Performance Analysis of Material Handling Tools for a Discrete Manufacturing System

Yanting Ni
School of Mechanical Engineering, Chengdu University, Chengdu, China
Institute of Mathematical Optimization, Otto-von-Guericke-University, Magdeburg, Germany
Email: niyanting@cdu.edu.cn

Frank Werner
Institute of Mathematical Optimization, Otto-von-Guericke-University
Magdeburg, Germany
Email: frank.werner@ovgu.de

Abstract: The improvement of the performance of material handling tools (MHTs) and the work in process (WIP) in a discrete manufacturing system have a great importance for increasing the efficiency of the production. To this end, the static and dynamic status of MHTs are analyzed in this paper. A Markov decision process (MDP) is used to model the MHT problems. The quantified relationships between MHTs and WIP will be discussed within the CONWIP (constant WIP) and Little's law methodologies. A dynamic programming (DP) based algorithm is developed to determine a solution for the MDP model. To reduce the computational complexity of the DP algorithm, an appropriate modification is introduced. Computational experiments are conducted in a discrete semiconductor factory and the proposed MDP+DP method is compared with simulation. The computational results show that the developed method produces rather good feasible solutions.

Key Words: Material handling tool; Markov decision process; Dynamic programming; Discrete manufacturing.

MSC Classification: 90 B 35

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1. Introduction

A material handling tool (MHT) is one of the essential components in a manufacturing system. Especially in a discrete manufacturing system, the MHT is responsible for the transitions of the lots between the stations. In the production planning period, the number of MHTs is one of the critical parameters to calculate the right production quantity in each week. In the production scheduling period, the scheduling of MHTs will impact the production process substantially. A wrong scheduling strategy of MHTs may cause a lack of work-in-process (WIP) at a bottleneck station and a loss of capacity. At the same time, the delivery of the lots will be strongly influenced, and the customer service level will be finally reduced. Production includes a processing time plus a queuing time. Except the processing time on the machines, a typical job spends the remaining time waiting on MHTs. Consequently, any improvement in the MHTs has a great potential for reducing the inventory, minimizing the cycle time for the production and enhancing the deliverable orders. In this paper, a Markov decision process (MDP) will be applied to model the

MHT system, and a dynamic programming algorithm will be used to solve this problem. So far, many approaches for analyzing the performance of MHTs have been proposed, e.g. a queuing theory model, a Markov chain model, etc. (Zhang et al. 2016). Due to the complexity of MHT problems, many researchers work under different aspects. However, only a few works deal with MHS problems considering the relationships with static and dynamic WIP control coherently.

In this paper, the following two contributions are discussed:

(1) A systematic management method of MHTs under a discrete manufacturing will be developed using a Markov decision process. The quantified relationships between MHTs and WIP will be discussed within the constant WIP (CONWIP) methodology and constant demand.

(2) The dynamic MHT replenishment method of MHTs will be discussed within the theory of Little's law.

This paper is organized as follows. Section 2 reviews the existing literature. Section 3 analyzes the MHT system in a discrete manufacturing system. Section 4 describes the Markov decision model. Section 5 develops a dynamic programming algorithm. Section 6 presents some experimental results. Finally, Section 7 gives some concluding remarks and suggests some subjects for future research.

2. Literature Review

There exist many works on MHT or MHS problems and in general, the approaches can be partitioned into simulation methods and mathematical methods.

Lau and Woo (2006) develop an agent-based dynamic routing strategy for a generic automated material handling systems (AMHS). A generic AMHS network is modeled with a simulation tool that represents a highly flexible material handling system in a typical distribution centre, where simulation studies are performed under normal and exceptional operating conditions. Huang et al. (2011) study the vehicle allocation problem in a typical 300 mm wafer fab. They formulate it as a simulation-optimization problem and propose a conceptual framework to handle the problem. A discrete event simulation model is developed to characterize the AMHS, and the technique of simulation-optimization is applied to obtain an optimal vehicle allocation for both interbay and intrabay systems. An empirical problem based on real data is conducted to show the viability of the proposed framework in practice. Chang et al. (2014) study the vehicle fleet sizing problem in semiconductor manufacturing and propose a formulation and solution method to facilitate the determination of the optimal vehicle fleet size that minimizes the vehicle cost while satisfying time constraints. The proposed approach is to construct sequentially a series of meta models to solve an approximate problem and evaluate the quality of the resulting solution. Extensive numerical experiments show that the presented methods outperform the existing methods and the computational advantage is increasing with the problem size and the level of the variance of the response variables. An empirical study based on real data is conducted to validate the viability of simulation sequential meta-modeling in practical settings.

To overcome the shortcomings of simulation, some mathematical models are developed to quantify the parameters of a material handling system (MHS), such as a queuing theory model, a queuing network model and a Markov chain model (MCM). Another shortcoming is the calculation efficiency problem, and the mathematical method shows a much higher efficiency than the simulation tool (Zhang et al. 2015). Nazzal and McGinnis (2008) present a computationally effective analysis of the throughput performance of a closed-loop multi-vehicle automated material handling system (AMHS) used in highly automated 300 mm wafer fabrication facilities (fabs). A probabilistic model is developed, based on a detailed description of the AMHS operations, and the system is analyzed as an extended Markov chain. The model represents the vehicle operations on the closed-loop considering the possibility of vehicle blocking. This analysis provides essential parameters such as the vehicle blocking probabilities and the throughput capacity of the AMHS. A numerical example is analyzed and simulated using Auto Mod to demonstrate and validate the stochastic model. Nazzal (2011) models a multi-vehicle material handling system as a closed-loop queuing network with finite buffers and general service times, and a new iterative approximation algorithm is presented that estimates the throughput capacity and decomposes the network consisting of S servers into S separate G/G/1 systems. Each subsystem is analyzed separately to estimate the work-in-process via a population constraint to ensure that the summation of the average buffer sizes across all servers equals the total number of vehicles. Numerical results show that the methodology proposed is accurate in a wide range of operating scenarios. Zhang et al. (2016) propose a modified Markov chain model (MMCM) to analyze and evaluate the performances of a closed-loop automated material handling system (AMHS) with shortcut and blocking in a semiconductor wafer fabrication system. The system characteristics are well considered in the MMCM, and the proposed MMCM is compared with a simulation analysis model. The results demonstrate that the proposed MMCM is an effective modeling methodology for a performance analysis of an AMHS at the system design stage. A comprehensive heuristic solution is evolved by Goswami and Tiwari (2006) to include all the three segments of a machine loading problem of flexible manufacturing systems. An iterative reallocation procedure has been devised to ensure a minimum positive system unbalance and a maximum throughput. A test problem is simulated to represent the real shop floor environment and the same has been solved using various steps of the proposed algorithm. Siegel et al. (2014) present a review about material handling systems. First, they survey the common maintenance practices of MHSs including three typical warehouse MHSs, like an automatic picking system (APS), goods to destination (GDS), and Erector. They also review previous works in predictive monitoring of MHSs categorized as the machine level, the component level, and the production level.

