An Artificial Neural Network Meta-model for Resource Allocation of Vehicle Fleets in the Automated Material Handling System

Che-Wei Chou, Wei-Cheng Chiu, Yu-Zhong Kang, Yao-Ting Chiang and Chia-Yu Lin

***Abstract*—With the continuous improvement of semiconductor wafer manufacturing technology, the wafer size has gradually increased from 200 mm to 300 mm, and the total weight of the front opening unified pod (FOUP) has made manual handling very difficult. As advanced manufacturing processes become more complex that lead to wafer movement frequently during production process. Foundries have adopted automated material handling systems (AMHS) to solve wafer transportation problems. As AMHS system grew in size and the number of overhead hoist transfers (OHTs) increased, the management complexity and the consequent traffic congestions were escalating, thus highlighting the efficiency of AMHS system and the importance of resource management. Therefore, this study proposes a meta-model function based on artificial neural network (ANN) architecture to predict the number of OHT vehicles with different transportation requirements. In addition, this study constructs an AMHS simulation model with a design of experiments (DOE) plan to explore the impact of performance metrics under different wafer dispatching strategies. Hence, according to the predicted number of OHTs and its wafer dispatch strategy, the managers can control and monitor the AMHS system to achieve the goals of AMHS performance metrics with high AMHS efficiency. In addition, meta-model can avoid intensive computation and numerical simulation to reduce computational cost. Satisfy manufacturing decisions at AMHS resource planning in a rapidly changing and complex foundry manufacturing site.**

Keywords: simulation optimization, meta-model, artificial neural network, intelligent manufacturing

I. Introduction

With the advancement of semiconductor wafer manufacturing technology, the diameter of the wafer gradually increases. As the diameter of the wafer increases, more integrated circuits can be produced. The total weight of a lot, called a FOUP, also makes manual handling very difficult, so foundries have introduced automated material handling systems (AMHS) to solve wafer handling demand in the transitional stage of wafer diameters from 200 mm to 300 mm [1].

The AMHS system usually adopts the structure shown in Figure 1. AMHS usually consists of four main components, namely interbay, intrabay, tool, and stocker. The interbay system is mainly responsible for the bay-to-bay transportation tasks, and the intrabay system is responsible for the transportation between tools. The tool is responsible for processing the wafer, and the stocker is in charge of storing FOUP temporarily. The AMHS system often uses the OHT for high-altitude transportation, because the OHT can effectively use the three-dimensional space of the fabrication plant (fab) without affecting the activity space on the ground. That also can achieve the best space utilization in the fab.

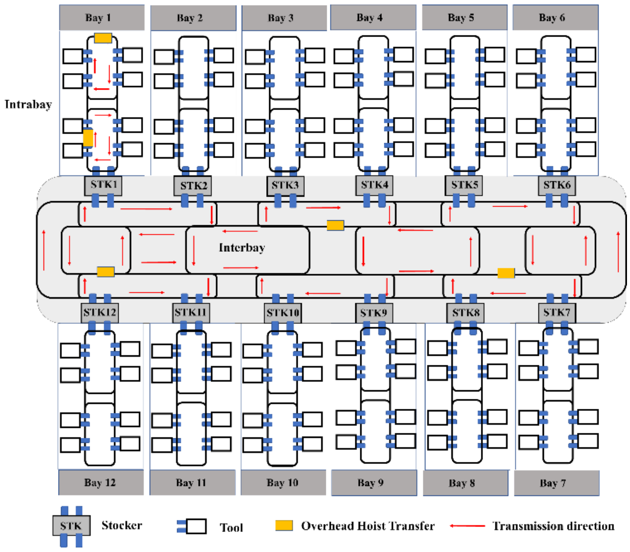

Figure 1. AMHS architecture based on interbay and intrabay

However, as the AMHS system becomes larger and complex with growing the number of OHTs rapidly, it accompanies the complexity of management. Therefore, many foundries are facing with the vehicle fleet sizing problem [2]. If there are too few OHTs, it will not be able to meet the transportation needs of the fab and may cause delays in delivery. If there are too many OHTs, it will increase the complexity of traffic, and even cause congestion that lead to relevant cost [3]. In addition, with the intensification of global competition, how to shorten the manufacturing cycle time and improve the equipment utilization is an important issue for the semiconductor industry. To evaluate the effectiveness of AMHS, three important scoring items proposed, namely delivery time, transportation time and waiting time [4]. It can be seen that if the vehicle transportation time can be effectively shortened, its competitiveness can be enhanced, such as improving the efficiency of the AMHS system.

