Network Partition of Switched Industrial Ethernet by Using Novel Particle Swarm Optimization *

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Abstract

In this paper, a novel particle swarm optimization is proposed to solve integer programming problem, which is name as an adaptive inertia weight integer programming particle swarm optimization (AIWIP-PSO). Then it is applied to solve the industrial Ethernet network partition problem, after the problem is formulated as multi-objective integer programming problem. This multi-objective integer programming problem includes two objectives: one is the minimum of the inter-network communication; the other is the evenness of the network traffic between the sub-networks. Furthermore, the switch capability must be considered when assigning devices to sub-networks. Two network partition cases are chosen for simulations. The results obtained by using AIWIP-PSO are compared with those from genetic algorithm. Simulation results show that the AIWIP-PSO is very effective and outperforms genetic algorithm in terms of the performance index

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Keywords: Switched industrial Ethernet; particle swarm optimization (PSO); adaptive inertia weight; network partition.

1. Introduction

Ethernet was developed as a communication network technology in the late 1970s. Ethernet is a cable-bound data network technology for local area data network (LAN) and it is an ideal medium to transport large volumes of data, at speed, across great distances. Now Ethernet is the most widely used technology in LAN. In the past the MAC access mechanism (CSMA/CD) adopted by traditional Ethernet was the main obstacle for its extensive use in industrial environment. However, the technical advancement of switched Ethernet has presented new hope for Ethernet to support typical real-time industrial communication. When the micro-segmentation full-duplex communication mode is adopted, the

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constraint of CSMA/CD protocol is completely eliminated, and each node in the Ethernet can send and receive data simultaneously without waiting for the other, which improves the real-time capability of Ethernet significantly.

With many people in the control community are making great efforts to remove the application obstacles of industrial Ethernet, there has seen an increasing usage of industrial Ethernet in factory floors, which were originally occupied by all kinds of field-buses. However, great importance must be attached to the network reliability and real-time capability when industrial Ethernet is used to connect field devices. On the one hand, these requirements can be fulfilled by selecting industrial-level Ethernet components; On the other hand, the network design should be seriously treated to make full usage of the network facilities. In order to realize this aim, Industrial Ethernet should be optimized to partition the field devices into sub-networks based on their communication relationships.

In the past decades, genetic algorithm (GA) has been successfully used to optimize the industrial Ethernet network partition problem[1-4]. However, many papers have proofed that the particle swarm optimization (PSO) outperforms the GA[1-3]. Because the PSO is not suitable to solve integer programming problem, based on the PSO, an inertia weight integer programming particle swarm optimization (AIWIP-PSO) is proposed to solve the industrial Ethernet network partition optimization problem with two-level tree topology in this paper, after the optimization problem is formed as integer programming problem. Then the comparisons of the simulation results obtained by using AIWIP-PSO and GA are made, in order to show the AIWIP-POS performs better than GA.

The paper is organized as follows: Section 2 states the switched industrial Ethernet network partition problem. Section 3 proposes the AIWIP-PSO strategy for the network partition problem. Section 4 investigates the effectiveness of the AIWIP-PSO through the simulations and comparisons. The paper is concluded in Section 5.

2. Statement of the problem

2.1 Problem definition

A switched industrial Ethernet model with two-level tree topology is depicted in Fig. 1. The definition about the industrial Ethernet network partition problem follows the model given in Ref.[4]. Set $A$ is the traffic matrix for industrial Ethernet network, where the element $a_{ij}$ represents the traffic sent from node $i$ (source node) to node $j$ (destination node). Considering the one-way communication characteristic of field devices, in general case $a_{ij} \neq a_{ji}$. The communicate nodes do not exchange data with themselves, so the diagonal elements in the traffic matrix are all zeros.