Based on the literature study, one can observe that there are only a few works reflecting the performance of an MHS with respect to WIP and cycle time simultaneously, and most papers consider an MHS under a constant demand scenario without dynamical considerations. In this paper, a Markov chain model will be proposed to measure the MHTs within a closed loop discrete manufacturing environment. As the MHT will be combined with the WIP together in the transportation and queuing time, the WIP quantity can be reflected together with the MHT state space. At the same time, another MHT inventory management method will be provided under a demand fluctuation scenario in a real life factory MHT management.

3. Analysis of the MHT System

In a discrete manufacturing factory, there exist many types of MHTs to carry the working lots between different stages. As shown in Figure 1, for the case of two types of vehicles, there might exist only two possible scenarios for each individual workstation - an MHT change or no change. If the MHT has no change, there exists only one MHT type X (or type Y) in the upload and load areas. If there is a change of the MHT, there are two types of an MHT at one station. The MHT X will be uploaded and the MHT Y will be loaded after processing the lots (or vice versa). For each station, the quantity of the arriving lots with the MHT is of stochastic nature (it has to meet the throughput with some probability) in the area of the waiting queue. After processing at the station, a unique MHT is required in the load area to carry the lot to the next station.

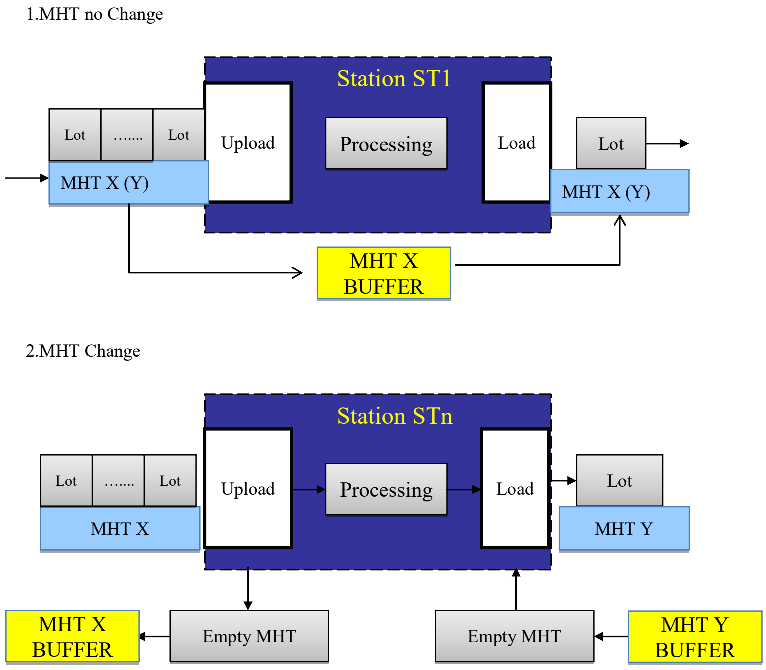

Figure 1: MHT Cycle Classification

3.1 Notations

The MHT problem includes the following sets and vectors:

(1) There is a non-empty set M of n stations STi .

(2) There is an n-dimensional vector W of the WIP quantities at the n stations.

(3) There is an n-dimensional vector X of the numbers of vehicles of type X at the n stations.

(4) There is an n-dimensional vector Y of the numbers of vehicles of type Y at the n stations.

(5) There is a transition mode sequence τ for all n stations of the whole production line.

In Table 1, the definition of sets and parameters used for the MHT problem formulation are summarized.

Table 1: Parameters of the MHT problem.

Sets and vectors	Ranges of variables	Description
$M=\{ST1,ST2,...,STi,...,STn\}$		Set of stations
$W=(w_1,w_2,...,w_i,...,w_n)$		Vector of WIP quantities
$X=(x_1,x_2,...,x_i,...x_n)$	$x_i\in\{0,1,2,...,\overline{X}\}$ $i\in\{1,2,...,n\}$	Vector of numbers of vehicles of type X
$Y=(y_1,y_2,...,y_i,...,y_n)$	$y_i\in\{0,1,2,...,\overline{Y}\}$ $i\in\{1,2,...,n\}$	Vector of numbers of vehicles of type Y
$\tau=(\tau_1,\tau_2,...,\tau_i,...,\tau_n)$	$\tau_i\in\{a,b,c,d\}$ $i\in\{1,2,...,n\}$	Sequence of MHT transition modes

3.2 Assumptions

(1) The processing time at each station is constant, and production meets an M/M/n queuing system.

(2) A lot arrives according to an exponential distribution with the associated parameter λ.

(3) Each MHT transports the lots based on the FIFO (first-in-first-out) rule.

(4) The loading time, the unloading time and the running speed of the vehicles have a deterministic value, and both acceleration and deceleration of vehicles are ignored.

(5) The WIP quantity meets the CONWIP scenario and the desired WIP level is w^*.

(6) The route of the MHT at a specific work station for one specific product is fixed within the product design period.

(7) The delivery quantity is aligned with the demand D of the master production schedule (MPS).

(8) Only one product is considered in this paper.

