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Deep reinforcement learning for dynamic distributed job shop scheduling problem with transfers

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ABSTRACT

Dynamic events and transportation constraints would significantly affect the full utilization of resources and the reduction of production costs in distributed job shops. Therefore, in this paper, a deep reinforcement learning algorithm (DRL)-based real-time scheduling method is developed to minimize the mean tardiness of the dynamic distributed job shop scheduling problem with transfers (DDJSPT) considering random job arrivals. Firstly, the proposed DDJSPT is modeled as a Markov decision process (MDP). Then, ten problem-oriented state features covering four aspects of factories, machines, jobs, and operations are elaborately extracted from the dynamic distributed job shop. After that, eleven composite rules considering the uniqueness of DDJSPT are constructed as a pool of actions to intelligently prioritize unfinished jobs and allocate the selected job to an appropriate factory. Moreover, a justified reward function adapted from the objective is designed for better convergence of DRLs. Subsequently, five DRLs are employed to address the DDJSPT, encompassing deep Q-network (DQN), double DQN (DDQN), dueling DQN (DlDQN), trust region policy optimization (TRPO), and proximal policy optimization (PPO). Finally, grounded in numerical comparison experiments under 243 production configurations of the DDJSPT, the effectiveness and generalization of DRL-based scheduling methods are credibly verified and confirmed.

1. Introduction

Distributed manufacturing is tightly grabbing the attention of researchers and manufacturers in the fast-changing market for its advantages including effectively mitigating environmental impacts on production, flexibly responding to urgent demands, rapidly satisfying consumers with diversified needs, and sharply reducing production and inventory costs by rationally utilizing resources (Gong et al., 2020; Li et al., 2022; Luo et al., 2022; Okwudire & Madhyastha, 2021; Zhang, Zhu, Tang, Zhou, & Gui, 2022). As a typical representative of distributed manufacturing, the distributed job shop scheduling problem (DJSP) has been extensively studied for decades (Jia, Fuh, Nee, & Zhang, 2002). Meanwhile, it is a variant of the job shop scheduling problem (JSP) which had been strictly demonstrated as an NP-hard problem by Garey, Johnson, and Sethi (1976), and could also be considered an NP-hard problem. To date, various approaches have been developed to sort out static DJSPs. However, in the realistic production environment, dynamic events such as random job arrivals (Wang, Zhang, & Yang, 2019), machine breakdowns (Liu, Piplani, & Toro, 2022), variable processing time (Zhang et al., 2023), and so on frequently and unavoidably disturb the process of planning and production, which would result in strict deterioration of efficiency and considerable raise of production and inventory costs. Furthermore, being a nonproductive operation in distributed manufacturing, job transportation also plays an important role in the smooth processing of jobs and economic efficiency (Du, Li, Luo, & Meng, 2021; Luo et al., 2020; Sanogo et al., 2023; Zhang et al., 2023). Therefore, it is of great practical significance to develop real-time scheduling methods for the dynamic distributed job shop scheduling problem with transfers (DDJSPT) considering random job arrivals.

In the past few decades, exact methods (Meng, Zhang, Ren, Zhang, & Lv, 2020), heuristics (Strahl & Gounaris, 2023), and metaheuristics (Zhao, Deng, Zhang, Han, & Li, 2023) have been the main approaches

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for tackling scheduling problems. The exact methods could obtain the optimal solutions of small-sized scheduling problems in an acceptable time, but their computational time would be exceptionally high with the increase of problem size, and it is difficult for them to acquire the optimal solutions when tackling large-scale models in a reasonable time (Naderi & Azab, 2014). These shortcomings of exact methods have limited their application to a variety of DJSPs, not to mention their inability to handle the complicated DDJSPT. Furthermore, by the advantages of being intuitive, fast, and time-saving, heuristics such as the priority dispatching rule (PDR) are applied to address scheduling problems (Chen, 2012; Holthau & Rajendran, 1997). However, a specific single scheduling rule would be hardly enough effective for reacting to DDJSPT, and great demands for rich experts' knowledge are aroused when designing the heuristics. With this, metaheuristics possessing the ability to find optimal or near-optimal solutions are preferred by researchers to resolve scheduling problems with various constraints and targets. For static scheduling problems, metaheuristics do achieve satisfactory solutions, but their disadvantages of being time-consuming and low responsiveness will hinder their application in DDJSPT, which requires real-time scheduling and is more in line with the actual production situation. In conclusion, the weakness of being learning-disabled, time-consuming, and myopic makes exact methods, heuristics, and metaheuristics hardly meet the requirements of solving the DDJSPT real-timely and effectively. Thus, it is necessary to develop a real-time scheduling method with the ability to learn and evolve in the fast-changing production environment of the DDJSPT.

In the above background, the approaches of handling dynamic scheduling problems via DRLs are receiving increasing research attention for their self-learning, self-evolving, and fast responsiveness. The DRL-based scheduling agents can not only interact with the environment to learn scheduling strategies but also react to dynamic events quickly, which makes them promising as an ideal approach to deal with dynamic scheduling problems. Recently, the DRL-based scheduling methods mainly include DRL-based *meta*-heuristics (Karimi-Mamaghan, Mohammadi, Pasdeloup, & Meyer, 2023), DRL-based DG (Huang, Gao, Li, & Zhang, 2023), and DRL-based PDRs (Wang et al., 2022)., which have already been applied to figure out various scheduling problems such as job shop scheduling problem (JSP) (Liu & Huang, 2023; Zhang et al., 2022), flexible job shop scheduling problem (FJSP) (Li et al., 2022; Luo, Zhang, & Fan, 2021), flow shop scheduling problem (FSP) (Brammer, Lutz, & Neumann, 2022; Yang, Wang, & Xu, 2022), assembly shop scheduling problem (ASP) (Neves, Vieira, & Neto, 2021; Wang, Sarker, Li, & Li, 2020), etc. It is noteworthy that DRL-based PDRs have become the most popular method for dynamic scheduling methods for their advantages of fastness and effectiveness. However, to our best knowledge, no research has employed the DRL-based PDRs for solving the DDJSPT.

Herein, this article combines the strong generalization of DRLs with the great flexibility of dispatching rules to handle the DDJSPT considering stochastic job arrivals with the objective of minimizing the mean tardiness of all jobs. The research mainly contributes to: (1) being the first attempt to work out the DDJSPT with advanced DRLs, (2) successfully employing five advanced DRLs containing PPO, TRPO, DlDQN, DDQN, and DQN to address the DDJSPT, (3) extracting ten efficient problem-specific state features covering four aspects of factories, machines, jobs, and operations from the dynamic distributed job shop, and constructing eleven effective composite rules to decrease mean tardiness of all jobs, (4) investigating the performance of five DRLs for DDJSPT by implementing comprehensive comparison experiments and confirming the effectiveness and generalization of DRLs for the DDJSPT.

The remainder of the article is organized as follows. In Section 2, a brief review of DRL-based approaches to tackle dynamic scheduling problems is done. Section 3 describes the background of three value-based and two policy-based DRLs. The problem description and mathematical model of DDJSPT with random job arrivals are provided in Section 4. In Section 5, the model employing five DRLs for the DDJSPT is established. Section 6 lists and analyzes the experimental results in detail. Section 7 draws a conclusion from the research.

2. Literature review

DJSP has obtained much attention since its emergence. Researchers proposed numerous approaches for dealing with static DJSP, especially exact methods and *meta*-heuristics. Jia, Nee, Fuh, and Zhang (2003) applied a modified GA to figuring out distributed scheduling problems with the aim of minimizing makespan. Successively, a GA integrating with the Gantt chart was reported by them to efficiently minimize the makespan, job tardiness, or manufacturing cost of scheduling problems with various scales in distributed manufacturing systems (Jia, Fuh, Nee, & Zhang, 2007). Additionally, to minimize the makespan of DJSP, Naderi and Azab (2014) established two mixed integer linear programming (MILP) models based on the sequence and location respectively, and took CPLEX as a solver to deal with small-size problems. Meanwhile, they adapted three heuristics including SPT, LPT, and LRPT, and designed three greedy heuristics iteratively inserting operations into a suitable position of sequence to tackle large-size DJSP. Furthermore, Chaouch, Driss, and Ghedira (2017) solved the DJSP utilizing the ant colony optimization, the ant colony system, and a modified ant colony optimization for minimization of makespan. Then, they designed a hybrid ant colony algorithm embedded with local search to minimize the makespan of DJSP (Chaouch, Driss, & Ghedira, 2019). After that, Xie, Gao, Pan, and Tasgetiren (2019) built a mixed programming model of DJSP and proposed a multi-objective artificial bee colony algorithm to simultaneously optimize makespan and total energy consumption. Recently, Jiang, Wang, and Peng (2020) reported a modified multi-objective evolutionary algorithm with decomposition for an energy-efficient DJSP with the aim of minimizing makespan and total energy consumption. Although the near-optimal or the optimal solutions of DJSP could be acquired by these exact methods and metaheuristics. With the increasing problem size and the number of objectives, it is difficult to pick a better solution for the DDJSPT. A more efficient and effective scheduling method for DDJSPT is urgently required.

In recent years, more and more researchers have concentrated on DRLs, which are promising and emerging methods in the field of shop-floor scheduling by virtue of excellent learning ability and superior generalizability. Several modes of applying DRLs to scheduling problems have been developed, including DRL-based *meta*-heuristics, DRL-based DG, and DRL-based PDRs, which are reviewed below.

A widely used method to employ DRLs for production scheduling is combining them with *meta*-heuristics. The main point of this method is to set suitable levels of critical parameters, develop efficient operators, and design effective *meta*-heuristics. Chen, Yang, Li, and Wang (2020) proposed a self-learning GA combined with SARSA and Q-learning selecting key parameters to sort out the flexible job shop scheduling problem (FJSP) with the aim of minimizing makespan. Subsequently, (Cao, Lin, & Zhou, 2021) addressed a variant of FJSP requiring minimum makespan via a knowledge-based cuckoo search algorithm trained by SARSA to save scheduling information. After that, based on Q-learning, Li et al., (2022) developed a parameter adaption strategy to select the best parameter for population diversity in MOEA/D when facing a multi-objective FJSP with fuzzy processing time. Also, a new artificial bee colony combined with Q-learning intelligently selecting search operator was studied by Wang et al., (2022) to minimize the maximum tardiness of a distributed three-stage assembly scheduling problem. Then, Cai, Lei, Wang, and Wang (2023) applied Q-learning for the selection of search strategies to a shuffled frog-learning algorithm to minimize makespan of the distributed hybrid flow shop scheduling problem. The same problem was investigated by Li, Gao, Duan, Li, and Zhang (2023) who developed an improved artificial bee colony algorithm with Q-learning to manipulate the premium neighborhood structures when optimizing makespan. Meanwhile, Yu, Gao, Ma, and Pan (2023) designed a local search strategy employing Q-learning to select the optimal local search operator from four and embedded it into four *meta*-heuristics encompassing artificial bee colony, particle swarm optimization, genetic algorithm, and Jaya algorithm for minimizing total flowtime of a distributed assembly permutation flow shop scheduling problem.

In addition, the application of DRL-based DG and GNN in scheduling problems has been considered as another hotspot for acquiring the end-to-end solution directly outputting the operation, job, or machines at each rescheduling point. The appropriate representation and structure of graphs for specific problems would be the key to this method. Han and Yang (2020) viewed DG as a multi-stage sequential decision-making problem and put states expressed as multi-channel images into the dueling double deep Q-network to minimize the makespan of JSP. Subsequently, an end-to-end DRL framework based on three-dimensional DG was proposed by them for FJSP with the same objective (Han & Yang, 2021). Then, grounded in DG representation of FJSP and the use of GNN embedding with local states, Lei et al. (2022) reported a PPO-based multi-pointer graph networks architecture to learn the policy of selecting the operation and distributing it to a machine for minimum makespan. Meanwhile, a DRL-based framework integrating DG embedding, an attention mechanism, and DRL was developed by Chen, Li, and Yang (2022) to minimize the maximum completion time of JSP whose DG features were extracted by graph embedding techniques. Recently, Hameed and Schwung (2023) utilized a PPO-based scheduler to address JSP with the target of minimizing makespan, of which the states were extracted by the GNNs. Moreover, the same method of combining PPO and GNN was employed by Cai, Bian, and Liu (2024) to minimize makespan of resource-constrained project scheduling problems with resource disruptions.

Finally, taking classical PDRs or self-designed scheduling rules as actions of DRLs has become the focus of figuring out dynamic scheduling problems, especially for FJSP. Researchers need to design effectively objective-oriented scheduling rules for successfully implementing this method. Aiming at minimizing total tardiness, Luo (2020) addressed the dynamic flexible job shop scheduling problem (DFJSP) with new job insertions where DQN considered six composite dispatching rules as actions. Subsequently, Li et al., (2022) took dispatching rules generated by genetic programming as the actions of the hybrid DQN and applied them to minimize the makespan and total energy consumption of the DFJSP with insufficient transportation resources. Furthermore, a distributed hierarchical architecture based on DQN adopting four PDRs as actions was proposed by Liu et al. (2022) to cope with the DFJSP. Meanwhile, Wang et al., (2022) investigated a multi-objective DFJSP to simultaneously optimize makespan, average machine utilization, and average job processing delay rate by DQN employing nine composite dispatching rules as actions. Yang et al. (2022) studied the distributed permutation flow-shop scheduling problem with dynamic job arrivals using DQN, DDQN, DlDQN, and an advantage actor-critic algorithm which regarded eight dispatching rules as actions. Besides, Gui, Tang, Zhu, Zhang, and Zhang (2023) investigated a scheduling method designed on a deep deterministic policy gradient algorithm for the DFJSP aiming to minimize the mean tardiness. Three PDRs for machine selection and four PDRs for operation sequencing were adopted in the model. Recently, Wang and Liao (2023) applied PPO to dealing with the dynamic JSP with random job arrivals, where eleven classic dispatching rules were taken as the actions of PPO. Moreover, a PPO-based scheduling model was developed by Zhang et al., (2023) to handle the DFJSP with variable processing times, which took eight hybrid scheduling rules constructed by PDRs as action and aimed to minimize makespan.

From the above, it can be discovered that due to the time-consuming updating of the DRL-based *meta*-heuristics and the complicated expression of DRL-based DG when facing a dynamic distributed manufacturing environment, most of them are utilized for static scheduling problems while the DRL-based PDRs are widely employed to address dynamic scheduling problems for its advantages of being intuitive, fast and effective. Furthermore, the DDJSPT is widespread in real manufacturing systems and has not been studied. Therefore, it is feasible and necessary to adopt DRL-based PDRs for the proposed DDJSPT.

3. Background of DRLs

Reinforcement learning (RL) is the third basic machine learning method besides supervised and unsupervised learning and is a powerful tool for working out sequential decision-making tasks. It investigates how to enable the agent to maximize the cumulative reward by interacting with a complex and uncertain environment. The interaction between the agent and the environment is shown in Fig. 1, the RL task is modeled as an MDP with five elements including a state space S, an action space A, a transition function P, a reward function R, and the discount factor γ. In the MDP, the agent observes the current state ($s_t \in S$) at the decision-making step t and then makes an action ($a_t \in A$) according to the policy $\pi(S \rightarrow A)$. Subsequently, the environment gets into the next state ($s_{t+1} \in S$) with the transition probability $p(s_{t+1}|(s_t, a_t)) \in P(S \times A \rightarrow S)$ from s_t and the agent receives the immediate reward ($r_t \in R$). The agent interacts with the environment continuously and eventually learns the optimal policy π^* achieving the maximum long-term cumulative reward.

According to the updating and learning methods of the policy, reinforcement learning algorithms can be categorized into value-based and policy-based algorithms. The details of these two methods are stated below.

3.1. Value-based DRLs

The value functions of value-based DRLs such as DQN and its variants DDQN or DlDQN are approximated by deep neural networks. The DQN model is proposed to train CNNs with a variation of Q-learning, which is a pioneering work in the field of DRLs. Two techniques incorporating experience replay mechanism and target network are adopted in DQN, which can relieve instability and non-convergence of neural networks when approximating the action-valued function (Volodymyr et al., 2013).

(1) Experience replay mechanism.

The experiences of the agent are stored to form a memory replay sequence at each time point. During the training process, a small batch of experiences are randomly sampled to update the network parameters by the stochastic gradient descent algorithm in each iteration step. This mechanism can make full utilization of historical data by repeatedly sampling and reducing the data dependency.

(2) Target network.

DQN has two networks namely the online network $Q(s, a; \theta_i)$ and the target network $\widehat{Q}(s, a; \theta_i^-)$. The former takes charge of choosing the action and the latter is applied for estimating the target state-action value. During Q-network training, parameters are updated by minimizing the following loss function.

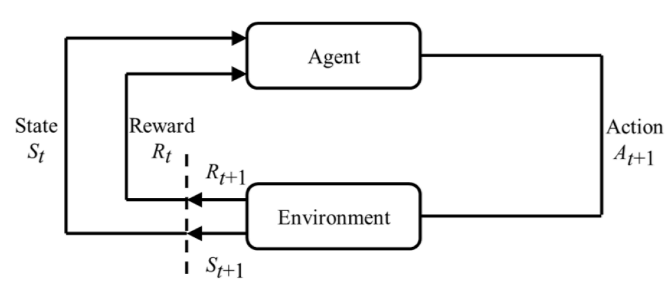

Fig. 1. The interacting process between the agent and the environment.

$$L(\theta) = E_{(s,a,r,s')}\left[(y - Q(s,a;\theta))^2\right] \tag{1}$$

where s' is the next state, Î¸ is the parameter of online network Q. The calculation of the target state-action value y is depicted as Eq. (2).

$$y = r + \gamma^* \underset{a'}{max}\widehat{Q}(s', a'; \theta^-) \tag{2}$$

where a' are all possible actions at next time, the θ^- is the parameter of the target network $\widehat{Q}$.

The target network and the online network have the same structure. The parameters of the target network can be updated by hard updating or soft updating techniques. The common hard updating technique directly copies the online network weights to the target network for C steps. while the common soft updating technique slowly tracks the online network $\widehat{Q} = \tau^* Q + (1-\tau)^*\widehat{Q}$ with the soft parameter $\tau \in (0,1)$ at every training step, and improving its robustness and adaptivity is gradually attracting the attention of some scholars (Kobayashi, 2022; Kobayashi & Ilboudo, 2021; Liang et al., 2021).

As described in Eq. (3), the maximum state-action value rather than the expected one is applied which will result in the selection of overestimated values in DQN. To avoid this, the DDQN was developed to adopt the state-action value of the action that has the maximum state-action value at the s' in the target network (Hasselt, Guez, & Silver, 2015). The target state-action value of DDQN is calculated as Eq. (3).

$$y = r + \gamma^* Q\left(s', \underset{a'}{\text{argmax}} Q(s', a'; \theta); \theta^-\right) \tag{3}$$

The DlDQN is also an improved variant of DQN with the state-action value $Q(s,a;\theta,\alpha,\beta)$ calculated by the state value $V(s;\theta,\beta)$ and advantage $A(s,a;\theta,\alpha)$ (Wang, Schaul, Hessel, Hasselt, Lanctot, & Freitas, 2016).

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + A(s,a;\theta,\alpha) \tag{4}$$

It can be observed from Eq. (4) that there is a non-uniqueness of a combination of $V(s;\theta,\beta)$ and $A(s,a;\theta,\alpha)$ for a certain $Q(s,a;\theta,\alpha,\beta)$. So, the baseline is applied as Eq. (5).

$$Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + A(s,a;\theta,\alpha) - \frac{1}{\varphi}^* \sum_{a'} A(s,a';\theta,\alpha) \tag{5}$$

where φ is the size of the action space.

A target network $Q(s,a;\theta^-,\alpha^-,\beta^-)$ is also used in DlDQN and y is calculated as Eq. (6).

$$y = r + \gamma^* \underset{a'}{\max}\widehat{Q}(s', a'; \theta^-, \alpha^-, \beta^-) \tag{6}$$

3.2. Policy-based DRL

The policy functions of DRLs like TRPO and PPO adopt neural networks to approximate their policies. To measure the performance of the policy, the strategy of the agent is parameterized and tries to maximize an objective function by gradient ascent for the optimal strategy as Eq. (7) exhibits.

$$\mathrm{J}(\theta) = \mathrm{E}_{s_0}[\mathrm{V}^{\pi_\theta}(s_0)] = \mathrm{E}_{\pi_\theta}\left[\sum\nolimits_{t=0}^{\infty} \gamma^t * r(s_t, a_t)\right] \tag{7}$$

$$\theta^* = \arg\max\nolimits_\theta J(\theta) \tag{8}$$

Generally, the θ^* displayed as Eq. (8) can be arrived when the policy gradient algorithm iteratively updates the policy parameters θ mainly along the direction of $\nabla_\theta J(\theta)$. But its fatal drawback is that updating the parameters along the policy gradient may result in a sudden and significant deterioration of the policy due to a too long step, which in turn affects the training results. In this context, the proposed TRPO would guarantee the monotonic improvement for strategy optimization (Schulman, Levine, Moritz, Jordan, & Abbeel, 2015). To find an improved policy, the objective function $J(\theta')$ can be inferred based on the old policy π_θ as expressed in Eq. (9).

$$J(\theta') = J(\theta) + \frac{1}{1-\gamma}^* E_{s\ \nu^{\pi_\theta}} E_{a\ \pi_{\theta'}(\hat{A}\cdot|s)}[A^{\pi_\theta}(s,a)] \tag{9}$$

where $A^{\pi_\theta}(s,a)$ is the advantage function in the old policy π_θ currently calculated by generalized advantage estimation (GAE).

It is not realistic to traverse all new strategies to collect data. An approximate operation ignoring the changes of state distribution is implemented to simplify the objective function and take actions obeying the new policy $\pi_{\theta'}$ as Eq. (10) calculates.

$$J(\theta') = J(\theta) + E_{s\ \nu^{\pi_\theta}} E_{a\ \pi_\theta(\hat{A}\cdot|s)}\left[\frac{\pi_{\theta'}(a|s)}{\pi_\theta(a|s)}^* A^{\pi_\theta}(s,a)\right] \tag{10}$$

Therefore, the new policy could be estimated and optimized. To make the old and the new policy more similar, a trust domain constraint defined by the Kullback Leibler (KL) dispersion is introduced to pick a suitable step size as declared in Eq. (11). It ensures that the optimization of the strategy always proceeds in the direction of no deterioration.

$$\underset{\theta'}{\max} L_\theta(\theta') s.t. E_{s\ \nu^{\pi_\theta}}[D_{\mathrm{KL}}(\pi_\theta|s), \pi_{\theta'}(\hat{A}\cdot|s) \le \delta] \tag{11}$$

where $\pi_{\theta'}$ is the new improved strategy, δ is a hyperparameter limiting the distance between old and new policy.

Based on the aforementioned deduction, only the Taylor expanded approximation adopting the Hessian matrix and Karush-Kuhn-Tucker condition, conjugate gradient method, and linear search algorithm are needed to subsequently update the network parameter Î¸.

The TRPO has been successfully applied in various scenarios, but its shortcomings of complex and computationally intensive calculation process at each updating step are also found. As an improved variant of TRPO, PPO is well-known for its simplification and easy implementation (Schulman, Wolski, Dhariwal, Radford, & Klimov, 2017). Specifically, there are two forms of PPO, namely PPO-penalty and PPO-clip.

PPO-Penalty puts the constraint of the KL dispersion directly into the objective function using the Lagrange multiplier method manifested in Eq. (12), which turns it into an unconstrained optimization problem, where the coefficients in front of the KL dispersion are constantly updated during the iterations.

$$\begin{aligned} &\underset{\theta'}{argmax} E_{s\ \nu^{\pi_{\theta_{\mathrm{old}}}}} E_{a\ \pi_{\theta_{\mathrm{old}}}(\hat{A}\cdot|s)}\Bigg[\frac{\pi_{\theta'}(a|s)}{\pi_{\theta_{\mathrm{old}}}(a|s)}^* A^{\pi_{\theta_{\mathrm{old}}}}(s,a) \\ &\quad - \beta^* D_{\mathrm{KL}}\left[\pi_{\theta_{\mathrm{old}}}(\hat{A}\cdot|s), \pi_{\theta'}(\hat{A}\cdot|s)\right]\Bigg] \end{aligned} \tag{12}$$

where let $d_{\mathrm{old}} = D_{\mathrm{KL}}^{\pi_{\theta_{\mathrm{old}}}}(\pi_{\theta_{\mathrm{old}}}, \pi_{\theta'})$, if $d_{\mathrm{old}} < \delta/1.5$, $\beta_{\mathrm{new}} = \beta_{\mathrm{old}}/2$; if $d_{\mathrm{old}} > \delta^* 1.5$, $\beta_{\mathrm{new}} = \beta_{\mathrm{old}}{}^*2$; Otherwise, $\beta_{\mathrm{new}} = \beta_{\mathrm{old}}$.

PPO-Clip sets a limit in the objective function to ensure a smaller gap between the new parameters and the old ones as Eq. (13) shows.

$$\begin{aligned} &\underset{\theta'}{\text{argmax}} E_{s\ \nu^{\pi_{\theta_{\mathrm{old}}}}} E_{a\ \pi_{\theta_{\mathrm{old}}}(\hat{A}\cdot|s)}\Bigg[\min\left(\frac{\pi_{\theta'}(a|s)}{\pi_{\theta_{\mathrm{old}}}(a|s)}^* A^{\pi_{\theta_{\mathrm{old}}}}(s,a), \text{clip}\left(\frac{\pi_{\theta'}(a|s)}{\pi_{\theta_{\mathrm{old}}}(a|s)}, 1-\epsilon, 1\right.\right. \\ &\quad \left.\left. +\epsilon\right)^* A^{\pi_{\theta_{\mathrm{old}}}}(s,a)\right)\Bigg] \end{aligned} \tag{13}$$

where $\mathrm{clip}(\mathrm{x},\ \mathrm{z},\ \mathrm{r}) = \max(\min(\mathrm{x},\ \mathrm{r}),\ \mathrm{z})$, namely limit x in the range of $[z, r]$, Ïµ is a hyperparameter limiting the clip range.

4. Model construction

4.1. Problem description

The DDJSPT with random job arrivals in this research can be introduced as follows. There are n successively arriving jobs $J = \{J_1, J_2, \ldots, J_i, \ldots, J_n\}$c to be processed on f factories $F = \{F_1, F_2, \ldots, F_q, \ldots, F_f\}$, the qth factory includes m_q machines $M^q = \{M^q_1, M^q_2, \ldots, M^q_k, \ldots, M^q_{m_q}\}$. Each job J_i contains n_i operations and $O_{i,j}$ represents the jth operation of J_i. The f factories are heterogeneous. Each operation $O_{i,j}$ can be processed in all factories. $PT_{i,j,q,k}$ is the processing time of operation $O_{i,j}$ on M^q_k. The arrival time and due date of the job J_i are AT_i and DD_i, respectively. The target is to minimize the mean tardiness of all jobs in the random arrival process. There are two aspects of decisions to be determined in DDJSPT, which are summarized below:

(1) screening out the unfinished job with the highest urgency level.
(2) allocating the first remaining operation of the selected job to a proper factory.

Additionally, several predefined constraints and assumptions for simplifying the DDJSPT with random job arrivals are proclaimed as follows.