Therefore, this research proposes a meta-model function based on ANN architecture to predict the number of OHT vehicles with different transportation requirements. In addition, this study constructs an AMHS simulation model with a DOE plan to explore the impact of performance metrics under different wafer dispatching strategies. Therefore, based on number of OHTs and its

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wafer dispatch strategy, the manager can control and monitor the AMHS system to achieve the goals of AMHS performance metrics with high AMHS efficiency. Moreover, the semiconductor production process is one of the most complex production processes in the world. The proposed meta-model can avoid complex numerical calculations and numerical simulations, shortening the profit climbing curve of the foundry manufacturing industry and enhancing competitiveness.

II. Literature Review

In recent years, the method of deep learning has been highly investigated by researchers, and has also been widely used in research and implemented in various fields. ANN is used to establish meta-model, because meta-model can reduce the complex simulation process and cost of simulation model, so it has developed rapidly in the past ten years [5]. Therefore, ANN is widely applied in manufacturing industry application. Simulation models and optimization methods have long received attention for their ability to improve complex systems. The metamodels can make decision-making more stable and efficient, helping users quickly find the best solution [6]. In addition, data collection is also a major pain point for validation, and meta-models built through neural networks can be trained with smaller datasets that generated by simulation model [7]. The foundry is a complex and large-scale manufacturing system. The method of establishing a meta-model through artificial neural networks can use those simulated data to make predictions and effectively allocate AMHS resources.

Parnianifard et al.[5] divided simulation optimization (SO) into two types: model-based and metamodel-based. The output data of the former model can be directly optimized, while the latter requires a robust design for optimal combination. The following lists some applications of SO methods in the foundry industry. Chang and Cuckler [8] developed a technique based on simulation optimization, Efficient search through adaptive most-promising hyperbox selection (ES-AMHS) to analyze the most optimum OHT quantity. The research confirmed the validity of the model through extensive numerical experiments. Chien et al.[9] developed a simulation-based AMHS model and addressed the problem of AMHS traffic congestion through different dispatch strategies. Hsieh and Chang [10] proposed a meta-model-based progressive simulation meta-modeling (PSM) method to solve the problem of normal batch delivery delays caused by urgent batches. The research validated the PSM feasibility in cooperation with foundries. Kong et al. [4] proposed a meta-model for AMHS using two stages for meta-modeling, the first stage used a factorial experimental design to collect data, and the second stage looked for functional relationships between decision variables. The research verified that artificial neural network is an effective way to construct meta-model. Mohammad et al. [11] proposed an ANN-based SO meta-model, and the meta-model proposed in the research can capture the nonlinear characteristics of ANN and avoid some unnecessary simulated observations.

Amaral et al.[6] sorted out some commonly used meta-models, including artificial neural network, response surface methodology, radial basis function, Kriging, and Spline. The ANN technique is to build the meta-model where represents a highly nonlinear relationship between different variables to achieve appropriate accuracy [12]. Kroetz et al. [13] compared common meta-models such as ANN, polynomial regression and Kriging, and found that all three meta-models can achieve the accuracy required by users, but the meta-model based on artificial neural network is computationally efficient. It is better than polynomial regression and Kriging. Xiao et al. [3] applied ANN for meta-modeling and combined with the error-correction module related to the recent observation, and finally proposed a dynamic Meta-ANN meta-model with three hidden layers, using historical datasets for training. And the proposed meta-model was validated to improve the overall computational efficiency. Carlone et al. [14] proposed a meta-model based on two artificial neural network structures, which reduced the time and cost required to generate datasets with high stability. Based on the above studies, artificial neural network architecture can reduce the calculation time and cost of analysis, and at the same time can achieve appropriate accuracy.

III. Research Framework

This research simulates the complex automated material handling system of the fab through simulation, constructing an AMHS simulation model in the foundry, and discusses the performance metrics of the AMHS system under different wafer dispatch strategies. This research also defines the key factors that affect the performance metrics of AMHS through the constructed simulation model, and conducts a DOE plan to simulate experiments with different delivery strategies. Finally, a meta-model based artificial neural network architecture was developed to predict the required number of OHTs in the AMHS system.

Three different dispatch strategies were adopted in this research, namely first in first out (FIFO), earliest due date (EDD), and Priority. FIFO is mainly carried out according to the order in which FOUPs enter the system. EDD is processed first with the earliest delivery date. Finally, priority is acted based on the respective priority of each FOUP. This research applied the above three dispatch methods in to the simulation model.