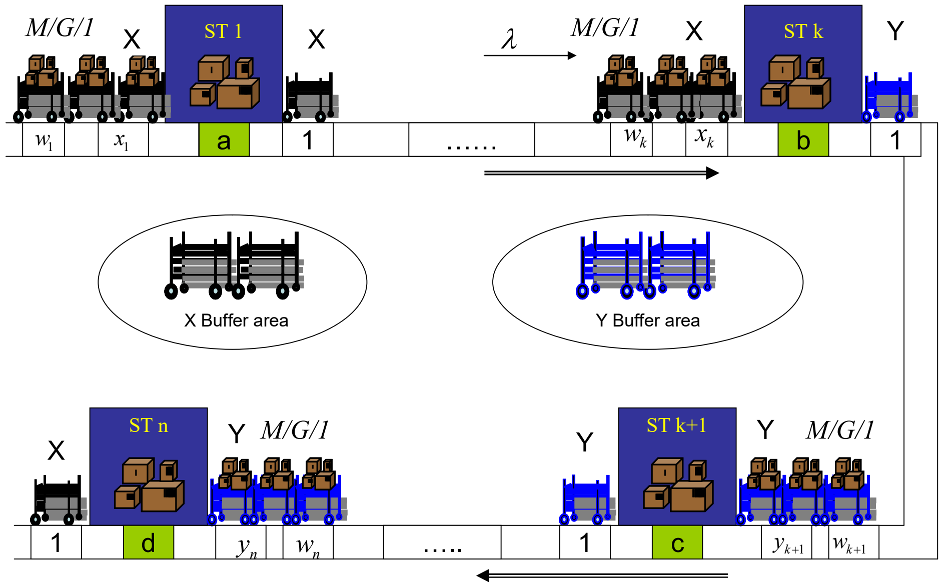

Figure 2: Model of a physical MHT system in discrete manufacturing

3.3 Dynamic analysis of the MHT *system*

In this subsection, we analyze the dynamic numbers of vehicles of types X and Y. According to the description of the model in Figure 2, the variable numbers of vehicles x_i and y_i as well as the corresponding WIP quantities w_i are influenced by the transition mode vector $\tau = (\tau_1, \tau_2, ..., \tau_n)$, which is defined specifically based on the design of the product route. The ratio between the number of vehicles x_i of type X and the WIP quantity w_i is denoted as A which means that a vehicle of type X can contain A units, and the ratio between the number of vehicles of type Y and the WIP quantity w_i is denoted as B which means that a vehicle of type Y can contain B units. In this paper, we consider two types of MHTs X and Y in the production line. Thus, we have four types of a transition mode $a: X \to X, b: X \to Y, c: Y \to Y, d: Y \to X$ which are subsequently described in detail. The transition modes a and c characterize a continuous working status of the MHT, b and d describe a transition status of the MHT. If $\tau_i = a$, the vehicle does not change in the load and unload areas with vehicle X at station STi, and the mode a is described by $x_i = \lceil w_i / A \rceil + 1, y_i = 0, i \in \{1, 2, ..., n\}$,where $\lceil w_i / A \rceil$ denotes the smallest integer not smaller than w_i / A. If $\tau_i = b$, the vehicle will change from type X to type Y during the load and unload area, and the mode b is described by $x_i = \lceil w_i / A \rceil, y_i = 1, i \in \{1, 2, ..., n\}$. After the vehicle change from type X to type Y, the vehicle Y will load the WIP and moves forward to the next stations. If $\tau_i = c$, the vehicle Y does not change in the load and unload areas, and the mode c is described by $x_i = 0; y_i = \lceil w_i / B \rceil + 1, i \in \{1, 2, ..., n\}$. The last scenario is that the vehicle changes from type Y to type X, and the mode $\tau_i = d$ is described by $x_i = 1, y_i = \lceil w_i / B \rceil, i \in \{1, 2, ..., n\}$. Since the real time WIP quantity w_i can be exported by the factory manufacturing execution system (MES), we can derive the real time numbers of the vehicles accordingly. According to the above quantitative relationships, the variables x_i and y_i can be calculated using the w_i values, and then we can determine the total number of vehicles of type X in the whole production line as $sum(X) = \sum_{i=1}^{n} x_i$ and the total number of vehicles of type MHT Y in the whole production line as $\text{sum}(Y) = \sum_{i=1}^{n} y_i$.

3.4 Static analysis of the MHT system

In the production planning process, the numbers of the MHTs need to be determined such that the vehicles can sustain the weekly manufacturing operations. Thus, one needs to analyze the steady numbers of the MHTs. According to Little's law: $WIP = CT \times TH$ (Hopp and Spearman 1990), this means that the WIP quantity can be obtained from the cycle time CT and the throughput TH. Once we have determined the static WIP quantity, we can determine the numbers of vehicles based on their quantitative relationships. The cycle time CT_i of station STi satisfies the equation $CT_i = PT_i + QT_i$, where PT_i is the processing time at station STi and QT_i is the queueing time at station STi. So the expectation value of the cycle time can be obtained as $E(CT) = \sum_{i=1}^{n} p_i^s(\overline{PT}_i + \overline{QT}_i)$, where $\overline{PT}_i$ is the expectation value of the processing time according to the station engineering definition and $\overline{QT_i}$ is the expectation value of the queueing time at station STi. Both these values $\overline{PT_i}$ and $\overline{QT_i}$ can be obtained from the average value of the history. Moreover, p_i^s is the priority coefficient for each station STi which is defined according to the priority of station STi and it is set to a value between 0.8 and 1.2 in this paper. The throughput TH can be obtained from the weekly demand D and is given by $TH = \frac{D}{T}$, where T denotes the weekly hours, i.e., $T = 24 \times 7 = 168$ hours. After one has confirmed the cycle time CT and the throughput TH, we can determine the expectation value of the WIP level

$$E(w^*) = \sum_{i=1}^{n} p_i^s (\overline{PT_i} + \overline{QT_i}) \frac{D}{T}$$

for the whole production line. At the same time, by the static analysis, we can also determine the expected WIP level for station STi according to

$$E\left(w_i^*\right) = E\left(CT_i\right) \times E\left(TH_i\right),$$

and the expected WIP level for the bottleneck station STk is

$$E(w_k) = E(\overline{PT_k} + \overline{QT_k}) \times TH_k .$$

Using the transition mode sequence τ, the expectation values of the vehicles of both types $E(X^*)$ and $E(Y^*)$ can be determined accordingly.

4. Development of the MDP Model

For developing a model, we use an MDP which can be described by the following 5-tuple:

$$\left(T, S, A, P_{trans}, v(SA)\right)$$

Here T describes the set of time moments, S denotes the state space, A describes the set of actions (policy set), P_{trans} gives the transition probabilities, and $v(SA)$ denotes the reward function for a solution SA described by a feasible sequence of states and actions. Subsequently, we describe the particular components more in detail.

1) Definition of decision times T

The supervisor of the production floor will decide which lots of production tasks will be released based on the numbers of available vehicles and the recycle status at each time $t \in T = \{0,1,2,...,L\}$, where L is the length of the defined production cycle. The following components are defined for each time $t \in T$, but for simplicity of the description, we omit t subsequently.

2) Definition of the set of states S

The set of states S is composed of n sets $S_1, S_2, ..., S_n$. For stage i, representing station STi, the set of states can be defined as $S_i = \left\{ s_i = (x_i, y_i) \middle| x_i \in \{0,1,2,...,\overline{X}\}, y_i \in \{0,1,2,...,\overline{Y}\} \right\}$,

$i \in \{1, 2, ..., n\}$, where x_i and y_i denote the numbers of vehicles of type X and Y, respectively, at station STi at a particular time t. Since the WIP will be kept in the vehicles to wait for the production or on the machine for processing, the numbers of the vehicles have direct relationships with the WIP quantity w_i.