(1) Each machine can only process at most one operation at a time.
(2) All operations of a job could be processed on specified machine positions in all factories one after another completed in a fixed order of precedence.
(3) No precedence constraint exists between the operations of different jobs.
(4) Each operation should not be interrupted when being processed.
(5) The transfer time of jobs is predetermined, and breakdown and setup times are neglected.
(6) An unlimited buffer between machines is assumed.

4.2. Mathematical formulation and its validation

The indices and notations used for parameter construction and mathematical formulation in the dynamic scheduling model are declared below.

(1) Parameters

Indices	
i, r	Index of jobs, $i, r = 1, 2, \ldots, n$
j, h	Index of operations, $j, h = 1, 2, \ldots, n_i$
q	Index of factories, $q = 1, 2, \ldots, f$
k	Index of machines in qth factory, $k = 1, 2, \ldots, m_q$
Parameters	
n	Total number of jobs
J_i	The ith job
J	Job set, $J = \{J_1, J_2, \ldots, J_n\}$
n_i	Total number of operations in J_i
$O_{i,j}$	The jth operation of J_i
f	Total number of factories
F_q	The qth factory
F	Factory set, $F = \{F_1, F_2, \cdots, F_f\}$
M^q	Set of machines in F_q
m_q	Total number of machines in F_q
M^q_k	The kth machine of F_q
$ST_{i,j}$	Starting time of $O_{i,j}$
$PT_{i,j,q,k}$	Processing time of $O_{i,j}$ on M^q_k
TM	Transfer time between machines in a factory
TF	Transfer time between two factories
$ET_{i,j,q,k}$	Ending time of $O_{i,j}$ on M^q_k
DDT	Due date tightness
AT_i	Arrival time of J_i
DD_i	Due date of J_i
CT_i	Completion time of J_i
MTJ	Mean tardiness of all jobs
L	A large enough positive number
Decision variables	
$X_{i,j,q,k}$	1, if $O_{i,j}$ is assigned on M^q_k; 0, otherwise.
$X_{r,h,q,k}$	1, if $O_{r,h}$ is assigned on M^q_k; 0, otherwise.
$Y_{i,j,r,h}$	1, if $O_{i,j}$ is processed directly before operation $O_{r,h}$; 0, otherwise.
$Z^M_{i,j}$	1, if $O_{i,j}$ is transferred between machines in a factory; 0, otherwise.
$Z^F_{i,j}$	1, if $O_{i,j}$ is transferred between two factories; 0, otherwise.

(continued on next column)

(continued)

(2) Objective and constraints

This article aims to minimize the mean tardiness of all jobs. The target can be depicted as follows.

$$\text{Minimize MTJ} = \frac{\sum_{i=1}^{n} \max(CT_i \text{ - } DD_i,\ 0)}{n} \tag{14}$$

Before proposing the constrains, the total time of transferring $O_{i,j}$ is defined.

$$TMF_{i,j} = TM * Z^M_{i,j} + TF * Z^F_{i,j} \tag{15}$$

The constrains of the aim are constructed as follows.

$$ST_{i,j} \geq 0,\ \hat{a} \pm i, j \tag{16}$$

$$ST_{i,1} - AT_i \geq 0,\ \hat{a} \pm i \tag{17}$$

$$ST_{i,j+1} - ST_{i,j} \geq \sum_{q=1}^{f} \sum_{k=1}^{m_q} PT_{i,j,q,k} * X_{i,j,q,k} + TMF_{i,j+1},\ j = 1, \cdots n_i - 1, \hat{a} \pm i \tag{18}$$

$$ST_{r,h} + L * \left(3 - Y_{i,j,r,h} - X_{i,j,q,k} - X_{r,h,q,k}\right) \geq ST_{i,j} + X_{i,j,q,k} * PT_{i,j,q,k},\ \hat{a} \pm i, j, r, h, q, k, \text{ and } i \neq r \tag{19}$$

$$ST_{i,j} + L * \left(2 + Y_{i,j,r,h} - X_{i,j,q,k} - X_{r,h,q,k}\right) \geq ST_{r,h} + X_{i,j,q,k} * PT_{i,j,q,k},\ \hat{a} \pm i, j, r, h, q, k, \text{ and } i \neq r \qquad \text{sid226(20)}$$

$$\sum_{q=1}^{f} \sum_{k=1}^{m_q} X_{i,j,q,k} = 1,\ \hat{a} \pm i, j \tag{21}$$

$$Z^M_{i,1} + Z^F_{i,1} = 0,\ \hat{a} \pm \overline{i} \qquad \text{sid16(22)}$$

$$1 \text{ - } \sum_{q=1}^{f} \sum_{k=1}^{m_q} X_{i,j,q,k} * X_{i\text{-}1,j,q,k} \geq Z^M_{i,j} + Z^F_{i,j},\ j = 2, \cdots n_i,\ \hat{a} \pm i \qquad \text{sid280(23)}$$

$$Z^M_{i,j} \geq \sum_{q=1}^{f} \sum_{k,k \neq k_1}^{m_q} X_{i,j,q,k} * X_{i\text{-}1,j,q,k_1},\ j = 2,\ \cdots n_i,\ \hat{a} \pm \overline{i} \qquad \text{sid41(24)}$$

$$Z^F_{i,j} \geq 1 \text{ - } \sum_{q=1}^{f} \left(\sum_{k}^{m_q} X_{i,j,q,k} * \sum_{k_1}^{m_q} X_{i\text{-}1,j,q,k_1} \right),\ j = 2, \cdots n_i,\ \hat{a} \pm \overline{i} \qquad \text{sid68(25)}$$

$$CT_i - ST_{i,n_i} \geq \sum_{q=1}^{f} \sum_{k=1}^{m_q} PT_{i,j,q,k} * X_{i,j,q,k},\ \hat{a} \pm i \qquad \text{sid99(26)}$$

Eq. (14) is the objective of minimizing the mean tardiness for all jobs. Constraint (16) means that the starting time of processing an operation should be non-negative. Inequality (17) indicates that the first operation of a job could be processed only after it has arrived at the shop floor. Constraint (18) ensures that the next operation of a job can be processed only after its current operation has been finished. Constraints (19) and (20) ensure that a machine can only process one operation at a time. Eq. (21) suggests that a job can be processed by only one machine at a time. Eq. (22) means that the first operation of all jobs does not need to be transferred. Constraint (23) requires that the job would not be transferred if the current operation and its last operation are processed in the same machine. Inequality (24) manifests that the time of the job transferred between machines in a factory is considered. Constraint (25) suggests that the time of the job transferred between two factories is considered. Inequality (26) is a constraint of completion time for all jobs.

To validate the above mathematical formulations, six small instances were run by CPLEX. These instances are named $f \times m \times n$, where f denotes the number of factories, m is the number of machines per factory, and n expresses the number of jobs. These instances are created by setting the number of operations per job as 3, the range of processing time for each operation as 1 to 50, the transfer time between machines in a factory as 1, and the transfer time between two factories as 3. The running results are shown in Table 1.

5. DRL-based scheduling method

The DDJSPT is a sequential decision-making process and can be formulated as an MDP represented as a tuple (S, A, P, γ, R). The schematic diagram of MDP for DDJSPT is shown in Fig. 2. At each scheduling decision point, the scheduling agent considers the current state s_t ($s_t \in S$) of the distributed job shop as input and takes an action a_t ($a_t \in A$) based on the policy $\pi(S \rightarrow A)$. Subsequently, the scheduling environment moves to the next state s_{t+1} ($s_{t+1} \in S$) according to the transition function P, and gives the agent an immediate reward r_t ($r_t \in R$). Through constant interaction, the scheduling agent can learn the optimal scheduling policy by maximizing the cumulative reward with a discount factor γ.

Herein, the DDJSPT is modeled as a MDP at first. Then, ten state features about factories, machines, jobs, and operations, eleven composite rules containing the selection of prioritized jobs and the assignment of the selected job to an appropriate factory, and a reward function closely related to the goal are elaborately designed and defined in detail. Finally, the network structure and overall training framework of five DRLs including PPO, TRPO, DlDQN, DDQN, and DQN are developed to sort out the DDJSPT.

For conveniently defining state features, actions, and the reward function, these key notations applied in the following part of this article are displayed below.

(1) t: the scheduling decision point when an operation is completed or a new job arrives.
(2) $CO_i(t)$: the number of completed operations of J_i at t.
(3) $UJ(t)$: the set of uncompleted jobs at t.

$$UJ(t) = \{J_i | CO_i(t) < n_i\} \tag{27}$$

(4) $CRJ_i(t)$: the completion rate of J_i at t.

$$CRJ_i(t) = \frac{CO_i(t)}{n_i} \tag{28}$$

(5) $CT_k^q(t)$: the completion time of the last operation having been assigned on M_k^q at t.
(6) $MU_k^q(t)$: the utilization rate of M_k^q at t.

$$MU_k^q(t) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{CO_i(t)} PT_{i,j,q,k} * X_{i,j,q,k}}{CT_k^q(t)} \tag{29}$$

Table 1
Results of six cases computed by CPLEX.

$f \times m \times n$	$2 \times 2 \times 2$	$2 \times 3 \times 3$	$3 \times 2 \times 2$	$3 \times 3 \times 3$	$4 \times 2 \times 2$	$4 \times 3 \times 3$
CPLEX	23	20	16	14.3	14	11.7

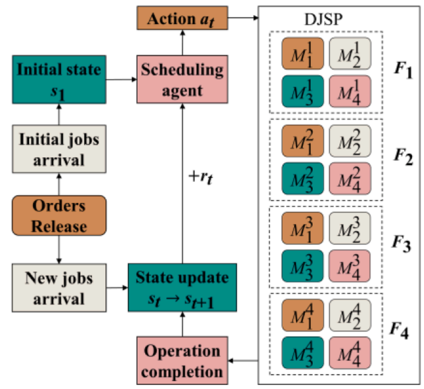

Fig. 2. The MDP of DDJSPT with random job arrivals.

(7) $FU_{ave}^q(t)$: average of machine utilization rate in Fq at t.

$$FU_{ave}^q(t) = \frac{\sum_{k=1}^{mq} MU_k^q(t)}{m_q} \tag{30}$$

(8) $FU_{std}^q(t)$: the standard deviation of machine utilization rate in Fq at t.

$$FU_{std}^q(t) = \sqrt{\frac{\sum_{k=1}^{mq} (MU_k^q(t) - FU_{ave}^q)^2}{m_q}} \tag{31}$$

(9) T_k^i: average completion time of the last operation having been assigned on the kth machine which can process the last uncompleted operation of J_i in all factories.

$$T_k^i = \frac{\sum_{q=1}^{f} CT_k^q(t)}{f} \tag{32}$$

(10) TJ(t): total tardiness of all jobs at t.
(11) MTJ(t): mean tardiness of all jobs at t, of which the calculation procedure is claimed in Eq. (33).

$$MTJ(t) = \frac{\sum_{i=1}^{n} (ET_{i,CO_i(t)} - DD_i)}{n}, \text{ if } ET_{i,CO_i(t)} > DD_i \qquad \text{sid130(33)}$$

(12) ATJ(t): the set of actually tardy jobs at t.

$$ATJ(t) = \{J_i \in UJ(t) | T_k^i > DD_i \& CO_i(t) < n_i\} \tag{34}$$

(13) $\overline{PT}_{i,j}$: average time of transferring and processing $O_{i,j}$ among all factories.

$$\overline{PT}_{i,j} = \frac{\sum_{q=1}^{f}\sum_{k=1}^{mq} PTi,j,q,k + TM + (f - 1) * TF}{f} \qquad \text{sid187(35)}$$

5.1. State features

The pivotal state features are extracted from factories, machines, jobs, and operations to reflect the current state of the DDJSPT as much as possible, which are employed as inputs of the policy network to manipulate the appropriate action at each scheduling decision point. Owing to the extremely large variation in the number of machines, jobs, and operations and the inconsistency of data dimensions in the actual production environment, the effectiveness and generalization of DRLs can't be acquired without any data processing. To improve the performance of DRL-based scheduling agents, the data processing method of normalization is adopted for mapping these indicators to the range of [0, 1] (Luo, 2020). Then, a well-trained model could be applied to other untrained production environments. In this research, ten state features of DDJSPT are elaborately designed.

Based on the aforementioned notations, ten state features of the dynamic distributed job shop at scheduling decision point t are defined as follows.

1. Completion rate of all operations at t, $\mathrm{CRO_{ave}(t)}$.

$$\mathrm{CRO_{ave}(t)} = \frac{\sum_{i=1}^{n}\mathrm{CO_i(t)}}{\sum_{i=1}^{n}\mathrm{n_i}} \tag{36}$$

2. The ratio of the number of uncompleted jobs $\mathrm{UJ(t)}$ to the number of jobs n at t, $\mathrm{UJR(t)}$.

$$UJR(t) = \frac{|UJ(t)|}{n} \tag{37}$$

3. Average completion rate of all jobs at t, $\mathrm{CRJ_{ave}(t)}$.

$$\mathrm{CRJ_{ave}(t)} = \frac{\sum_{i=1}^{n}\mathrm{CRJ_i(t)}}{\mathrm{n}} \tag{38}$$

4. The standard deviation of job completion rate at t, $\mathrm{CRJ_{std}(t)}$.

$$\mathrm{CRJ_{std}(t)} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{CRJ_i(t)} - \mathrm{CRJ_{ave}(t)})^2}{\mathrm{n}}} \tag{39}$$

5. Average of $\mathrm{FU^q_{ave}(t)}$ for all factories at t, $\mathrm{FU_{ave}(t)}$.

$$\mathrm{FU_{ave}(t)} = \frac{\sum_{q=1}^{f}\mathrm{FU^q_{ave}(t)}}{\mathrm{f}} \tag{40}$$

6. The standard deviation of $\mathrm{FU^q_{ave}(t)}$ for all factories at t, $\mathrm{FU_{std}(t)}$.

$$\mathrm{FU_{std}(t)} = \sqrt{\frac{\sum_{q=1}^{f}(\mathrm{FU^q_{ave}(t)} - \mathrm{FU_{ave}(t)})^2}{\mathrm{f}}} \tag{41}$$

7. Average of $\mathrm{FU^q_{std}(t)}$ for all factories at t, $\mathrm{FU'_{ave}(t)}$.

$$\mathrm{FU'_{ave}(t)} = \frac{\sum_{q=1}^{f}\mathrm{FU^q_{std}(t)}}{\mathrm{f}} \tag{42}$$

8. The standard deviation of $\mathrm{FU^q_{std}(t)}$ for all factories at t, $\mathrm{FU'_{std}(t)}$.

$$\mathrm{FU'_{std}(t)} = \sqrt{\frac{\sum_{q=1}^{f}(\mathrm{FU^q_{std}(t)} - \mathrm{FU'_{ave}(t)})^2}{\mathrm{f}}} \tag{43}$$

9. Estimated tardiness rate of all jobs at t namely $\mathrm{ETRO(t)}$, of which the calculation is given in Algorithm 1.

Algorithm 1 The calculation of ETRO(t)

Input: $\mathrm{CT^q_k(t)}$, $\mathrm{CO_i(t)}$, $\mathrm{\overline{PT}_{i,j}}$, $\mathrm{DD_i}$
Output: ETRO(t)
$\mathrm{N_{tardy}} \leftarrow 0$
$\mathrm{N_{left}} \leftarrow 0$
for $i = 1$: n **do**
  if $\mathrm{CO_i(t)} < \mathrm{n_i}$ **then**
    $\mathrm{N_{left}} \leftarrow \mathrm{N_{left}} + \mathrm{n_i} - \mathrm{CO_i(t)}$
    $\mathrm{T_{left}} \leftarrow 0$
    for $j = \mathrm{CO_i(t)} + 1 : \mathrm{n_i}$ **do**
      $\mathrm{T_{left}} \leftarrow \mathrm{T_{left}} + \mathrm{\overline{PT}_{i,j}}$
    if $\mathrm{T^i_k} + \mathrm{T_{left}} > \mathrm{DD_i}$ **then**
      $\mathrm{N_{tardy}} \leftarrow \mathrm{N_{tardy}} + \mathrm{n_i} - \mathrm{j} + 1$
      break
    end if
    end for
  end if
end for
$\mathrm{ETRO(t)} \leftarrow \frac{\mathrm{N_{tardy}}}{\mathrm{N_{left}}}$
Return ETRO(t)

10. Actual tardiness rate of all jobs at t $\mathrm{ATRO(t)}$, of which the calculation is announced in Algorithm 2.

Algorithm 2 The calculation of ATRO(t)

Input: $\mathrm{CO_i(t)}$, $\mathrm{DD_i}$
Output: ATRO(t)
$\mathrm{N_{tardy}} \leftarrow 0$
$\mathrm{N_{left}} \leftarrow 0$
for $i = 1$: n **do**
  if $\mathrm{CO_i(t)} < \mathrm{n_i}$ **then**
    $\mathrm{N_{left}} \leftarrow \mathrm{N_{left}} + \mathrm{n_i} - \mathrm{CO_i(t)}$
    if $\mathrm{ET_{i,CO_i(t)}} > \mathrm{DD_i}$ **then**
      $\mathrm{N_{tardy}} \leftarrow \mathrm{N_{tardy}} + \mathrm{n_i} - \mathrm{CO_i(t)}$
    end if
  end if
end for
$\mathrm{ATRO(t)} \leftarrow \frac{\mathrm{N_{tardy}}}{\mathrm{N_{left}}}$
Return ATRO(t)

5.2. Actions

Two subproblems exist in DDJSPT, which contain the selection of a prioritized job and the allocation of it to a proper factory at each scheduling decision point. As is known to all, a single scheduling rule will perform poorly in various production environments. To address a complex shop scheduling problem, scheduling rules should be combined to form a union of composite rules for strong adaptability and effectiveness under different shop configurations. Meanwhile, what principles of designing scheduling rules must be emphasized is that these composite rules serve the aim of minimizing mean tardiness. Thus, eleven composite rules are elaborately designed by considering the unique characteristics of DDJSPT and regarded as actions of DRLs. The details of these rules are expressed as follows.

(1) Composite rule 1. If the set of tardy jobs $\mathrm{ATJ(t)}$ is not empty at t, tardy jobs are ranked by the estimated average tardiness of remaining operations i.e. $\frac{\mathrm{T^i_k} + \sum_{j=\mathrm{CO_i(t)}+1}^{\mathrm{n_i}}\mathrm{\overline{PT}_{i,j}} - \mathrm{DD_i}}{\mathrm{n_i} - \mathrm{CO_i(t)}}$ for $\mathrm{J_i} \in \mathrm{ATJ(t)}$. Then, the next operation of the job possessing the maximum estimated average tardiness of remaining operations is selected. Otherwise, all jobs are prioritized by the average slack time of remaining operations namely $\frac{\mathrm{DD_i} - \mathrm{T^i_k}}{\mathrm{n_i} - \mathrm{CO_i(t)}}$ for $\mathrm{J_i} \in \mathrm{UJ(t)}$. Then the next operation of the job with the minimum average slack time of remaining operations is selected. Meanwhile, all factories are sorted by the total time of transferring and processing $\mathrm{O_{i,j}}$ namely $\mathrm{TMF_{i,j}} + \mathrm{PT_{i,j,q,k}}$ at t. Then the factory with the minimum total time of transferring and processing $\mathrm{O_{i,j}}$ is assigned to machine the operation of the selected job. The content of composite rule 1 is given in Algorithm 3.

Algorithm 3 Composite rule 1

1: **if** $ATJ(t) \neq \emptyset$ **then**
2: $J_i \leftarrow \arg\max_{i\in UJ(t)}(\frac{T_k^i + \sum_{j=CO_i(t)+1}^{n_i}\overline{PT}_{i,j} - DD_i}{n_i - CO_i(t)})$
3: **else**
4: $J_i \leftarrow \arg\min_{i\in UJ(t)}(\frac{DD_i - T_k^i}{n_i - CO_i(t)})$
5: **end if**
6: $j \leftarrow CO_i(t) + 1$
7: $F_q \leftarrow \arg\min_{q\in[1,f]}(TMF_{i,j} + PT_{i,j,q,k})$
8: Assign $O_{i,j}$ to F_q

(2) Composite rule 2. It employs the same method of choosing jobs to process as composite rule 1, but with the difference that it distributes the selected job to the earliest available factory namely $\max(CT_k^q(t),\ ET_{i,CO_i(t)} + TMF_{i,j},\ AT_i)$.The procedure of calculating the factory number is declared in Eq. (44).

$$q = \arg\min_{q\in[1,f]}(\max(CT_k^q(t),\ ET_{i,CO_i(t)} + TMF_{i,j},\ AT_i)) \tag{44}$$

(3) Composite rule 3. It uses the same method of prioritizing jobs to process if the set of tardy jobs at *t* $ATJ(t)$ is not empty and selecting the factory as composite rule 1, but with the difference that if $ATJ(t)$ is empty, all jobs are ordered by the number of the remaining processing time dividing the slack time i.e. $\frac{\sum_{j=CO_i(t)+1}^{n_i}\overline{PT}_{i,j}}{DD_i - T_k^i}$ for $J_i \in UJ(t)$ as Eq. (45) shows.

$$i = \arg\max_{i\in UJ(t)}(\frac{\sum_{j=CO_i(t)+1}^{n_i}\overline{PT}_{i,j}}{DD_i - T_k^i}) \qquad \text{sid12(45)}$$

(4) Composite rule 4. The method of it to select jobs to machine is the same as composite rule 3, but with the difference that the selected job is allotted to the earliest available factory with the identical expression mentioned in Eq. (44).
(5) Composite rule 5. It takes the same method of prioritizing jobs to process if the set of tardy jobs at *t* $ATJ(t)$ is not empty and choosing factories as composite rule 1, but with the difference that if $ATJ(t)$ is empty, all jobs are ordered by the product of the completion rate and the slack time $\frac{CO_i(t)}{n_i} * (DD_i - T_k^i)$ for $J_i \in UJ(t)$ as Eq. (46) shows.

$$i = \arg\min_{i\in UJ(t)}(\frac{CO_i(t)}{n_i} * (DD_i - T_k^i)) \qquad \text{sid70(46)}$$

(6) Composite rule 6. It utilizes the same method of prioritizing jobs to process as composite rule 5, but with the difference that the earliest available factory with the identical expression mentioned in Eq. (44) is selected to machine the selected job.
(7) Composite rule 7. All jobs are ranked by the estimated average tardiness of remaining operations i.e. $\frac{T_k^i + \sum_{j=CO_i(t)+1}^{n_i}\overline{PT}_{i,j} - DD_i}{n_i - CO_i(t)}$ for $J_i \in ATJ(t)$. Then the next operation of the job owning the maximum estimated average tardiness of remaining operations is selected. Meanwhile, all factories are sorted by the total time of transferring and processing $O_{i,j}$ namely $TMF_{i,j} + PT_{i,j,q,k}$ at *t*. Then the factory with the minimum total time of transferring and processing $O_{i,j}$ is distributed to process the operation of the selected job. Algorithm 4 gives the procedure of composite rule 7.

Algorithm 4 Composite rule 7

1: $J_i \leftarrow \arg\max_{i\in UJ(t)}(\frac{T_k^i + \sum_{j=CO_i(t)+1}^{n_i}\overline{PT}_{i,j} - DD_i}{n_i - CO_i(t)})$
2: $j \leftarrow CO_i(t) + 1$
3: $F_q \leftarrow \arg\min_{q\in[1,f]}(TMF_{i,j} + PT_{i,j,q,k})$
4: Assign $O_{i,j}$ to F_q

(8) Composite rule 8. It employs the same method of prioritizing jobs to machines as composite rule 7, but with the difference that the earliest available factory with the identical expression mentioned in Eq. (44) is determined to machine the selected job.
(9) Composite rule 9. The next operation of the job is decided at random. Meanwhile, all factories are sorted by the total time of transferring and processing $O_{i,j}$ namely $TMF_{i,j} + PT_{i,j,q,k}$ at *t*. Then the factory with the minimum total time of transferring and processing $O_{i,j}$ is assigned to process the operation of the selected job. Algorithm 5 depicts the procedure of composite rule 9.

Algorithm 5 Composite rule 9

1: Randomly choose an uncompleted job from $UJ(t)$
2: $j \leftarrow CO_i(t) + 1$
3: $F_q \leftarrow \arg\min_{q\in[1,f]}(TMF_{i,j} + PT_{i,j,q,k})$
4: Assign $O_{i,j}$ to F_q

(10) Composite rule 10. The method of it to select jobs to process is the same as composite rule 9, but with the difference that the selected job is distributed to the earliest available factory with the identical expression mentioned in Eq. (44).
(11) Composite rule 11. The next operation of the job is selected at random. Meanwhile, a factory is also randomly determined. The procedure of composite rule 11 is displayed in Algorithm 6.

Algorithm 6 Composite rule 11

1: Randomly choose an uncompleted job from $UJ(t)$
2: $j \leftarrow CO_i(t) + 1$
3: Randomly choose a F_q from F
4: Assign $O_{i,j}$ to F_q

5.3. Reward

The reward function represents the performance of actions taken by DRLs in a given state. It can greatly affect the speed and degree of convergence when DRLs are being trained. Due to the sparse reward problem, a dense but not sparse reward function should be designed, which could give instant feedback to realize the sub-goals at each step and eventually minimize the mean tardiness of all jobs. For a global optimization objective of DRLs, e.g., to minimize makespan or others, a well-known and effective idea for reward designing is to subtract the makespan in the last step from the makespan of the current step and regard the difference value as a timely reward at the current step (Gui et al., 2023; Huang et al., 2023; Liu et al., 2023). Grounded in this, the reward at each scheduling decision point is modeled below.

$$r_t = MTJ(t-1) - MTJ(t) \tag{47}$$

Based on the reward function manifested in Eq.(47), it can be inferred that the cumulative reward (*CR*) can be expressed from Eq. (47) to Eq. (50).

$$CR(t) = r_1 + r_2 + \cdots + r_t \quad (48)$$

$$CR(t) = MTJ(0) - MTJ(1) + MTJ(1) - MTJ(2) + \cdots + MTJ(t-1) - MTJ(t) \quad (49)$$

$$CR(t) = MTJ(0) - MTJ(t) = 0 - MTJ(t) = -MTJ(t) \quad (50)$$

5.4. Network structure of DRLs

Five DRLs encompassing PPO, TRPO, DlDQN, DDQN and DQN are employed in this article. To make the comparison experiment fairer, the neural network structure of the five DRLs is the same, which consists of one input layer with 10 nodes equaling the number of state features, three hidden layers with 128 nodes, and one output layer with 11 nodes equaling to the number of actions. The Rectified Linear Unit (ReLU) function is used as an activation function. Meanwhile, the Adam is set as an optimizer, and mean square error (MSE) is adopted for the loss function.

5.5. Overall framework of the training method

In this section, DlDQN and PPO are considered as the representatives for displaying the training framework of DRLs in detail, which are embedded into the scheduling agent in Fig. 2. Algorithm 7 and Fig. 3 depict the training framework of DlDQN adopting experience replay and soft target update technique. The framework of training PPO with clip is stated in Algorithm 8 and Fig. 4.

