A Support Vector Machine Approach for AGV Dispatching

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Abstract

With the development of highly automated manufacturing lines, the application of Automated Guided Vehicles (AGVs) in Material Handling System (MHS) has drawn a lot of attention. An AGV dynamic dispatching in Flexible Manufacturing System (FMS) by using Support Vector Machine (SVM) is presented in this paper. The objective is to minimize mean tardiness of orders in FMS. The simulation run will be carrying out for generating the training data for SVM. The system attributes that might affect the performance of SVM will also be discussed. Finally, simulation model is used to test the feasibly of the SVM dispatching model.

Keywords: Automated guided vehicle, dispatching rules, machine learning, support vector machine, simulation

1. Introduction

Automated guided vehicles (AGVs) system is widely applied in many automated manufacturing industrial, especially in the flexible manufacturing system (FMS). Managing and Controlling AGVs system can be divided into following parts: Vehicle scheduling, Vehicle positioning, Battery management, and Vehicle routing (Tuan & Koste, 2006). AGVs scheduling, which decides the point in time when the loads transported by vehicles takes place, is the main issue discussed in this studies. In AGVs scheduling, dispatching rules are often used in practical because it is a relatively simple approach to apply. Instead of planning the whole scheduling period, dispatching rules decided which vehicle to transport which load only when the transportation is about to take place.

AGV dispatching rules are categorized into: vehicle-initiated dispatching and workload-initiated dispatching according to point in time the AGV dispatching occur (Egbelu & Tanchoco, 1984), which mean the dispatching occurs when (1) an AGV drop-off the load and become idle, (2) the load arrived at the system or release by machines, respectively. The dispatching rules they proposed are single-attribute dispatching rules, which means the rules make decisions according to a certain criteria of the system. Some important information might be ignored if single-attributed dispatching rules are applied. For example, STT (Shortest traveling time) rule only consider the traveling distance between the vehicles and loads, and the information about importance of jobs (due-date) is neglected.

Since there is no dispatching rule proved to be dominant to the others, this paper study the machine learning-based AGV dispatching, which make decisions of vehicle dispatching by considering the current states of the environment. In last decades, some researches (Shiue, 2009; Manupati et al., 2013) have suggested that it is possible to improve system performance by implement a dynamic dispatching selection strategy rather than using single-attribute dispatching rules.

The rest of the article is organized as follows: The related researches about AGV dispatching rules, machine learning-based dispatching rules, and the knowledge of support vector machine (SVM) are investigated in section 2. Section 3 describes the overviews of the problem focused and the environment of the studied system. The detailed of the SVM based dispatcher and the training sample generation processes are in section 4. Section 6 discuss the implementation of the proposed model and the performance will be tested. Lastly, this paper ends with conclusions and future research.

2. Literature Review

2.1 AGV dispatching

The AGVs dispatching problem in this research is the problem of assigning loads to vehicle or vehicle to load when they are available. Egbelu and Tanchoco (1984) are one of the pioneers in the field of AGVs dispatching problems in FMS. They sort out some most commonly used dispatching rules in AGV systems. Such issue has drawn a lot of attention in last few decades, except using single-attribute dispatching rule, many researches also deal the issue with heuristic method, mathematical programming, or machine learning-based dispatching.

Applying dispatching rules in real-world system by simulation model is studied by Tuan and Meer (2004). They compared the performance of some well-known dispatching rules with the rule used in practical case of glass factory, distribution center, and container terminal. The result shows that taking pre-arrival information of load will improve performance when dispatching AGVs.

Workload balance of production line is also considered in the research of Marvizadeh and Choobineh (2014). They take the workload balance into consideration with the idea of information entropy. The research shows when performing AGVs dispatching in manufacturing system, the factors related to workstations should also be considered.

Performing vehicle dispatching by meta-heuristic or mathematical programming has also been studied by some researches (Saidi-Mehrabad et al., 2015, ; Mousavi, et al., 2017) since dispatching rule does not consider the optimality of the whole scheduling period. Instead of making the dispatching decisions instantly like most of the dispatching rules, these two approach obtain the solutions by planning all transportation of AGV in whole planning horizon, hence, but they both are relatively time consuming method despite the optimality of performance.