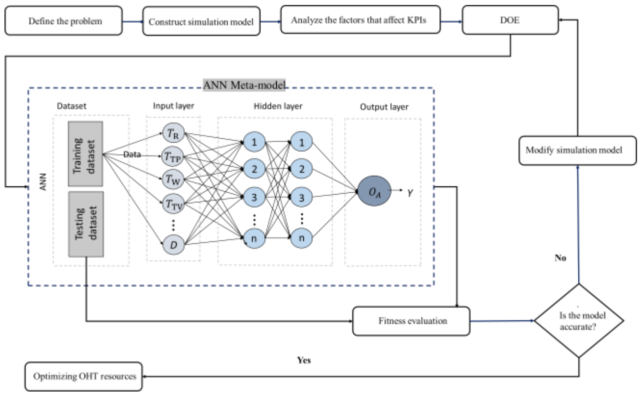

Figure 2. ANN-based meta-model framework

Figure 2 shows the architecture of meta-modeling using artificial neural network. First of all, this research identifies the problem of AMHS in the foundry, and clearly defines the goal is to predict the required number of OHTs and manage the OHT resources. An AMHS model was constructed to address the factors that have impacts on the performance metrics, and applies a DOE plan to analyze what affects under different delivery strategies. After generating data of different delivery strategies, the data is randomly divided into training dataset and test dataset and as input to the proposed ANN-based meta-model for prediction. After the number of OHT is determined, the test data set is used to verify the accuracy, and then allocate the OHT resource and the wafer dispatch strategy. It expects to achieve the goals of the AMHS system performance metrics.

This research considers the combination of different variables to conduct the DOE plan, and collects datasets of various performance metrics as the input features of ANN. In this research, three factors were used for DOE scenarios, namely the number of OHTs, the delivery strategy, and the total shipping demand of FOUPs.

An ANN architecture consists of input layer, hidden layer and output layer. The model needs to define several components, namely input features, number of hidden neurons, activation function and output target. The neurons in the ANN connect the input features to the output targets respectively, and update the bias value through the weights until the model has an acceptable accuracy.

In this research, we take the key factors as the input features of the input layer, and define those notations which are listing as below:

1. Retrieval time (T_{R}): the time while FOUP receives the dispatch command and has not yet move to the load port where waiting for an OHT arriving.
2. Waiting time (T_{W}): the time that FOUP waits for OHT arriving on load port.
3. Traveling time (T_{TV}): the time of OHT carried a FOUP from departure stocker to destination stocker.
4. Transportation time (T_{TP}): FOUP's waiting time plus loading time and travelling time.
5. Total delivery time (T_{T}): the time starts from a FOUP received a transportation request to finish a shipping demand.
6. Number of shipping FOUPs (N_{T}): the total number of shipping FOUPs during the simulation period.
7. Number of tardy jobs (N_{D}): the number of FOUPs that were not shipping within the limited time window.
8. Tardy rate of FOUP (T_{RF}): the percentage of FOUPs that are not shipping within the limited time window.
9. Average loading rate of OHTs (A_{LR}): the average of OHT's usage rate.
10. Average number of waiting FOUPs (A_{W}): the number of FOUPs received request that wait for transportation but not shipping.
11. Demand (D): total shipping requests.

In addition to those input features, the number of OHTs (O) is defined as the output target of the ANN meta-model for prediction for the AMHS system depended on different scenarios.

Figure 3 illustrates the transport process and timeline definition of the OTH and FOUP. The top diagram represents the process of transportation, and the upper and lower timelines represent the detail procedure of OHT and FOUP, respectively. For OHT, the vehicle will move to the load port after receiving the transport request, and the time between receiving the order and arriving at the load port is called retrieval, and then OHT will start to pick up the lot, which is loading process. After the loading is completed, OTH departs to the destination stocker and unloads the FOUP, then a transportation request is finished. From the perspective of FOUP, the timeline is divided into retrieval time, waiting time, loading time, traveling time and unloading time. The period from receiving a transportation request to finish a shipping demand is called the total delivery time.