At each scheduling decision point of the training process, the method of selecting actions is different for value-based and policy-based DRLs. For DQN, DDQN, and DlDQN, the current states of the production environment are fed into the $Q-$network shown in Fig. 3, which would score the 11 composite rules by the value. Then, the $\varepsilon-$greedy strategy in line 7 of Algorithm 7 is used for the action selection, where the scheduling agent would select the composite rule owing the highest value as the current appropriate action with the probability of $1-\varepsilon$, otherwise, all composite rules will be selected randomly. Whereas for TRPO and PPO, the selection of an appropriate action will be based on the probability of each composite rule named as policy π_{old} in line 6 of Algorithm 8, which is generated by the actor network shown in Fig. 4. The higher the probability of the composite rule, the more likely it is to be selected.

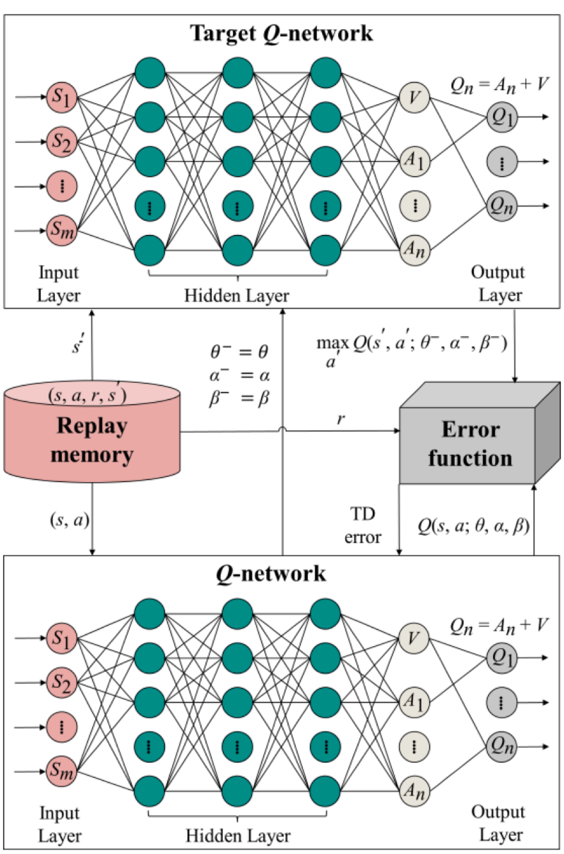

Fig. 3. The structure of DlDQN.

Algorithm 7 Dueling Deep Q-network

1: Initialize replay memory D with capacity N
2: Initialize the online network Q(; Î¸, Î±, β) with random weights Î¸, Î±, β
3: Initialize target network $\widehat{Q}$(; θ¯, Î±¯, β^-) with weights θ¯ = Î¸, Î±¯ = Î±, $\beta^- = \beta$
4: **for** episode = 1: EP **do** (EP is the number of training epochs)
5: Observe the initial state s_1 with the feature vector φ_1
6: **for** $t = 1$, TT **do** (TT stands for the terminal time)
7: With probability ε select a random action a_t
8: Otherwise select $a_t = \arg\max_a Q(\varphi_t, a$; Î¸, Î±, $\beta)$
9: Execute action a_t, observe reward r_t and next state s_{t+1}
10: Extract the feature vector φ_{t+1} of state s_{t+1}
11: Store transition $(\varphi_t, a_t, r_t, \varphi_{t+1})$ in D
12: Sample random minibatch of transitions $(\varphi_j, a_j, r_j, \varphi_{j+1})$ from D
13: Set $y_i = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma * \max_{a'} \widehat{Q}(\varphi_{j+1}, a'; \theta^-, \text{Î±}^-, \beta^-) & \text{otherwise} \end{cases}$
14: Perform a gradient descent step on $(y_i - Q(\varphi_j, a_j$; Î¸, Î±, $\beta))^2$ for network parameters Î¸, Î±, β
15: Update soft target weight $\widehat{Q} = \tau * Q + (1-\tau) * \widehat{Q}$ at every step
16: **end for**
17: **end for**

Algorithm 8 Proximal Policy Optimization with Clip

1: Initialize policy network parameters θ_0
2: Initialize critic network parameters Î¼$_0$
3: **for** episode = 1: EP **do**
4: Observe the initial state s_1 with the feature vector φ_1
5: **for** $t = 1$, TT **do**6: Attain action a_t and $p(a_t)$ by putting s_t into the policy network $\pi_{old} = \pi(\theta_{old})$
7: Obtain $V(s_t)$ from the critic network Î¼$_{old}$ with s_t as input
8: Execute action a_t, observe reward r_t, and next state s_{t+1}
9: Collect trajectories $D_{old} = \{\tau_t\}, \tau_t = (\varphi_t, a_t, r_t, V(s_t), p(a_t))$
10: **if** $|D_{old}| = batchsize$ **do**
11: **for** epoch = 1: RT **do** (RT is the repeat times)
12: Compute advantage estimates $\widehat{A}_t$ by GAE
13: **for** each mini-batch **do**
14: Compute rewards-to-go $\widehat{R}_t$ and the current value function $V_{\text{Î¼}_{old}}$
15: Update the policy by maximizing the PPO-Clip objective:

$$\theta_{new} = \underset{\theta}{argmax} \frac{1}{|D_{old}|T} \sum_{\tau\in D_{old}} \sum_{t=0}^{T} \left[min\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} * A^{\pi_{\theta_{old}}}(s_t, a_t), clip\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)}, 1-\epsilon, 1+\epsilon \right) * A^{\pi_{\theta_{old}}}(s, a) \right) \right]$$

via stochastic gradient ascent algorithm with Adam (T is the end of sampling trajectory)
16: Fit value function by regression on mean-squared error:

$$\text{Î¼}_{new} = \underset{\varphi}{argmin} \frac{1}{|D_{old}|T} * \sum_{\tau\in D_{old}} \sum_{t=0}^{T} (V_{\text{Î¼}_{old}}(s_t) - \widehat{R}_t)^2$$

via stochastic gradient descent algorithm with Adam
17: **end for**

6. Numerical experiments

In this section, the experimental parameter settings of the training and testing process are displayed first. Then, the training process of PPO, TRPO, DlDQN, DDQN, and DQN is detailedly explained. Additionally, to credibly verify the generalization and validity of DRLs-based scheduling agents under various production configurations of the DDJSPT, numerical comparison experiments are comprehensively implemented. Finally, the effectiveness of the proposed states, actions, and reward function is validated through comparison experiments.

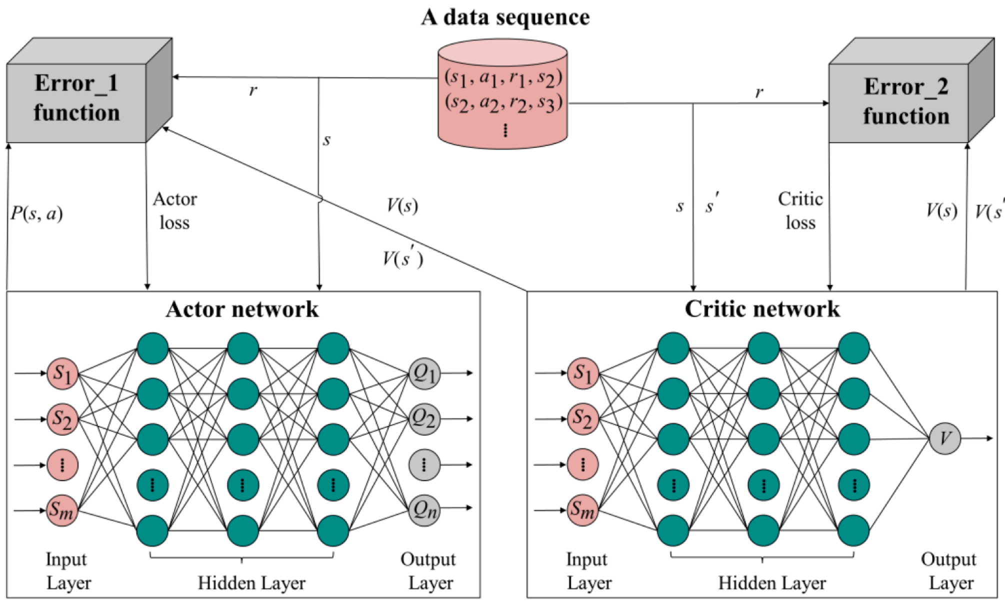

Fig. 4. The structure of PPO.

6.1. Parameter settings

Given that the DDJSPT with random job arrivals has not been investigated, there is no benchmark available in the current literature. A set of instances utilized for training and testing is randomly generated to enhance robustness and generalization. 10 % of the number of new jobs are assumed to be initial jobs existing in the distributed job shopfloor at the very beginning. Those new jobs arrive following the Poisson distribution, which means that the interval time between two successive new jobs obeys an exponential distribution. To facilitate parameter settings, UI is employed to represent a uniform distribution and *round* denotes its literal meaning. The parameter settings for generating production configurations are declared in Table 2.

As Table 2 describes, the number of operations and their processing time for all jobs are produced within specific ranges at random. To testify the generalization of DRLs under various shop configurations, the number f of factories, the number m_q of machines, the number n_{new} of newly added jobs, the due date tightness *DDT*, and the parameter Î»$_{job}$ of exponential distribution are regarded as variables to construct various production configurations. Besides, the equation for calculating the due date DD_i of J_i can be inferred below.

$$DD_i = AT_i + \left(\sum_{j=1}^{n_i} \overline{PT}_{i,j}\right) * DDT \tag{51}$$

Table 2
Parameter settings of production configurations.

Parameter	Value
Number of factories (*f*)	[2, 3, 4]
Number of machines for each factory (m_q)	[5, 10, 15]
Number of newly added jobs (n_{new})	[50, 150, 250]
Number of initial jobs at the beginning	*round*(10 % $*$ n_{new})
Number of operations per job (n_i)	UI[1, M^q]
Processing time of operation $O_{i,j}$ on M_k^q ($PT_{i,j,q,k}$)	UI[1, 50]
Due date tightness (*DDT*)	[0.5, 1.0, 1.5]
Average of exponential distribution between two successive new job arrivals (Î»$_{job}$)	[25, 50, 100]
Time of jobs transferred in the same factory (*TM*)	5
Time of jobs transferred to another factory (*TF*)	10

6.2. Training process of DRLs

The five DRLs are coded and run in Python 3.9 and Pytorch 2.0.1 The training and test experiments are conducted on a PC with Intel(R) Xeon (R) Gold 6242R CPU @ 3.10 GHz, 128 GB RAM, and Windows 10 64-bit operating system. The parameter settings for training PPO, TRPO, DlDQN, DDQN, and DQN are listed in Table 3, Table 4, and Table 5, respectively. To better demonstrate the training details, five production configuration variables encompassing f, m_q, n_{new}, *DDT* and Î»$_{job}$, are set as 3, 10, 150, 1, and 50.

During the training process, a new instance is randomly produced under the five given configuration parameters at the beginning of each episode. The scheduling agent will store the cumulative reward and mean tardiness when each training episode ends. As explicitly depicted in Fig. 5 and Fig. 6, the moving average of the initial convergence curves of the five DRLs is drawn in different colors respectively.

Fig. 5 reveals that the cumulative reward rises with the increasing training episodes and then gets into a stable status, which means the policy network has acquired the policy of maximizing the cumulative reward by training the scheduling agents. Meanwhile, it is illustrated by Fig. 6 that the mean tardiness declines as the number of training episodes increases and then stabilizes at a specific range, indicating that the knack for efficiently manipulating the most suitable dispatching rules under various situations has been learned by the DRLs.

6.3. Comparison experiments

6.3.1. Comparisons between DRLs

To find appropriate DRLs for working out the proposed DDJSPT, PPO, TRPO, DlDQN, DDQN, and DQN are utilized and comprehensively

Table 3
Parameter settings for training PPO.

Parameter	Value
Number of training epochs (EP)	2000
GAE parameter	0.98
Maximum KL divergence constraint	5e-4
Discount factor (γ)	0.9
Learning rate (ξ)	1e-3
Step size for updating	0.5
Optimizer	Adam

Table 4
Parameter settings for training TRPO.

Parameter	Value
Number of training epochs (EP)	2000
GAE parameter	0.98
Maximum KL divergence constraint	5e-4
Discount factor (γ)	0.9
Learning rate (ξ)	1e-3
Step size for updating	0.5
Optimizer	Adam

Table 5
Parameter settings for training DlDQN, DDQN, and DQN.

Parameter	Value
Number of training epochs (EP)	2000
Replay memory size (*N*)	1,000,000
Batch size	32
Discount factor (γ)	0.9
Learning rate (ξ)	1e-3
Greedy parameter (ε)	1e-2
Soft target update parameter (τ)	5e-3
Optimizer	Adam

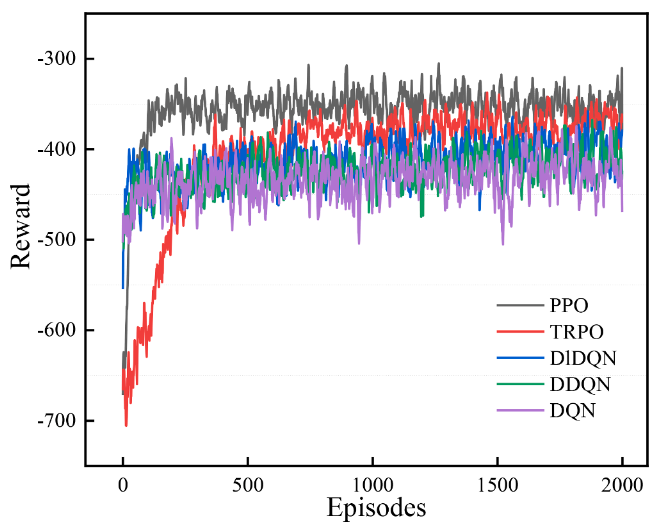

Fig. 5. Reward of five DRLs at each episode.

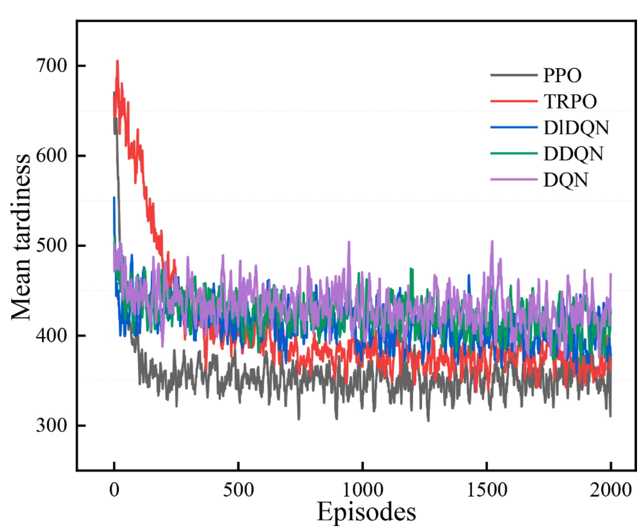

Fig. 6. Mean tardiness of five DRLs at each episode.

compared with each other. 243 classes of production configurations with five different parameter settings namely f, m_q, n_{new}, *DDT* and Î»$_{job}$ are created for comparing the validity and generalization of the five DRLs according to Table 2. Under each production configuration, 20 instances generated randomly are employed to evaluate the mean tardiness of each DRL. Therefore, a total of 4860 instances are formed for comparative experiments. In Appendix A, Tables 6-8 list the mean values and standard deviations of mean tardiness obtained by five DRLs with the best result highlighted in bold. Fig. 7 depicts the win rate of five DRLs when compared with each other. Fig. 8 displays the win rate of three value-based DRLs when compared with each other. Here, the win rate is defined as the number of shop configurations where the method acquires the best performance divided by 243.

The results in Tables 6-8 suggest that the parameter settings of scheduling configurations would affect the performance of the five DRLs. As expected, mean tardiness declines with more factories, a smaller number of machines in each factory, a smaller number of new arriving jobs, a lower frequency of new job arrivals, and looser due dates.

From the results recorded in Tables 6-8 and Fig. 7, it can be discovered that PPO attains the best result under 76.1 % configurations and gets the highest win rate when compared with TRPO, DlDQN, DDQN, and DQN. It indicates that PPO has learned the optimal policy of effectively differentiating various production states and matching the states with appropriate composite rules at each scheduling decision point. Meanwhile, compared with TRPO, PPO would be a better and more effective choice when applying policy-based DRLs to coping with the DDJSPT.

Additionally, for valued-based DRLs, the better performance of DlDQN than that of DDQN and DQN under 77.8 % production configurations is demonstrated by Fig. 8. This result affirms DlDQN as the priority selection when adopting value-based DRLs to sort out the DDJSPT.

6.3.2. Comparisons between DRLs and composite rules

To verify the superiority of DRLs, the performance of DRLs is compared with each composite rule. Based on the results above, PPO obtains the highest win rate when compared with TRPO, and DlDQN attains the highest win rate of the contrast experiments with the other two value-based DRLs namely DDQN and DQN. Here, they are treated as representatives to implement the comparison with composite rules. All instances utilized for comparison are the same instances used in the last section. Tables 9-11 display the mean values and standard deviations of mean tardiness acquired by eleven composite rules where the abbreviation C1 stands for composite rule 1 and it is the same for other

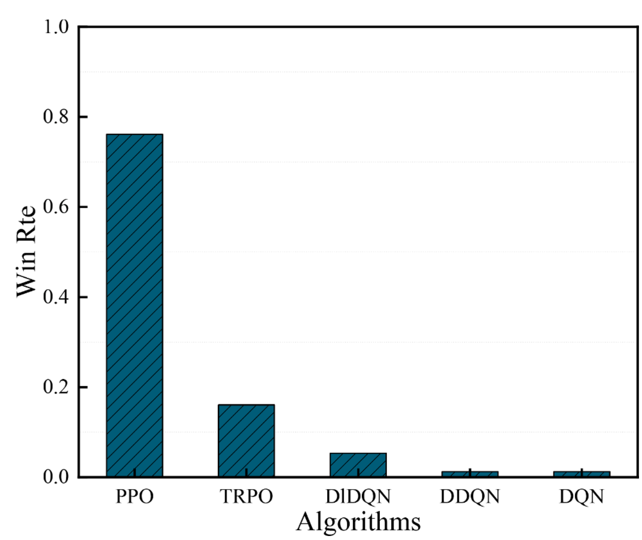

Fig. 7. Win rate of five DRLs when compared with each other.

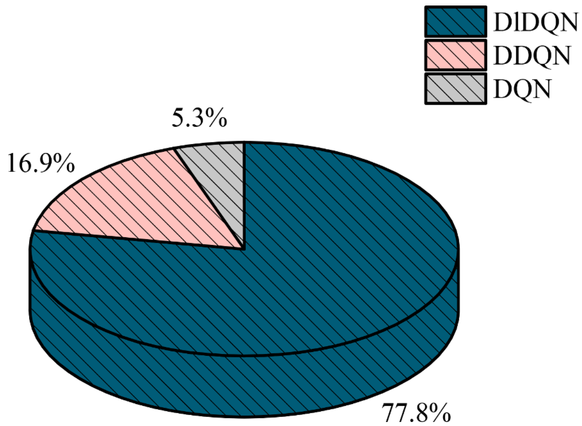

Fig. 8. Win rate of three value-based DRLs when compared with each other.

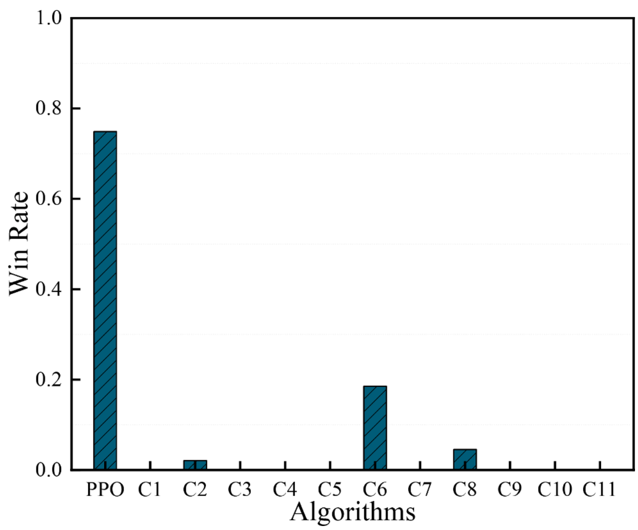

Fig. 9. Win rate of PPO and each composite rule when compared with each other.

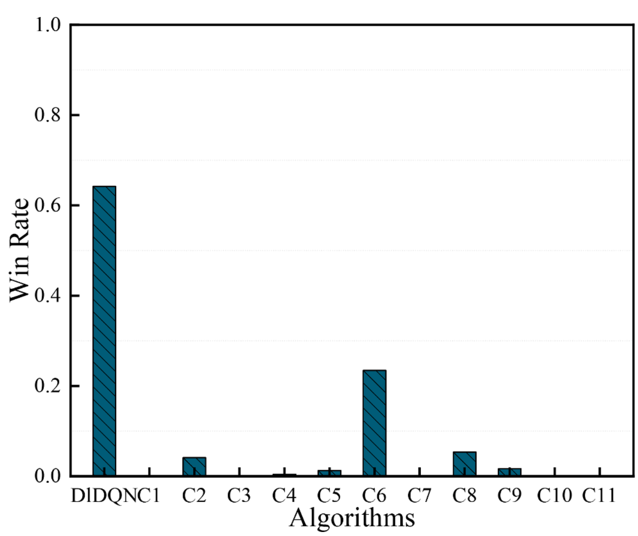

Fig. 10. Win rate of DlDQN and each composite rule when compared with each other.

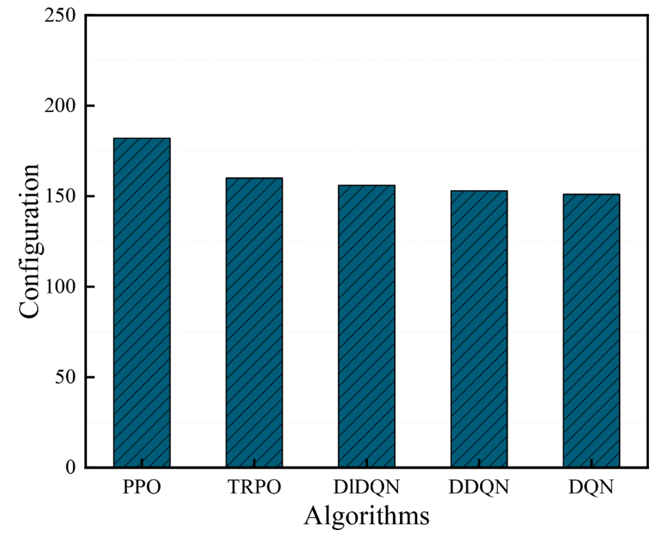

Fig. 11. Number of configurations where each DRL wins compared with all composite rules.

composite rules. The win rate of PPO and each composite rule when compared with each other is given in Fig. 9. The win rate of DlDQN and each composite rule when compared with each other is recorded in Fig. 10. Fig. 11 records the number of configurations where each DRL wins compared with all composite rules.

Tables 9-11 manifest that the performance of composite rules can also be affected by parameter settings of production configurations which is similar to that of DRLs. A phenomenon within expectation has arisen where fewer factories, a larger number of machines in each factory, a higher number of new arriving jobs, a higher frequency of new job arrivals, and tighter due dates would result in the increase of mean tardiness.

Grounded in Fig. 9 and Fig. 10, it can be credibly concluded that the eleven composite rules are hard to outperform PPO and DlDQN under 74.9 % and 64.2 % production configurations, respectively. The results confirm the correctness of applying PPO and DlDQN for DDJSPT. Additionally, Fig. 11 indicates that the five DRL-based scheduling agents can manipulate an appropriate composite rule at each scheduling decision point and outperform all composite rules under at least 151 production configurations. These results enhance the fact that there is no single composite rule being able to achieve the best performance in most production configurations, which has proved the superiority of DRLs in analyzing the production states and making the most suitable decision at each scheduling decision point of the DDJSPT.

6.3.3. Comparisons between DRLs and classic PDRs

For further testifying the advantage of DRLs, comparison experiments between the DRLs and 6 classic PDRs are developed and conducted on the base of 4860 instances used before. The details of those PDRs are introduced as follows.

(1) First in first out (FIFO): select the job with the earliest arrival time, AT_i.
(2) Earliest due date (EDD): choose the job with the earliest due date, DD_i.
(3) Shortest remaining processing time (SRT): select the job with the shortest remaining processing time, $\min_{J_i} \sum_{j=CO_i(t)+1}^{ni} \frac{\sum_{q=1}^{f}\sum_{k=1}^{mq} PT_{i,j,q,k}}{f}$.
(4) Most remaining processing time (MRT): choose the job with the most remaining processing time, $\max_{J_i} \sum_{j=CO_i(t)+1}^{ni} \frac{\sum_{q=1}^{f}\sum_{k=1}^{mq} PT_{i,j,q,k}}{f}$.

(5) Shortest processing time (SPT): select the job with the shortest average processing time of its next operation $O_{i,CO_i(t)+1}$, $\min\limits_{J_i}\frac{\sum_{q=1}^{f}\sum_{k=1}^{m_q}PT_{i,CO_i(t)+1,q,k}}{f}$.

(6) Longest processing time (LPT): choose the job with the longest average processing time of its next operation $O_{i,CO_i(t)+1}$, $\max\limits_{J_i}\frac{\sum_{q=1}^{f}\sum_{k=1}^{m_q}PT_{i,CO_i(t)+1,q,k}}{f}$.

Given that the aforementioned classic PDRs do not take charge of assigning the prioritized job to a suitable factory and are unable to address the two sub-problems of DDJSPT simultaneously. Hence, for a fairer and more accurate comparison, the two assigning rules (ARs) utilized in the actions of DRLs are incorporated with each PDR to form new PDRs for realizing the job selection and the assignment of the selected job to an appropriate factory. Here, the distribution of a selected job to the factory with the minimum total time of transferring and processing and to the factory with the earliest available time is defined as AR_1 and AR_2, respectively. Combining the 6 classic PDRs and the two ARs, total 12 new PDRs are generated and tested on the same 4860 instances formed under 243 production configurations.

The mean values and standard deviations of mean tardiness attained by twelve new PDRs are listed in Tables 12-14 where P1 − P12 represent AR_1 + FIFO, AR_1 + EDD, AR_1 + SRT, AR_1 + MRT, AR_1 + SPT, AR_1 + LPT, AR_2 + FIFO, AR_2 + EDD, AR_2 + SRT, AR_2 + MRT, AR_2 + SPT, AR_2 + LPT, respectively. Fig. 12 exhibits the win rate of PPO and each new PDR when compared with each other. Fig. 13 depicts the win rate of DlDQN and each new PDR when compared with each other. Fig. 14 records the number of configurations where each DRL wins compared with all new PDRs. Fig. 15 describes the win rate of all composite rules and all new PDRs.