2.2 Machine learning-based dispatching

The machine learning-based (ML) dispatching issue can be presented in the term of {O, M, D, R, S} (Park, 1997). O means the objective of the system; M is Manufacturing pattern, which means what system attributes should be considered; D is the candidate dispatching rules, which means the set of dispatching rules the ML dispatcher selected from; R is the heuristic for scheduling rules, means what ML approach to apply for dispatching; S is the possible system states, which means the possible combinations of system attributes that should be considered as the features of training samples. The {O, M, D, R, S} term is used for SVM dispatcher in this paper and will be described more detail in later section.

In recent years, machine learning-based dispatching also be used in AGV dispatching problem for dynamically selecting the dispatching rule to use in each dispatching decision. Zeng (2011) scheduling the operations of container terminals with reinforcement learning-based approach. Reinforcement learning is a machine learning technique that learns better decision policies by dynamically interacting with environment. Choe et al. (2016) used online preference learning approach to select the loads to be transport by AGVs between the yard cranes and stack crane of container terminal.

Except AGV dispatching, machine learning-based dispatching is applied in job dispatching in manufacturing shops as well. Shiue (2009) dispatched jobs in FMS with some supervised learning method like Support Vector Machine (SVM), Decision Tree (DT), and Artificial Neural Network (ANN). Manupati et al. (2013) also used SVM approach to deal with jobs dispatching problem in flexible manufacturing cells (FMC). Both research shows that supervised learning-based dispatching like SVM dispatching outperforming single-attribute dispatching rules.

Using SVM approach for jobs dispatching (Idle machine select jobs) is studied by the researches mentioned, but not for AGVs dispatching (vehicle select loads or load select vehicle). AGVs dispatching problem in manufacturing system is a more complicated issue since not only the factor of jobs and machines are considered but also the factors of vehicle transportation. So this paper will focus on applying SVM technique to the AGVs dispatching and it performance.

3. Problem Definition

3.1 AGV dispatching

The FMS system in the research is shown as Figure 1. The FMS consist of *NW* workstation with single machine and corresponding input queue and output queue in it. The orders arrived at the warehouse randomly with an individual due date and job types. Each job type has a corresponding operating sequence. The task of AGV is to pick up orders at the loading station at the warehouse and then deliver it to the P/D (Pickup and delivery) point of workstations. When a job finished all of its operating sequence, it will be delivery by AGV to the unloading station of the warehouse. There is an AGV charging station in the system. The vehicles will go to the charging station in following two situations: (1) Once the electricity of vehicle is lower than a certain level. (2) If the vehicle is Idling at a P/D point of a workstation and another vehicle is requiring the same P/D point for picking up or unloading the loads. Vehicles are traveling on a grid-like network guide-path, and the traveling direction of vehicles are: upward, downward, leftward, and rightward.

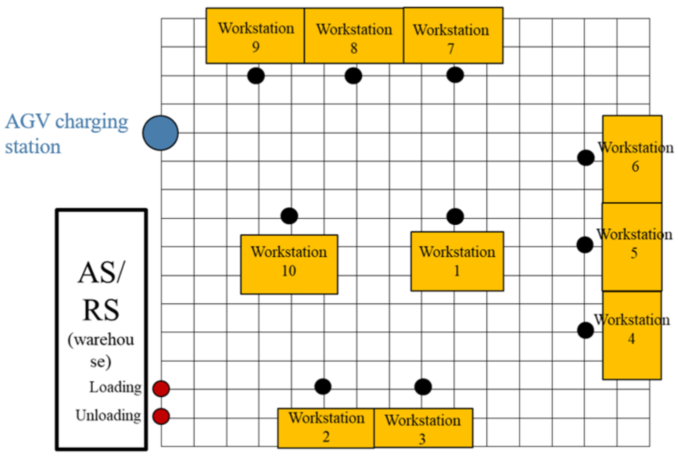

Figure 1. Layout of the FMS

The dispatching rule used in the AGVs system will change for every certain scheduling period, and which dispatching rule should be adopted for the following scheduling period is the main issue in this paper. The objective of the dispatching problem is minimizing mean tardiness of jobs (T). This performance measure is defined as function (1). The mean tardiness of jobs finished and jobs in the system are both included. This is for advoiding the AGVs from the intention of only delivering the jobs with loosing due date.

$$\mathrm{T} = \sum_{j\in\theta}\frac{max(d_j - c_j, 0)}{|\theta|} + \sum_{j\in\mu}\frac{max(d_j - n, 0)}{|\mu|} \qquad (1)$$

, where θ is the set of all finished jobs and μ is the set of jobs within the system whose process are not completed yet. d_j and c_j are the due-date and completion time of job j, respectively. n means the current time while the performance measure is recorded.