![Fig. 1 The switched industrial Ethernet with two-level tree topology.](image)

Note how the caption is centered in the column.
Define \\
\[ A = \begin{bmatrix} 0 & a_{12} & \ldots & a_{1n} & a_{1,n+1} \\ a_{21} & 0 & \ldots & a_{2n} & a_{2,n+1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{n1} & a_{n2} & \ldots & 0 & a_{n,n+1} \\ a_{n+1,1} & a_{n+1,2} & \ldots & a_{n+1,n} & 0 \end{bmatrix} \] \quad (1)

as assignment matrix. \( x_{ik} = \begin{cases} 1 & \text{if node } i \text{ subnet } k, \\ 0 & \text{if node } i \not\subseteq \text{ subnet } k. \end{cases} \quad (2)

The total traffic burden on sub-network \( k \) can be defined as
\\n\[ w(k) = \sum_{j \in k} \sum_{i \not\in k} a_{ij} + \sum_{i \in k} \sum_{j \not\in k} a_{ij} - \sum_{i \not\in k} \sum_{j \not\in k} a_{ij}. \quad (4)\]

The sending data and receiving data of sub-network \( k \) are the first two parts in (4). The intra-network communication of sub-network \( k \) is the last part of (4). Therefore, the communication imbalance among all sub-networks can be defined as follows
\\n\[ I = \sum_{j=1}^{k-1} \sum_{i=1}^{k-1} (w(i) - w(j))^2. \quad (5)\]

The industrial Ethernet network partition problem is formed to multi-objective optimization problem as
\\n\[ f = \sum_{j=1}^{K} \sum_{i=1}^{n} x_{ik} (1-x_{jk}) a_{ij} + \beta \sum_{j=1}^{k-1} \sum_{i=1}^{k-1} (w(i) - w(j))^2, \quad (6)\]

where \( \beta \in [0,1] \) is a weight coefficient. Equation (6) is object function.

The multi-objective optimization problem has three constrains:

1. The number of devices assigned to each sub-network cannot exceed the corresponding two-level switch’s port number.
2. The sum of up traffic and down traffic of each sub-network cannot exceed the corresponding two-level switch’s port speed.
3. The total communication burden on each sub-network cannot exceed the corresponding two-level switch’s packet switching capability.

The last two constraints are easy to be satisfied if full duplex line speed switches are used. The first constrain must be taken into account.

2.2 Encoding method

Following Ref. [4], the integer encoding is also used in this paper, which provides a convenient and natural way of expressing the mapping from representation to solution domain. An integer vector represents the network partition. If the device \( i \) is assigned to sub-network \( k \), the \( i \)-th element of the integer vector is \( k \). For example, when there are twelve devices which are assigned to three sub-networks, i.e. \( n = \{1,2,3,4,5,6,7,8,9,10,11,12\} \) are assigned to \( k = \{1,2,3\} \), and a integer vector is
the corresponding network partitions are \( \{1,7,8,11\} \), \( \{2,5,6,10\} \) and \( \{3,4,9,12\} \). After integer encoding, the network partition optimization problem becomes the integer programming problem. Next section a novel algorithm based on PSO is proposed to solve the network partition optimization problem.

3. **Adaptive inertia weight integer programming particle swarm optimization**

3.1 Particle swarm optimization[5]

PSO is proposed by James Kennedy and R. C. Eberhart[6] in 1995, inspired by social behaviour of organisms such as bird flocking and fish schooling.

Assuming that the searching space is \( d \)-dimensional, the \( i \)-th particle of the swarm is represented by a \( d \)-dimensional position vector \( X_i = (x_{i1}, x_{i2}, \cdots, x_{id}) \). The best particle of the swarm is \( P_{g,best} = (p_{g1}, p_{g2}, \cdots, p_{gd}) \). The best visited position of \( i \)-th particle is recorded and represented as \( P_{i,best} = (p_{i1}, p_{i2}, \cdots, p_{id}) \). The velocity of the \( i \)-th particle is denoted by \( V_i = (v_{i1}, v_{i2}, \cdots, v_{id}) \). Then the particles are manipulated according to the following equations:

\[
\begin{align*}
V_i(t+1) &= \omega V_i(t) + C_1 r_1 (P_{i,best} - X_i(t)) \\
&+ C_2 r_2 (P_{g,best} - X_i(t)), \\
X_i(t+1) &= X_i(t) + V_i(t),
\end{align*}
\]

where \( i = 1,2,\cdots,N \), \( N \) is the size of swarm; \( \omega \) is the inertia weight; \( C_1 \) and \( C_2 \) are two positive constants, called the cognitive and social parameter respectively; \( r_1 \) and \( r_2 \) are two random numbers uniformly distributed within the range \([0,1]\). An upper bound is placed on the velocity in all dimensions \( V_{max} \). This limitation prevents the particle from moving too rapidly from one region in search space to another.

3.2 Adaptive inertia weight integer programming particle swarm optimization

PSO is more suitable to solve real-value optimization problems than integer-value optimization problems, because \( r_1 \) and \( r_2 \) in (7) always make \( X_i(t+1) \) become real number. However, the integer encoding is applied to form the industrial Ethernet network partition problem in this paper. In order to use PSO to solve partition problem, the \( X_i(t+1) \) is rounded to the nearest integer and the \( r_1 \) and \( r_2 \) are changed to two random numbers uniformly distributed within the range \([-1,1]\), to enlarge searching space. At the same time, the inertia weight \( \omega \) controls the impact of the previous velocity. A large inertia weight favors global search, while a small inertia weight favors local search. When inertia is used, it is sometimes decreased linearly during the iteration of the PSO[7]. Therefore, adaptive inertia weight integer programming particle swarm optimization (AIWIP-PSO) is proposed as
\[
\begin{align*}
V_i(t+1) &= \omega(t)V_i(t) + C_1r_1\left(P_{i,\text{out}} - X_i(t)\right) \\
&\quad + C_2r_2\left(P_{i,\text{out}} - X_i(t)\right), \\
X_i(t+1) &= \text{round}\left(X_i(t) + V_i(t)\right), \\
\omega(t+1) &= (1 - \lambda)\omega(t),
\end{align*}
\]  

(8)

where \text{round} is function to realize rounding the \(X_i(t+1)\) to the nearest integer; the \(\lambda\) is decreasing step.

4. Simulation research

Two practical cases about network partition problem are chosen for simulation to verify the efficiency of the proposed AIWIP-PSO. In these two practical cases, there are 40 devices which are needed to be partitioned to four sub-networks (each switch has 16 ports). The first traffic matrix for practical case comes from Ref.[4] and the second is randomly generated, in which the traffic loads between arbitrary two nodes are represented by integers from 1 to 10.

As a contrast, a random network partition is firstly considered: the devices 1–10, 11–20, 21–30 and 31–40 are separately assigned into four sub-networks. The inter-network communication and the total traffic burden on each sub-network can be calculated using (3) and (4), respectively.

AIWIP-PSO and GA[4] are applied to optimize these two practical cases and comparisons are made between these two algorithms to show the efficiency of the AIWIP-PSO. The performance index includes inter-network communication, sub-network traffic burdens and the max different. The max different means the absolute value of the different between the biggest sub-network traffic burden and the smallest it.

For first practical case, the parameters for AIWIP-PSO are set as follows: the initialization population size \(Pop_{\text{size}} = 100\), the maximum generation \(\text{gen}_{\text{max}} = 1000\), the cognitive and social parameter \(C_1 = C_2 = 2\), the initial inertia weight \(\omega(0) = 0.8\), decreasing step \(\lambda = 0.001\), upper bound of the velocity \(V_{\text{max}} = 4\), the weight coefficient for partition problem \(\beta = 0.0005\). The result which is obtained by AIWIP-PSO is compared with the better result of Ref.[4]. The comparative results for the first practical case are shown in Table 1.