Based on the comparison results of Tables 6-8, Tables 12-14, Fig. 12, Fig. 13, and Fig. 14, it can be observed that all new PDRs are outperformed by PPO and DlDQN under 95.1 % and 92.2 % configurations, respectively. Although DQN has the worst win rate compared with the other four DRLs, it also could outperform all new PDRs under 210 configurations. Therefore, it can be inferred that without the addition of AR_1 and AR_2, the performance of these classic PDRs will be even worse owing to the lack of the function to assign the selected job to an appropriate factory. Compared with PDRs, this result would be a strong

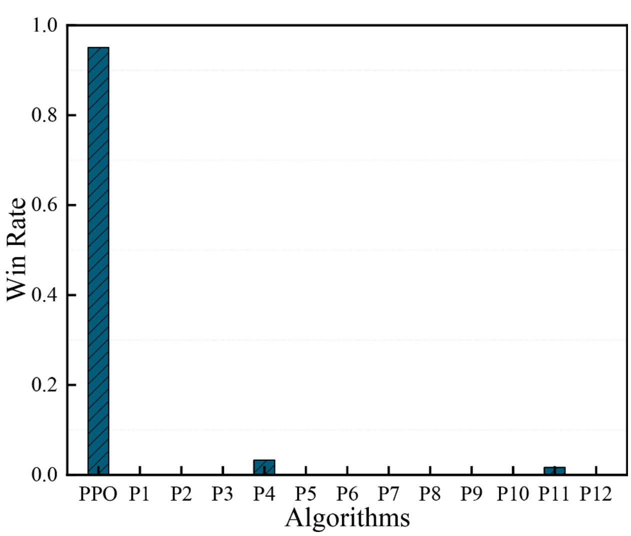

Fig. 12. Win rate of PPO and each new PDR when compared with each other.

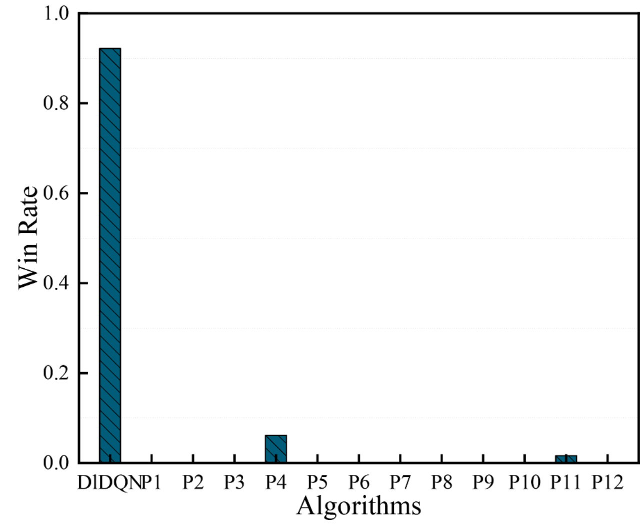

Fig. 13. Win rate of DlDQN and each new PDR when compared with each other.

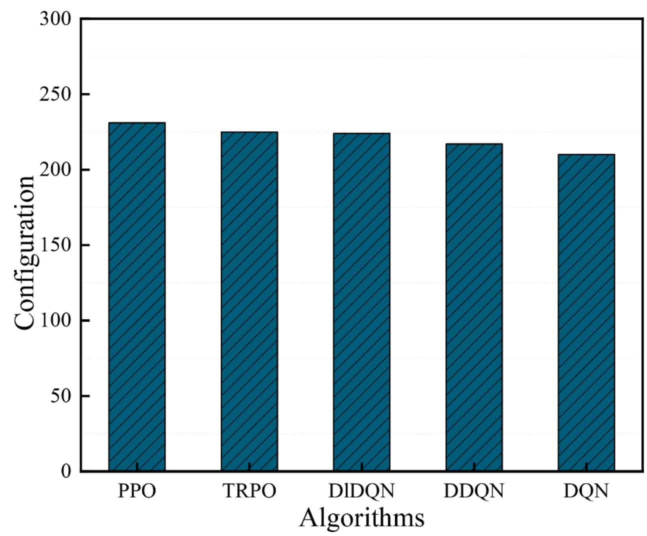

Fig. 14. The number of configurations where each DRL wins compared with all new PDRs.

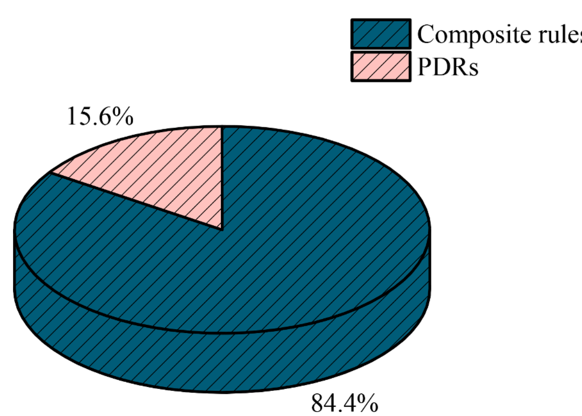

Fig. 15. Win rate of all composite rules and all new PDRs.

demonstration of the effectiveness and generalization of DRLs in figuring out the DDJSPT. Moreover, Fig. 15 illustrates that all composite rules outperform all new PDRs under 84.4 % configurations. It powerfully admits the effectiveness of these composite rules and emphasizes the great significance of designing reasonable and problem-oriented dispatching rules.

6.3.4. Comparisons between DRLs and metaheuristics

To further validate the superiority of our DRL-based methods, comparative experiments have been conducted between them and two metaheuristics including the IGA (Improved Genetic Algorithm) (Ali, Telmoudi, & Gattoufi, 2020) and PSO (Particle Swarm Optimization) (Wang et al., 2019). All instances utilized for comparison are the same 4860 instances used before. The mean tardiness and computation time are employed as metrics to evaluate the solution performance and time complexity. There is a lack of metaheuristics especially for dynamic DJSPs, while the IGA and PSO are developed to sort out the dynamic JSP considering new job arrivals, which is similar to the dynamic DJSPs. Thus, it is reasonable to modify the IGA and PSO for dealing with the DDJSPT. Table 15 is the mean values and standard deviations of mean tardiness attained by the IGA and PSO. Tables 16-18 records the average computation time obtained by the DRLs, IGA, and PSO. Fig. 16 depicts the win rate of the DRLs compared with the IGA in mean tardiness. The win rate of the DRLs compared with the PSO in mean tardiness is shown in Fig. 17.

Fig. 16 and Fig. 17 suggest that the mean tardiness of the five DRLs is smaller than that of IGA and PSO under at least 84.0 % and 93.8 % production configurations respectively, which could strongly confirm the effectiveness and generalization of our DRL-based methods when compared to these two metaheuristics. The good performance of the DRLs can be attributed to the problem-specific design of the overall state features, effective actions, and the provable reward function, as well as the generalizability of the neural network. In this case, the DRLs can dynamically select the best composite rule from the action space at the scheduling decision point, and gradually achieve the optimization goal.

As shown in Tables 16-18, under 100 % production configurations, the computation time of the DRLs outperforms that of the IGA and PSO, and the average computation time of DRLs is only 1.1 ‰ and 2.3 ‰ average computation time of the IGA and PSO respectively, which is almost negligible when compared with the IGA and PSO. At each scheduling decision point, the DRLs require only the environmental state features to be fed for decision-making and would be suitable choices for real-time scheduling in smart manufacturing. Although each DRL takes about 4 h to train its policy in a production configuration, the

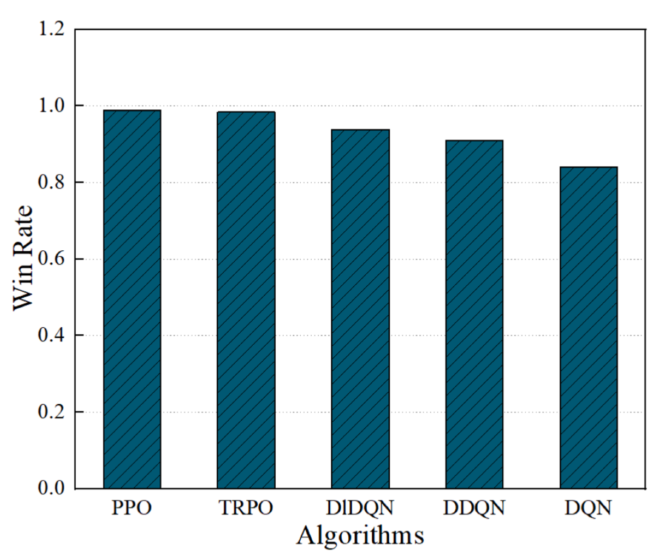

Fig. 16. Win rate of the DRLs compared with the IGA.

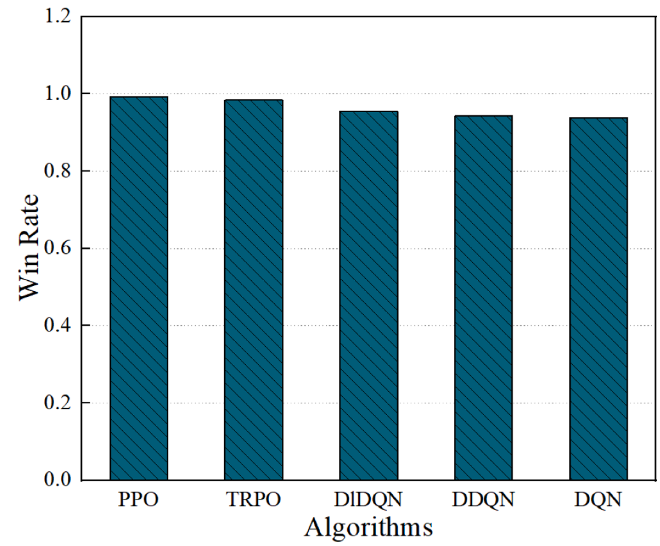

Fig. 17. Win rate of the DRLs compared with the PSO.

training can be done offline or on other computers. However, it is difficult for the IGA and PSO to reduce the computational time by pre-training. The above results undoubtedly confirm the fact that the DRLs outperform the metaheuristics in terms of responsiveness, effectiveness, and generalizability.

6.4. Validation of the proposed states, actions, and reward function

To further verify the effectiveness of our designed states, actions, and reward function, we analyze the effect of different states, actions, and reward functions on the training convergence of DlDQN and PPO regarded as representatives. We define DlDQN_ours and PPO_ours as the algorithms containing states, actions, and the reward function designed by us. As for the comparison algorithms, the DlDQN_wang and PPO_wang are the algorithms with the states designed by Wang et al., (2022), while the actions and reward function are kept the same as our algorithms. The DlDQN_chang and PPO_chang stand for the algorithms with actions designed by Chang et al., (2022), while the states and reward function are consistent with our algorithms. DlDQN_luo and PPO_luo are considered as algorithms with the reward function designed by Luo (2020), while states and actions are the same with our algorithm. Fig. 18 shows the training convergence curves of DlDQN and PPO with different

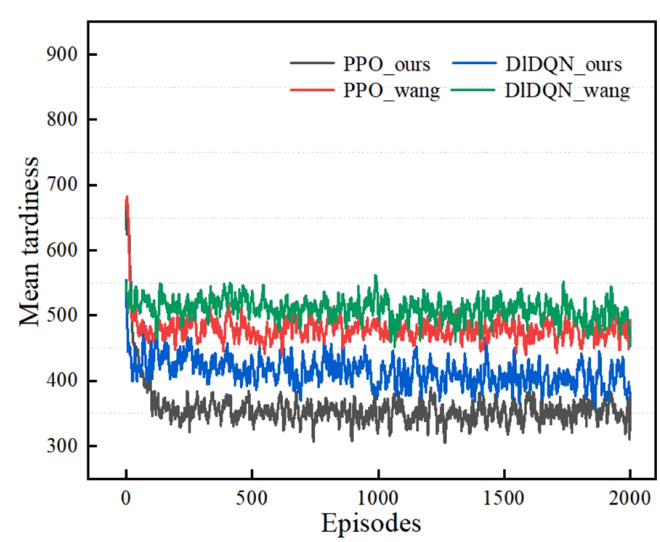

Fig. 18. Training convergence curves of DlDQN and PPO with different states.

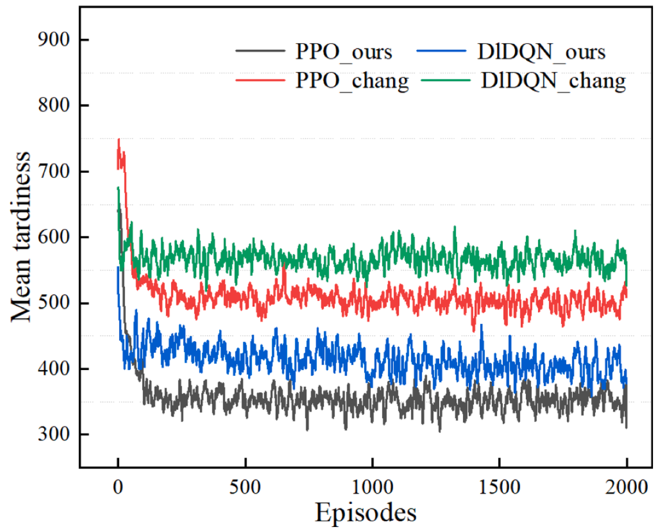

Fig. 19. Training convergence curves of DlDQN and PPO with different actions.

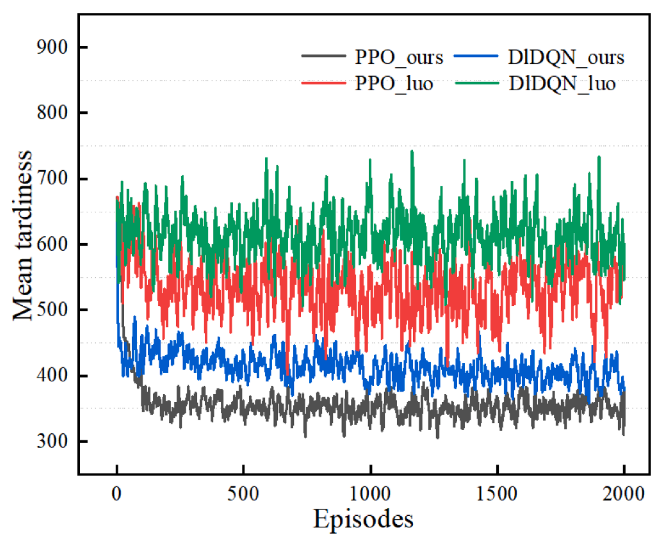

Fig. 20. Training convergence curves of DlDQN and PPO with different reward functions.

states, Fig. 19 depicts the training convergence curves of DlDQN and PPO with different actions, and Fig. 20 illustrates the training convergence curves of DlDQN and PPO with different reward functions.

Fig. 18 shows that our states outperform that of Wang's. Compared with their states, our states add the description of factory-level states of the DDJSPT, and can more fully reflect the current state of the production environment. It would expand the state space suitably and enhance the ability of the scheduling agent to differentiate between similar states, which facilitates the agent to learn better mapping relationship of state-action named as the optimal scheduling policy and take the most effective action under certain states. Therefore, it is necessary to extract overall production states for improving the effectiveness of the DRL-based methods.

Furthermore, based on the training curves of Fig. 19, it can be concluded that our actions are superior to those actions designed by Chang. In terms of job selection, our actions are tightly designed around the global goal of mean tardiness, while Chang puts much attention on the remaining processing time of all jobs. When it comes to machine selection, we develop the rule of selecting the machine with the shortest processing and transferring time for the selected job, which directly reduces the possibility of the mean tardiness of the job. It also increases the space of the action appropriately, which is conducive to the agent for choosing the optimal action under a specific state, and improves the effectiveness of the DRL-based methods for the DDJSPT.

Additionally, as illustrated in Fig. 20, our reward function is more effective than Luo's reward function. The reason is that the reward function we adopted can quantitatively evaluate the value of the selected action, while Luo's reward function only qualitatively analyzes whether the selected action has value based on the evaluation indicators rather than the magnitude of its value, which hinders the scheduling agent from recognizing the optimal action under certain state. Moreover, our cumulative rewards computed according to the reward function are mathematically provable to be directly equal to the negative of the scheduling goal, and theoretically and practically can direct the realization of minimizing mean tardiness.

To summarize, the states, actions, and reward function we designed have been proven to be effective, as an important part of the DRLs, the three complement each other, and one is indispensable to ultimately realize the superiority of the DRLs to solve the DDJSPT as a whole.

6.5. Discussions

From the results of the above experiments, it can be seen that our proposed DRL-based methods exhibit stronger effectiveness and generalization than PDRs, composite scheduling rules, and metaheuristics in most production configurations of the DDJSPT.

The reasons for the effectiveness of our methods are given as follows. First, the state features extracted by us can comprehensively reflect the real-time state of the production environment, and enable the scheduling agent to distinguish between similar states and select the best action under a particular state, which is conducive to the realization of the global goal; second, based on the characteristics of the DDJSPT, the actions are proposed to specifically serve the objective of minimizing the mean tardiness. Each action contains both the selection of a specific job and the assignment of the selected job to a suitable factory, and they are designed to directly or indirectly optimize the target, which facilitates the scheduling agent to make decisions in favor of the optimization objective; third, the quantitative and provable design of the reward function can effectively guide the scheduling agent to obtain the maximum cumulative rewards and minimize mean tardiness; fourth, the large amount of training also contributes to the improvement of the model performance.

The generalizability of our method is due to the reasons below. First, the normalization of the state features can weaken the impact of differences between various instances on the performance of the DRL-based method, which enables the scheduling agent to adapt to various states of different instances and make the most appropriate choices; second, the action space provides appropriately optional actions and improves the ability of the scheduling agent to adapt to different production conditions, which is beneficial for maintaining the effectiveness of our methods under various states; third, the neural network in the DRL-based method is capable of storing the complex mapping relationship of optimal state-action and guides the choice of the scheduling agent, which enhances the generalizability of our methods.

7. Conclusion

In this research, a DRL-based scheduling method is developed to sort out the distributed job shop with transfers considering random job arrivals (DDJSPT), of which the target is to minimize the mean tardiness of all jobs. In the proposed model, ten state features covering four aspects of factories, machines, jobs, and operations, eleven composite rules employed as actions of DRLs, and a reward function serving the target are elaborately designed and defined given the unique characteristics of DDJSPT. Five DRLs containing PPO, TRPO, DlDQN, DDQN, and DQN are trained for the optimal policy to select a prioritized unfinished job and allot it to a suitable factory at each scheduling decision point. A large number of comparison experiments between DRLs and other algorithms are conducted under 243 production configurations. Based on the results of numerical experiments, summaries can be drawn below.

(1) Mean tardiness would decrease with more factories, a smaller number of machines in each factory, a smaller number of new arriving jobs, a lower frequency of new job arrivals, and looser due dates.
(2) Policy-based PPO significantly surpasses the other four DRLs namely TRPO, DlDQN, DDQN, and DQN under 76.1 % production configurations, which means that PPO would be the better selection for the DDJSPT. Besides, for value-based DRLs, DlDQN performs relatively well in 77.8 % of production configurations of the DDJSPT and would be a better choice when compared with DDQN and DQN.
(3) PPO and DlDQN are superior to all composite rules under 74.9 % and 64.2 % production configurations, respectively. The five DRL-based scheduling agents outperform all composite rules under at least 151 production configurations. This result demonstrates the validity and generalization of DRLs for tackling the proposed DDJSPT and confirms the fact that single composite rules will hardly get a high win rate when participating in comparison with DRLs.
(4) PPO and DlDQN perform better than all new PDRs under 95.1 % and 92.2 % configurations, respectively. The five DRL-based scheduling agents can outperform all new PDRs under at least 210 configurations. This result would be a strong demonstration of the effectiveness and generalization of DRLs compared with PDRs for addressing the DDJSPT. Additionally, the eleven self-designed composite rules as a whole outperform the whole twelve new PDRs under 84.4 % production configurations, which confirms the importance of designing problem-oriented dispatching rules when figuring out scheduling problems.
(5) The five DRL-based scheduling agents get smaller mean tardiness than IGA and PSO do under at least 84.0 % and 93.8 % of production configurations, respectively. Under 100 % production configurations, the average computation time of the DRL-based method is only 1.1 ‰ and 2.3 ‰ of the computation time of IGA and PSO, respectively. Besides, the computation time of DRL-based methods can be reduced by pre-training while IGA and PSO cannot. These results fully prove the superiority of the DRL-based methods for the DDJSPT.
(6) Overall features reflecting the state of the dynamic production environment, goal-oriented action design, the provable and effective reward function, and the application of neural networks together contribute to the effectiveness and generalization of DRL-based methods in solving the DDJSPT.

In the future, more research will be done.

(1) More realistic features of the shop floor, such as limited buffers, and setup time are worthy of investigation. Besides, other objectives like material consumption, makespan, production costs, machine utilization rate, and energy consumption will be considered.
(2) Other uncertainties encompassing material shortages, machine breakdowns, machine tool replacement, job cancellation, job operation modification, and stochastic processing time should be fully studied.
(3) Recently, genetic programming (GP) has been widely utilized to dig for new rules and can improve the performance of classic dispatching rules. It can be inferred that DRL-based algorithms combined with GP to generate new effective scheduling rules will be a hotspot in the field of dynamic scheduling problems.

CRediT authorship contribution statement

Yong Lei: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Software. **Qianwang Deng:** Project administration, Funding acquisition, Resources, Supervision. **Mengqi Liao:** Validation, Writing – original draft. **Shuocheng Gao:** Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data supporting the findings of this study are available upon reasonable request.

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Appendix A

Table 6
Mean values and standard deviations of mean tardiness obtained by five DRLs ($DDT = 0.5$).

f	mq	n_{new}	Î»$_{job}$	DQN	DDQN	DlDQN	TRPO	PPO
2	5	50	25	259.8/26.5	252.7/24.2	250.3/26.0	258.1/26.9	**249.3/23.9**
			50	241.0/24.4	234.6/24.6	233.9/24.7	232.6/23.2	**231.9/23.5**
			100	228.3/23.5	224.5/23.0	223.7/21.9	218.4/20.8	**198.8/21.8**
		150	25	825.6/73.4	820.6/78.2	806.0/76.1	805.4/74.5	**795.4/72.1**
			50	742.5/70.9	741.5/68.9	740.6/69.6	**731.2/64.6**	732.5/67.5
			100	673.6/64.5	665.6/63.5	661.7/62.6	651.5/59.9	**646.1/61.1**
		250	25	1389.2/71.0	1323.1/84.7	1386.8/84.5	1360.5/78.2	**1309.4/76.1**
			50	1233.8/77.4	1211.7/84.3	1279.5/75.6	1209.3/83.6	**1198.8/70.9**
			100	1177.0/78.5	1148.6/79.8	1128.8/75.1	1163.9/77.9	**1100.9/71.1**
	10	50	25	364.6/35.6	345.1/33.7	340.1/34.1	333.5/34.8	**329.4/32.4**
			50	323.9/33.5	321.1/31.8	297.0/29.4	**296.7/31.6**	305.4/31.3
			100	280.2/27.8	276.0/29.4	275.3/27.8	274.3/26.0	**264.5/26.4**

(continued on next page)

Table 6 (*continued*)

f	mq	n_{new}	Î»$_{job}$	DQN	DDQN	DlDQN	TRPO	PPO
		150	25	926.7/81.4	922.9/80.5	920.0/74.0	**905.8/75.2**	909.5/76.1
			50	883.7/77.0	868.5/73.7	859.9/72.3	862.4/79.4	**852.5/78.2**
			100	848.9/73.0	839.0/76.5	827.1/73.5	813.7/70.2	**799.3/75.3**
		250	25	1419.7/79.8	1455.7/86.7	1446.2/75.9	1439.7/84.4	**1404.5/74.9**
			50	1312.1/85.2	1305.6/86.0	1331.0/78.0	1316.7/83.1	**1296.7/78.6**
			100	1271.6/81.0	1248.5/79.0	1218.6/82.0	1215.5/72.4	**1209.8/78.3**
	15	50	25	474.5/50.7	485.4/49.8	473.6/46.0	467.3/47.1	**452.3/44.3**
			50	418.5/43.3	413.0/42.8	**402.9/41.2**	405.4/42.7	415.4/40.1
			100	362.0/37.6	348.5/35.1	343.4/34.7	339.0/34.8	**327.6/33.8**
		150	25	985.8/86.0	986.9/84.3	976.7/76.3	**960.4/81.9**	961.9/77.8
			50	931.4/71.1	924.3/78.9	926.9/79.1	919.8/71.8	**902.7/72.1**
			100	883.2/81.5	877.3/79.6	860.6/75.7	855.0/75.7	**844.1/73.9**
		250	25	1536.3/83.4	1549.4/88.4	1531.6/80.6	1527.0/86.8	**1507.7/80.3**
			50	1507.7/88.0	1498.2/77.8	1509.4/74.2	1484.9/88.2	**1463.1/79.3**
			100	1461.7/81.1	1442.0/76.1	1444.2/81.9	1417.2/77.5	**1403.2/83.1**
3	5	50	25	148.9/14.0	129.2/14.0	126.9/12.8	119.9/13.7	**113.4/11.2**
			50	113.9/12.9	110.2/10.2	115.0/11.4	**106.6/10.5**	108.0/11.8
			100	99.8/11.0	92.8/11.2	85.5/10.0	88.1/10.1	**81.3/9.2**
		150	25	441.7/42.6	427.6/41.6	422.5/40.1	416.7/41.6	**404.1/41.6**
			50	382.4/39.0	368.9/37.5	361.6/35.5	359.8/35.4	**346.0/35.9**
			100	339.3/35.2	319.4/30.0	317.1/31.7	310.8/31.0	**294.3/28.9**
		250	25	640.8/61.5	631.0/59.0	625.1/56.1	627.6/58.0	**623.8/54.9**
			50	588.1/57.4	579.5/54.7	568.9/53.8	565.1/55.6	**550.4/55.3**
			100	543.4/53.1	538.6/47.9	536.0/50.2	527.2/49.9	**508.7/46.7**
	10	50	25	229.9/24.4	207.4/19.1	213.3/22.4	199.9/20.7	**183.0/17.5**
			50	174.6/17.8	169.1/17.5	159.3/14.8	152.9/16.7	**141.0/15.6**
			100	130.0/14.2	131.7/12.7	133.5/14.4	129.0/13.2	**124.1/12.2**
		150	25	542.8/54.8	538.7/49.1	525.0/53.5	518.0/48.9	**509.8/46.5**
			50	484.1/49.5	476.5/45.4	478.1/49.3	**468.2/46.2**	470.0/46.5
			100	438.9/42.2	433.6/44.9	421.2/42.7	418.0/42.3	**401.4/40.4**
		250	25	925.2/76.1	929.3/82.7	919.6/77.6	**911.3/74.3**	914.0/79.4
			50	857.0/79.9	847.1/76.0	841.3/82.9	835.2/73.6	**832.8/75.4**
			100	805.7/74.6	793.2/74.7	781.6/75.0	779.3/68.8	**769.4/69.2**
	15	50	25	254.4/27.5	264.8/25.2	**249.5/23.4**	253.4/25.5	255.4/25.6
			50	233.7/24.6	228.1/20.1	224.7/23.3	221.4/23.5	**199.6/21.4**
			100	172.5/19.8	180.7/17.8	173.9/18.4	166.1/15.1	**152.0/15.3**
		150	25	630.7/62.3	619.9/58.1	625.4/59.1	**606.6/54.3**	613.0/59.0
			50	604.1/58.7	594.4/53.4	581.7/52.5	580.2/54.9	**575.0/55.3**
			100	569.2/53.3	558.6/48.8	547.8/51.7	542.8/47.8	**537.2/49.9**
		250	25	984.5/81.4	961.0/76.9	967.6/79.5	953.9/77.7	**945.7/78.3**
			50	938.8/80.5	925.7/74.8	901.4/77.5	908.3/76.7	**892.3/74.8**
			100	881.7/75.4	879.7/71.8	863.4/73.1	860.8/79.9	**853.2/71.9**
4	5	50	25	85.1/11.2	84.1/10.4	**75.7/11.0**	78.0/9.8	76.8/8.1
			50	74.5/12.3	68.6/9.6	67.6/11.5	**65.2/10.6**	66.7/9.8
			100	54.5/10.2	55.9/9.3	49.3/9.5	**46.5/9.7**	47.7/8.5
		150	25	226.1/23.9	213.6/22.4	211.8/21.4	207.7/21.1	**200.3/20.2**
			50	198.1/19.6	192.4/20.8	189.2/18.7	**186.1/17.4**	187.1/18.4
			100	176.0/18.3	168.5/17.6	165.8/17.2	162.5/16.0	**154.3/15.7**
		250	25	457.0/46.2	450.7/45.3	448.7/43.8	449.3/44.5	**431.4/43.4**
			50	389.8/38.9	384.0/39.5	386.8/37.9	**380.1/39.8**	387.4/38.1
			100	343.1/35.9	330.8/33.6	328.7/34.5	327.2/33.1	**319.4/32.5**
	10	50	25	131.8/15.0	112.9/12.3	117.9/11.9	109.1/10.5	**108.3/11.3**
			50	108.4/10.4	104.1/12.3	90.6/10.2	91.7/10.0	**86.5/9.4**
			100	82.4/12.6	75.1/11.8	70.6/9.7	69.2/10.4	**66.3/9.7**
		150	25	356.3/36.9	341.3/34.1	324.0/31.6	321.4/33.6	**301.1/30.9**
			50	293.0/30.1	285.2/29.7	279.5/27.9	**278.9/28.2**	285.1/27.9
			100	250.4/25.4	243.5/25.4	241.3/24.4	232.2/24.3	**229.0/23.5**
		250	25	619.8/59.5	599.2/58.5	587.0/57.5	**585.5/56.7**	591.7/53.6
			50	560.5/53.4	550.0/52.0	540.2/49.6	541.5/50.7	**533.0/48.1**
			100	505.7/49.1	495.8/48.1	488.9/46.6	481.2/47.2	**478.2/45.0**
	15	50	25	180.8/19.2	174.9/16.4	171.4/18.7	**165.9/17.3**	167.7/15.4
			50	154.3/16.5	144.4/13.7	133.4/14.1	129.6/13.9	**126.8/12.4**
			100	102.3/11.7	95.2/11.7	100.4/11.9	93.5/11.4	**86.8/9.5**
		150	25	475.3/47.3	470.6/44.6	468.0/49.8	**460.7/45.9**	463.9/44.1
			50	437.0/44.9	427.8/39.9	425.9/42.9	421.6/43.7	**406.9/39.2**
			100	381.8/39.0	377.1/37.0	375.1/38.4	365.8/37.5	**362.0/35.9**
		250	25	755.5/69.0	726.3/68.0	735.7/67.1	721.8/65.6	**707.8/64.5**
			50	691.4/67.2	679.1/63.5	659.7/64.4	653.9/65.3	**646.2/63.4**
			100	634.9/57.6	635.7/54.4	618.0/54.7	**617.7/58.6**	628.6/53.5