3) Definition of the set of actions A

The operation supervisors will schedule the vehicles according to certain scheduling policies. This means that at a decision moment t, the decision maker will take the action $a_i \in \{0,1\}$ and according to the transition probability $P_{trans} = P\left\{s_i^{'} \middle| s_i, a_i\right\}$ described subsequently, the numbers of vehicles at station STi may change from state s_i at time t to state $s_i^{'}$ at time $t+1, i \in \{1, 2, ..., n\}$. The vector $A=\left(a_1,a_2,...,a_i,...,a_n\right)$ with $a_i \in \{0,1\}$, $i \in \{1, 2, ..., n\}$, is the production strategy vector. According to the CONWIP methodology, if the WIP is higher than the desired value at station STi, the station needs to stop running to avoid an excessive inventory, this means that the action $a_i=0$ is taken, otherwise the WIP is running normally according to the first-in-first-out (FIFO) strategy, and the action $a_i=1$ is taken. At time $t \in T = \{0, 1, 2, ..., L\}$, once a decision a_i has been taken, the lots will be released with the vehicle.

4) State transition probabilities P_{trans}

(a) It is assumed that the vehicles arrive at station STi according to a Poisson distribution with the mean arrival rate λ_i. Thus, the probability that k vehicles arrive is given by

$$P_i^a=P(X=k)=\frac{\lambda_i^k e^{-\lambda_i}}{k!}.$$

In the production environment, λ_i is equal to the mean throughput of the preceding station $\overline{TH}_{i-1}$.

(b) It is assumed that the breakdown rate of work station STi is q_i^d and thus, the probability of the effective utilization of station STi is

$$P_i^b = \binom{M_i}{k} (q_i^d)^k (1\text{-}q_i^d)^{M_i-k},$$

where M_i is equal to the number of machines at station STi.

(c) It may happen that abnormal lots are encountered, which will be cancelled. It is assumed that the lot cancellation rate is q_l^c , so the probability of the interruption of k lots is

$$P_i^c = \binom{M_i}{k} (q_l^c)^k (1\text{-}q_l^c)^{M_i-k} .$$

Normally, the lots will be processed one by one at each station and follow an M/M/1 queue. The numbers of vehicles of type X and Y, respectively, are in linear relationship with the WIP quantity. The state will change when new lots arrive, tasks are cancelled or a machine has a breakdown. These three events can separately occur and so the state transition probability from state s_i at the current time t to state $s_i^{'}$ at the next time $t+1$ is

$$P_{trans}\left(s_i^{'} \middle| s_i\right) = P_i^a \times P_i^b \times P_i^c \quad \text{for } i \in \{1, 2, ..., n\} .$$

5) Reward Function v(SA)

One can note that both a higher or lower WIP level is not good for a smooth production process. An overflowing WIP will have the potential risk that a bottleneck station is blocked by a vehicle shortage and it also induces an inventory cost. On the other hand, a lower WIP will reduce the utilization rate of the station and waste productivity. The purpose of the vehicle management is to minimize the penalties for late deliveries of each product and to control the WIP level in the whole line within certain lower and upper limits.

To reach this goal, we can formulate the following optimization problem for finding an optimal solution (i.e., an optimal sequence of states and actions) *SA* with maximal total reward value:

$$v(SA) = Max E[\sum_{t=0}^{L}\sum_{i=1}^{n} R_t(s_i, a_i) | s_i = (x_i, y_i), a_i \in \{0,1\}] \tag{1}$$

s.t.

$$R_t(s_i, a_i) = e^{-\frac{\gamma}{D_t}} \tag{2}$$

$$\gamma = \sigma(D_t - \sum_{i=1}^{n} w_i) \tag{3}$$

$$\sum_{i=1}^{n} x_i \le \overline{X} \tag{4}$$

$$\sum_{i=1}^{n} y_i \le \overline{Y} \tag{5}$$

$$\sum_{i=1}^{n} w_i \le \sum_{i=1}^{n} w_i^* = w^* \tag{6}$$

The reward function can be obtained according to equation (1). Constraints (2) and (3) denote the reward ratio $R_t(s_i, a_i) = e^{-\frac{\sigma(D_t - \sum_{i=1}^{n} w_i)}{D_t}}$ depending on the state s_i and action a_i which is used to maintain a rather constant WIP status (within lower and upper bounds), where $\sigma(D_t - \sum_{i=1}^{n} w_i)$ is the standard deviation to measure the offset-overflow or shortage between the demand D_t at time t and the overall WIP quantity $\sum_{i=1}^{n} w_i$ of all stations. Thus, the reward function measures the decision cost to avoid an overflow and a shortage. Constraints (4) and (5) denote that the numbers of vehicles of type X and Y are not allowed to exceed the upper bounds $\overline{\mathrm{X}}$ and $\overline{\mathrm{Y}}$, respectively. Constraint (6) expresses that the total WIP quantity should be not greater than the total desired WIP level $\sum_{i=1}^{n} w_i^* = w^*$.

5. Algorithm

5.1 MHT Calculation Algorithm

According to the analysis of Subsection 3.3, the WIP quantity w_i has a linear relationship with the variable numbers x_i, y_i and τ_i. If we know the WIP quantity w_i, we can obtain the numbers of vehicles x_i and y_i according to the transition mode τ_i. In Figure 3, the algorithm is described to calculate the numbers of vehicles of types X and Y.

