Material Handling Tools for a Discrete Manufacturing System: A Comparison of Optimization and Simulation

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Overview of the Talk

• Introduction
• Literature Review
• Markov Decision Process Model
• Dynamic Programming Algorithm
• Numerical Experiments
• Conclusion
Introduction

Background:

- A material handling tool (MHT) is one of the essential components in a manufacturing system.
- MHTs are responsible for the transitions of the lots between the stations.
- The strategy of MHTs will impact the delivery rate, cycle time and WIP level.
Introduction

- A Markov decision process (MDP) will be applied to model the MHT system.

- A dynamic programming algorithm will be used to solve this problem.
Introduction

Two contributions are discussed in this paper:

• 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.

• The dynamic MHT replenishment method of MHTs will be discussed within the theory of Little’s law.
Literature Review

• Many approaches for analyzing the performance of MHTs have been proposed, etc.:

• Huang et al. (2011) study the vehicle allocation problem in a typical 300 mm wafer fabrication. They formulate it as a simulation-optimization problem and propose a conceptual framework to handle the problem.

• Chang et al. (2014) study the vehicle fleet sizing problem in semiconductor manufacturing and propose a formulation and a solution method to facilitate the determination of the optimal vehicle fleet size that minimizes the vehicle cost while satisfying time constraints.
Literature Review

• 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, queuing network model and a Markov chain model.
• Nazzal and McGinnis (2008) model a multi-vehicle material handling system as a closed-loop queuing network with finite buffers and general service times.
• Zhang et al. (2015) propose a modified Markov chain model to analyze and evaluate the performance of a closed-loop automated material handling system.
MDP Model

System Analysis

• In a discrete manufacturing factory, there exist many types of MHTs to carry the working lots between different stages.

• There might exist only two possible scenarios for each individual workstation - an MHT change or no change.
MDP Model

System Analysis

1. MHT no Change – Single Cycle

2. MHT Change – Two-Loop Cycle

Figure 1: MHT Cycle Classification
MDP Model

Some basic notations:

\( i : \) Station \( i \) consisting of \( M_i \geq 1 \) machines

\( w_i : \) WIP quantity of station \( i \)

\( X : \) Total number of vehicles of type \( X \)

\( Y : \) Total number of vehicles of type \( Y \)

\( x_i : \) Number of vehicles \( X \) at the station \( i \)

\( y_i : \) Number of vehicles \( Y \) at the station \( i \)
MDP Model

**Assumptions:**

1. The processing time at each station is constant, and production meets an M/G/1 queuing system.
2. A lot arrives according to an exponential distribution with the associated parameter $\lambda$.
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.
MDP Model

Assumptions (cont’d):

(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 of the master production schedule (MPS).

(8) Only one product is considered in this paper.
We use an MDP which can be described by the following 5-tuple: \((T, S, A, P_{trans}, v(SA))\)

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.
Lots of production tasks will be released based on the numbers of available vehicles and the recycle status at each time, 
$t \in T = \{0, 1, 2, \ldots, L | L \in \mathbb{N}_+\}$
where $L$ is the length of the defined production cycle.
MDP Model

Definition of the set of states $S$

The set of states $S$ is composed of $n$ sets $S_1, S_2, \ldots, S_n$. For stage $i$, representing station $i$, the set of states can be defined as $S_i = \{ s_i = (x_i, y_i) \mid x_i \in \{0,1,2,\ldots,X\}, y_i \in \{0,1,2,\ldots,Y\} \}$, $i \in \{1,2,\ldots,n\}$, where $x_i$ and $y_i$ denote the numbers of vehicles of type $X$ and $Y$, respectively, at station $i$ at a particular time $t$. 
MDP Model

**Definition of the set of actions** $A$

At a decision moment $t$, the decision maker will take the action $a_i \in \{0,1\}$ and according to the transition probability $P_{\text{trans}} = P\{s'_i | s_i, a_i\}$ described subsequently, the numbers of vehicles of station $i$ may change from state $s_i$ at time $t$ to state $s'_i$ at time $t+1$, $i \in \{1, 2, ..., n\}$. 
The set $A = \{a_1, a_2, ..., a_i, ..., a_n \mid a_i \in \{0,1\}, i \in \{1,2,\ldots,n\}\}$ is the production strategy set. According to the CONWIP methodology, if the WIP is higher than the desired value at station $i$, 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 first-in-first-out (FIFO) strategy, and the action $a_i = 1$ is taken. At time $t \in T = \{0,1,2,\ldots,L \mid L \in \mathbb{N}_+\}$, once a decision $a_i$ has been taken, the lots will be released with the vehicle.
MDP Model

State transition probabilities $P_{\text{trans}}$

(a) It is assumed that the vehicles arrive at station $i$ according to a Poisson distribution with the mean arrival rate $\lambda_i$. Thus, the probability that $k$ vehicles arrive is given by $P_i^a(k) = P(X = k) = \frac{\lambda_i^k e^{-\lambda_i}}{k!}$. In the production environment, $\lambda_i$ is equal to the mean throughput of the preceding station $TH_{i-1}$. 
MDP Model

State transition probabilities $P_{\text{trans}}$

(b) It is assumed that the breakdown rate of work station $i$ is $q_i^d$ and thus, the probability of a breakdown of $l$ machines of station $i$ is $P_i^b(l) = \binom{M_i}{l} (q_i^d)^l (1-q_i^d)^{M_i-l}$, where $M_i$ is equal to the number of machines at station $i$. 
MDP Model