The number of neurons in the hidden layer is an important element of ANN. Here, we denote the total number of samples *N* with *m* features, *k* neurons and a single output *y* as follows:

$$v_k = \sum_{i=1}^{m} x_i W_{ki} + b_i \tag{1}$$

$$y_k = \varphi\left(\sum_{i=1}^{m} x_i W_{ki} + b_i\right) \tag{2}$$

In equation (1) and equation (2), v_k is the number of neurons in the input layer, W_{ki} is the weight of the connection between the neuron *k* and the feature *i*, φ is the activation function, and *b* is the bias value.

In addition, rectification linear unit (ReLU) function is the activation function here to perform simple nonlinear transformation. With a given element x, the ReLU function is defined as the maximum of that element x that denotes the input of neuron. If the parameter calculated by ReLU is negative, it will be regarded as not contributing to the model, so the output value is 0. The representation of the ReLU function is formulated in equation (3).

$$\mathrm{ReLU}(\mathrm{x}) = \max(0, \mathrm{x}) \tag{3}$$

In order to verify the accuracy of the ANN-based meta-model, here we applied mean square error (MSE) that used to measure the performance of the regression model to evaluate the gap between the predicted value $\widehat{y}_i$ and the target value y_i. The more smaller MSE value is, the more accurate of the developed model. The definition of MSE is shown as equation (4).

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(\hat{y}-\bar{y})^2}{N} \tag{4}$$

After the meta-model is validated through testing dataset that generated by simulation model, then the predicted number of vehicles can apply to the AMHS system for further OHT resource allocation. Otherwise, the simulation model will modify and re-train ANN-based meta-model to improve its accuracy.

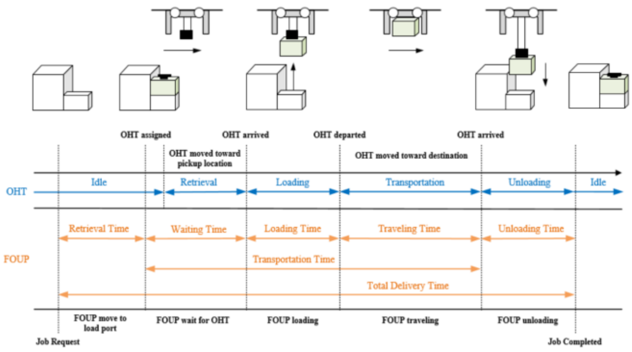

Figure 3. Timeline of OHT and FOUP

IV. EXPERIMENTS

4.1 Simulation Model

The AMHS simulation model is constructed based on a 8-inch fab in semiconductor manufacturing industry. In this AMHS system, there are 25 stockers that design for storing FOUPs temporally before shipping to next production process. An OHT is responsible for the transportation between the stocker and the stocker, and the transportation track is a one-way circulation operation. The simulation period set two-days, and the FOUP shipping request were based on a from-to table that indicated the transport demand among stockers. For instance, according to the from-to table, the expected number of FOUPs transported is denoting the mean rate for the Poisson distribution defined over the delivering lots between from source stocker *a* to destination stocker *b*. Besides, the location of stocker was also set by a distance matrix that denoted the stockers layout in a fab.

The Interbay system dispatch strategy combines FIFO EDD, Priority for FOUP, and the closest vehicle for OHT. The priority order is randomly determined by the uniform distribution U(1,100) where 1 to 100 is used as the FOUP delivery order. The delivery date is randomly assigned by normal distribution N(720,180), and the delivery date is randomly determined when the FOUP is generated.

The number of OHT is the decision variable that represents the number of vehicles in the AMHS system. The speed of the OHT on the track set 2 meter per second, and the loading and unloading time of the FOUP are fixed at 10 seconds. Each stocker contains 2 loading and 2 unloading ports, and it is assumed that the capacity of each stocker is unlimited.

4.2 The DOE Plan and ANN Meta-modeling

This research takes 11 features that affect the number of OHT as input into the meta-model, namely T_{R}, T_{TP}, T_{W}, T_{TV}, T_{T}, N_{T}, N_{D}, T_{RF}, A_{LR}, A_{W}, and *D*. The DOE plan also addresses three different factors, namely transportation demand (*D*), the dispatch strategy, and the number of OHTs (*O*).

Table 1. simulated scenario design

Factor	Level
Transportation demand (*D*)	D_H, D_M, D_L
Dispatch strategy	FIFO, EDD, Priority
The number of OHTs (*O*)	$O_{30}, O_{40}, O_{45}, O_{50}, O_{60}$

Table 1 shown the simulated scenario design. First of all, we divided the transportation demand into three levels: high, medium and low as 55500, 41712, and 36763, respectively. Three dispatch strategies setting were FIFO, EDD, and Priority. The five OHT quantities setting in this research were 30, 40, 45, 50, and 60. Therefore, the DOE plan conducted a total of 45 scenarios (5×3×3) where replicated 15 runs to generate the prediction results for the ANN meta-model. Through the DOE plan, we can analyze the influence of multiple variables on the target value and obtain more accurate results.