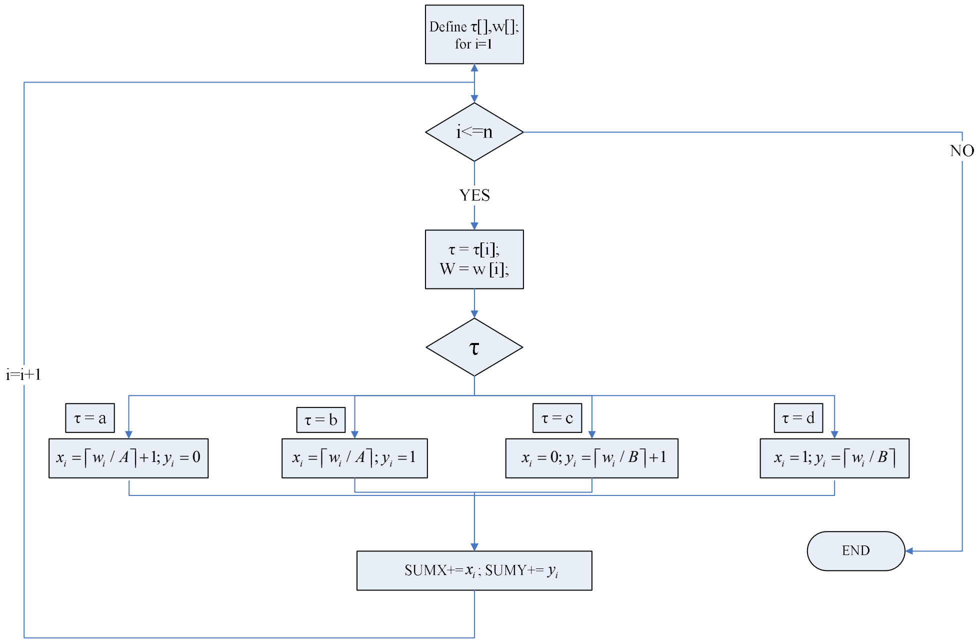

Figure 3: Vehicle calculation algorithm

5.2 Dynamic Programming Solution

The MDP model will be solved by a dynamic programming algorithm, where both forward and backward runs are used in the recurrence process. This dynamic programming algorithm has to be run for each time $t \in T$. To reduce the computational times, improve the effectiveness of the algorithm and ensure at the bottleneck station both the desired WIP and vehicle status, the whole set of stages are grouped into 3 parts: a bottleneck group, a front group and a backend group. The CONWIP methodology is used for the front group and the FIFO rule is used for the backend group. First, we determine the set of actions and the reward function values for the bottleneck station STk, then the front area from station $ST1$ to station $ST(k-1)$ will be considered in a second part, and finally the group of backend stations will be considered from station $ST(k+1)$ to station STn. In Steps 1 - 5 below and in Figure 4, we describe and illustrate the algorithm for a fixed but arbitrary time $t \in T$ in more detail.

Step 1: Initialization: Determine the n stages representing the stations for the problem and the states to be considered at each stage. Here we can reduce the number of states at each stage since we maintain a WIP level within lower and upper bounds. The actions will be taken at stage i, $i \in \{1,2,..,k,..,n\}$, for station STi. To stage k, there is assigned s_k as the initial state, i.e., $S_k = \{s_k\}$. Both the front groups and the backend groups are initialized from stage k to make sure that the whole line WIP is controlled by the bottleneck station.

Step 2: Since the bottleneck station STk is considered as the initial stage in this algorithm, we assign to action a_k and the WIP w_k the desired initial numbers. Then the reward value for any state $s_i = (x_i, y_i) \in S_i, i \in \{k-1, k-2, ..., 1\}$, of the front group can be determined by means of s_k in the next step.

Step 3: Evaluate the recurrence equations from stage $k-1$ to stage 1 and calculate the reward function value for each possible stage of the front group. Let $v_i(s_i, a_i)$ be the reward combination for station STi when action a_i is taken for state s_i, and $s_{i+1} = tr_i(s_i, a_i(s_i))$ be the state in stage $i+1$ resulting from the action $a_i(s_i)$ applied to s_i. The reward function for state s_i is given by $f_i^*(s_i) = \max\left\{v_i(s_i, a_i(s_i)) + f_{i+1}^*(s_{i+1}) \middle| a_i(s_i) \in \{0,1\}\right\}, i=k-1, k-2, ..., 1$.

Step 4: Evaluate the recurrence equations from stage $k+1$ to stage n and calculate the reward function value for each possible stage of the backend group. Let $s_{i\text{-}1} = tr_i(s_i, a_i(s_i))$ be the state in stage i-1 resulting from the action $a_i(s_i)$ applied to s_i. The reward function for state s_i is given by $f_i^*(s_i) = \max\left\{v_i(s_i, a_i(s_i)) + f_{i\text{-}1}^*(s_{i\text{-}1}) \middle| a_i(s_i) \in \{0,1\}\right\}, i=k+1, k+2, ..., n$.

Step 5: Determine the states $s_1^* \in S_1$ and $s_n^* \in S_n$ with the maximal reward function values $f^*(s_1^*) = \max\left\{ f^*(s_1) \middle| s_1 \in S_1 \right\}$ and $f^*(s_n^*) = \max\left\{ f^*(s_n) \middle| s_n \in S_n \right\}$.

Combine the optimal solution $(s_1^*, a_1^*(s_1^*), s_2^*, a_2^*(s_2^*), \ldots, s_k^* = s_k)$ for the front group and the optimal solution for the backend group $(s_k^* = s_k, a_k^*(s_k^*), s_{k+1}^*, a_{k+1}^*(s_{k+1}^*) \ldots, s_n^*)$. Accordingly, we can obtain an optimal state and action sequence $SA^t = (s_1^*, a_1^*(s_1^*), s_2^*, a_2^*(s_2^*), \ldots, s_k^*, a_k^*(s_k^*), s_{k+1}^*, a_{k+1}^*(s_{k+1}^*), \ldots, s_n^*)$ for time t.

If such an optimal sequence S^t has been determined for each $t \in T$, the overall solution $(SA^0, SA^1, \ldots, SA^t, \ldots, SA^L)$ is obtained for the production cycle of length L.

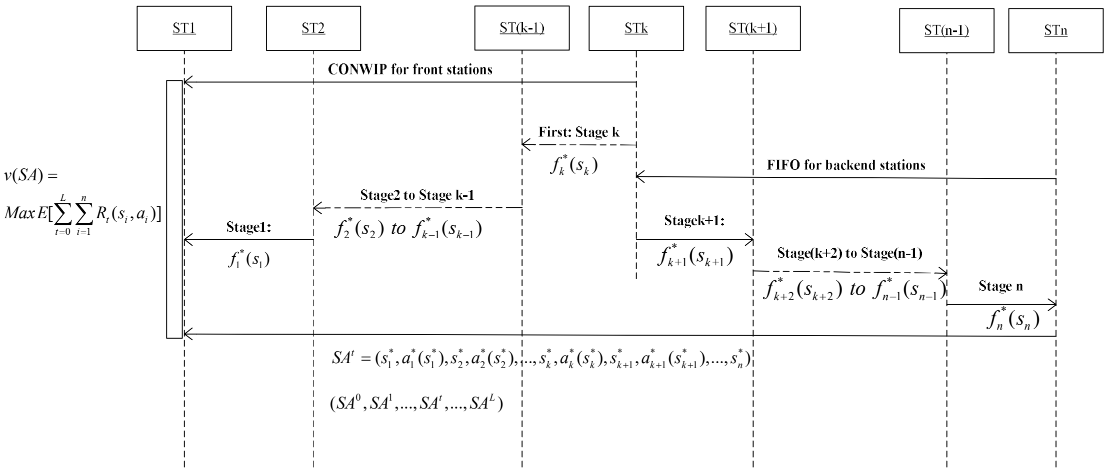

Figure 4: Workstation flow in the case factory

6. Development of the MHT platform and Design of the Experiments

6.1 Analysis of parameters

We implemented our approach in a 300 mm semiconductor assembly and test factory and collected the required data for performing the experiments. As shown in Figure 5, there are 8 key stations in this semiconductor factory.

