Production Lead-time Estimation System Based on Neural Network

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Abstract

In distributed autonomous production control system, each facility (work-cell, transporter, etc.) and each job on shop floor has intelligence to control its own activity related to production progress. In order to keep the due time, job needs to have the function to estimate the production lead-time. we show a basic neural network model for lead-time estimation, and examine the validity of this model comparing it with the conventional estimation formula. Furthermore, after we indicate some problems in the application of this model, we discuss some solutions. One of problems is that the accuracy of the lead time estimation by neural network loses, when workload of the shop or the composition of orders changes. We tried to solve it by means of an addition of the input parameter. We show the result of experiments.

1. Introduction

Manufacturing industries have made an effort to realize “multi-product small-batch production” to meet various customers’ needs, and has introduced FMS which can easily correspond to a change of products by revising instruction program. In recent years, CIM has been developed, which intensively controls the information flow from production to selling by means of computer network. But in order to correspond to various changes of products and production volume, the production system including hardware and software has to be replaced, and such replacement requires much time and money.

It is necessary to develop a more advanced technology to respond rapidly to the extreme change of demand, frequent appearances of new products and introductions of new facilities. Distributed autonomous production control system [1] is lately drawing the attention, because the system can realize real-time response and concurrent processing. Some examples of distributed autonomous production systems (Biological-oriented production system [2], etc.) have been proposed. In distributed autonomous production system, each facility (work-cell, transporter, etc.) and each job on shop floor has intelligence to control its own activity related to production progress by itself through communications among facilities and jobs. Each job decides process route by itself through communications with facilities. In order to keep the due time, job needs to have the function to estimate job completion time. Therefore, an estimation formula is required.

The way to estimate lead-time in proportion to the processing time of job, the number of necessary operations for job completion and/or the number of WIP in a shop floor is generally used. But whenever types or amounts of orders changes, we need to modify the linear estimation formula of lead-time. Neural network, which learns from stored data and doesn’t have a fix function, is considered to be a useful approach for estimating lead-time [3].

In this paper, we show a basic neural network model for lead-time estimation, and examine the validity of this model in comparison with the linear estimation formula. Furthermore, after we indicate some problems in the application of this model, we discuss some solutions. One of problems is that the accuracy of the lead time estimation by neural network loses, when workload of the shop or the composition of orders changes. We tried to solve it by means of an addition of the input parameter. We show the result of experiments about our solutions.

2. Outline of lead-time estimation system by neural network

Fig.1 shows an outline of lead-time estimation system by neural network. The neural network used in the system is the most basic network structure which has 3 layers (input layer, output layer and hidden layer). The number of units in input layer is the same as the number of input patterns. The number of units in output layer is one. It's the estimated lead-time. The number of units in hidden layer is two as the result of a calculation by the algorithm of AIC (Akaike Information Criterion). There is a connection weight between units. Values of input patterns turned into an estimated lead-time. Input patterns are concerned with the type of the job and the condition of the shop floor when the job arrived. Input patterns are:

- Number of necessary operations for job completion
- Type of each operation for job completion
- Standard processing time of each operation for job completion
- Number of WIP on the shop floor
- Actual results of average processing time of each operation
- Actual results of setup time, transfer time between each facility
- Actual results of average waiting time

. This neural network learns by the algorithm of back propagation, which is to do feed back the difference between an estimated and an actual lead-time to a connection weight between units. We made the simulator of a job shop production instead of getting actual data.