Table 7
Mean values and standard deviations of mean tardiness obtained by five DRLs ($DDT = 1.0$).

f	mq	n_{new}	Î»$_{job}$	DQN	DDQN	DlDQN	TRPO	PPO
2	5	50	25	225.9/23.4	226.7/23.8	224.9/23.4	227.5/22.1	**213.4/21.0**
			50	210.0/21.9	204.8/21.0	201.2/19.8	198.0/21.9	**190.1/20.0**
			100	175.7/19.7	170.9/17.1	169.7/16.3	**164.1/17.9**	167.9/16.6
		150	25	766.0/70.7	757.9/68.1	741.5/64.4	739.1/67.5	**735.8/65.2**
			50	681.9/64.9	676.6/66.4	675.3/61.5	664.6/63.7	**662.2/65.8**
			100	645.6/62.1	631.6/59.4	621.1/60.3	624.3/58.0	**615.0/57.7**
		250	25	1315.4/84.6	1282.8/75.5	1268.0/78.5	1249.7/79.2	**1216.3/80.1**
			50	1170.7/76.3	1130.4/73.9	1194.3/81.7	1091.7/77.9	**1077.1/75.9**
			100	1019.3/79.1	1006.1/80.4	1055.2/78.2	1003.5/73.9	**1000.7/79.8**
	10	50	25	283.9/27.1	288.7/27.9	285.0/28.2	278.0/29.8	**273.5/26.7**
			50	269.9/26.6	266.8/26.8	256.4/26.7	**248.8/25.4**	251.0/24.3
			100	224.1/23.6	214.1/21.4	211.9/21.0	**207.6/20.8**	219.2/21.8
		150	25	872.3/83.2	861.5/76.8	860.5/80.6	851.7/78.1	**848.8/70.8**
			50	782.8/73.3	783.4/71.6	775.5/70.7	773.2/68.4	**764.3/69.8**
			100	740.1/69.5	735.5/65.4	728.6/67.9	735.8/63.5	**723.7/64.9**
		250	25	1322.1/82.5	1360.2/76.9	1335.4/89.6	1328.1/76.1	**1298.4/81.5**
			50	1288.6/85.2	1281.6/81.7	1253.8/79.4	**1223.9/80.4**	1225.6/82.4
			100	1114.4/77.0	1159.8/72.7	1124.4/76.8	1104.4/74.2	**1097.2/78.2**
	15	50	25	363.8/37.3	360.8/37.6	358.3/36.2	355.1/35.4	**347.4/35.0**
			50	329.2/34.0	334.6/33.1	323.3/32.6	313.1/31.2	**299.8/30.2**
			100	269.7/26.5	266.4/24.6	268.1/26.7	258.3/26.1	**248.5/24.1**
		150	25	885.1/80.9	879.6/82.1	873.3/77.2	866.9/79.2	**859.6/76.5**
			50	837.9/77.7	824.2/70.9	827.0/75.1	819.5/75.8	**801.1/76.2**
			100	770.4/73.7	763.3/72.1	752.6/70.7	759.3/67.1	**746.9/69.8**
		250	25	1404.0/84.2	1418.1/87.4	1413.7/79.2	**1403.9/83.0**	1420.7/84.4
			50	1350.3/81.9	1339.4/79.2	1368.5/81.7	**1323.6/85.0**	1324.6/82.3
			100	1287.9/83.0	1290.5/84.1	1267.2/82.8	1277.2/79.8	**1247.2/77.0**
3	5	50	25	100.2/12.5	103.7/12.5	98.2/11.9	**89.6/10.5**	90.1/9.4
			50	87.1/9.9	85.1/9.5	75.2/10.1	80.3/9.4	**74.0/7.3**
			100	72.0/11.7	69.2/11.3	65.2/10.1	62.6/8.7	**59.1/9.2**
		150	25	371.8/39.4	369.6/37.7	362.5/37.8	**360.9/36.9**	363.9/35.5
			50	339.1/35.0	320.9/32.7	326.3/33.7	316.9/32.7	**297.3/28.7**
			100	283.6/27.0	272.5/27.1	269.1/26.2	262.6/26.7	**259.7/26.2**
		250	25	577.3/54.6	565.6/52.7	566.4/50.2	562.9/54.8	**554.5/51.7**
			50	533.9/52.5	519.7/48.3	516.4/52.5	512.8/49.4	**498.8/47.7**
			100	**461.8/44.2**	467.4/44.0	463.5/45.1	468.8/47.9	465.1/44.7
	10	50	25	137.6/14.9	134.9/12.4	128.3/13.9	123.9/12.2	**119.2/12.2**
			50	105.7/12.1	100.8/10.8	98.5/11.7	94.5/10.8	**93.3/9.6**
			100	77.1/11.4	76.3/10.3	71.1/8.4	70.6/9.8	**65.4/8.0**
		150	25	478.9/49.2	**456.8/45.1**	468.2/45.2	459.7/46.0	457.5/42.7
			50	435.0/42.7	422.8/40.6	413.0/39.9	387.4/38.5	**378.1/37.2**
			100	363.4/37.4	349.2/35.1	348.5/35.4	345.1/35.2	**341.4/32.5**
		250	25	844.5/77.7	837.5/72.5	827.5/74.5	819.4/79.9	**811.5/73.6**
			50	767.0/71.2	758.2/68.3	756.5/69.4	751.0/73.3	**743.7/67.5**
			100	715.0/69.3	701.4/66.9	696.4/67.5	692.1/64.4	**683.9/65.7**
	15	50	25	161.7/18.4	164.7/15.7	152.5/16.4	146.6/14.7	**141.3/15.6**
			50	123.6/14.2	108.2/10.5	114.7/12.5	113.8/11.0	**104.1/11.0**
			100	98.0/11.0	87.8/8.1	**85.0/11.0**	90.9/9.7	89.0/9.7
		150	25	526.4/53.0	514.0/46.0	512.4/51.3	496.3/47.2	**495.4/48.4**
			50	476.0/48.9	463.4/44.2	461.0/42.9	453.2/44.8	**447.3/43.1**
			100	431.5/44.0	428.1/40.6	422.3/41.1	**411.6/42.7**	417.2/40.8
		250	25	933.5/81.7	916.5/79.7	911.4/80.7	907.4/82.6	**893.5/75.0**
			50	874.2/84.0	864.8/75.6	862.5/70.9	850.7/76.8	**845.1/71.3**
			100	836.7/77.1	829.4/80.7	814.9/74.3	811.7/73.6	**805.3/73.5**
4	5	50	25	54.5/10.2	52.7/7.1	**45.3/9.9**	48.8/8.1	47.6/9.6
			50	40.4/8.9	38.8/8.2	39.5/8.0	**37.8/7.9**	39.1/8.6
			100	35.1/6.5	32.9/7.1	**30.5/6.0**	35.0/6.5	34.2/7.5
		150	25	180.3/17.4	178.7/18.2	176.9/16.6	172.2/17.1	**169.6/17.6**
			50	173.0/18.9	168.1/16.5	164.1/17.0	156.2/15.7	**149.4/13.5**
			100	138.6/15.0	134.3/12.1	125.7/11.5	120.4/13.2	**116.4/12.8**
		250	25	376.9/37.9	362.5/37.2	360.9/37.6	357.9/34.1	**343.7/33.0**
			50	330.5/34.3	**312.2/32.5**	323.7/33.5	317.7/32.2	313.0/30.1
			100	283.5/29.7	286.5/29.5	276.3/27.6	272.5/27.6	**263.9/27.8**
	10	50	25	107.5/10.8	95.8/9.3	93.3/11.3	92.2/10.5	**86.5/8.0**
			50	86.5/10.6	72.5/11.2	63.6/8.0	64.9/7.3	**62.7/8.4**
			100	61.0/9.7	52.1/7.6	55.9/8.6	51.1/7.0	**45.6/6.0**
		150	25	285.1/29.2	280.0/28.0	278.4/28.9	275.7/27.7	**265.8/26.8**
			50	231.5/24.1	229.2/22.5	230.5/24.0	224.2/23.8	**220.7/21.1**
			100	205.8/21.7	199.5/20.1	198.5/20.1	**184.7/19.8**	188.1/17.0
		250	25	541.0/53.8	531.7/51.2	535.6/46.8	534.7/51.9	**526.4/48.8**
			50	504.5/49.7	491.6/49.7	486.8/51.0	484.3/47.8	**476.5/46.0**
			100	464.2/47.5	447.3/45.8	442.3/44.2	437.5/44.6	**422.7/43.3**
	15	50	25	136.1/13.6	128.4/13.7	125.0/12.5	112.8/12.6	**106.0/10.5**
			50	96.5/12.1	89.3/11.8	**88.3/9.9**	91.7/10.2	92.2/8.0

(*continued on next page*)

Table 7 (*continued*)

			100	79.1/10.5	77.5/8.4	72.6/8.6	69.2/9.7	**59.6/7.4**
		150	25	378.9/38.5	367.6/35.0	365.1/37.2	**357.6/34.7**	359.9/34.2
			50	329.9/33.2	326.1/32.4	321.5/33.0	316.0/30.3	**306.6/31.3**
			100	288.6/27.9	274.0/28.3	270.3/27.7	269.7/25.9	**253.6/25.9**
		250	25	670.7/64.8	654.2/59.2	657.0/63.0	654.9/58.5	**648.4/59.6**
			50	635.2/58.1	624.7/57.4	617.2/55.1	616.4/59.1	**606.2/56.7**
			100	575.1/56.8	561.0/47.4	554.9/52.7	565.5/48.6	**547.4/49.3**

Table 8
Mean values and standard deviations of mean tardiness obtained by five DRLs ($DDT = 1.5$).

f	mq	n_{new}	λ_{job}	DQN	DDQN	DlDQN	TRPO	PPO
2	5	50	25	180.8/19.9	179.3/18.8	172.3/18.2	**168.9/17.1**	169.9/16.8
			50	150.0/16.1	149.9/14.4	144.3/15.5	141.4/15.3	**135.0/14.6**
			100	128.6/13.0	120.3/13.8	125.7/12.3	112.1/12.2	**110.9/12.6**
		150	25	717.7/70.7	706.6/69.6	698.6/65.5	692.3/68.8	**684.9/64.3**
			50	640.4/61.8	634.8/59.6	**633.0/58.9**	635.1/62.2	640.0/60.0
			100	584.9/57.0	576.7/54.1	566.9/55.4	565.0/53.3	**563.5/52.1**
		250	25	**1125.9/82.4**	1209.4/80.4	1194.8/77.0	1182.2/79.0	1133.1/75.8
			50	1109.8/86.7	1090.4/73.8	1055.9/80.3	1043.7/82.1	**998.5/77.0**
			100	937.6/81.1	930.3/81.8	927.2/76.1	920.4/79.9	**913.2/72.0**
	10	50	25	256.9/26.7	239.4/24.3	244.4/23.5	234.6/24.7	**229.4/21.7**
			50	224.7/23.8	211.8/20.7	209.8/21.6	**197.3/20.6**	199.4/18.2
			100	169.6/16.7	164.5/17.6	160.7/17.4	158.7/16.1	**147.6/15.0**
		150	25	829.2/79.3	819.4/74.0	812.7/72.4	805.0/76.4	**798.0/78.2**
			50	751.3/71.5	745.4/69.4	740.3/69.8	738.6/68.9	**727.8/70.5**
			100	703.0/70.1	699.0/65.5	684.4/67.4	683.8/66.0	**672.4/68.5**
		250	25	1239.7/86.2	1269.0/84.8	1254.3/77.5	**1236.3/84.2**	1240.7/79.4
			50	1187.9/81.9	1154.4/76.1	1166.2/81.8	1123.0/79.6	**1110.9/75.0**
			100	1096.1/81.2	1060.4/76.4	1001.3/79.6	997.2/75.3	**992.7/79.5**
	15	50	25	330.6/35.4	315.0/32.5	317.8/32.9	308.4/31.2	**301.0/30.5**
			50	283.7/29.6	270.4/26.4	**258.9/26.5**	266.1/27.9	263.8/24.4
			100	236.0/24.2	227.1/23.9	212.5/22.0	207.1/22.1	**198.5/20.1**
		150	25	838.7/81.6	815.1/76.3	809.4/73.0	823.1/79.2	**798.0/77.7**
			50	787.4/73.3	771.7/71.3	761.8/69.6	759.7/70.2	**750.3/68.6**
			100	731.4/69.0	720.3/70.3	710.1/67.4	705.9/64.5	**697.8/68.5**
		250	25	1370.6/86.9	**1350.9/86.6**	1372.3/74.8	1363.8/79.2	1356.3/83.6
			50	1288.2/87.1	1291.2/74.9	1294.0/75.4	1247.1/82.3	**1210.6/75.0**
			100	1189.6/84.9	1132.3/77.1	1152.4/79.7	1108.1/78.2	**1094.2/78.0**
3	5	50	25	96.5/10.1	85.1/11.0	83.3/9.8	80.8/10.4	**70.7/8.9**
			50	63.2/11.5	62.9/9.2	57.7/9.1	**54.4/8.4**	58.7/7.4
			100	54.5/9.7	53.8/7.3	52.6/9.8	50.6/8.5	**49.6/6.1**
		150	25	334.6/34.7	321.7/31.9	314.8/30.3	294.5/31.7	**293.5/28.2**
			50	282.4/30.7	275.0/27.1	266.5/27.3	263.6/27.1	**261.7/26.8**
			100	245.7/25.2	239.8/23.2	230.5/24.4	237.9/23.4	**228.3/21.9**
		250	25	522.2/53.7	502.6/49.5	516.5/47.7	515.3/52.7	**497.2/51.2**
			50	479.9/48.9	464.2/48.4	460.2/46.8	459.8/44.8	**449.8/42.3**
			100	425.8/43.8	422.9/41.7	421.4/44.7	416.5/42.2	**408.1/41.4**
	10	50	25	112.9/12.7	107.2/12.1	105.1/12.6	**101.3/10.9**	108.1/9.9
			50	80.4/10.7	81.6/8.7	83.5/8.2	79.6/9.3	**75.1/9.9**
			100	57.9/9.1	58.9/9.6	56.4/6.1	**49.4/8.2**	51.1/7.4
		150	25	366.2/38.8	353.4/34.3	352.4/35.3	349.9/36.0	**346.0/35.0**
			50	311.3/33.8	309.2/31.8	**304.1/32.5**	305.7/31.0	306.0/31.8
			100	277.5/28.4	274.1/28.2	262.5/25.4	260.4/26.9	**254.4/24.9**
		250	25	741.9/70.1	736.9/68.7	729.5/69.3	716.0/66.3	**701.0/64.9**
			50	674.0/58.6	660.6/57.2	657.8/59.7	653.5/62.1	**649.0/60.5**
			100	637.9/62.6	618.7/57.7	**608.0/58.7**	616.8/55.8	609.5/59.5
	15	50	25	133.6/15.9	124.1/13.1	122.6/11.2	117.9/12.5	**112.2/12.8**
			50	98.3/12.0	90.9/10.8	89.8/9.3	83.2/10.1	**76.6/9.4**
			100	65.2/9.5	56.1/8.4	47.6/7.0	42.7/9.2	**39.0/7.2**
		150	25	437.7/45.9	426.1/43.8	416.3/42.6	**415.8/42.4**	420.1/41.5
			50	371.3/37.1	356.0/36.3	362.6/37.4	356.1/36.6	**341.9/34.7**
			100	331.9/34.9	328.7/34.1	317.1/32.0	310.3/31.6	**299.2/30.6**
		250	25	740.6/71.4	728.9/70.7	725.8/69.4	717.3/66.6	**702.3/68.3**
			50	689.7/65.4	672.9/65.8	660.6/59.7	665.2/63.0	**655.9/65.4**
			100	643.7/61.7	632.2/60.3	619.4/58.2	614.2/54.6	**603.8/57.0**
4	5	50	25	40.6/9.3	42.1/10.0	**35.7/8.9**	36.8/9.7	36.7/7.8
			50	31.9/7.2	26.6/8.2	24.2/6.2	**22.6/7.1**	25.6/6.6
			100	14.8/6.7	15.9/8.6	13.7/9.8	12.8/7.1	**11.4/6.9**
		150	25	152.0/16.4	144.6/15.3	145.2/14.0	142.3/14.6	**138.8/13.9**
			50	138.3/13.5	131.6/12.7	127.8/12.1	129.9/13.8	**123.3/13.6**
			100	**104.9/12.4**	110.8/12.4	108.8/11.7	107.7/9.2	109.9/10.5
		250	25	337.4/34.4	322.1/34.1	320.6/33.9	315.2/32.4	**309.8/30.8**
			50	288.1/30.5	269.5/27.1	272.3/28.5	268.9/27.2	**264.9/26.6**
			100	237.6/25.4	230.2/23.0	229.4/23.8	**225.5/21.8**	226.2/22.8
	10	50	25	14.8/16.4	3.8/3.4	3.2/4.3	0.7/0.9	**0.0/0.0**
			50	11.6/8.5	2.9/3.5	1.6/1.8	0.6/1.8	**0.0/0.0**

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Table 8 (*continued*)

			100	5.9/7.6	2.8/4.8	0.8/1.2	0.1/0.2	**0.0/0.0**
		150	25	238.5/25.2	236.0/24.1	228.5/23.3	220.7/23.4	**213.1/20.9**
			50	174.8/18.1	170.6/16.0	**168.1/17.4**	169.6/18.1	169.7/16.9
			100	137.4/15.7	136.0/13.5	131.1/12.5	128.0/13.5	**121.1/13.5**
		250	25	522.6/52.0	514.1/49.1	508.1/50.8	484.3/47.8	**481.8/45.1**
			50	458.7/46.0	445.6/45.1	439.4/42.0	437.2/44.5	**432.1/44.5**
			100	411.4/41.9	398.2/40.5	383.6/39.4	381.9/37.0	**371.1/38.4**
	15	50	25	6.8/8.1	4.2/6.2	3.9/4.1	3.7/3.3	**0.1/0.2**
			50	3.7/8.9	2.1/1.6	1.0/0.8	2.0/1.4	**0.0/0.0**
			100	2.5/2.2	0.5/0.8	0.3/0.6	0.4/1.0	**0.0/0.0**
		150	25	275.5/26.1	260.4/26.5	252.8/26.3	**246.7/25.2**	247.7/24.6
			50	238.6/24.3	222.7/22.0	212.0/22.2	219.1/20.5	**204.9/20.0**
			100	183.1/20.7	177.8/18.9	173.2/18.5	170.9/17.2	**166.4/16.0**
		250	25	532.9/51.8	523.4/49.4	526.2/50.8	510.7/49.4	**496.6/47.3**
			50	468.5/48.2	458.3/46.1	451.9/45.0	440.1/42.2	**438.0/44.0**
			100	417.0/40.4	396.7/38.4	392.5/39.4	390.5/40.9	**385.7/37.3**

Appendix B

Table 9
Mean values and standard deviations of mean tardiness acquired by eleven composite rules ($DDT = 0.5$).

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2	5	50	25	332.0/52.5	265.9/56.5	324.3/50.8	**265.7/46.9**	321.0/35.1	266.1/60.5	354.6/43.1	276.2/48.4	386.3/61.3	469.4/51.0	522.5/77.0
			50	321.6/38.4	265.8/42.7	338.1/53.1	280.7/58.8	311.2/41.7	**253.3/49.0**	337.9/33.6	278.1/60.6	353.1/54.5	451.4/55.6	512.7/68.4
			100	296.1/48.4	234.5/63.0	293.3/59.5	230.5/50.9	300.4/61.2	**220.3/64.7**	289.8/56.6	224.9/66.6	326.1/61.8	399.7/65.8	475.4/66.5
		150	25	1158.4/75.7	947.5/91.4	1135.6/73.9	**928.3/82.4**	1138.4/75.0	957.7/111.7	1168.7/76.6	954.7/76.5	1141.2/102.2	1419.0/90.6	1456.7/120.3
			50	1151.8/107.8	**980.5/124.6**	1174.5/163.7	988.6/153.9	1212.5/127.9	986.5/137.9	1173.6/128.4	1010.8/129.7	1061.5/123.5	1346.7/118.8	1432.1/136.6
			100	1253.6/188.0	1082.3/193.9	1232.6/178.2	1076.8/221.4	1214.1/166.3	1084.0/216.2	1252.4/179.7	1050.3/177.9	**980.4/174.2**	1264.7/167.6	1338.2/168.0
		250	25	2091.9/168.3	1733.6/175.9	2117.5/129.5	**1721.9/170.5**	2157.5/194.9	1726.6/154.8	2183.7/172.2	1746.8/156.5	1844.0/173.8	2338.8/182.4	2417.2/232.9
			50	2204.9/247.0	1829.6/243.3	2215.9/241.3	1836.3/224.4	2243.5/242.2	**1793.3/195.8**	2173.4/243.4	1821.0/169.6	1797.0/238.2	2260.1/209.9	2323.7/227.6
			100	2332.5/196.6	1925.7/196.1	2265.7/195.7	1893.5/242.7	2281.3/192.4	1963.1/209.9	2378.3/161.1	1977.9/182.5	**1698.2/183.0**	2181.5/206.9	2306.0/226.6
	10	50	25	525.3/98.7	508.6/90.6	511.6/105.4	532.2/75.4	455.5/63.7	**452.5/82.4**	533.9/100.9	472.7/86.4	539.5/85.2	576.6/67.1	709.6/103.7
			50	499.5/86.4	483.6/97.5	489.7/75.1	480.0/95.4	**420.9/84.2**	424.7/90.6	487.4/71.8	432.7/92.4	471.6/76.9	534.0/93.1	656.2/133.1
			100	483.2/73.7	481.6/89.3	457.8/86.3	460.6/81.7	392.5/98.1	**353.8/79.4**	445.1/76.1	411.9/91.3	412.4/85.7	464.0/82.6	617.7/125.2
		150	25	1735.0/204.3	1819.8/273.2	1782.1/169.0	1801.1/254.5	1761.5/150.4	1714.7/221.3	1840.8/211.5	1830.7/202.4	**1381.3/195.4**	1529.0/162.6	1748.3/195.1
			50	1846.9/142.7	1830.3/233.0	1786.3/153.6	1798.6/203.4	1786.6/187.6	1721.6/227.6	1846.4/162.4	1776.8/185.6	**1334.0/141.0**	1515.9/144.7	1736.3/162.7
			100	1897.0/166.1	1828.9/203.9	1891.1/185.7	1897.3/206.2	1807.6/208.9	1771.8/179.3	1944.9/212.8	1782.7/234.9	**1261.6/135.4**	1435.3/145.8	1730.2/152.1
		250	25	3132.4/284.3	3059.6/342.6	3126.5/288.7	3039.5/305.1	3187.1/332.0	2995.2/331.7	3275.4/418.3	3099.6/355.0	**2106.0/246.5**	2492.2/254.9	2709.5/306.1
			50	3269.3/289.0	3084.0/282.6	3226.8/273.3	3136.4/286.9	3208.6/315.2	3056.3/235.9	3276.1/273.2	3085.7/293.4	**2034.3/210.7**	2439.1/197.2	2673.6/248.8
			100	3410.2/317.9	3272.1/351.9	3424.5/282.5	3228.5/327.1	3368.2/255.0	3145.6/228.6	3448.3/226.8	3089.5/171.6	**1947.6/181.4**	2352.8/165.1	2662.2/237.3
	15	50	25	704.7/115.6	801.5/163.2	735.3/131.6	780.8/159.8	**620.2/128.0**	633.7/140.0	727.5/91.0	704.2/165.6	674.6/156.0	649.8/123.6	893.7/158.6
			50	701.0/123.2	735.0/153.7	731.9/140.7	748.8/184.2	**571.3/140.7**	572.5/149.9	670.6/98.3	668.8/129.8	572.4/133.0	607.3/118.3	849.4/150.8
			100	663.7/124.6	724.8/148.0	650.8/115.5	680.0/162.7	521.6/117.0	**506.4/121.6**	594.8/117.7	557.0/109.5	508.0/117.0	537.2/102.7	721.5/132.2
		150	25	2401.6/264.6	2712.3/298.2	2398.0/199.1	2756.7/285.0	2302.0/266.2	2482.8/265.8	2449.6/247.3	2591.9/256.3	**1526.9/167.1**	1650.0/171.5	1965.0/219.1
			50	2407.8/217.8	2796.9/202.6	2416.8/239.9	2646.7/312.1	2261.1/192.2	2429.2/193.1	2480.3/242.6	2671.2/302.5	**1492.0/139.4**	1605.2/126.9	1957.9/188.7
			100	2356.7/183.3	2632.5/226.9	2477.3/256.9	2739.1/266.2	2252.6/234.1	2398.7/306.0	2357.8/270.6	2593.3/290.9	**1383.0/138.1**	1474.5/114.6	1853.0/172.4
		250	25	4243.7/311.5	4754.2/443.2	4282.9/374.4	4726.3/353.9	4170.9/376.8	4645.0/489.2	4411.3/363.1	4815.4/387.7	**2360.3/212.1**	2589.2/165.4	3050.2/281.7
			50	4217.6/374.4	4647.3/347.1	4188.3/331.3	4668.6/396.7	4192.2/260.8	4395.7/395.8	4255.7/302.4	4597.3/454.6	**2270.0/183.7**	2530.1/148.7	2948.8/216.8