This paper generates data in different scenarios through the DOE plan, and divides the generated data into a training dataset and a test dataset to predict the number of OHTs. The performance metrics T_{R}, T_{TP}, T_{W}, T_{TV}, T_{T}, N_{T}, N_{D}, T_{R}, A_{LR}, and A_{W} are used for the input features of the ANN model and connected with the neurons in the hidden layer to increase the complexity of the neural network. The artificial neural network was designed based on the above-mentioned architecture, and the ReLU function is used as the activation function in the ANN model.

4.3 Meta-model Performance Evaluation

In this research, observations were obtained through the simulation model. Here, the transportation demand was fixed at the highest level of 55500. We compared the differences among retrieval time (T_{R}), transportation time (T_{TP}), total delivery time (T_{T}), number of shipping FOUPs (N_{T}) and tardy rate of FOUP (T_{RF}) through different dispatch strategies and the number of OHTs.

Table 2. Performance metrics by simulation model

	Number of OHT				
	O_{30}	O_{40}	O_{45}	O_{50}	O_{60}
EDD					
N_{T}	32,766	40,564	43,282	47,095	51,731
T_{T} (min.)	692.1	478.5	389.9	353.9	279.2
T_{R} (min.)	684.8	472.5	384.3	348.5	274.2
T_{TP} (min.)	7.2	6.0	5.6	5.4	5.0
T_{W} (min.)	4.5	3.2	2.8	2.6	2.1
T_{RF} (%)	41.3	27.3	22.1	19.7	13.5
FIFO					
N_{T}	30,318	38,239	41,266	44,125	48,397
T_{T} (min.)	777.8	577.7	492.5	417.1	307.3
T_{R} (min.)	770.4	571.5	486.7	411.6	302.2
T_{TP} (min.)	7.4	6.2	5.8	5.5	5.1
T_{W} (min.)	4.7	3.4	3.0	2.7	2.2
T_{RF} (%)	46.9	34.5	29.8	24.5	15.3
Priority					
N_{T}	33,110	41,828	45,328	48,540	53,374
T_{T} (min.)	345.7	315.2	292.5	269.6	247.8
T_{R} (min.)	338.5	309.2	286.7	268.3	253.7
T_{TP} (min.)	7.2	6.0	5.7	5.4	5.0
T_{W} (min.)	4.5	3.3	2.9	2.5	2.1
T_{RF} (%)	15.5	14.2	13.1	12.6	11.1

Table 2 shown the performance metrics obtained by the simulation model. The total number of shipping FOUPs (N_{T}) during the simulation period is depended on the amount of OHTs (*O*), namely, more vehicles, more shipping demand can be delivered. Then, there is the significant difference under different dispatch strategy where p-value < 0.05 by

ANOVA. Among three dispatch strategies, Priority dispatching has better performance of total shipping FOUPs and tardy rate (T_{RF}) that comparing each other where p-value < 0.05 by T-test. That is, higher N_{T} and lower T_{RF}, where compared with FIFO and EDD. Further, we found that there were no significant differences in transportation time (T_{TP}) and waiting time (T_{W}) metric by the different number of OHTs scenarios where p-value < 0.05 by ANOVA among three dispatch strategies.

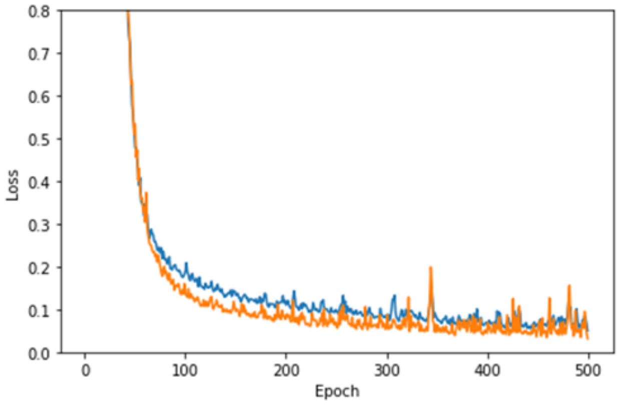

Figure 4. The training loss of MSE

This research applied MSE as the loss function to evaluate the meta-model. Figure 4 shown the loss of MSE in the ANN meta-model for each period. We can observe that the MSE gradually decreases as the epoch increasing in both of training loss and test loss. It shown that the proposed meta-model has the ability to minimize the error. As the result, ANN-based meta-model can achieve the high level of performance.