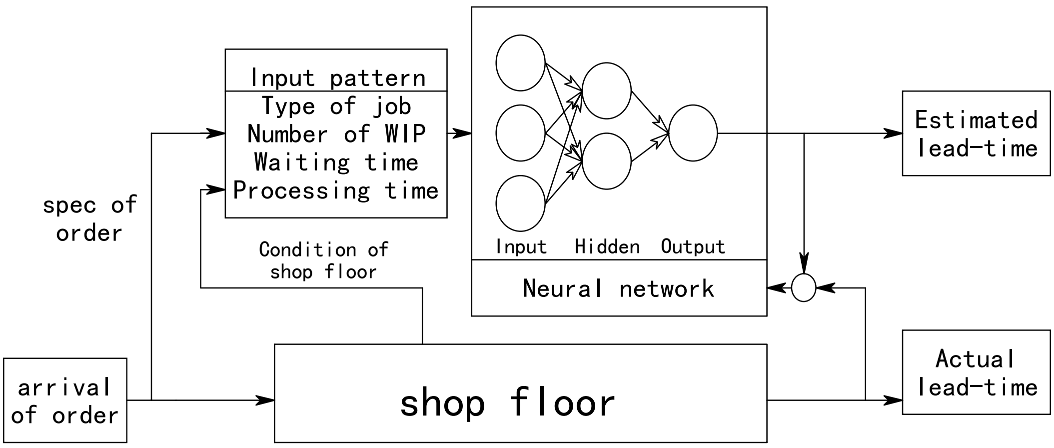

Fig.1 Lead-time estimation system by neural network

3. Performance of neural network

3.1 The number of times of learning

In order to decide the number of times of learning, We estimated lead-time using 125 data for learning. As the result, Fig.2 shows the relationship between the number of times of learning and the processing time for learning, and between the number of times of learning and the square root of average square error, which is the difference between an estimated and an actual lead-time. The processing time for learning increases in proportion to the number of times of learning. The square root of average square error is the minimum value when the number of times of learning is 75. We use 75 times of learning in examinations after this, because the processing time for learning is short, too.

3.2 The number of data for learning

Fig.3 shows the relationship between the number of data for learning and the average error between an estimated and an actual lead-time in 75 times of learning. The average error is the minimum value when the number of data for learning is 125. We use 125 data for learning in examinations after this.

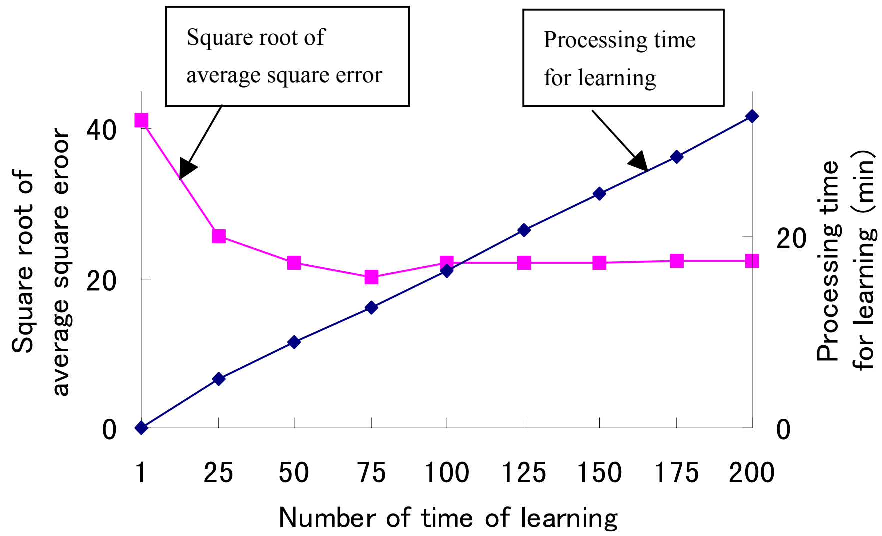

Fig.2 Time for learning and convergence of learning

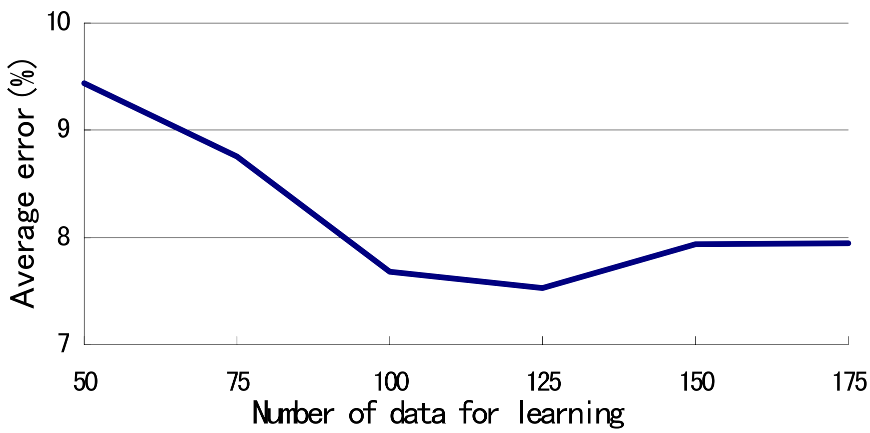

Fig.3 Number of data for learning and average estimation error

4. The effect on lead-time estimation by neural network

Formula 1 often defines lead-time. We compare the lead-time estimated by neural network with one by Formula.1. The aim of the estimation error between an estimated and an actual estimation is within 20%.

Formula 1 LT = [the number of all operations processed × (average processing time + average setup time + average waiting time)] +[(the number of operations－1) × average transfer time]

4.1 Estimation in stable production

In stable production, production workload is always about 70% and 5 types of jobs are arrived repeatedly. Fig.4 shows the average error of estimations by neural network and by Formula 1 in 50 times of estimation. From this figure, the estimation by neural network is more accurate and effective than one by Formula 1 because the average estimation error is about 7%. Formula.2 was made by neural network automatically.