The assumptions of FMS are considered as follow:

(1) The loading time and unloading time of AGVs are constant value.
(2) The speed of AGVs are constant value.
(3) Each vehicle can only accommodate single unit load on it.
(4) The collisions between vehicles is not allowed, which means AGVs cannot occupy a node of guide-path at the same time.
(5) The breakdown of the AGVs and machines are not considered.

4. SVM Approach to AGV Dispatching

In this section, the detail of the training sample generation process will be discussed. The training samples in supervised learning are consisting of features and label. In this AGV dispatching problem, the optimal dispatching rules is dynamically selected according to the current system states. Here, current system states are the features of training samples and the optimal dispatching rule means the label of the sample. The concept of training samples in AGV dispatching problem is shown in Figure 2.

	Features				**Lables**
	System Attribute 1	**System Attribute 2**	**…**	**System Attribute k**	**Optimal dispatching rules**
Training sample 1	**…**	**…**	**…**	**…**	**STT**
Training sample 2	**…**	**…**	**…**	**…**	**FCFS**
…	**…**	**…**	**…**	**…**	**STT**

Figure 2. Training samples illustration

The SVM dispatching model will be introduced in the term of {O, M, D, R, S} which is mentioned in previous section. The objective of the AGVs system is the mean tardiness of the jobs, which is already decided in section 3. The rest of the term are manufacturing pattern and candidate dispatching rule, and heuristic for scheduling rules, which will be introduced in detail in this section.

4.1 SVM background knowledge

Support Vector Machine (SVM) is a supervised learning technique, which return a hyperplane with the maximum margin, which means the hyperplane perfectly separates two training samples with two different classes. For example, given a training samples set $\{\omega_1, \ldots, \omega_i, \ldots, \omega_m\}$ with *m* samples corresponding feature vector $\{x_1, \ldots, x_i, \ldots, x_m\}$ in it. For each training sample, the class (y_i) of it is known and labeled as +1 or -1. And SVM yield the classifier by obtains a hyperplane that will maximizing the margin to these two classes of training samples.

The primal problem for SVM can be represented as equations (2), (3), and (4).

$$\text{Minimize } \frac{1}{2}\|\omega\|^2 + C\sum_i \eta_i \tag{2}$$

$$\text{s.t.}\, y_i(\omega^T x_i + b) + \eta_i = 0, for\ \ \forall i \tag{3}$$

$$\eta_i \geq 0, for\ \ \forall i \tag{4}$$

where w is the weight vector, *b* is a scalar, and minimizing $\frac{1}{2}\|\omega\|^2$ is converted from maximizing $\min_{i\in(1,m)} \frac{|\omega \cdot x_i + b|}{\|\omega\|}$, which means creating a perfectly separating hyperplane by maximizing the margin. And sometimes there will be some outlier training samples dose not lying on the correct side of the space. In such case the SVM classifier will add a penalty term $C\sum_i \eta_i$ to it. Here η_i means the distance of i^{th} sample from the correct side.

Sometimes the training sample set is not linear separable, which means it cannot be separated very well by a linear hyperplane. In such case, the feature vector (f) will be mapped into higher dimensional Hilbert space (H) by kernel function skill ($\Phi\colon \mathrm{f} \rightarrow \mathrm{H}$). In this study, Gaussian kernel (or radial basis function, RBF) will be used for reproducing the Hilbert space, where are the user-defined parameters for RBF.

$$\text{Gaussian kernel: } \mathrm{K}(x, x') = e^{\frac{-\|x-x'\|^2}{2\gamma^2}} \tag{5}$$

More detail description of SVM can be found in Vapnik (1995). In this paper, the performance for predefined parameters C for SVM model and γ for RBF kernel will be tested, and the best combination will be used in SVM dispatching model.