In addition, we applied support vector regression (SVR) model with radial basis function (RBF) kernel to solve this AMHS vehicle fleet sizing problem.

Table 3. Comparison of ANN meta-model and SVR

MSE	Training	Testing
ANN-based	2.78×10^{-2}	2.91×10^{-2}
SVR	4.91×10^{-2}	8.29×10^{-2}

In this research, 80% of the dataset is used for model training, and the other 20% is used for testing the performance of the model. 10-fold cross-validation is adopted to validate the ANN meta-model, and obtained the loss of MSE. The corresponding MSE obtained by ANN-based meta-model and the SVR model is shown in Table 3. The MSE of training and testing are 2.78×10^{-2} and 2.91×10^{-2} respectively in ANN-based meta-model. Comparing to the MSE of training and testing are 4.91×10^{-2} and 8.29×10^{-2} respectively in SVR model, ANN-based meta-model has smaller MSE than SVR model. And the SVR model seems to have an overfitting problem. Therefore, based on the experiment result, the proposed ANN meta-model has a high explanatory ability.

Table 4. MSE comparison among scenarios

	Total transportation demand								
	$D_H = 55500$			$D_M = 41712$			$D_L = 36763$		
Dispatch strategy	EDD	FIFO	Priority	EDD	FIFO	Priority	EDD	FIFO	Priority
O_{30}	0.59	1.20	0.38	1.29	0.36	2.01	1.28	0.82	7.78
O_{40}	2.94	7.29	0.02	0.54	0.55	1.25	1.80	1.51	1.90
O_{45}	1.73	3.31	0.05	1.25	0.24	0.82	0.68	0.31	0.70
O_{50}	1.73	0.16	0.21	1.34	0.30	1.91	3.74	3.23	0.24
O_{60}	0.33	1.44	0.44	1.37	0.30	0.94	0.56	1.70	0.12

Unit 10^{-2}

Meanwhile, to compare the accuracy of prediction in different scenarios, we summarized the MSE by three design factors, total transportation demand, dispatch strategy, and the number of OHTs in Table 4. There are small MSE in various situations, indicating that the model predicts the requested number of OHTs with highly accuracy. By using 10-fold cross-validation, the ANN meta-model can be made with higher complexity, which in turn makes the model more robust. Overall, the use of artificial neural networks to build meta-models has good generalization ability.

V. Conclusion

At present, fabs rely on the AMHS system for wafer transfer and handling. With the increasing scale and complexity in the fabs, the shipping demand in AMHS system is also increasing. How to effectively allocate OHT resource has become a critic topic in fabs. This research developed an AMHS simulation model, finding out the key factors that affect the performance metrics in the AMHS system. Meanwhile, an ANN-based meta-model was developed to predict the number of OHTs for different scenarios. The main contributions in this research are as follows:

1. This study constructs a high fidelity AMHS simulation model with designed scenarios to explore the impact of performance metrics.
2. The proposed ANN-based meta-model can predict the requested OHTs with high accuracy, and it was validated by various transportation situations and turn out generality and robustness.
3. The developed AMHS simulation model and ANN-based meta-model was based on the real setting in an 8-inch fab. It provided a suggestive solution for the managers to control

and monitor the AMHS system to achieve the goals of AMHS performance metrics with high AMHS efficiency.

4. In addition, meta-model can avoid intensive computation and numerical simulation to reduce computational cost. Satisfy manufacturing decisions at AMHS resource planning in a rapidly changing and complex foundry manufacturing site.

Although the proposed meta-model is effective for AMHS transportation system, we aware that our research practically has several limitations. For example, we didn't consider the optimal OHTs that perform effective metric. How to optimally allocate OHT vehicles all over the AMHS system is also a critic topic. Another practical issue that needs to be investigated is transportation in intrabay. In this research, we only consider the transportation in interbay. However, the actual AMHS system cover the FOUP shipping from tools to stockers, stockers to stockers, and tools to tools. Therefore, we can incorporate all FOUP transportation in intrabay and interbay, and optimize the requested number of OHTs over all AMHS system.

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