Formula 2 LT = (the number of times of each operation processed × average processing time of each operation) + (the number of times of setup × average setup time) + (the number of times of transfer between each facility × average transfer time) + (the number of all operations processed × average waiting time)

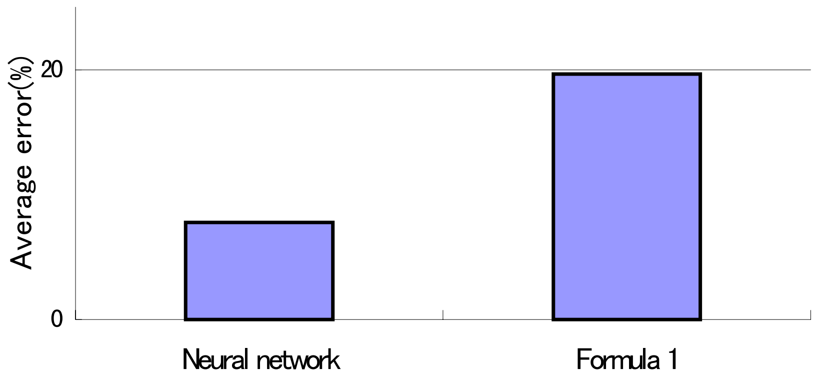

Fig.4 Estimation error in stable production

4.2 Estimation in variable production

4.2.1 Change of job types

In variable production, types of job change, or production workload changes. We made 2 conditions about the change of job types. On one hand, 3 types out of 5 types of jobs arrived repeatedly change into the other 3 types. On the other hand, all of 5 types change into the other 5 types. As the result of 50 estimations on these conditions, we show the average error of estimations by neural network and by Formula 1 (Fig.5). In Fig.5, we use 125 data for learning collected before the change of job types. The average error of estimations by neural network is within 20% in both condition, and the estimation by neural network is more accurate than one by Formula.1.

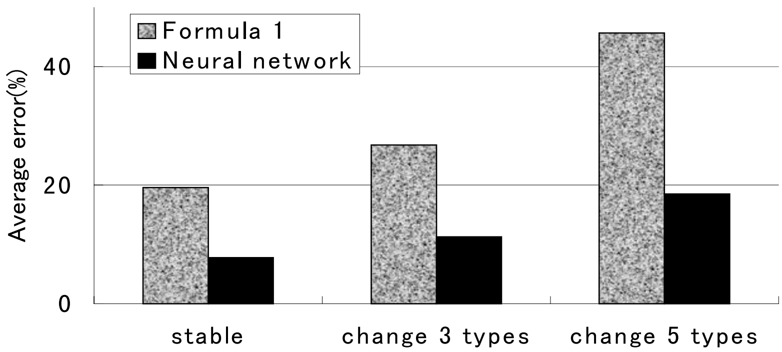

Fig.5 Estimation error when job types change

When 0～75 data after the change of job types are included in 125 data for learning, we show the shift of the average error of estimations by neural network (Fig.6). When the number of data after the change of job types is more than 25, the average estimation error is small and the shift of it is stable. Even if the number of data for learning after the change of job types is small, the estimation system by neural network could correspond to the change of job types.

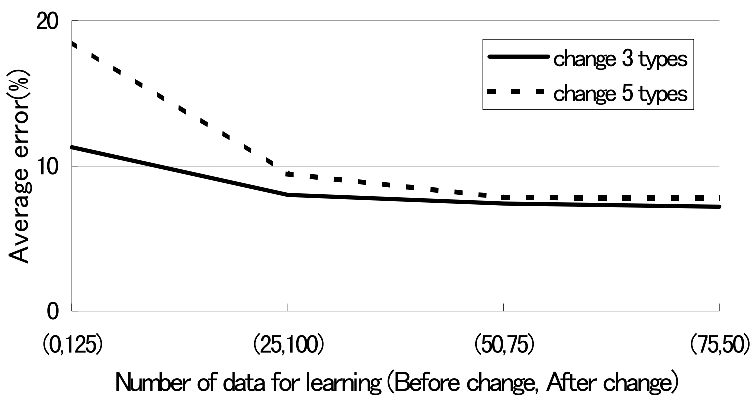

Fig.6 Estimation error and number of data after change of job types

4.2.2 Change of production workload

Production workload changes from 70% to 85% / 65% gradually, because jobs before the change of production workload exist on shop floor as WIP. When production workload is changing like these, we estimated lead-time 50 times. Fig.7 shows the average error of estimations by neural network and by Formula.1. In Fig.7, we used 125 data for learning collected before the change of production workload. From Fig.7, the average error of estimations by neural network and by Formula.1 is more than 20%, and the effective estimation is impossible.