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Table 9 (*continued*)

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
			100	4314.9/298.0	4632.2/440.6	4128.2/302.2	4597.0/406.1	4204.6/443.7	4413.1/465.4	4314.9/378.0	4545.7/407.6	**2216.7/197.2**	2446.6/180.6	2970.6/248.7
3	5	50	25	204.9/35.8	123.9/31.1	188.5/31.7	122.3/30.6	186.8/27.4	**114.9/26.4**	201.5/27.3	117.5/27.0	195.4/36.9	295.1/39.5	375.0/41.4
			50	182.9/32.5	121.8/31.1	184.8/39.9	123.5/33.7	171.9/28.2	**111.7/29.3**	193.8/26.7	112.3/24.3	166.2/36.4	265.4/30.7	357.1/43.8
			100	151.8/34.7	79.8/29.7	150.7/31.7	81.0/27.5	137.9/25.0	**69.9/30.3**	139.8/22.9	85.9/23.1	137.3/31.4	227.7/36.0	336.5/37.1
		150	25	693.8/73.1	504.8/82.6	700.0/70.5	**474.1/83.3**	735.4/91.9	486.9/81.7	724.7/84.0	497.2/72.8	586.2/86.0	923.0/96.0	1053.4/113.7
			50	722.0/72.8	479.9/75.9	711.0/58.7	502.9/68.9	703.1/82.8	493.8/58.5	713.9/63.9	**466.5/67.4**	533.3/74.8	864.8/95.7	997.1/118.9
			100	715.8/71.8	531.4/105.1	727.1/83.8	507.9/94.2	715.2/69.4	472.5/71.9	725.3/87.5	**463.8/105.5**	488.4/107.6	801.2/98.9	942.7/121.4
		250	25	1247.2/85.1	**848.3/87.9**	1231.3/105.4	863.9/104.1	1255.5/98.0	861.0/99.2	1273.6/108.9	853.0/89.7	944.0/102.7	1466.5/116.9	1680.5/165.2
			50	1331.4/120.9	909.8/120.0	1301.8/121.4	928.8/130.0	1304.7/136.7	901.0/91.9	1299.9/114.4	**869.5/101.5**	892.0/121.4	1465.4/145.4	1619.9/150.0
			100	1321.9/103.6	978.4/126.3	1336.0/129.6	977.8/99.7	1337.6/153.0	941.9/111.8	1316.2/115.2	898.5/118.3	**815.8/109.9**	1360.2/137.8	1565.4/159.8
	10	50	25	274.6/50.4	236.4/56.9	280.9/44.3	223.2/55.4	234.8/34.6	184.7/43.8	282.2/26.2	**174.9/39.3**	270.9/44.9	343.2/37.1	502.0/64.9
			50	267.4/48.0	214.0/73.4	253.4/49.2	207.3/66.4	218.3/38.8	**145.0/33.7**	272.3/46.6	156.6/32.8	219.0/48.6	299.3/38.5	462.8/60.7
			100	225.2/46.9	147.0/52.4	222.9/49.9	151.0/57.9	172.5/35.8	131.2/39.8	224.7/50.8	**124.6/43.8**	173.3/38.2	265.2/40.0	444.0/53.8
		150	25	976.4/72.1	917.8/113.6	993.2/80.2	942.9/128.8	961.1/93.2	835.7/110.6	1044.6/59.5	872.0/96.5	**731.9/98.2**	944.9/86.4	1290.9/115.4
			50	979.5/95.2	864.4/116.2	972.8/108.1	906.9/117.6	940.1/100.0	820.7/107.0	972.3/81.6	821.7/126.6	**669.6/82.5**	889.7/77.3	1231.9/113.0
			100	999.8/111.5	932.7/118.0	1000.3/123.3	896.0/157.1	925.2/109.0	778.2/95.5	939.7/101.5	791.4/112.9	**621.3/86.2**	824.9/100.9	1195.4/111.3
		250	25	1732.4/91.7	1646.1/131.0	1748.7/122.3	1649.9/147.6	1734.5/153.8	1566.9/131.1	1839.5/115.3	1628.3/143.8	**1115.8/93.8**	1552.6/110.6	1926.0/160.4
			50	1797.7/140.6	1649.1/177.8	1777.3/134.4	1699.8/176.3	1785.0/168.5	1579.6/160.9	1835.4/139.9	1665.8/171.8	**1105.7/116.2**	1511.7/103.7	1900.2/148.9
			100	1855.0/163.7	1803.8/167.9	1879.2/158.8	1755.0/187.2	1832.3/146.1	1640.1/201.3	1847.5/127.6	1601.9/180.5	**1039.6/119.2**	1466.8/117.1	1852.7/184.5
	15	50	25	399.8/72.2	376.7/108.0	384.1/75.3	340.1/91.8	319.4/63.0	**258.9/70.0**	376.2/56.4	271.2/72.6	310.4/70.6	405.0/83.5	668.3/117.1
			50	394.2/77.6	312.2/102.2	362.1/71.4	325.5/104.9	282.1/62.6	**219.1/85.9**	359.3/50.9	235.8/67.2	292.5/78.9	395.8/76.9	661.2/104.1
			100	350.8/62.3	277.3/136.4	328.6/64.1	274.6/70.4	234.2/47.4	**163.3/56.4**	325.3/34.8	189.0/51.1	232.4/86.9	316.3/78.1	563.2/94.1
		150	25	1263.0/136.2	1340.3/173.7	1243.8/99.8	1393.1/165.2	1177.7/116.6	1147.1/141.9	1237.9/128.3	1177.4/155.6	**765.4/94.1**	979.7/85.6	1405.3/150.6
			50	1338.9/124.2	1440.2/178.0	1340.4/130.8	1495.5/209.4	1214.2/103.3	1219.3/154.1	1283.6/102.6	1319.8/190.2	**799.7/105.1**	990.6/117.2	1473.7/151.2
			100	1338.3/116.8	1490.9/164.3	1324.1/114.8	1474.1/166.5	1151.2/79.2	1088.7/116.3	1235.6/104.4	1178.6/131.6	**748.0/98.1**	922.1/89.3	1398.5/113.3
		250	25	2321.3/169.2	2486.3/189.5	2244.9/181.5	2554.5/233.3	2179.2/166.7	2342.5/215.2	2332.3/216.0	2446.8/288.9	**1321.9/130.1**	1597.8/131.8	2162.6/218.5
			50	2288.2/140.1	2681.5/294.1	2319.6/205.3	2637.1/266.6	2242.6/167.7	2325.3/211.4	2342.3/202.5	2402.2/284.6	**1228.7/149.0**	1578.3/119.1	2197.8/210.3
			100	2392.2/252.7	2653.4/348.9	2405.4/226.3	2647.0/275.6	2245.7/256.6	2248.5/210.0	2344.5/226.9	2369.5/253.6	**1138.9/123.6**	1526.0/131.8	2147.1/223.0
4	5	50	25	128.1/17.3	63.3/18.8	126.4/14.3	60.6/15.8	122.9/17.2	**54.0/12.1**	137.0/17.8	58.8/15.0	101.3/16.5	200.4/28.9	288.0/39.5
			50	120.2/15.3	45.9/14.0	124.3/17.8	53.1/22.7	112.0/21.1	44.2/19.8	127.5/17.7	**40.0/10.3**	87.8/21.9	183.7/24.5	288.8/38.7
			100	90.6/23.2	20.6/18.2	86.7/22.9	19.5/15.4	75.4/18.6	21.0/11.2	80.5/20.2	**13.6/9.4**	62.5/14.7	147.5/29.6	242.0/38.6
		150	25	487.6/34.7	269.0/44.5	480.7/35.0	275.9/45.2	490.6/36.4	**263.7/47.3**	521.7/34.9	265.4/33.4	346.6/42.4	655.5/49.1	814.0/77.2
			50	464.0/39.5	302.2/60.3	485.3/39.7	306.3/44.5	476.5/42.2	272.8/42.0	479.2/38.3	**247.2/35.5**	310.9/43.7	627.0/35.0	795.0/64.3
			100	490.3/49.9	280.3/38.6	486.6/42.4	292.1/48.1	465.2/45.4	247.8/46.6	466.4/46.5	**209.8/37.4**	269.6/44.2	558.1/48.4	739.7/53.9
		250	25	881.1/69.1	514.1/72.0	886.3/58.1	502.4/58.3	860.5/47.2	**489.3/54.4**	913.5/68.7	496.7/44.5	586.1/63.9	1090.2/77.7	1281.6/116.7
			50	901.8/54.0	544.0/61.6	906.8/60.8	552.9/92.8	909.7/97.7	535.2/78.1	882.5/53.8	**513.3/86.9**	559.7/81.2	1076.8/81.7	1273.3/100.8
			100	914.8/61.9	541.9/90.1	918.0/79.4	561.3/85.9	910.8/67.9	521.2/67.2	919.4/72.7	**464.3/65.3**	492.1/75.5	995.4/65.9	1229.6/115.8
	10	50	25	206.6/31.4	99.4/27.9	201.0/26.3	101.2/32.5	170.8/24.8	**69.5/23.7**	200.5/26.0	88.3/20.2	152.5/34.9	267.8/31.4	470.2/64.5

(*continued on next page*)

Table 9 (*continued*)

			50	172.8/29.3	67.8/30.4	172.1/35.7	70.8/24.5	140.2/25.8	**44.4/19.1**	177.2/24.1	60.6/20.7	106.1/31.1	222.7/36.9	413.7/53.3
			100	157.4/35.0	48.1/34.0	158.7/47.1	54.2/35.9	115.1/31.5	**33.2/17.9**	148.5/33.2	51.1/28.6	103.5/39.6	199.6/35.7	370.1/48.4
		150	25	660.3/76.9	540.5/99.2	651.2/53.4	522.4/85.6	626.0/55.0	437.7/68.1	682.1/65.1	438.2/79.1	**421.5/77.6**	692.4/65.7	1066.7/123.1
			50	661.1/46.9	550.7/93.5	652.7/53.1	542.4/80.9	609.4/60.2	454.1/63.6	635.9/58.5	405.5/78.1	**395.0/79.6**	640.4/88.1	960.4/95.6
			100	673.4/57.9	525.1/80.9	659.3/56.3	524.6/79.5	602.8/54.5	417.7/69.1	641.1/52.0	370.3/95.6	**342.9/72.4**	597.1/59.1	933.0/86.7
		250	25	1187.4/93.7	991.6/83.2	1185.8/87.1	1048.4/102.6	1176.5/65.1	933.9/110.6	1216.3/75.6	947.4/95.2	**698.3/63.3**	1125.4/76.9	1570.0/134.0
			50	1193.3/110.5	1026.0/116.9	1191.9/73.5	998.0/160.7	1176.7/70.1	909.2/130.0	1206.7/91.6	858.4/69.2	**661.7/65.1**	1081.1/84.4	1506.2/125.7
			100	1218.3/88.8	1070.3/113.2	1232.2/81.6	1014.7/124.6	1218.6/75.7	904.6/99.0	1225.8/73.8	862.2/95.7	**598.7/61.2**	1046.9/64.1	1487.3/124.1
	15	50	25	266.9/49.3	144.3/53.6	255.7/44.8	133.2/58.2	193.8/36.7	**90.2/36.9**	249.6/31.2	105.5/17.8	167.9/42.2	306.3/37.9	550.0/52.5
			50	227.2/43.0	115.5/36.1	227.6/40.4	102.4/37.3	177.5/30.0	**63.0/21.9**	233.5/32.3	99.9/19.9	142.3/38.3	272.9/39.6	524.4/48.7
			100	208.0/45.6	80.4/45.8	214.2/47.2	77.2/35.6	143.8/28.9	**33.3/21.9**	206.5/31.6	57.2/16.9	109.3/29.8	235.9/42.2	464.1/44.3
		150	25	894.5/111.3	884.6/158.7	877.8/101.6	895.1/172.6	778.2/93.7	663.9/111.9	878.2/105.5	595.2/93.1	**495.7/84.4**	744.5/79.9	1191.5/130.6
			50	850.8/90.4	856.1/89.5	861.3/70.7	843.3/110.5	754.4/67.0	671.4/124.6	822.9/86.2	580.8/100.1	**445.4/86.5**	693.4/86.3	1177.4/124.1
			100	864.3/71.2	861.4/117.7	848.9/91.0	844.2/114.2	737.4/54.7	578.0/95.5	788.1/63.1	595.2/115.4	**431.5/88.5**	656.6/78.2	1119.3/122.2
		250	25	1585.4/104.2	1652.6/164.7	1571.2/75.4	1638.5/170.7	1481.1/85.2	1392.5/138.4	1557.9/88.8	1325.8/147.6	**787.0/89.3**	1186.4/62.3	1762.7/142.4
			50	1528.8/131.8	1623.6/147.8	1531.6/133.3	1610.8/176.8	1479.3/96.4	1367.3/105.8	1522.9/116.5	1355.5/184.7	**742.9/78.3**	1141.9/72.6	1735.3/161.3
			100	1583.5/95.7	1636.1/179.6	1572.0/90.9	1629.4/119.5	1453.7/89.9	1323.8/186.3	1520.3/69.3	1369.0/173.3	**680.6/95.3**	1088.2/47.6	1700.0/154.9

Table 10
Mean values and standard deviations of mean tardiness acquired by eleven composite rules ($DDT = 1.0$).

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2	5	50	25	276.8/64.3	**215.8/55.1**	268.6/54.4	226.6/66.6	264.5/41.7	217.5/57.8	275.1/60.4	217.0/50.6	332.1/71.7	426.5/58.0	478.1/63.9
			50	261.3/53.6	**195.0/57.5**	261.5/55.3	208.5/60.4	259.1/59.0	198.4/63.1	277.3/51.9	200.4/46.1	317.3/63.2	392.9/63.5	464.1/64.2
			100	225.4/50.0	168.8/44.5	224.9/47.0	179.9/57.7	194.7/44.8	154.0/54.3	213.4/47.7	**152.6/46.4**	249.3/52.3	329.5/52.8	425.5/58.2
		150	25	960.7/118.7	784.9/100.4	940.6/90.3	**775.2/103.6**	985.1/92.6	794.7/79.1	1002.6/73.8	797.1/80.6	1066.3/97.9	1341.7/99.3	1413.9/130.3
			50	981.4/97.2	839.1/100.4	996.7/105.1	841.2/111.3	975.6/81.4	**798.6/99.4**	1024.8/86.9	814.7/111.6	1060.9/129.6	1309.7/105.8	1363.5/125.3
			100	1083.4/171.9	905.1/181.2	1095.3/149.9	892.4/127.6	1045.5/164.7	874.9/118.3	1079.4/150.0	**869.5/151.1**	968.1/142.4	1230.4/147.2	1355.1/144.5
		250	25	1694.9/121.5	1372.1/163.2	1720.2/145.5	**1370.8/139.9**	1737.6/116.7	1418.0/156.6	1762.5/167.0	1452.0/171.8	1793.5/162.9	2323.6/182.8	2358.5/214.0
			50	1814.9/207.3	1551.7/173.6	1884.4/210.2	1576.0/153.2	1943.2/233.8	1553.2/229.9	1845.2/146.6	**1527.1/169.9**	1739.8/178.7	2197.1/162.0	2292.1/204.2
			100	2108.8/181.1	1808.2/237.2	2164.9/201.0	1787.2/204.2	2110.3/157.9	1796.0/224.3	2131.5/194.5	1736.4/153.7	**1696.4/187.4**	2211.2/191.5	2282.2/191.8
	10	50	25	424.4/78.8	397.4/104.0	400.2/79.2	382.2/91.8	334.3/60.2	**311.3/69.5**	402.4/76.0	364.5/71.5	407.7/84.9	434.8/78.3	618.2/109.5
			50	372.9/74.5	338.6/83.2	386.5/77.0	360.6/79.9	302.5/41.0	**257.0/64.8**	376.2/70.5	314.2/51.0	405.5/82.6	423.7/67.8	605.8/77.9
			100	356.3/56.4	314.1/100.8	384.1/83.9	287.6/64.8	281.5/52.3	**235.9/74.1**	328.7/55.6	270.7/81.3	324.4/71.1	384.0/59.8	526.6/78.3
		150	25	1435.2/157.7	1453.1/203.4	1440.1/159.0	1488.7/248.7	1402.6/166.5	1362.1/181.9	1482.9/226.2	1474.4/184.0	**1225.9/167.4**	1376.0/175.3	1596.7/193.5
			50	1469.6/155.0	1514.9/226.8	1527.3/175.6	1530.3/169.0	1421.5/162.4	1373.7/223.4	1468.5/151.5	1445.8/215.5	**1153.5/169.2**	1311.4/155.6	1541.4/161.6
			100	1521.9/124.9	1530.9/121.3	1573.5/166.4	1534.7/174.0	1475.5/198.4	1391.8/176.7	1559.7/170.4	1509.8/152.8	**1101.2/139.0**	1322.4/118.0	1546.9/144.4
		250	25	2608.6/176.4	2731.2/271.2	2603.8/203.5	2690.9/358.2	2570.7/176.8	2600.7/253.3	2636.7/272.8	2616.2/297.9	**2011.5/289.1**	2336.6/206.1	2643.7/299.7
			50	2775.8/216.8	2824.6/350.4	2689.7/247.2	2715.2/206.0	2711.9/251.4	2698.5/207.2	2744.1/165.9	2703.5/277.4	**1932.2/204.6**	2326.2/196.3	2633.4/268.9
			100	2807.4/204.8	2830.2/305.8	2796.4/188.7	2729.3/187.2	2801.6/277.1	2743.2/275.8	2890.2/225.9	2781.5/160.0	**1822.1/124.6**	2171.0/132.4	2431.4/227.1
	15	50	25	522.3/91.6	502.3/114.0	487.3/97.9	519.9/124.2	361.0/68.4	**293.1/60.7**	515.2/103.5	457.8/121.1	452.0/97.9	453.6/78.2	747.2/126.9

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Table 10 (*continued*)

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
			50	494.0/112.2	478.5/141.0	494.8/93.9	478.9/160.8	351.9/74.0	**349.8/115.6**	463.1/106.5	439.9/155.7	400.3/119.9	431.0/125.8	669.4/146.0
			100	470.4/116.8	432.0/103.0	463.7/106.9	420.0/104.5	269.9/76.9	**256.1/99.7**	419.0/87.0	375.2/99.8	369.7/81.7	392.6/64.0	599.7/124.5
		150	25	2046.1/175.2	2332.7/300.5	2033.2/193.4	2270.4/341.0	1827.9/163.8	1936.2/254.4	2095.1/213.6	2309.9/227.8	**1350.0/153.5**	1425.3/110.6	1791.5/160.9
			50	2122.9/246.5	2369.4/280.5	2074.3/249.6	2300.2/333.1	1812.7/261.5	2054.7/293.4	2038.4/209.5	2253.7/274.9	**1286.4/141.4**	1403.0/151.9	1771.4/217.1
			100	2107.5/270.3	2231.7/227.7	2066.5/153.7	2319.7/263.5	1797.2/161.1	1942.6/186.8	2085.1/243.5	2244.8/255.3	**1211.2/110.7**	1336.0/86.5	1650.3/135.7
		250	25	3625.4/252.0	4170.8/423.0	3655.5/271.2	4059.9/354.1	3504.7/285.8	3813.3/391.2	3692.4/297.6	4021.4/399.0	**2155.2/176.8**	2350.5/144.1	2799.4/193.6
			50	3764.5/282.7	4112.8/381.9	3707.2/356.8	4177.0/334.6	3645.4/285.9	3861.0/406.4	3663.2/233.4	4057.0/387.6	**2135.7/158.0**	2346.2/146.7	2857.5/204.8
			100	3863.8/358.5	4249.8/464.1	3796.2/358.9	4125.2/463.7	3590.3/353.1	3772.3/396.6	3817.5/362.1	4187.5/394.7	**2041.7/206.1**	2294.8/186.7	2792.8/262.0
3	5	50	25	151.2/20.1	72.5/29.3	148.9/19.4	78.1/28.3	144.6/28.5	**67.5/18.3**	150.9/21.7	74.6/22.7	141.9/28.4	254.7/40.7	349.1/55.0
			50	123.7/24.4	49.9/25.2	121.3/20.7	50.9/22.5	114.1/18.1	48.0/21.7	115.3/24.7	**44.9/24.0**	109.3/24.3	202.3/35.4	302.6/49.5
			100	84.1/19.0	22.0/22.2	100.0/32.6	24.7/24.3	82.0/20.1	28.7/16.5	86.4/24.2	**17.4/12.3**	87.5/31.7	159.1/33.3	266.3/43.8
		150	25	579.8/68.8	**385.2/60.9**	576.2/53.7	388.9/60.2	580.3/54.0	403.2/83.9	599.1/56.6	388.3/67.7	518.1/73.0	841.8/79.0	986.8/117.1
			50	591.0/35.4	413.4/62.4	577.5/56.2	425.5/80.0	605.4/44.2	389.3/69.6	595.3/50.9	**365.5/42.1**	497.2/48.2	826.8/55.5	987.3/71.1
			100	608.6/85.1	439.2/89.4	614.1/74.2	428.3/74.9	584.3/79.8	376.3/65.4	590.1/85.9	**372.1/80.3**	425.9/86.1	717.7/102.0	908.7/119.9
		250	25	1038.8/76.3	700.6/102.0	1039.7/69.5	**684.8/65.5**	1037.2/81.7	689.7/62.8	1082.5/73.9	721.9/67.7	911.8/89.4	1428.2/127.9	1634.8/160.9
			50	1050.3/81.5	**719.3/85.0**	1074.8/80.9	741.5/121.0	1061.9/73.9	733.5/80.4	1097.8/97.2	748.3/108.5	866.4/118.5	1373.4/145.1	1624.6/151.8
			100	1217.4/134.2	881.0/157.4	1201.7/121.5	886.9/154.8	1189.0/107.5	835.3/126.8	1208.7/121.5	807.2/118.5	**806.7/123.4**	1334.0/136.4	1527.5/158.4
	10	50	25	181.3/60.0	86.1/44.9	162.5/44.0	83.8/38.1	124.9/38.0	**61.7/31.0**	173.2/47.9	66.6/34.8	140.5/38.6	223.5/46.4	412.3/67.8
			50	160.1/35.5	57.5/26.6	152.7/34.4	68.4/44.5	115.0/32.4	**32.4/19.1**	142.5/40.7	52.3/24.3	118.0/33.5	216.1/39.2	416.0/62.4
			100	137.4/43.1	32.4/26.6	139.5/46.5	33.7/23.8	86.7/29.2	**13.2/15.8**	114.9/42.2	26.3/21.3	103.7/27.7	186.3/31.2	364.1/56.2
		150	25	814.8/79.0	757.1/86.0	813.9/76.2	793.3/127.5	749.9/63.2	582.0/81.5	828.7/73.5	699.8/87.8	**570.7/69.4**	831.8/78.5	1170.8/129.9
			50	805.5/91.2	771.9/113.0	824.9/95.6	736.6/107.3	757.6/90.1	**556.9/89.9**	789.7/94.1	667.7/77.1	560.6/78.6	792.9/90.6	1067.5/121.7
			100	825.7/107.0	739.1/112.4	820.1/87.1	721.9/105.5	716.1/82.8	574.6/114.2	807.2/88.8	624.7/136.6	**491.8/107.4**	731.6/82.2	1033.5/127.4
		250	25	1382.7/125.3	1329.9/159.6	1422.1/134.7	1400.1/164.3	1357.2/123.4	1263.9/139.4	1451.4/154.0	1327.9/179.7	**1003.7/116.9**	1382.9/112.6	1822.4/186.8
			50	1526.6/129.8	1453.8/152.1	1530.6/117.7	1466.5/142.0	1483.0/103.9	1320.1/145.5	1515.9/107.4	1430.9/163.1	**991.1/108.5**	1396.9/99.4	1817.3/172.3
			100	1630.7/176.1	1489.6/150.8	1575.1/170.7	1505.1/129.3	1522.0/142.3	1285.3/127.7	1555.3/150.3	1368.1/179.9	**916.8/104.0**	1349.6/131.8	1736.3/161.6
	15	50	25	223.0/66.8	94.8/53.7	201.1/67.6	78.1/65.3	132.1/51.5	**46.7/32.4**	205.3/53.7	70.5/47.2	163.4/57.6	234.7/46.5	490.6/72.4
			50	168.9/44.5	57.0/40.2	170.8/43.9	58.4/31.2	98.2/30.4	**24.3/26.8**	169.5/36.0	49.4/39.6	122.1/44.4	203.9/44.4	463.0/66.8
			100	160.6/53.4	60.9/56.8	148.1/50.9	45.6/39.3	71.8/26.8	**19.8/20.2**	146.9/60.1	49.6/49.2	105.1/42.5	181.0/41.4	421.6/55.2
		150	25	1098.0/133.5	1165.1/180.9	1106.9/129.4	1177.6/197.2	916.6/83.7	853.5/136.1	1049.0/95.9	1068.9/146.9	**651.9/104.0**	822.7/77.7	1305.2/144.2
			50	1127.1/94.0	1133.9/154.2	1110.0/99.1	1148.0/154.8	951.7/83.5	790.8/126.1	1106.4/105.7	1064.0/142.3	**614.4/79.3**	823.5/75.1	1254.0/144.3
			100	1143.3/127.9	1121.9/144.7	1147.0/115.4	1145.5/153.2	940.3/89.4	808.4/148.3	1098.1/111.0	1005.7/159.4	**587.1/65.8**	775.9/71.6	1280.3/129.3
		250	25	1999.2/176.3	2218.0/237.7	1986.4/164.6	2223.0/298.3	1848.5/130.7	1858.3/204.1	1970.6/166.8	2073.5/257.0	**1098.5/155.1**	1409.4/134.3	2082.0/224.7
			50	2054.8/192.2	2294.5/251.6	2040.0/151.1	2304.9/275.9	1830.1/149.1	1966.8/185.1	2007.6/141.0	2272.8/248.3	**1053.9/135.9**	1418.3/126.6	2018.4/190.5
			100	2080.3/145.9	2214.7/236.3	2064.9/143.9	2209.5/209.1	1835.1/168.9	1807.4/192.6	2020.9/163.7	2080.8/266.3	**988.1/126.4**	1340.0/123.3	1965.7/197.9
4	5	50	25	89.0/17.8	13.7/9.4	87.8/24.4	16.1/13.4	77.7/17.9	**12.6/11.1**	88.6/14.1	15.8/11.5	60.9/23.4	149.9/24.0	251.9/40.0
			50	75.5/23.5	7.6/8.7	74.0/25.3	8.6/8.8	59.3/20.4	8.1/6.6	69.2/18.9	**6.6/6.1**	46.9/14.3	129.9/22.7	238.7/36.5
			100	35.8/17.7	1.8/2.0	38.3/23.3	1.9/2.2	38.4/12.7	2.5/2.7	31.6/15.1	**1.7/2.2**	29.7/13.0	93.5/23.9	183.6/32.9