4.2 Candidate dispatching rules

As mentioned previously, the SVM dispatcher is proposed to select candidate dispatching rules. So the dispatching rules will be treated as the labels of SVM. Instead of considering only dispatching rules for AGV dispatching rules (Egbelu & Tanchoco, 1984), the dispatching rules relative to the due date of orders will also be candidate dispatching rule because the performance measure is mean tardiness of jobs.

Some of the AGV dispatching rules are for vehicle choosing order to deliver, while the others are for loads choosing vehicle for delivering. So there are two sets of candidates dispatching rules should be considered separated. One is for vehicle-initiated SVM dispatching and the other is for workload-initiated SVM dispatching.

Candidate dispatching rules for vehicle-initiated dispatching:

(1) STT (shortest traveling time): Select the job which located at the position nearest to the vehicle.

(2) FCFS (first come-first serve): Select the job which requests vehicles for transportation earliest.

(3) MROQS (minimum remaining output queue space): Select the job which located at the output queue with highest remaining space.

(4) EDD (earliest due date): Select the job with earliest due date.

(5) CR (critical ratio): Select the job with lowest critical ratio (CR= (Due date - now) / (remaining operation time)).

(6) DS (dynamic slack): Select the job with lowest slack time (slack time = remaining due date- remaining operation time).

Candidate dispatching rules for workstations-initiated dispatching:

(1) NV (nearest vehicle): Select the vehicle which located at the nearest position to the location of the job.

(2) LIV (longest idling vehicle): Select the vehicle with longest idling time.

(3) LU (least utilization vehicle): Select the vehicle with lowest utilization.

4.3 Features selection – Manufacturing pattern

In machine learning, every system attribute that might affect the performance of the system should be considered as the environment states. Considering the manufacturing environment in this study, system attributes relative to the AGVs and the charging system are selected, and since the system in this research is FMS, some of the system attributes are also selected based the research of jobs dispatching in FMC (Manupati et al., 2013). There are 9 system attributes in total selected empirically as the features for training samples.

(1) Number of jobs in system.

(2) Mean remaining time of system jobs until its due date.

(3) Standard deviation of remaining time of system jobs until its due date.

(4) Mean operation time (Processing time plus least traveling time) of system jobs.

(5) Standard deviation of operation time of system jobs.

(6) Mean workload of workstations.

(7) Standard deviation workload of workstations.

(8) Number of idling vehicles in system.

(9) Number of low electricity (lower than 5% maximum electricity) level AGVs in system.

4.4 Training samples

In machine learning, every system attribute that might affect the performance of the system should be considered as the environment states. Considering the manufacturing environment in this study, system attributes relative to the AGVs and the charging system are selected, and since the system in this research is FMS, some of the system attributes are also selected based the research of jobs dispatching in FMC (Manupati et al., 2013). Total 20 system attributes are selected empirically as the features for training samples.

The process of generating training data for SVM by carrying out a simulation run for N dispatching rules is illustrated in Figure 3. Each training sample consist of the features $\{f_i\}$, which is the system attributes recorded at the point in time after a warm up period following by a Δt scheduling period. And the performance measure of mean tardiness will be recorded at the end of the scheduling period. After N times simulation runs with fixed random seed, the performance for N dispatching rules is recorded, and the dispatching rule with the best performance will be the label of the training samples.

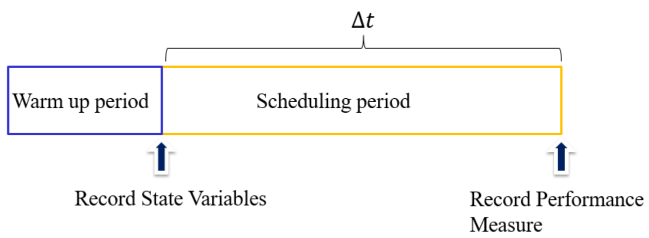

Figure 3. Training sample illustration

For generating the training data with higher features diversity, the simulation will be run with different warm up time period. The length of scheduling period Δt is a preset parameter. In practical, Δt should be set by considering how long the system attributes change significantly. Since the testing instance is not a practical FMS, the value of Δt will be obtained by a trial and error process for different Δt.