<table>
<thead>
<tr>
<th>Partition method</th>
<th>Random method</th>
<th>GA algorithm</th>
<th>AIWIP-PSO algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub-network 1</td>
<td>1–10</td>
<td>3,9,13,14,19,21,2</td>
<td>3,9,13,14,19,21,2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>7,31,32,35</td>
<td>21,27,31,32,35</td>
</tr>
<tr>
<td>Sub-network 2</td>
<td>11–20</td>
<td>2,5,12,20,23,24,2</td>
<td>1,4,6,8,11,16,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8,36,37,39</td>
<td>20,25,38,40</td>
</tr>
<tr>
<td>Sub-network 3</td>
<td>21–30</td>
<td>10,15,17,18,29</td>
<td>7,10,15,17,18,2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30,33,34,40</td>
<td>6,29,30,33,34</td>
</tr>
<tr>
<td>Sub-network 4</td>
<td>31–40</td>
<td>1,4,6,7,8,11,16,</td>
<td>2,5,12,22,23,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>22,25,26,38</td>
<td>24,28,36,37,39</td>
</tr>
<tr>
<td>Inter-network communicatio n</td>
<td>1419</td>
<td>1027</td>
<td>1022</td>
</tr>
<tr>
<td>Sub-network traffic burdens</td>
<td>1080,928,</td>
<td>791,793,</td>
<td>791,810,</td>
</tr>
<tr>
<td>The max different</td>
<td>333</td>
<td>35</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 1: The comparison of the results for first practical case between the AIWIP-PSO and the GA
For second practical case, the initialization population size \( Pop_{\text{size}} = 100 \) and the maximum generation \( gen_{\text{max}} = 500 \) for the GA are the same as for the AIWIP-PSO. Other parameters for GA are set as the crossover probability \( p_c = 0.8 \), the mutation probability \( p_m = 0.01 \) and other parameters for AIWIP-PSO are the cognitive and social parameter \( C_1 = C_2 = 2 \), the initial inertia weight \( \omega(0) = 0.8 \), decreasing step \( \lambda = 0.001 \), upper bound of the velocity \( V_{\text{max}} = 4 \), the weight coefficient for partition problem \( \beta = 0.0005 \). The comparison between the AIWIP-PSO and GA for the second practical case is shown in the Table 2.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>THE COMPARISON OF THE RESULTS FOR SECOND PRACTICAL CASE BETWEEN THE AIWIP-PSO AND THE GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partition method</td>
<td>Random method</td>
</tr>
<tr>
<td>Sub-network 1</td>
<td>1–10</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-network 2</td>
<td>11–20</td>
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<tr>
<td>Sub-network 3</td>
<td>21–30</td>
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</tr>
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<td>Sub-network 4</td>
<td>31–40</td>
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<td></td>
<td></td>
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<tr>
<td>Inter-network communication</td>
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</tr>
<tr>
<td>Sub-network traffic burdens</td>
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</tr>
<tr>
<td>The max different</td>
<td>724, 737</td>
</tr>
</tbody>
</table>

From Table 1 and Table 2, it is revealed that the inter-network communication and the max different are less, when the AIWIP-PSO is used. The comparison results in Table 1 and Table 2 indicate that the AIWIP-PSO outperform GA when these two algorithms are applied to solve the industrial Ethernet network partition problem in terms of inter-network communication, inter-network traffic burdens and the max different. It means that the AIWIP-PSO more significantly improves the real-time capability of Ethernet network than the GA.

5. Conclusion

In this paper, in order to solve the industrial Ethernet network partition problem, an AIWIP-PSO is proposed. After the industrial Ethernet network partition problem is formed as integer programming problem, two practical cases are chosen to be solved by the AIWIP-PSO and GA. In order to show the AIWIP-PSO is more effective than GA, the comparisons are made between the AIWIP-PSO and GA. The simulations reveal that the AIWIP-PSO outperforms the GA in terms of the performance index, which includes inter-network communication, sub-network traffic burdens and the max different, when they are applied to solve the industrial Ethernet network partition problem.

References