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Table 10 (*continued*)

		150	25	383.4/25.3	213.7/23.3	388.6/35.7	222.7/47.2	395.7/37.5	193.2/46.1	407.2/24.8	**191.6/32.9**	277.0/38.9	594.2/64.7	770.7/78.8
			50	401.3/54.8	207.4/44.2	404.9/47.6	213.3/36.7	390.8/36.7	182.4/45.0	396.6/38.2	**178.2/32.3**	267.0/39.5	559.7/54.0	720.7/76.2
			100	398.6/40.2	179.8/41.8	378.5/46.6	188.9/34.4	383.6/42.6	161.8/38.2	391.7/54.6	**142.2/36.8**	211.8/35.4	507.6/48.7	655.3/58.4
		250	25	713.4/48.3	397.9/61.0	703.2/51.2	417.1/77.6	717.5/59.0	397.7/41.0	736.4/56.2	**383.1/33.7**	512.4/62.6	1029.0/87.8	1246.5/121.0
			50	724.5/44.8	433.1/54.0	737.6/65.1	452.6/61.0	736.6/58.7	410.2/40.5	756.5/66.7	**408.2/55.6**	502.3/62.9	976.4/73.2	1201.6/119.6
			100	800.5/81.7	457.1/59.7	822.0/76.9	463.2/61.1	782.3/67.6	418.7/70.7	801.8/80.7	**413.7/46.9**	425.5/63.5	918.8/79.2	1132.3/102.6
	10	50	25	97.3/20.7	7.3/9.6	93.9/25.9	5.9/7.1	68.1/18.3	**4.2/6.2**	91.6/23.2	5.4/4.9	56.4/14.0	147.0/22.3	350.5/46.9
			50	66.7/18.1	4.6/5.3	60.5/14.7	3.5/2.2	36.3/9.9	**0.6/0.7**	56.5/16.4	2.9/2.6	38.2/9.4	118.4/20.2	298.1/40.2
			100	58.6/21.3	1.8/2.6	52.1/21.9	3.1/4.5	28.0/14.0	**0.4/0.7**	44.1/22.9	1.0/1.7	36.0/17.8	100.4/23.7	287.7/36.1
		150	25	501.9/66.6	380.0/58.8	519.1/57.8	366.5/83.1	455.9/46.5	**269.5/48.3**	518.7/63.6	317.2/47.9	307.2/50.4	550.1/47.6	886.7/107.4
			50	525.4/64.3	371.1/86.7	524.3/57.4	363.2/81.7	448.4/54.8	**281.9/73.6**	519.4/47.3	323.8/88.2	284.6/86.2	527.7/78.0	882.7/112.7
			100	513.5/56.6	257.4/72.4	516.3/66.6	266.4/83.9	440.5/49.5	**197.9/52.9**	482.8/39.6	221.9/69.9	250.2/73.6	496.1/75.6	835.9/100.1
		250	25	979.7/94.5	855.4/111.7	982.5/87.8	813.6/104.7	964.5/65.2	656.7/76.6	998.6/85.9	769.7/117.0	**583.6/94.0**	1012.6/96.7	1459.2/152.5
			50	1023.4/101.8	805.7/127.9	1029.9/99.1	851.4/143.8	958.7/86.4	680.1/111.9	1035.2/94.4	767.9/132.4	**537.6/87.8**	977.7/105.3	1405.2/142.0
			100	1106.3/70.3	828.1/100.0	1081.3/97.4	860.7/115.7	1000.0/74.0	686.9/94.8	1066.9/98.4	754.2/107.2	**514.0/74.1**	939.5/72.0	1437.9/130.0
	15	50	25	85.6/34.2	6.0/4.9	78.1/24.4	4.4/3.1	50.0/18.1	**1.2/3.8**	77.1/20.3	3.6/1.9	35.4/7.1	121.6/26.2	406.3/59.6
			50	80.1/22.4	9.6/15.0	78.5/26.8	5.5/5.0	40.8/11.3	**1.1/3.1**	82.6/24.6	4.4/6.2	36.6/6.5	125.3/26.9	376.5/54.9
			100	58.2/28.4	4.4/3.9	55.4/29.4	2.7/2.1	24.5/13.1	**0.1/0.3**	56.5/23.5	1.9/3.4	27.9/5.3	96.4/18.3	354.7/47.3
		150	25	706.8/95.3	573.8/144.0	721.3/104.3	575.8/138.9	580.3/82.3	**342.1/83.3**	701.6/93.6	460.4/108.3	373.1/103.4	564.4/78.9	1044.8/142.9
			50	692.3/72.8	521.3/117.7	670.9/88.1	473.7/103.9	523.1/55.8	**312.1/61.3**	662.1/77.8	419.1/92.4	313.5/72.5	530.1/52.1	994.3/123.1
			100	637.5/60.9	405.0/101.9	629.0/68.9	388.4/138.1	459.6/55.1	276.6/62.4	608.3/77.3	339.5/100.6	**256.8/82.5**	482.8/48.0	940.5/110.4
		250	25	1361.6/86.9	1347.8/136.4	1382.5/89.6	1417.8/149.6	1180.2/92.5	971.8/143.9	1347.3/99.9	1251.5/140.4	**660.3/68.6**	1019.9/79.0	1687.3/165.8
			50	1355.7/113.3	1292.3/145.7	1322.0/113.9	1292.5/166.8	1130.7/79.3	920.4/134.1	1287.3/102.6	1157.5/127.3	**611.9/65.6**	969.1/81.0	1571.4/167.3
			100	1333.6/100.7	1221.9/172.0	1326.6/110.3	1217.3/116.8	1131.1/80.8	848.1/128.7	1285.6/114.1	1070.5/86.2	**555.0/66.8**	893.8/78.8	1555.2/145.8

Table 11
Mean values and standard deviations of mean tardiness acquired by eleven composite rules ($DDT = 1.5$).

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
2	5	50	25	217.3/45.0	165.6/52.9	221.4/48.3	172.9/53.1	207.4/34.9	**158.8/38.5**	210.4/36.3	161.1/40.7	282.7/64.2	371.1/64.7	442.4/79.0
			50	203.9/41.5	139.1/34.8	208.0/37.9	162.3/48.8	189.1/44.3	**137.1/28.0**	199.9/35.8	150.8/50.9	244.6/56.1	336.9/57.9	417.4/68.1
			100	160.5/44.7	**83.3/36.0**	165.8/48.7	108.1/49.3	138.5/39.9	92.7/28.7	152.1/34.6	102.0/42.4	193.9/46.9	259.4/48.9	342.4/57.5
		150	25	830.0/73.1	**653.0/71.4**	829.4/78.9	662.7/75.0	847.9/61.5	686.3/110.7	837.6/66.6	655.0/92.8	989.1/138.8	1256.2/106.5	1346.6/121.2
			50	910.5/142.5	**760.4/171.1**	887.7/134.3	803.9/182.6	919.7/143.5	800.9/154.7	922.5/168.2	767.0/145.9	959.8/165.5	1250.0/120.2	1320.6/140.2
			100	1021.1/146.2	858.3/139.9	970.9/136.1	864.2/147.2	979.5/158.5	843.3/122.4	945.2/93.9	**814.5/126.0**	905.4/137.9	1156.0/110.8	1290.1/107.5
		250	25	1479.7/92.9	**1168.9/114.7**	1494.9/110.0	1221.3/151.9	1528.6/130.4	1252.7/132.5	1518.1/109.9	1186.2/91.0	1718.7/160.8	2191.5/149.6	2298.7/215.8
			50	1566.7/147.1	**1309.5/199.8**	1641.1/190.5	1365.9/153.0	1657.1/226.6	1361.5/151.4	1656.5/188.9	1329.0/139.2	1647.6/175.1	2131.4/179.0	2188.0/195.7
			100	1866.2/156.6	**1519.3/159.3**	1890.2/172.2	1565.2/168.4	1888.0/173.3	1589.1/230.6	1960.3/209.9	1575.0/174.2	1592.2/172.7	2105.3/143.8	2147.8/170.1
	10	50	25	284.8/59.8	194.6/55.7	276.2/49.4	215.2/65.5	203.8/58.0	**140.0/46.2**	245.9/41.2	216.6/76.4	292.8/63.0	321.9/55.7	470.2/90.7
			50	265.7/67.7	187.1/84.8	258.1/63.4	196.7/72.1	178.6/64.8	**132.3/69.8**	238.5/62.8	195.2/92.8	258.4/85.0	296.2/66.3	467.5/77.2
			100	206.1/79.0	138.6/70.4	214.8/67.2	134.3/85.1	143.0/54.7	**72.5/51.7**	210.1/82.2	152.9/89.0	205.0/63.2	263.5/69.0	424.4/82.5

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Table 11 (*continued*)

f	mq	n_{new}	Î»$_{job}$	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
		150	25	1290.3/125.5	1297.7/195.5	1319.7/170.9	1365.2/193.1	1267.5/135.5	1151.7/146.1	1293.3/140.2	1267.2/217.2	**1141.2/161.6**	1266.7/135.6	1583.7/187.5
			50	1313.6/123.7	1285.4/204.1	1391.4/152.6	1370.8/216.9	1205.4/137.7	1158.2/167.2	1287.3/142.1	1261.2/201.2	**1049.3/157.8**	1230.6/133.1	1497.8/146.0
			100	1414.9/168.3	1331.2/170.0	1401.8/161.5	1370.4/150.9	1280.0/168.3	1142.1/154.3	1363.1/196.9	1353.0/222.6	**985.6/115.0**	1178.3/131.5	1443.7/133.9
		250	25	2296.5/185.3	2329.4/204.2	2306.8/204.6	2398.8/233.1	2303.0/210.6	2249.9/180.4	2324.4/193.3	2314.6/206.5	**1868.6/155.3**	2184.6/195.9	2524.3/239.9
			50	2406.0/197.6	2505.1/209.9	2478.6/212.6	2449.3/197.3	2419.7/171.0	2360.9/209.5	2435.0/173.7	2353.1/167.1	**1875.7/128.2**	2214.3/126.1	2481.9/161.4
			100	2692.6/248.8	2621.4/281.8	2758.0/247.7	2719.4/276.4	2712.6/284.1	2495.8/193.2	2735.9/223.6	2662.6/277.0	**1757.4/125.9**	2140.3/116.9	2473.2/131.4
	15	50	25	330.0/140.5	277.0/166.9	336.4/144.9	262.6/147.2	187.1/76.9	**174.0/84.1**	354.9/136.5	273.2/108.3	297.2/120.8	299.9/105.4	551.0/125.7
			50	307.4/101.7	209.4/99.8	272.8/99.1	229.9/121.0	147.9/61.5	**86.0/40.0**	308.1/90.2	272.0/103.3	228.0/99.1	284.4/96.9	512.4/110.2
			100	291.5/152.3	226.2/136.1	266.2/122.2	182.5/101.3	112.9/59.1	**86.6/54.0**	300.8/93.4	299.9/119.9	227.8/107.8	244.1/88.4	452.2/105.6
		150	25	1799.3/176.2	1938.3/249.9	1898.0/246.7	2025.6/335.0	1529.1/170.1	1632.9/184.7	1713.5/191.7	1954.4/364.2	**1144.6/152.1**	1257.3/122.5	1674.8/215.3
			50	1859.5/227.1	2032.5/300.4	1863.4/202.3	1969.4/233.6	1557.5/158.5	1677.1/236.8	1797.1/185.0	2024.9/233.9	**1114.8/141.0**	1234.7/119.7	1615.3/181.7
			100	1824.9/203.4	2028.4/242.0	1865.8/189.1	1992.4/228.5	1598.8/204.7	1580.4/236.7	1845.3/167.2	2077.7/173.3	**1134.2/135.4**	1179.3/106.4	1551.5/172.0
		250	25	3254.3/300.7	3751.4/362.2	3272.1/364.2	3735.4/421.7	3050.7/315.0	3335.3/331.7	3225.1/295.8	3556.0/269.2	**1962.6/191.0**	2211.2/212.1	2666.8/246.7
			50	3212.9/330.0	3666.5/318.2	3304.7/285.1	3717.2/310.5	3076.0/245.3	3199.0/318.8	3284.1/339.2	3638.5/229.1	**1922.8/177.2**	2170.6/193.9	2683.5/235.2
			100	3311.7/400.0	3568.3/374.0	3310.4/366.7	3646.9/322.6	3007.9/295.2	3020.9/340.1	3272.3/340.5	3525.7/439.9	**1823.5/163.7**	2060.4/185.8	2521.8/227.9
3	5	50	25	96.2/30.5	22.4/22.4	94.5/36.8	22.8/19.7	86.9/23.9	26.0/21.3	89.5/33.4	**21.4/21.3**	100.8/28.1	181.9/42.1	301.3/64.5
			50	85.2/26.6	**8.7/6.7**	78.4/27.5	12.1/12.1	75.1/20.8	9.9/9.0	78.1/28.0	17.4/17.8	68.9/20.6	152.6/37.7	247.9/52.0
			100	53.1/21.1	**3.1/3.7**	47.6/27.5	4.0/4.5	52.2/24.3	4.4/3.6	45.7/20.9	5.3/6.0	58.6/14.6	130.0/31.1	225.9/39.8
		150	25	504.1/49.7	348.3/66.0	524.0/60.7	376.0/57.7	511.2/45.7	**330.1/48.6**	526.0/58.9	335.3/56.6	481.2/54.0	804.5/66.4	950.0/73.3
			50	503.5/68.1	340.3/53.2	520.8/58.4	364.4/66.6	511.6/62.9	**321.4/54.4**	505.3/61.0	337.3/43.8	442.0/53.9	744.4/76.5	942.4/113.5
			100	530.2/51.2	312.0/88.0	531.0/66.7	333.3/67.3	525.6/60.7	**286.8/68.1**	539.1/69.3	307.9/85.4	393.1/69.7	672.6/84.2	845.4/132.6
		250	25	902.7/67.4	606.7/81.8	886.2/78.8	609.5/84.4	911.4/69.0	599.2/73.7	903.4/68.9	**587.5/76.6**	809.5/97.1	1353.6/99.7	1510.4/162.8
			50	951.9/77.3	**627.9/67.7**	965.3/67.7	661.0/81.0	968.0/83.0	633.8/68.0	966.7/53.9	628.5/57.3	782.0/67.4	1328.6/102.1	1515.3/157.0
			100	1084.8/105.8	745.7/79.3	1092.9/136.2	784.4/105.9	1084.2/85.3	722.6/125.8	1090.5/130.0	**722.2/101.5**	723.5/108.4	1266.4/138.2	1430.4/158.4
	10	50	25	70.6/35.4	7.0/9.3	74.2/29.4	8.1/8.9	41.1/24.6	**2.9/4.1**	88.3/35.0	13.9/27.4	74.1/26.8	131.3/35.4	336.8/48.4
			50	48.9/34.5	4.2/4.5	53.8/37.8	4.8/5.0	26.7/25.1	**2.1/3.5**	62.2/30.9	7.0/8.5	47.7/9.8	118.1/14.1	316.9/43.5
			100	44.5/27.0	4.4/6.3	33.2/25.6	3.4/4.5	13.4/12.0	**0.5/1.0**	50.7/30.2	5.0/10.5	39.7/24.5	100.0/31.6	250.3/37.1
		150	25	704.0/111.2	601.8/91.8	703.8/108.2	594.1/86.8	604.3/90.4	**437.8/84.5**	683.9/106.3	593.2/120.2	488.4/72.0	698.1/102.1	1072.3/129.7
			50	728.9/68.2	588.4/97.7	736.5/71.6	602.6/63.8	599.3/67.2	455.6/103.0	710.2/84.7	573.2/111.5	**434.2/62.4**	692.7/62.5	1073.3/117.1
			100	701.8/95.0	499.4/108.5	692.5/102.9	529.0/102.3	578.3/89.8	**358.8/87.2**	682.0/97.3	528.8/105.5	387.3/106.1	624.5/110.1	1011.8/114.0
		250	25	1342.7/118.0	1246.8/137.8	1340.2/132.3	1282.9/139.0	1251.8/126.0	1011.4/150.0	1289.1/119.3	1151.7/160.2	**926.4/117.4**	1343.3/103.9	1743.6/176.7
			50	1335.5/111.2	1279.8/147.0	1393.4/109.5	1242.0/155.1	1251.3/124.5	1002.5/96.4	1343.4/140.2	1226.3/90.0	**874.7/93.2**	1284.8/110.5	1692.1/144.8
			100	1443.6/111.0	1200.2/92.5	1434.5/72.4	1229.6/158.0	1313.8/105.3	1001.4/136.4	1399.5/119.8	1245.2/168.2	**794.8/100.6**	1212.2/108.5	1698.2/178.0
	15	50	25	47.2/28.1	6.5/5.5	48.5/47.7	5.2/4.3	14.5/20.2	**0.9/3.2**	71.7/35.1	11.2/20.2	49.3/26.0	104.6/35.4	368.7/58.6
			50	40.2/26.9	9.3/14.0	26.4/17.3	7.6/10.4	9.1/7.6	**0.4/1.3**	47.4/24.7	1.9/2.4	36.1/20.7	79.5/19.2	318.7/44.4
			100	28.3/29.2	3.1/3.0	20.2/15.0	2.7/2.3	3.9/5.8	**0.1/0.2**	46.1/38.4	6.1/10.7	32.6/19.9	73.6/15.5	303.6/42.7
		150	25	932.4/78.0	810.9/143.1	948.3/99.0	847.1/142.9	732.6/68.9	508.4/121.7	894.5/101.7	926.9/147.1	**468.0/137.2**	679.7/76.4	1208.1/116.4
			50	894.4/117.6	764.6/134.7	890.5/137.5	798.6/126.5	659.1/84.6	464.6/127.1	872.2/109.2	859.3/187.7	**424.6/125.9**	628.8/106.6	1137.2/135.5

(*continued on next page*)

Table 11 (*continued*)

			100	835.9/140.0	679.0/158.4	877.1/127.2	718.5/154.7	622.1/102.4	423.0/112.8	835.2/102.0	756.3/174.1	**380.1/93.0**	585.3/89.4	1084.0/162.9
		250	25	1803.6/137.3	1962.6/245.0	1794.6/150.5	1962.7/232.5	1521.8/164.4	1544.4/178.1	1746.5/148.5	1943.4/236.1	**948.2/114.3**	1268.1/98.8	1872.7/148.0
			50	1851.0/153.1	2002.0/219.6	1923.1/131.3	2010.6/186.6	1565.4/97.4	1491.3/155.3	1813.3/157.7	1939.0/202.0	**892.7/87.2**	1272.3/82.8	1869.5/137.7
			100	1815.7/187.1	1891.2/246.5	1807.4/148.5	1815.6/248.8	1538.1/145.9	1342.4/158.2	1779.4/153.6	1874.5/208.1	**806.2/107.8**	1194.7/127.8	1825.0/168.0
4	5	50	25	39.0/11.6	1.0/0.9	39.2/10.8	1.2/1.6	33.6/10.9	**0.8/0.7**	40.5/9.4	1.0/1.4	24.4/16.3	90.8/20.5	204.3/38.7
			50	23.2/10.6	0.7/0.9	21.6/8.3	0.9/1.3	24.0/9.6	0.4/0.8	23.4/11.7	**0.2/0.4**	19.3/9.7	75.1/19.7	180.8/33.2
			100	10.0/6.6	0.4/0.8	10.5/7.6	0.5/0.7	14.6/11.6	0.3/0.4	12.6/10.7	**0.0/0.2**	17.5/10.3	65.3/18.7	155.2/26.4
		150	25	320.2/41.9	155.6/45.2	317.2/35.3	151.2/38.7	328.0/35.3	**120.9/26.9**	331.0/41.1	139.1/39.9	216.8/54.1	523.9/59.3	731.3/87.2
			50	331.0/33.2	**135.0/36.9**	339.3/40.6	157.2/32.7	333.3/28.2	137.0/27.6	333.6/37.7	146.2/37.8	199.6/37.3	497.3/40.6	709.9/73.8
			100	330.0/55.5	**94.5/35.4**	337.9/45.0	99.5/31.3	322.0/38.6	101.9/29.3	324.5/50.9	104.8/32.0	185.2/36.4	446.6/39.2	613.9/65.3
		250	25	637.5/47.1	346.9/44.9	645.5/50.3	373.1/48.0	640.8/46.5	331.0/48.6	658.0/45.8	**312.6/32.2**	486.2/50.4	983.1/76.4	1182.5/97.3
			50	674.4/65.5	386.2/57.1	656.8/63.9	410.7/73.7	679.6/69.8	**336.8/53.2**	669.9/58.8	367.0/46.8	436.9/44.5	960.3/61.5	1144.7/77.4
			100	728.7/55.1	400.8/53.1	717.3/46.9	389.1/60.5	706.3/66.7	**331.9/57.2**	716.6/61.5	360.4/67.2	383.5/51.7	876.8/69.3	1100.7/78.1
	10	50	25	16.4/10.6	**0.5/1.1**	14.5/8.3	0.6/1.0	3.3/3.4	0.9/0.2	16.4/12.8	0.7/0.6	14.2/9.8	57.9/14.3	256.6/46.3
			50	6.0/4.8	0.4/0.3	5.5/7.1	**0.3/0.6**	1.5/1.6	0.6/0.7	7.1/6.4	0.5/4.0	10.6/7.1	42.5/12.5	203.6/39.7
			100	3.3/3.1	**0.1/0.1**	2.2/2.0	0.2/0.2	0.6/1.0	0.4/0.8	3.8/3.9	0.2/0.4	7.4/4.5	34.2/10.5	169.1/32.5
		150	25	439.4/57.3	196.6/62.1	461.8/56.3	208.7/57.3	361.3/45.5	**111.4/39.5**	412.7/51.1	220.9/41.2	223.7/37.0	443.9/57.5	824.7/109.3
			50	424.2/52.4	145.5/64.6	433.7/51.3	171.4/75.9	351.0/44.8	**88.4/40.2**	413.2/54.2	205.8/63.8	195.0/53.0	449.7/62.2	782.6/98.3
			100	404.9/54.7	74.5/58.3	405.4/60.9	85.2/58.6	317.0/45.7	**43.8/29.6**	390.3/50.9	141.5/59.3	145.3/42.9	379.2/45.4	717.6/103.9
		250	25	890.9/69.3	666.9/87.7	889.7/83.6	725.8/118.9	803.8/66.5	500.6/93.4	865.3/91.8	686.7/88.5	**497.3/87.8**	900.3/91.0	1392.1/129.1
			50	896.0/60.6	685.1/120.9	914.1/61.0	698.9/76.1	796.2/64.6	493.3/71.4	888.7/63.2	681.5/124.3	**433.7/85.3**	867.2/74.1	1345.2/115.6
			100	894.9/86.4	523.9/114.8	885.3/102.6	580.1/101.1	798.3/78.8	409.2/100.1	882.8/80.8	599.6/96.1	**385.1/76.2**	791.7/69.3	1299.7/112.8
	15	50	25	3.4/1.8	0.7/0.8	3.9/2.8	0.4/0.5	**0.2/0.4**	0.3/0.4	7.6/6.5	0.4/0.5	9.9/8.2	35.7/14.9	273.4/40.6
			50	3.0/2.5	0.4/0.4	2.7/1.9	0.3/0.4	**0.1/0.2**	0.2/0.3	3.5/4.8	0.3/0.7	7.2/5.4	31.7/12.7	252.1/41.7
			100	2.1/2.3	0.3/0.4	2.0/2.1	0.2/0.4	**0.1/0.2**	**0.1/0.2**	4.2/5.7	0.3/0.6	4.4/4.3	25.2/8.2	189.5/36.0
		150	25	534.1/104.3	194.6/92.1	522.4/95.8	179.8/88.0	331.1/68.7	**73.7/42.4**	504.4/86.0	280.8/95.1	177.7/101.1	383.5/69.9	879.8/104.0
			50	512.9/64.0	120.4/68.8	511.7/80.2	104.2/72.6	305.5/41.8	**42.8/25.1**	498.0/50.4	225.9/70.1	151.7/84.3	371.7/68.5	896.2/112.6
			100	446.8/76.6	53.8/65.9	452.9/86.1	53.8/69.9	256.5/44.8	**18.7/30.3**	436.4/68.5	197.7/86.5	117.9/67.4	324.4/77.5	816.4/119.2
		250	25	1171.8/107.7	926.5/114.0	1172.0/93.5	1042.8/113.7	948.5/71.7	601.2/108.4	1116.2/97.3	990.3/126.6	**547.2/87.2**	838.0/72.5	1473.4/143.0
			50	1147.8/131.8	869.4/180.7	1147.7/122.7	921.2/157.8	920.9/96.9	515.9/144.4	1084.5/120.0	945.8/145.4	**506.4/75.5**	786.3/69.0	1398.7/129.3
			100	1115.0/102.8	748.1/154.1	1127.1/99.0	803.4/158.5	899.0/86.0	**422.9/103.4**	1091.0/82.8	887.8/161.2	481.2/63.8	726.4/67.4	1387.0/121.0

Appendix C

Table 12
Mean values and standard deviations of mean tardiness attained by twelve new PDRs ($DDT = 0.5$).

f	mq	n_{new}	Î»$_{job}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
2	5	50	25	470.8/57.8	381.0/61.3	328.3/72.4	430.9/48.3	340.4/50.9	425.9/52.5	461.8/96.4	356.0/56.4	288.3/44.0	457.1/40.9	**276.9/49.8**	427.8/79.2
			50	486.8/78.2	393.0/55.0	301.5/52.7	389.8/41.8	341.0/40.1	414.3/59.5	484.8/88.8	363.2/63.7	291.5/51.5	432.0/29.1	**267.7/45.4**	408.0/74.5
			100	455.2/80.8	417.2/79.9	284.3/40.3	339.4/56.8	308.8/42.9	377.0/51.7	424.6/64.2	387.2/75.5	262.1/48.3	381.1/39.7	**233.8/37.9**	376.5/77.2

