$K_i \geq 0.300 \text{ or } K_j \geq 0.300 \quad d_i \geq 1.000 \quad \text{and} \quad d_j \geq 1.000$$ \hspace{1cm} (11)

But the method is comparatively ineffective for the over-cooperation pairs.

Figure 9 (a) and (b) show, respectively, the distributions of $(K_i, K_j)$ and $(d_i, d_j)$ for the heterogeneous pairs $i$ and $j$ obtained from mixed pair. These pairs are obtained from fifty initial solutions by using ILS algorithm.

In Figure 9 (a), the average value of correctness rate is 0.791 for 286 heterogeneous pairs. The pairs, whose values of both $K_i$ and $K_j$ are equal to or more than 0.800, show almost the same correctness rate as the average value. There are no pairs whose both $K_i$ and $K_j$ are less than 0.400. As shown in Figure 9 (b), most of $d_i$ and $d_j$ are above two straight lines. Therefore, the pairing method for the heterogeneous pairs is effective when the following condition is satisfied:

$$K_i \geq 0.400 \text{ or } K_j \geq 0.400 \quad d_j \geq -d_i + 3.000 \quad \text{and} \quad d_j \geq d_i - 2.000$$ \hspace{1cm} (12)
Figure 8: Distributions of cooperative ability and aptitude measure for the homogeneous pairs

Figure 9: Distributions of cooperative ability and aptitude measure for the heterogeneous pairs
Table 4: Cooperativeness ability and aptitude measure for the experimental pairs

<table>
<thead>
<tr>
<th></th>
<th>$K_i$</th>
<th>$K_j$</th>
<th>$d_i$</th>
<th>$d_j$</th>
<th>$C_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homogeneous pair (A)</td>
<td>0.500</td>
<td>0.500</td>
<td>3.040</td>
<td>3.285</td>
<td>0.922</td>
</tr>
<tr>
<td>Homogeneous pair (B)</td>
<td>0.500</td>
<td>0.500</td>
<td>1.035</td>
<td>1.252</td>
<td>0.822</td>
</tr>
<tr>
<td>Homogeneous pair (C)</td>
<td>0.500</td>
<td>0.250</td>
<td>1.100</td>
<td>1.493</td>
<td>0.716</td>
</tr>
<tr>
<td>Homogeneous pair (D)</td>
<td>0.750</td>
<td>0.250</td>
<td>0.833</td>
<td>0.177</td>
<td>0.195</td>
</tr>
<tr>
<td>Homogeneous pair (E)</td>
<td>0.250</td>
<td>0.250</td>
<td>1.669</td>
<td>1.300</td>
<td>0.002</td>
</tr>
<tr>
<td>Heterogeneous pairs (A')</td>
<td>0.500</td>
<td>0.750</td>
<td>1.341</td>
<td>2.306</td>
<td>0.796</td>
</tr>
<tr>
<td>Heterogeneous pairs (B')</td>
<td>1.000</td>
<td>0.000</td>
<td>2.185</td>
<td>1.119</td>
<td>0.752</td>
</tr>
<tr>
<td>Heterogeneous pairs (C')</td>
<td>0.750</td>
<td>0.500</td>
<td>3.175</td>
<td>1.423</td>
<td>0.559</td>
</tr>
<tr>
<td>Heterogeneous pairs (D')</td>
<td>0.250</td>
<td>0.250</td>
<td>2.633</td>
<td>1.064</td>
<td>0.280</td>
</tr>
<tr>
<td>Heterogeneous pairs (E')</td>
<td>0.500</td>
<td>0.500</td>
<td>2.818</td>
<td>0.726</td>
<td>0.155</td>
</tr>
</tbody>
</table>

Table 4 shows cooperativeness ability and aptitude measure of 16 pairs obtained by the experimental result. In Table 4, homogeneous pairs (A), (B) and (C) satisfy the condition (11). Therefore, those pairs show high correctness rates. On the other hand, $K_j$ of the homogeneous pair (D) is less than 0.300 and $d_i$ and $d_j$ are less than 1.000. $K_i$ and $K_j$ of (E) are less than 0.300. Therefore, those pairs show low correctness rates.

Heterogeneous pairs (A') and (B') satisfy the condition (12). Therefore, those pairs show high correctness rates. $K_i$ and $K_j$ of the heterogeneous pair (D') are less than 0.400. $d_i$ and $d_j$ of (E') do not satisfy the condition (12). Therefore, heterogeneous pairs (D') and (E') have low correctness rates.

5 Conclusion

A pairing method to improve the learning effect in the case of collaborative learning has been proposed. First, aptitudes of students are investigated. Experiments have been done to count the number of errors in the PCB design for individuals and pairs. NN-models have been constructed for predicting the correctness rates and their validity has been verified. Secondly, an improved local search method (ILS) has been applied for obtaining a suboptimal pair of students. The pairs obtained have been classified into homogeneous pairs and heterogeneous pairs by using non-similarity measure. Finally, a pairing method has been proposed by using the results of ILS.

As the results of the ILS, it was found that the mixed pairs improve the learning effect. It is shown that good features of homogeneous pairs and heterogeneous pairs are combined. Moreover, we proposed the pairing method for the homogeneous pairs and the heterogeneous pairs.

Teachers can perform educational activities effectively by using the results of ILS. In many cases, teachers instruct students by using the same problems for several years.
Before students start to learn the PCB design problem, the prediction models $\text{NN}_s$ and $\text{NN}_p$ are used, and suboptimal pairs can be determined. Consequently the students are expected to attain a certain level required for the design problem. Therefore, this pairing method is very effective in technical high school education.

References


Authors list

KAZUHIRO SHIN-IKE
He received the B.E. degree in Electrical Engineering from Kansai University in 1976 and M.E. degree in Industrial Arts Education from Kyoto University of Education in 2000. Since 2000, he has been the doctor-course student at Division of Information and Production Science, Graduate School of Kyoto Institute of Technology. His research interests include modeling and optimization techniques for collaborative learning at school education. Since 1986 he has been the Teacher at Rakuyo Technical High School in Kyoto.

HIROSHI NAKAMINE
He received the B.E., M.E. and D.E. degrees in Electrical Engineering all from Kyoto Institute of Technology in 1987, 1989 and 1994, respectively. Since 1998 he has been the Associate Professor at the Department of Industrial Arts Education, Kyoto University of Education. His present research interests include simulation of fish behavior against environmental variation.

NOBUO SANNOMIYA
He received the B.E., M.E. and D.E. degrees in Electrical Engineering all from Kyoto University in 1962, 1964 and 1969, respectively. Since 1986 he has been the Professor at the Department of Electronics and Information Science, Kyoto Institute of Technology. His present research interests include modeling and optimization techniques, and their applications. Especially his research works are directed toward genetic algorithm approach to the optimal scheduling of manufacturing systems.

*Proceedings of the 2002 American Society for Engineering Education Annual Conference & Exposition*

Copyright ©2002, American Society for Engineering Education