State transition probabilities $P_{\text{trans}}$

(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 $m$ lots is $P_i^c(m) = \binom{M_i}{m} (q_l^c)^m (1-q_l^c)^{M_i-m}$.
MDP Model

State transition probabilities \( P_{\text{trans}} \)

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 is:

\[
P_{\text{trans}} \left( s_i' \mid s_i, a_i, k, l, m \right) = P_i^a (k) \times P_i^b (l) \times P_i^c (m)
\]
MDP Model

Reward Function $v(SA)$

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. We can formulate the following optimization function as:

$$v(SA) = \text{Max} E \left[ \sum_{t=0}^{L} \sum_{i=1}^{n} R_t(s_i, a_i) \mid s_i = (x_i, y_i), a_i \in \{0, 1\} \right]$$  \hspace{1cm} (1)
MDP Model

Maximize the Reward Function $v(SA)$

s.t.

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

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.
MDP Model (cont’d)

\[ \sum_{i=1}^{n} x_i \leq X \]
\[ \sum_{i=1}^{n} y_i \leq Y \]

\[ \sum_{i=1}^{n} w_i \leq \sum_{i=1}^{n} w_i^* = w^* \]

The numbers of vehicles of type X and Y are not allowed to exceed the upper bounds X and Y.

The total WIP quantity should be not greater than the total desired WIP level \( \sum_{i=1}^{n} w_i^* = w^* \).
Dynamic Programming Algorithm

• 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 backend group.
Dynamic Programming Algorithm

**Step 1:** Initialization: Determine the $n$ stages representing the stations (consisting of one or more machines) for the problem and the states to be considered in 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 in stage $i$, $i \in \{1, 2, \ldots, k, \ldots, n\}$, for station $i$. 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.
Dynamic Programming Algorithm

Step 2: Since the bottleneck station $k$ 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.
Dynamic Programming Algorithm

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 of station $i$ when action $a_i$ is taken for state $s_i$. The reward function for state $s_i$ is given by

$$f_i^*(s_i) = \max \left\{ v_i(s_i, a_i(s_i)) + f_{i+1}^*(s_{i+1}) \middle| a_i(s_i) \in \{0, 1\} \right\},$$

$i = k - 1, k - 2, \ldots, 1.$
Dynamic Programming Algorithm

*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. The reward function for state $s_i$ is given by

$$f_i^*(s_i) = \max \left\{ v_i(s_i, a_i(s_i)) + f_{i-1}^*(s_{i-1}) \mid a_i(s_i) \in \{0,1\} \right\},$$

$i = k+1, k+2, \ldots, n$. 


Dynamic Programming Algorithm

Step 5: Determine the states \( s_1^* \in S_1 \) and \( s_n^* \in S_n \) with the maximal reward function values \( f^*(s_1^*) = \max\{f^*(s_1) \mid s_1 \in S_1\} \) and \( f^*(s_n^*) = \max\{f^*(s_n) \mid s_n \in S_n\} \).
Dynamic Programming Algorithm

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

\[SA^t = (s_1^*, a_1^*(s_1^*), s_2^*, a_2^*(s_2^*), ..., s_k^*, a_k^*(s_k^*), s_{k+1}^*, a_{k+1}^*(s_{k+1}^*), ..., s_n^*)\]

for time \(t\).
Dynamic Programming Algorithm

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

Figure 2: Sequence graph for dynamic programming
Experiments

We implemented our approach in a 300 mm semiconductor assembly and test factory and collected the required data for performing the experiments.

Figure 3: Workstation flow in the case factory
Experiments

• Experiment 1: $\lambda_1 = 3.64$ lots/hour

<table>
<thead>
<tr>
<th>WIP Quantity</th>
<th>Cycle Time</th>
<th>Vehicle Utilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDP+DP</td>
<td>Simulation</td>
<td>MDP+DP</td>
</tr>
<tr>
<td>Exper1</td>
<td>84.289</td>
<td>6.748</td>
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<td>Exper2</td>
<td>84.159</td>
<td>6.715</td>
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<td>Exper3</td>
<td>83.854</td>
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<td>Exper4</td>
<td>83.852</td>
<td>6.811</td>
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<td>Exper5</td>
<td>83.825</td>
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<td>Exper6</td>
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Deviation: $-1.55\%$, $-2.09\%$, $2.58\%$
Experiments

- Experiment 1: $\lambda_1 = 3.64$ lots/hour
Experiments

- Experiment 2: $\lambda_2 = 4.42$ lots/hour

<table>
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<tr>
<th>Exper</th>
<th>WIP Quantity MDP+DP</th>
<th>Simulation</th>
<th>Cycle Time MDP+DP</th>
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<th>Vehicle Utilization MDP+DP</th>
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<tbody>
<tr>
<td>Exper 1</td>
<td>81.765</td>
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<td>83.015</td>
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<td>80.854</td>
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<td>0.720</td>
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Deviation: -2.00%  -10.21%  2.58%
Experiments

• Experiment 2: $\lambda_2 = 4.42$ lots/hour
Experiments

- Experiment 3: $\lambda_3 = 3.09$ lots/hour

<table>
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<td>MDP+DP</td>
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Deviation: 
-3.66%  
-2.45%  
2.58%
Experiments

- Experiment 3: $\lambda_3 = 3.09$ lots/hour
Conclusion

• 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.
Future work

• A first extension is to generalize the model since we simplified the model by including only one product with several stations in contrast to real complex discrete manufacturing systems.

• An effective traceability method for the MHTs for the daily operations will be developed. In this way, we want to provide a practical method for manufacturing managers and supervisors.