5. Experiment

5.1 Experiment setting

The test environment is comprised of 10 workstations, which can process ten job type. Different job types have different operation sequence and different processing time. The inter-arrival time between jobs arriving is exponentially distributed with a mean of 34 seconds, which is 100% operation cycle in bottleneck workstations respectively. The due date of arriving job is uniformly distributed between one to three times shortest operation cycle of the job. The portion of each job types is also uniform distributed. There are 7 AGVs operating in the system. The jobs dataset from Bagchi (1999) will be used as the job set for experiment. The loading and unloading time of AGVs are set to be 1 seconds.

For training sample collection, 500 random seeds are used. In each random seeds, the warmup time of 1000, 3000, 5000, and 7000 seconds followed by Δt time period is simulated to create 2,000 training sample in total. For each training samples, data scaling is applied for advoiding the attributes lay on the wider range dominate those lie on the smaller range. Here, the min-max scaling method is adopted for data preprocessing. Before training SVM dispatcher, the scale of training data attributes is in range of [0, 10] with the following equation.

$$f(X \rightarrow [0,10]) = \frac{10\times(X_i - z_i)}{Z_i - z_i} \quad (6)$$

where Z_i and z_i are the maximum and minimum value of the attributes among 2,000 training samples (500×4).

The performance measure is the mean tardiness of the 8,000 seconds experiment period following by a 2,000 seconds warm-up period. The testing for SVM dispatcher is assorted into two phase. In the primary phase, the preset parameters Δt and kernel function parameters of SVM *r* and *C* are tested using grid search technique (Hsu et al., 2003). The testing range for Δt is 1,000/2,000/3,000/4,000/5,000, and $2^{-5}, 2^{-4}, \ldots, 2^{4}, 2^{5}$ for *r* and *C*. In second phase, the parameters setting with best performance are selected to be the setting for the SVM dispatcher and compared with the performance of competed method. The best setting for parameters is found as following.

Table 1. Parameter setting of SVM dispatcher

SVM dispatcher			
Vehicle initiated		**Workstation initiated**	
parameter	**value**	**parameter**	**value**
Δt	2,000	Δt	2,000
r	2^{-2}	r	2^{2}
C	2^{2}	C	2^{0}

5.2 Experiment result

The testing simulations is carried out with different combinations of single-attribute dispatching rules and the SVM dispatching approach as well. For each dispatching approach, the performance measures are tested with 30 replications using common random number (CRN) technique. Table 2 present the comparison between performance of single-dispatching rules and the performance of SVM dispatcher. The comparison value means that the mean tardiness value of using single-dispatching rules divided by the mean tardiness value of using SVM dispatcher. The statistical analysis of results (pairwise t-test) has also been carried out to determine the significance of SVM dispatcher better than single-attribute dispatching rule. It is obvious that the performance of SVM dispatcher is significantly better than most of single-attribute dispatching rules.

Table 2. Experiment result for each dispatching rules

Vehicle initiated dispatching rules	Workstation initiated dispatching rules			
	NV	LIV	LU	SVM dispatcher
	Mean Tardiness	Mean Tardiness	Mean Tardiness	Mean Tardiness
STT	275.02	278.05	279.27	-
MROQS	655.87	727.90	657.08	-
FCFS	1237.31	1235.06	1243.26	-
EDD	746.85	734.53	735.35	-
DS	671.71	671.90	674.12	-
CR	600.33	602.18	602.29	-
SVM dispatcher	-	-	-	253.99

6. Conclusion and Future Research

This paper presents a SVM-based approach to solve AGV dispatching problem. The experiment result shows that the SVM approach outperform single-attribute AGV dispatching rules. When selecting the AGV dispatching rules for system, all the systems attributes that might have impact on the dispatching performance should be taken into considered to improve the efficient of AGV dispatching.

This work only implement supervised learning technique to perform AGVs dispatching. Reinforcement learning (RL), which might be a potential future studying, is another machine learning method can be applied in such dynamic control problem. Instead of considering only current state of system like SVM-based dispatching, RL also focus on what future state might take place after a dispatching rule is select. RL learn things by dynamically interacting with the environment, so it is an online learning process.

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