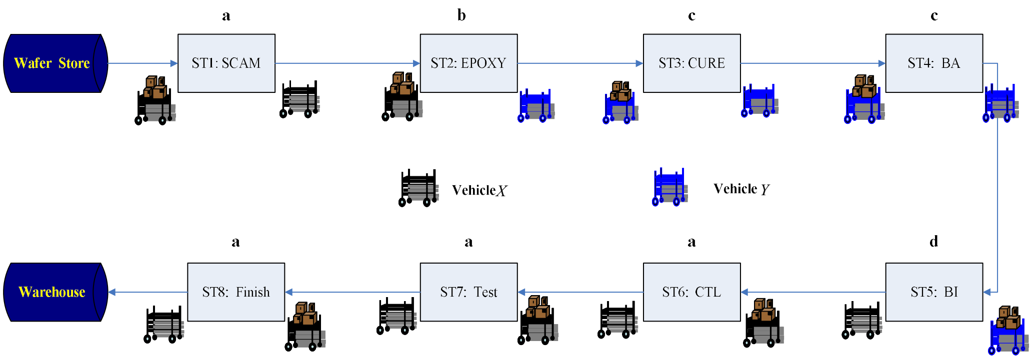

Figure 5: Workstation flow in the case factory

Table 2: Production Parameters of the case factory

STi	ST1	ST2	ST3	ST4	ST5	ST6	ST7	ST8
TH_i (thousand units)	3.87	5.13	4.52	3.245	3.67	4.12	4.656	5.84
TH_i (lots/hour)	3.23	4.28	3.77	2.70	3.06	3.43	3.88	4.87
CT_i (days)	0.74	1.05	0.93	0.57	0.73	0.79	1.01	1.10
$E(w_i^*)$	2.38	3.59	3.50	1.85	2.24	2.70	3.91	4.27

The cycle time CT_i can be obtained according to the formula

$$E(CT) = \sum_{i=1}^{n} p_i^s (\overline{PT}_i + \overline{QT}_i)$$

(note that $\overline{PT}_i$ and $\overline{QT}_i$ can be obtained from the MES system of the case factory) and TH_i can be obtained based on the factory design. According to the analysis of Subsection 3.4, one can obtain

$$E(w^*) = \sum_{i=1}^{n} p_i^s (\overline{PT}_i + \overline{QT}_i) \frac{D}{T},$$

and these values are displayed in Table 2.

According to the parameters in Table 3 and the analysis in Subsections 3.3 and 3.4, one can obtain the expected numbers of vehicles of $E(X_i)$ and $E(Y_i)$ for station STi. Then the total numbers of vehicles of type X and Y can be determined as given in Table 4.

Table 3: Expected WIP quantity and expected numbers of vehicles of types X and Y

STi	ST1	ST2	ST3	ST4	ST5	ST6	ST7	ST8
$E(w_i^*)$	2.38	3.59	3.50	1.85	2.24	2.70	3.91	4.27
τ_i	a	b	c	c	d	a	a	a
$E(X_i)$	3	4	0	0	1	3	4	5
$E(Y_i)$	0	1	4	3	3	0	0	0

Table 4: Investigated factors

Factor	Number
X	20
Y	11
A	1200 units
B	1200 units

The breakdown rate q_m^d and the lot cancellation rate q_l^c are set based on historical data. These parameters together with the values λ_i are summarized in Table 5.

Table 5: Parameter values of the work stations

STi	ST1	ST2	ST3	ST4	ST5	ST6	ST7	ST8
λ_i	3.64	3.87	5.13	4.52	3.245	3.67	4.12	4.656
q_i^b	0.028	0.077	0.02	0.04	0.03	0.005	0.007	0.055
q_i^c	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Table 6: Initial transition parameters

STi	ST1	ST2	ST3	ST4	ST5	ST6	ST7	ST8
P_i^a	0.096	0.081	0.030	0.049	0.126	0.093	0.067	0.044
P_i^b	0.069	0.132	0.087	0.090	0.121	0.024	0.067	0.111
P_i^c	0.134	0.205	0.188	0.141	0.244	0.274	0.127	0.233

We use the time interval of one hour and each simulation cycle has a length of 12 hours as one shift which means $t \in T=\{0,1,2,...,L\}$ with L =12. An action of the MDP will be taken at the beginning of each hour. At the start time $t=0$, the initial state transition probability can be determined using the values of parameters given in Table 6. As the initialization, we use the state with $x_i = E(X_i)$, $y_i = E(Y_i)$, and the numbers of vehicles with the WIP quantity at each station are equal to the expected numbers $E(X_i)$ and $E(Y_i)$ of vehicles of type X and Y, respectively.

6.2 Comparison of the approaches and discussion of the results

Based on the experimental data for the case factory, the MDP model is comprehensively compared with the simulation model. We tested the performance for different release rates representing different capacity levels of constraint scenarios in the same factory, namely in total three scenarios were considered with a release of the lots according to a Poisson distribution with the following release rates λ : λ^1 =3.64 lots/hour, λ^2 =4.42 lots/hour, and λ^3 =3.09 lots/hour). For each scenario, we run the experiments 14 times (14 shifts $\times$ 12 hours/shift=168 hours for one experiment), so in total we considered 2352 hours on overall. The simulation was developed under VS2008 C# and SQL Server 2008 in the Win7 x64 version.

The major goal was the comparison of the three indicators (WIP quantity, cycle time and mean vehicle utilization rate). The results are presented in the following Tables 7-9 and Figures 4-6. In the tables, we compare the mean values of the three indicators obtained in the 14 experiments while in the figures; we visualize graphically the mean values and the standard deviations of the three indicators. In Table 7 and Figure 6, the results are given for λ^1 =3.64 lots/hour. In Table 7, the mean values of the relative deviations of the three indicators WIP quantity, cycle time and mean vehicle utilization between MDP+DP and simulation are 1.55%, 2.09%, and 2.58%, respectively. It can be noted that on average, all three indicators are improved when applying the MDP+DP approach. In particular, the MDP+DP approach obtained a lower WIP quantity in 13 runs, a shorter cycle time in 13 runs and a higher vehicle utilization rate in 10 runs of the 14 experiments.