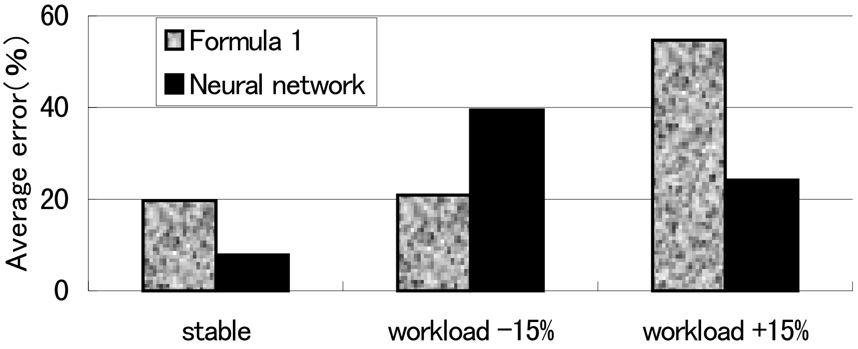

Fig.7 Estimation error when production workload change

When 0～75 data after the change of production workload are included in 125 data for learning, we show the shift of the average error of estimations by neural network (Fig.8). From Fig.8, when the number of data after the change of production workload is more than 25, the average estimation error is within 20% and the shift of it is stable. If there are some number of data for learning after the change of production workload, the estimation system by neural network could correspond to the change of production workload. Moreover, the number of data to correspond to the change of production workload is more than the number of data to correspond to the change of job types.

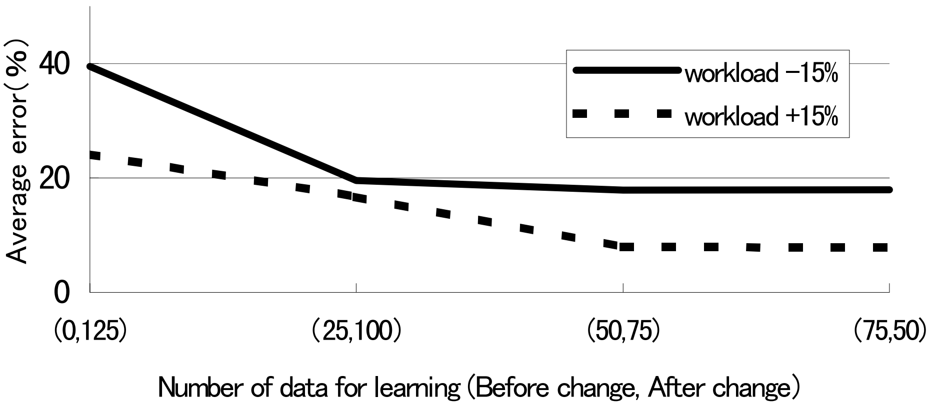

Fig.8 Average estimation error and number of data after change of production workload

5. Improvement of the estimation system by neural network

In order to estimate accurately no matter when production workload is changing, we suggest the addition of an input pattern. We thought that the problem of this system is unstable learning, which is caused by the condition that a waiting time of each job is gradually increasing or decreasing when production workload is changing. The input pattern added in order to learn the trend of the change of a job's waiting time is the difference of a waiting time between a job and next job. We examined an influence on the addition of input pattern (Fig.9). From Fig.9, the system seldom improved. The neural network used only when production workload is changing is necessary. That neural network needs to learn the trend of the change of production workload in advance.

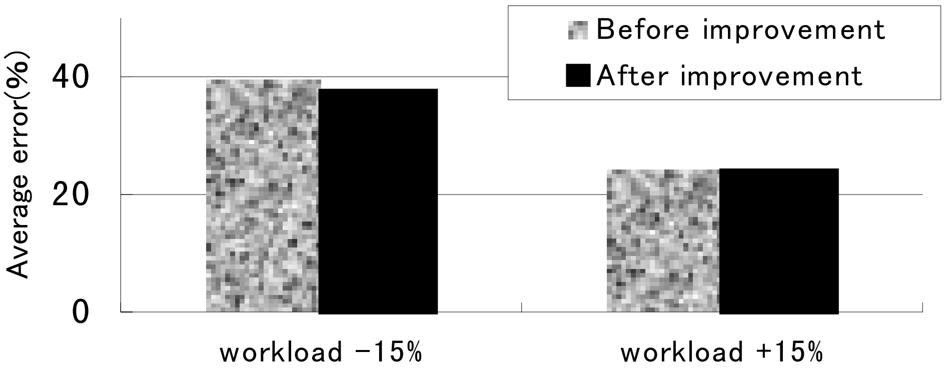

Fig.9 Influence on the addition of input pattern

6. Conclusion

We proposed the lead-time estimation system by neural network, and examined if the neural network used in this system can correspond to the change of arrived jobs and the production workload. This system can estimate accurately even if the combination of arrived jobs changes. But when production workload is changing, it can't estimate accurately. It is necessary to improve the neural network.

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