Table 7: Comparison of the performance between MDP+DP and simulation for the arrival rate λ^1 =3.64 lots/hour

	WIP quantity			Cycle time			Mean vehicle utilization rate		
	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation
Exper1	84.289	85.976	-2.00%	6.748	6.917	-2.50%	0.818	0.709	13.42%
Exper2	84.159	85.235	-1.28%	6.715	6.894	-2.66%	0.948	0.937	1.14%
Exper3	83.854	84.201	-0.41%	6.741	6.917	-2.60%	0.897	0.918	-2.41%
Exper4	83.852	85.437	-1.89%	6.811	6.680	1.92%	0.918	0.965	-5.06%
Exper5	83.825	85.035	-1.44%	6.637	6.828	-2.89%	0.993	0.812	18.24%
Exper6	83.466	85.098	-1.96%	6.661	6.903	-3.63%	0.885	0.872	1.42%
Exper7	82.889	86.026	-3.78%	6.662	6.835	-2.58%	0.946	0.852	9.97%
Exper8	83.937	84.885	-1.13%	6.649	6.932	-4.25%	0.820	0.735	10.39%
Exper9	83.508	83.496	0.01%	6.713	6.943	-3.42%	0.992	0.893	9.93%
Exper10	83.956	85.710	-2.09%	6.689	6.818	-1.93%	0.939	0.884	5.85%
Exper11	84.163	85.429	-1.50%	6.741	6.894	-2.27%	0.855	0.884	-3.42%
Exper12	83.830	85.231	-1.67%	6.811	6.917	-1.55%	0.992	0.834	15.92%
Exper13	83.860	84.885	-1.22%	6.637	6.680	-0.65%	0.749	0.970	-29.51%
Exper14	83.941	85.091	-1.37%	6.661	6.680	-0.28%	0.890	0.977	-9.74%
Mean	83.82	85.12	-1.55%	6.71	6.85	-2.09%	0.90	0.87	2.58%

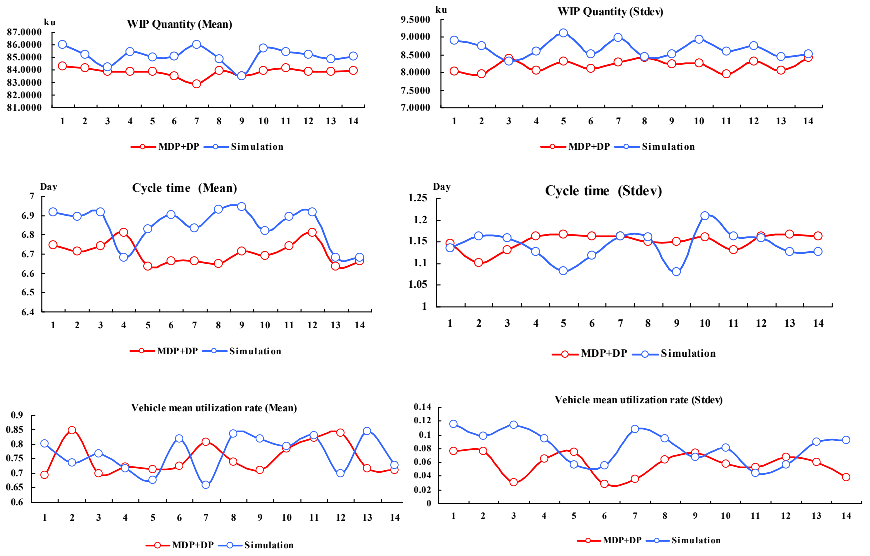

Figure 6: Statistical results for the arrival rate λ^1 =3.64 lots/hour

In Table 8 and Figure 7, we present the results for the release rate λ^2 =4.42 lots/hour. In Table 8, the mean relative deviations of the three indicators WIP quantity, cycle time and mean vehicle utilization between MDP+DP and simulation are 2.00%, 10.21%, and 5.56%, respectively. In this scenario, the relative deviations for all three indicators are larger than for the release rate

λ^1 =3.64 lots/hour. With an increase of the release rate, more WIP enters the floor and induces a higher variability of the WIP quantity. From Figure 5, we also see that the MDP+DP approach obtained a lower WIP quantity in 11 runs, a shorter cycle time in 13 runs and a higher vehicle utilization rate in 10 runs of the 14 experiments.

In Table 9 and Figure 8, we present the results for the release rate λ^3 =3.09 lots/hour. From Table 9, it can be seen that the mean relative deviations of the WIP quantity, the cycle time and the mean vehicle utilization rate of the MDP+DP approach from simulation are 3.66%, 2.45%, and 2.58%, respectively. In this scenario, the indicators and the relative deviations of the mean values of the three indicators are similar to the release rate λ^1 =3.64 lots/hour. From Figure 6, it also can be observed that the indicators are mostly improved by the MDP+DP approach compared with simulation. We obtained a lower WIP quantity in 13 runs, a shorter cycle time in 14 runs and a higher vehicle utilization rate in 9 runs of the 14 experiments. It can be observed that the strongest superiority of the MDP+DP approach was obtained for the cycle time. From the experiments with the three different release rates, one can observe that the variability of the release rate has also a large impact on the variability of the indicators WIP quantity, cycle time and vehicle utilization rate.

Table 8: Comparison of the performance between MDP+DP and simulation for the arrival rate λ^2 =4.42 lots/hour

	WIP quantity			Cycle time			Mean vehicle mean utilization rate		
	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation
Exper1	81.7651	82.8140	-1.28%	7.5019	7.4703	0.42%	0.9529	0.9345	1.93%
Exper2	83.0154	87.2711	-5.13%	6.7054	7.0748	-5.51%	0.9099	0.8623	5.23%
Exper3	82.0781	86.6749	-5.60%	6.4165	7.0356	-9.65%	0.8766	0.7415	15.42%
Exper4	80.8538	82.0996	-1.54%	6.3995	7.6853	-20.09%	0.8356	0.7103	15.00%
Exper5	83.5931	86.0189	-2.90%	6.4901	7.5032	-15.61%	0.8374	0.9670	-15.48%
Exper6	79.4867	84.6598	-6.51%	6.9107	7.0351	-1.80%	0.8576	0.8690	-1.33%
Exper7	81.1687	78.1917	3.67%	6.6120	7.6032	-14.99%	0.8760	0.8115	7.36%
Exper8	80.6953	82.0031	-1.62%	6.8537	6.8089	0.65%	0.9306	0.7279	21.78%
Exper9	80.9692	84.1201	-3.89%	6.5695	6.9850	-6.32%	0.8150	0.9295	-14.04%
Exper10	80.5327	83.2525	-3.38%	6.4704	7.2999	-12.82%	0.8893	0.7098	20.19%
Exper11	82.6439	82.6467	0.00%	6.3382	7.6959	-21.42%	0.8262	0.7213	12.70%
Exper12	85.5853	88.1202	-2.96%	6.3388	7.7315	-21.97%	0.8746	0.7053	19.35%
Exper13	85.3632	83.9843	1.62%	6.5725	6.9354	-5.52%	0.7681	0.9829	-27.97%
Exper14	79.0825	77.8280	1.59%	6.9921	7.5773	-8.37%	0.8754	0.7205	17.69%
Mean	81.92	83.55	-2.00%	6.66	7.32	-10.21%	0.87	0.81	5.56%

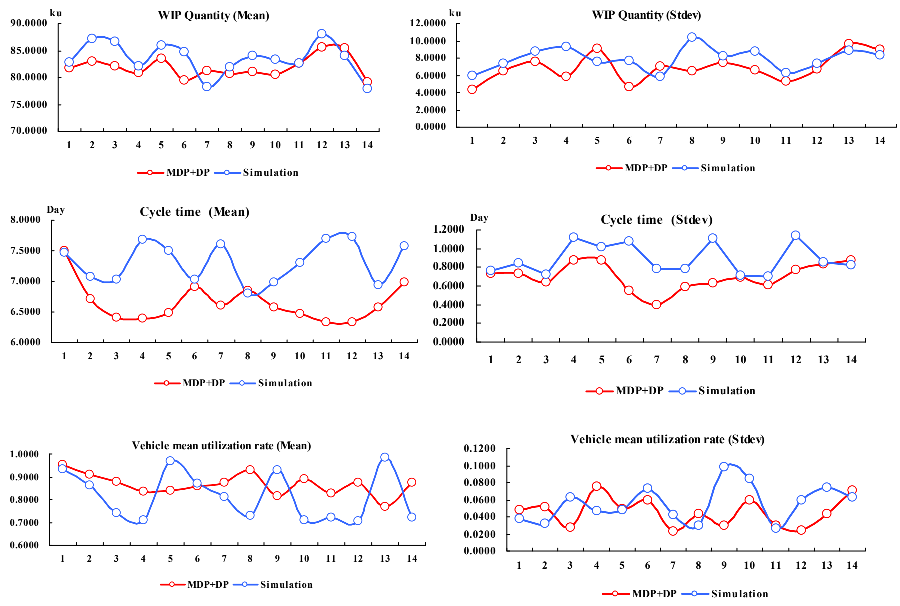

Figure 7: Statistical results for the arrival rate λ^2 =4.42 lots/hour

Table 9: Comparison of the performance between MDP+DP and simulation for the arrival rate λ^3 =3.09 lots/hour

	WIP quantity			Cycle time			Mean vehicle utilization rate		
	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation	MDP+DP	Simulation	Deviation
Expert1	92.7774	95.4862	-2.92%	8.1257	8.4437	-3.91%	0.8184	0.7085	13.42%
Expert2	91.6990	94.0675	-2.58%	8.1658	8.2839	-1.45%	0.9478	0.9370	1.14%
Expert3	86.5577	95.1051	-9.87%	8.1336	8.4072	-3.36%	0.8967	0.9184	-2.41%
Expert4	92.5697	97.8664	-5.72%	8.1923	8.5123	-3.91%	0.9183	0.9648	-5.06%
Expert5	90.9228	92.8304	-2.10%	8.2055	8.4288	-2.72%	0.9934	0.8122	18.24%
Expert6	90.1575	93.0872	-3.25%	8.1550	8.2649	-1.35%	0.8850	0.8724	1.42%
Expert7	87.7126	95.3625	-8.72%	8.1608	8.2924	-1.61%	0.9464	0.8520	9.97%
Expert8	91.3620	93.0272	-1.82%	8.1714	8.2444	-0.89%	0.8205	0.7352	10.39%
Expert9	93.2541	93.7638	-0.55%	8.2106	8.3904	-2.19%	0.9920	0.8935	9.93%
Expert10	91.4546	92.7630	-1.43%	8.1254	8.4911	-4.50%	0.9386	0.8837	5.85%
Expert11	89.9360	95.1985	-5.85%	8.2029	8.2360	-0.40%	0.8552	0.8845	-3.42%
Expert12	91.0359	98.0639	-7.72%	8.1670	8.3596	-2.36%	0.9922	0.8342	15.92%
Expert13	94.7863	90.9042	4.10%	8.2382	8.4962	-3.13%	0.7491	0.9701	-29.51%
Expert14	91.1242	93.6827	-2.81%	8.2637	8.4743	-2.55%	0.8902	0.9769	-9.74%
Mean	91.10	94.37	-3.66%	8.18	8.38	-2.45%	0.90	0.87	2.58%

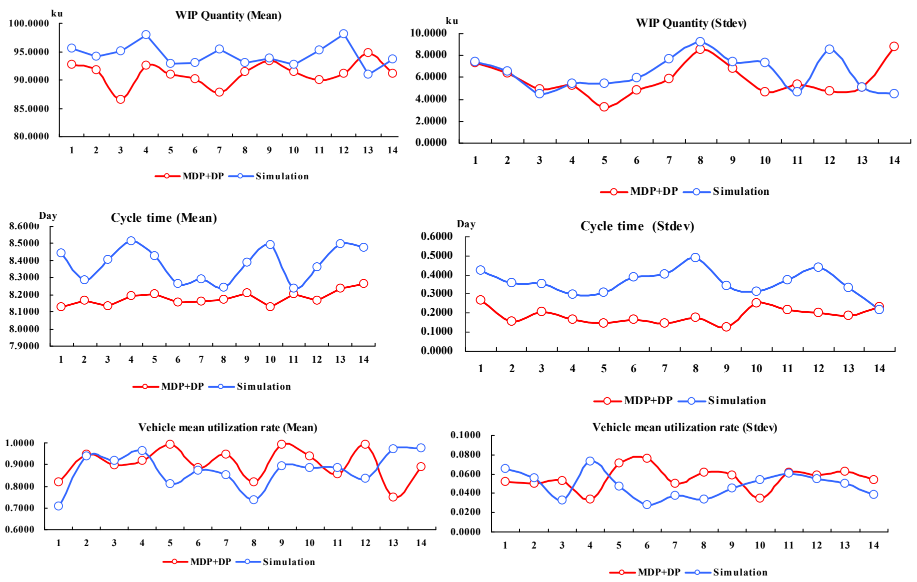

Figure 8: Statistical results for the arrival rate λ^3 =3.09 lots/hour

7. Concluding Remarks

MHTs play a critical role for the transitions of the lots between the stations in a discrete manufacturing system. In order to improve the performance of the MHTs and the WIP quantity effectively, we analyzed the process of the MHTs and quantified the relationships between the related parameters of the MHTs. According to the "no memory" property of an MHT transition, we applied an MDP to build up the model and used DP to determine an optimal solution for the underlying mathematical problem. For our experiments, we considered a 300mm semiconductor assembly and test factory, collected the required data and compared the developed MDP+DP approach with simulation for different release rates of the lots. The results of the experiments showed some improvements of the MDP+DP approach over simulation for the majority of the runs and confirmed that the proposed approach is both feasible and effective.

For future work, a first extension is to further discuss the queueing status of the MHT model with the combination of queueing theory and the Markov chain methodology. Another possible extension consists in an effective traceability method for the MHTs for the daily operations. In this way, we want to provide a practical method for manufacturing managers and supervisors.

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