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Table 12 (*continued*)

f	mq	n_{new}	Î»$_{job}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
		150	25	1307.1/ 76.7	1042.2/ 106.8	952.8/ 86.3	1237.9/ 81.3	1067.7/ 94.4	1321.1/ 99.8	1260.4/ 110.3	997.3/ 101.6	929.2/ 132.3	1367.9/ 54.1	**890.7/ 107.7**	1288.4/ 135.8
			50	1380.0/ 107.7	1186.5/ 92.7	921.2/ 70.0	1189.1/ 64.0	1035.8/ 86.5	1253.6/ 95.5	1365.4/ 124.0	1186.0/ 91.7	885.0/ 93.0	1327.2/ 61.9	**842.5/ 90.4**	1267.2/ 140.6
			100	1370.4/ 144.1	1285.0/ 151.1	906.5/ 92.5	1117.8/ 107.8	1026.4/ 103.4	1236.6/ 121.5	1369.2/ 113.3	1302.5/ 197.6	840.4/ 104.2	1260.0/ 79.4	**811.7/ 116.1**	1218.9/ 108.1
		250	25	2006.6/ 103.1	1726.6/ 139.3	1605.0/ 107.2	2080.0/ 135.1	1806.3/ 108.8	2215.9/ 140.7	1947.5/ 146.8	1690.6/ 135.4	1539.0/ 157.7	2300.4/ 86.3	**1503.3/ 95.4**	2222.9/ 158.0
			50	2199.9/ 153.6	1995.0/ 147.9	1583.4/ 119.7	1994.9/ 115.7	1822.6/ 137.6	2182.0/ 177.6	2152.7/ 173.3	1913.9/ 146.6	1537.0/ 125.7	2271.1/ 98.0	**1483.1/ 138.7**	2134.3/ 224.1
			100	2267.5/ 94.5	2184.6/ 138.8	1514.6/ 111.8	1942.3/ 89.4	1718.7/ 121.4	2139.5/ 149.5	2289.3/ 162.1	2188.6/ 116.8	1508.5/ 110.4	2201.5/ 90.0	**1421.4/ 117.3**	2152.7/ 190.4
	10	50	25	855.6/ 125.8	569.1/ 79.6	573.8/ 72.6	571.8/ 62.0	604.2/ 103.6	712.2/ 125.4	891.3/ 135.6	631.1/ 115.9	637.2/ 97.9	**547.1/ 51.1**	562.1/ 110.8	816.7/ 160.7
			50	862.3/ 111.3	616.0/ 85.8	525.0/ 78.2	507.7/ 66.9	561.5/ 97.1	651.5/ 62.7	963.0/ 141.9	668.9/ 107.7	558.8/ 102.0	**504.9/ 53.3**	519.2/ 80.5	733.3/ 83.8
			100	859.7/ 135.6	718.1/ 124.0	505.0/ 111.5	**442.8/ 64.9**	501.9/ 109.8	646.0/ 122.1	962.4/ 168.9	797.8/ 159.8	561.6/ 112.6	447.2/ 47.7	475.4/ 84.4	723.0/ 161.5
		150	25	2174.7/ 147.4	1684.5/ 140.2	1676.1/ 177.9	**1464.5/ 111.3**	1739.7/ 191.1	2062.3/ 198.9	2274.7/ 201.5	1872.8/ 203.4	1893.7/ 190.0	1490.8/ 77.1	1721.2/ 180.3	2392.0/ 319.6
			50	2368.1/ 196.4	1895.2/ 252.1	1638.7/ 204.2	**1436.1/ 86.1**	1765.8/ 190.9	2039.9/ 214.9	2667.8/ 195.0	2114.4/ 241.3	1841.2/ 207.1	1455.6/ 72.4	1731.3/ 226.4	2283.4/ 266.6
			100	2514.4/ 179.5	2235.7/ 220.6	1663.0/ 210.8	**1323.3/ 114.6**	1724.6/ 195.9	2025.4/ 218.4	2769.0/ 259.8	2515.2/ 238.4	1891.1/ 306.0	1395.7/ 77.2	1712.8/ 181.3	2285.9/ 264.1
		250	25	3192.0/ 194.4	2663.0/ 257.9	2806.6/ 295.7	**2329.9/ 160.9**	2913.3/ 241.0	3400.5/ 285.7	3291.0/ 262.5	2905.3/ 310.8	3158.9/ 345.4	2435.1/ 126.5	2904.6/ 191.1	4010.3/ 342.8
			50	3696.8/ 191.4	3030.4/ 213.8	2743.3/ 222.5	**2182.6/ 85.0**	2879.8/ 188.5	3303.7/ 245.4	3925.0/ 228.6	3304.0/ 249.5	3113.1/ 265.5	2355.0/ 82.1	2904.5/ 186.9	3888.4/ 333.9
			100	4034.0/ 268.5	3638.0/ 213.9	2747.1/ 212.4	**2166.5/ 125.7**	2895.4/ 201.6	3312.6/ 293.2	4473.7/ 427.0	3972.3/ 296.8	3081.3/ 305.9	2339.5/ 125.1	2831.8/ 184.8	3745.4/ 306.2
	15	50	25	1230.9/ 179.5	856.4/ 128.6	869.2/ 145.5	683.3/ 77.3	851.8/ 132.7	984.5/ 187.1	1344.5/ 177.0	1049.9/ 209.8	1024.5/ 222.4	**640.8/ 38.6**	921.1/ 189.3	1269.0/ 225.1
			50	1338.3/ 238.0	916.4/ 177.5	831.7/ 208.4	652.9/ 64.2	786.1/ 120.3	995.5/ 194.3	1432.3/ 226.2	1082.3/ 204.9	935.6/ 229.3	**620.9/ 41.1**	843.1/ 192.9	1156.3/ 216.0
			100	1322.0/ 209.8	1020.4/ 206.4	771.0/ 132.2	543.9/ 55.0	757.9/ 145.7	856.7/ 128.6	1510.1/ 225.3	1216.1/ 216.6	873.2/ 156.4	**531.7/ 45.4**	815.9/ 144.8	989.0/ 146.7
		150	25	3138.5/ 214.5	2448.5/ 231.0	2483.4/ 242.1	1573.1/ 107.3	2558.1/ 281.2	2862.6/ 337.9	3366.3/ 235.2	2800.6/ 336.0	3027.0/ 369.1	**1569.0/ 89.5**	2802.8/ 321.1	3452.6/ 350.6
			50	3520.8/ 308.0	2711.5/ 265.9	2481.1/ 244.7	1542.4/ 82.0	2497.4/ 255.3	2887.7/ 290.7	3983.5/ 242.6	3069.0/ 313.6	3043.1/ 335.1	**1525.7/ 62.0**	2769.5/ 261.6	3515.6/ 366.7
			100	3670.6/ 250.4	3015.5/ 271.2	2319.3/ 237.2	**1458.1/ 92.6**	2418.5/ 183.2	2704.8/ 255.2	4191.7/ 333.3	3551.5/ 295.8	2810.0/ 350.8	1469.8/ 106.1	2626.9/ 260.5	3352.7/ 370.0
		250	25	4540.4/ 201.7	3825.9/ 229.8	4111.5/ 233.1	**2457.7/ 101.9**	4122.8/ 299.6	4768.5/ 302.5	4685.1/ 245.9	4406.1/ 280.2	4988.5/ 307.0	2488.7/ 89.2	4619.9/ 363.6	5887.8/ 359.5
			50	5254.1/ 278.5	4235.1/ 273.4	3978.8/ 296.0	**2418.7/ 99.9**	4040.2/ 303.6	4600.8/ 418.2	5760.2/ 265.8	4848.2/ 281.3	4891.3/ 364.3	2483.2/ 94.2	4513.9/ 390.5	5839.2/ 498.4
			100	5793.9/ 265.7	4929.0/ 332.9	4002.2/ 382.8	**2341.4/ 139.7**	4016.6/ 365.9	4613.7/ 320.6	6474.3/ 325.2	5788.9/ 386.5	4860.7/ 345.9	2386.0/ 102.3	4444.3/ 421.5	5741.3/ 551.4
3	5	50	25	279.8/ 44.8	222.8/ 43.2	195.6/ 28.0	206.6/ 36.1	205.6/ 30.1	258.5/ 46.1	251.9/ 60.7	187.3/ 41.0	158.9/ 34.9	286.7/ 35.3	**130.0/ 31.2**	225.3/ 65.6
			50	276.9/ 42.0	217.9/ 32.7	178.2/ 22.7	181.8/ 21.7	193.3/ 26.7	238.3/ 33.9	246.8/ 34.3	197.4/ 40.0	148.8/ 46.0	260.0/ 29.8	**122.9/ 25.4**	207.5/ 42.0
			100	252.9/ 43.3	221.2/ 48.2	166.4/ 31.1	139.5/ 38.0	186.6/ 32.4	213.5/ 34.3	198.0/ 48.5	183.5/ 50.1	120.7/ 25.5	222.5/ 26.9	**103.0/ 32.8**	163.0/ 40.6
		150	25	836.0/ 85.0	692.6/ 64.6	588.1/ 70.1	622.5/ 44.0	674.6/ 55.4	809.5/ 68.6	767.4/ 86.6	615.8/ 67.1	549.2/ 81.9	886.2/ 53.4	**475.7/ 54.9**	726.0/ 99.3
			50	864.3/ 75.4	727.6/ 51.0	557.4/ 53.1	561.3/ 41.8	667.4/ 68.2	767.1/ 70.8	789.1/ 68.5	676.9/ 92.5	504.7/ 59.5	847.2/ 36.3	**456.8/ 52.7**	679.9/ 85.9
			100	830.0/ 61.3	783.0/ 62.2	542.2/ 31.1	510.1/ 36.6	617.7/ 27.5	743.6/ 34.2	816.9/ 111.5	780.2/ 115.8	497.6/ 44.4	793.8/ 25.9	**422.4/ 52.4**	639.6/ 75.5
		250	25	1301.8/ 73.1	1086.6/ 63.6	982.3/ 56.3	1019.5/ 83.7	1130.7/ 80.8	1321.0/ 86.7	1186.3/ 78.3	990.8/ 65.7	881.2/ 99.7	1473.0/ 57.8	**830.6/ 87.1**	1226.2/ 136.6
			50	1387.2/ 79.3	1223.0/ 51.2	942.3/ 82.0	974.9/ 70.3	1111.5/ 77.7	1309.0/ 93.0	1282.1/ 97.3	1104.9/ 89.1	865.5/ 101.0	1450.3/ 71.1	**801.8/ 90.8**	1149.3/ 140.5
			100	1388.2/ 97.5	1317.4/ 96.4	908.5/ 90.1	899.2/ 68.3	1067.2/ 74.2	1252.4/ 97.3	1347.0/ 111.9	1276.0/ 132.8	826.8/ 119.1	1378.6/ 67.7	**760.7/ 81.8**	1140.2/ 149.8
	10	50	25	499.7/ 64.8	330.5/ 57.4	315.6/ 46.3	280.6/ 43.0	320.6/ 43.7	362.1/ 59.3	528.9/ 77.1	357.0/ 69.1	339.2/ 71.4	349.9/ 27.5	**273.9/ 45.5**	420.7/ 98.3
			50	493.8/ 85.7	339.1/ 58.6	287.4/ 55.5	256.8/ 35.1	292.8/ 64.4	342.7/ 68.2	580.5/ 106.5	397.8/ 82.9	321.2/ 92.9	317.5/ 22.3	**248.8/ 52.5**	414.2/ 112.6
			100	447.3/ 73.5	366.1/ 59.5	279.7/ 46.5	**200.0/ 46.3**	271.3/ 47.6	320.2/ 52.6	514.5/ 117.0	416.1/ 93.7	300.8/ 53.4	285.9/ 28.9	236.6/ 59.5	355.2/ 89.7
		150	25	1354.9/ 93.3	967.7/ 78.8	934.2/ 84.1	**725.4/ 47.2**	1011.1/ 90.3	1157.7/ 91.2	1458.8/ 148.0	1051.9/ 93.8	1071.1/ 107.6	930.4/ 54.5	967.1/ 90.7	1385.3/ 189.8
			50	1419.0/ 137.3	1072.4/ 128.1	905.3/ 107.9	**679.9/ 59.7**	1006.0/ 114.5	1099.9/ 107.1	1585.3/ 192.1	1244.6/ 157.0	1055.5/ 142.0	880.7/ 54.2	978.3/ 159.0	1308.7/ 178.7

(*continued on next page*)

Table 12 (*continued*)

			100	1419.2/130.6	1225.7/116.4	912.2/98.4	**625.4/48.8**	948.1/107.8	1094.2/117.5	1671.9/194.8	1498.2/166.4	1055.6/115.9	853.2/59.3	839.1/111.1	1256.5/158.7
		250	25	2076.1/120.6	1588.5/106.0	1590.3/133.4	**1133.2/45.1**	1733.4/95.8	1916.1/105.4	2108.4/166.8	1771.8/144.6	1894.6/147.4	1508.6/53.7	1691.5/106.8	2272.4/187.4
			50	2279.6/172.7	1809.1/139.8	1545.9/131.6	**1115.5/66.2**	1704.7/130.6	1899.8/132.8	2478.8/212.8	2079.8/171.1	1828.6/151.8	1492.2/78.1	1666.9/173.5	2252.4/226.7
			100	2416.0/146.1	2090.0/129.4	1556.8/145.1	**1050.5/59.1**	1655.6/122.2	1921.5/131.0	2788.8/220.3	2485.2/213.3	1884.5/161.3	1449.0/63.2	1608.8/164.0	2271.4/219.2
	15	50	25	770.0/130.4	493.1/97.0	474.1/110.6	**356.3/47.4**	493.1/90.1	506.1/86.3	885.9/170.5	609.4/170.7	598.6/158.3	426.0/31.1	505.8/113.4	654.7/172.6
			50	751.5/121.4	511.9/99.4	463.0/94.2	**321.3/34.9**	468.9/87.3	527.4/87.0	925.3/167.0	645.7/133.3	583.8/146.2	418.4/32.7	492.3/113.7	661.8/123.5
			100	713.3/103.0	508.2/86.4	426.8/78.9	**280.1/49.1**	407.8/66.5	485.7/112.6	899.1/148.3	710.0/156.2	498.4/124.9	366.0/32.8	430.6/97.3	625.5/131.4
		150	25	1848.7/164.6	1257.2/150.0	1271.1/142.2	**803.0/53.7**	1300.4/162.0	1461.9/151.8	2099.6/188.1	1602.2/154.4	1675.2/194.0	962.0/56.7	1438.5/216.6	1935.5/250.4
			50	2083.3/153.0	1505.8/135.7	1338.6/138.8	**816.6/68.2**	1414.7/148.6	1568.5/152.0	2478.1/266.5	1933.0/191.1	1787.3/256.7	954.1/53.9	1570.4/202.8	2035.7/234.1
			100	2149.6/129.4	1681.2/136.1	1287.7/110.7	**707.4/53.3**	1396.1/126.7	1531.5/132.0	2618.6/250.1	2266.9/252.7	1760.6/153.4	913.8/40.6	1546.9/212.2	1992.6/205.2
		250	25	2763.7/170.7	2156.2/186.7	2200.4/163.7	**1290.0/114.5**	2308.2/243.9	2561.5/229.8	2968.3/223.8	2660.5/271.7	2983.4/279.8	1582.1/79.0	2554.7/172.7	3370.2/315.0
			50	3248.7/215.3	2403.3/162.9	2207.2/185.7	**1240.4/56.7**	2344.2/162.2	2519.9/215.0	3689.5/226.0	2996.0/236.5	2970.4/355.2	1534.9/56.5	2628.0/273.9	3265.2/295.7
			100	3448.4/262.1	2856.2/271.6	2222.5/231.7	**1152.5/69.3**	2319.8/229.7	2504.3/215.9	4197.9/335.4	3597.6/314.5	2937.7/319.0	1507.7/65.4	2661.2/348.6	3349.0/325.5
4	5	50	25	195.7/32.8	147.0/24.0	125.9/23.0	117.7/19.0	142.3/18.3	170.1/30.4	154.1/31.4	107.8/28.4	83.3/22.1	201.9/19.4	**75.3/14.3**	126.6/28.6
			50	195.8/25.8	156.2/17.5	127.4/20.8	90.8/20.3	141.9/20.9	158.8/21.2	164.0/35.0	130.3/29.1	93.7/29.2	180.1/20.4	**71.8/20.9**	113.9/37.4
			100	148.7/23.6	129.2/23.9	109.0/24.8	55.7/12.6	117.3/21.1	130.9/23.4	109.6/34.8	97.1/36.7	70.0/24.4	139.3/18.4	**52.8/18.5**	83.9/28.6
		150	25	595.5/35.5	471.7/46.6	407.8/46.1	355.0/34.1	475.5/40.5	565.0/42.8	527.0/58.6	397.6/49.3	343.0/50.5	649.4/41.1	**291.3/45.7**	434.7/58.9
			50	612.5/35.0	515.6/34.5	397.8/33.8	329.2/27.9	458.4/37.7	542.2/35.2	523.6/46.6	448.8/60.7	311.8/41.8	616.4/23.3	**270.6/30.8**	450.7/67.3
			100	585.0/54.2	534.5/47.7	371.3/30.1	270.1/24.6	434.4/39.0	510.1/40.2	498.8/61.6	477.8/70.4	302.5/35.8	562.6/22.5	**258.1/38.0**	389.9/57.9
		250	25	973.9/51.4	796.3/57.2	702.5/50.5	594.9/29.2	830.2/53.1	951.3/55.3	809.1/62.3	660.7/49.4	597.5/76.9	1083.6/42.2	**536.1/50.8**	763.7/79.2
			50	968.7/60.0	867.2/75.1	678.3/56.9	562.3/50.6	809.7/47.4	920.1/64.7	852.9/99.0	762.0/71.2	559.6/53.3	1070.8/55.9	**517.5/53.3**	763.7/74.9
			100	981.0/69.3	945.0/73.9	651.7/47.0	482.7/44.1	779.7/55.7	876.0/73.1	891.9/112.3	834.0/85.2	549.5/51.1	1002.6/39.7	**480.0/52.9**	681.2/81.5
	10	50	25	362.6/41.3	246.0/36.0	233.0/36.1	**170.8/29.1**	256.2/39.1	251.3/33.6	352.1/67.9	249.4/67.2	233.2/51.3	267.7/12.2	207.9/37.2	265.9/61.2
			50	339.3/59.5	245.1/53.0	199.6/30.4	**127.1/24.1**	215.0/29.8	238.2/39.6	331.4/69.2	246.5/61.2	203.1/57.2	236.5/20.9	169.2/42.0	247.2/61.2
			100	314.9/64.5	238.3/54.7	208.4/47.7	**105.8/22.5**	202.2/34.6	222.6/41.7	320.8/89.7	241.2/56.2	195.2/48.4	209.5/18.7	145.0/39.1	219.5/53.8
		150	25	962.3/74.5	677.2/75.0	638.2/87.4	**426.8/31.9**	714.9/74.9	774.9/72.3	973.9/78.1	735.9/150.4	717.2/123.5	675.1/42.1	635.8/84.3	839.3/140.0
			50	1016.8/73.7	743.8/63.1	618.0/54.6	**415.1/49.7**	672.5/72.2	741.5/57.6	1136.2/88.1	837.9/99.2	690.3/87.3	647.6/31.4	589.5/74.7	836.2/84.2
			100	991.0/75.8	837.8/63.2	614.9/60.9	**326.8/38.8**	678.4/57.4	707.0/59.2	1111.8/109.1	994.0/117.9	689.3/85.2	602.5/38.2	583.4/87.7	770.7/125.7
		250	25	1510.1/98.9	1112.6/77.9	1073.2/94.2	**718.0/42.8**	1183.8/88.1	1306.9/97.1	1490.4/70.8	1190.5/107.3	1260.6/141.3	1110.6/51.5	1099.2/123.9	1401.0/172.3
			50	1585.9/82.2	1230.3/66.8	1045.4/71.8	**653.0/41.7**	1139.1/62.1	1275.6/90.6	1678.1/127.8	1365.1/115.1	1203.0/79.7	1081.4/35.8	1020.8/79.3	1434.2/127.3
			100	1627.7/101.5	1407.0/114.7	1042.7/89.4	**585.5/32.6**	1160.8/81.9	1270.9/90.4	1840.0/155.4	1621.6/135.4	1185.4/134.3	1039.1/49.2	1021.4/82.6	1393.0/141.6
	15	50	25	529.2/66.8	338.1/64.3	329.0/63.4	**211.6/33.4**	325.0/67.8	360.7/61.4	570.0/114.0	405.5/95.7	379.4/98.7	339.5/27.1	316.5/79.0	434.2/118.7
			50	508.0/73.6	332.6/50.7	293.5/52.4	**197.0/29.6**	304.4/59.1	337.5/60.9	631.7/154.7	398.9/95.0	364.7/89.6	315.7/29.7	296.4/84.1	401.7/101.0
			100	471.4/59.9	341.9/67.8	290.0/60.2	**131.9/22.9**	280.6/43.7	304.1/48.5	595.3/120.6	417.6/119.8	337.2/75.5	280.1/27.9	248.2/55.6	342.9/78.6
		150	25	1348.9/119.8	924.3/98.1	911.1/97.3	**516.8/44.9**	953.9/109.9	1051.1/102.1	1526.2/172.6	1153.0/157.8	1218.7/194.9	732.9/31.8	1058.8/151.3	1371.0/181.7
			50	1442.7/72.3	1006.7/92.4	904.5/74.4	**474.9/52.5**	912.5/84.4	999.3/119.9	1723.4/120.9	1347.1/139.1	1200.7/122.7	700.0/23.2	1011.7/120.2	1293.8/226.3
			100	1466.9/90.8	1137.5/101.4	890.9/98.5	**416.2/44.6**	917.4/77.6	993.3/88.9	1832.5/176.8	1535.6/181.7	1203.7/188.6	660.2/27.8	992.9/134.2	1328.5/152.6
		250	25	2038.1/92.9	1505.6/100.2	1510.0/120.0	**785.6/31.1**	1618.0/112.0	1700.5/92.8	2151.0/126.4	1877.5/118.3	2057.2/163.2	1158.8/32.0	1810.4/167.3	2206.7/186.9

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Table 12 (*continued*)

			50	2262.3/ 135.9	1632.4/ 143.3	1474.8/ 149.9	**753.7/ 53.5**	1547.6/ 113.3	1688.7/ 128.0	2619.9/ 241.2	2108.3/ 184.6	2063.5/ 244.3	1121.7/ 49.9	1774.7/ 161.1	2275.1/ 223.8
			100	2369.4/ 161.9	1868.3/ 116.2	1470.4/ 106.4	**690.9/ 41.8**	1569.3/ 96.0	1690.2/ 89.7	3001.1/ 244.7	2487.1/ 230.3	2019.4/ 148.2	1088.8/ 36.9	1759.9/ 125.5	2183.5/ 180.8

Table 13
Mean values and standard deviations of mean tardiness attained by twelve new PDRs (*DDT* = 1.0).

f	mq	n_{new}	Î»$_{job}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
2	5	50	25	448.8/ 82.1	309.3/ 44.2	297.0/ 60.6	376.0/ 61.0	318.8/ 64.3	410.8/ 81.9	433.4/ 83.5	268.6/ 65.3	275.8/ 77.8	421.5/ 55.7	**259.4/ 62.6**	370.3/ 109.9
			50	441.5/ 55.1	326.1/ 56.1	259.4/ 50.5	342.5/ 51.4	282.0/ 48.3	391.3/ 66.9	453.6/ 100.7	289.5/ 70.0	246.8/ 54.3	387.9/ 50.2	**209.5/ 47.7**	375.2/ 81.5
			100	395.1/ 61.5	315.3/ 59.1	243.9/ 49.4	283.4/ 40.5	268.7/ 43.6	344.4/ 66.2	380.3/ 66.0	316.8/ 76.5	220.2/ 48.0	329.2/ 32.6	**190.5/ 43.4**	323.5/ 58.8
		150	25	1265.6/ 92.0	947.2/ 87.1	909.4/ 88.0	1189.0/ 89.0	1019.4/ 103.8	1256.8/ 91.0	1220.4/ 114.5	902.3/ 94.5	870.0/ 78.6	1329.9/ 62.8	**849.3/ 84.1**	1276.4/ 137.1
			50	1356.7/ 131.5	1070.0/ 104.0	930.9/ 91.2	1161.4/ 86.1	1031.2/ 88.9	1258.5/ 87.8	1353.2/ 122.6	1036.6/ 137.7	878.1/ 86.5	1300.4/ 85.6	**824.9/ 79.7**	1238.4/ 166.6
			100	1334.3/ 124.2	1134.0/ 142.2	854.2/ 100.4	1073.7/ 108.7	973.5/ 107.0	1202.1/ 121.1	1374.8/ 194.6	1061.7/ 137.1	824.5/ 128.8	1255.3/ 94.1	**785.3/ 108.6**	1195.6/ 158.3
		250	25	2039.5/ 120.1	1582.9/ 107.6	1581.6/ 131.9	2066.5/ 171.5	1790.5/ 141.2	2218.4/ 159.8	1947.3/ 75.0	1512.3/ 125.7	1571.1/ 130.3	2301.3/ 126.4	**1504.6/ 144.5**	2146.2/ 182.4
			50	2222.8/ 155.8	1736.4/ 136.2	1537.5/ 155.6	1974.7/ 111.9	1719.6/ 159.5	2198.5/ 204.3	2215.9/ 194.6	1685.5/ 193.1	1495.5/ 159.7	2226.6/ 114.1	**1451.3/ 170.5**	2155.9/ 212.8
			100	2314.1/ 128.6	2035.5/ 182.2	1529.3/ 126.5	1922.6/ 131.8	1760.5/ 154.1	2150.5/ 139.7	2313.3/ 177.0	2003.0/ 129.7	1512.4/ 149.8	2206.5/ 94.5	**1496.8/ 152.5**	2097.5/ 193.3
	10	50	25	816.5/ 103.5	504.3/ 101.2	489.5/ 103.6	444.2/ 60.9	518.6/ 85.2	595.1/ 119.2	839.0/ 113.5	537.2/ 98.2	544.3/ 104.2	**437.2/ 32.9**	495.6/ 99.6	674.6/ 99.8
			50	786.4/ 95.3	510.8/ 74.2	502.3/ 89.9	**412.9/ 49.8**	515.7/ 89.2	612.7/ 113.3	842.8/ 138.1	596.5/ 123.1	577.7/ 97.4	440.4/ 38.5	472.9/ 86.7	714.1/ 131.2
			100	798.3/ 134.2	583.8/ 100.9	461.6/ 72.3	**342.4/ 51.6**	466.4/ 83.2	558.2/ 121.5	905.2/ 137.9	642.7/ 107.5	510.2/ 101.1	383.1/ 48.6	433.1/ 100.8	652.1/ 150.2
		150	25	2083.6/ 146.2	1518.0/ 128.1	1506.6/ 173.1	**1313.9/ 115.1**	1665.9/ 160.9	1925.8/ 210.6	2185.6/ 140.5	1654.1/ 150.5	1704.9/ 201.3	1349.8/ 70.1	1665.9/ 152.4	2257.0/ 315.6
			50	2311.0/ 266.6	1632.0/ 189.4	1467.3/ 192.0	**1258.2/ 113.8**	1550.8/ 220.2	1839.5/ 187.0	2458.6/ 267.0	1784.1/ 193.7	1707.7/ 235.1	1293.2/ 87.4	1556.3/ 194.3	2112.2/ 256.7
			100	2442.3/ 187.1	1831.0/ 147.4	1536.6/ 145.1	**1222.4/ 98.8**	1597.9/ 166.0	1897.0/ 199.2	2699.3/ 182.4	2000.5/ 218.4	1725.7/ 169.8	1293.6/ 89.2	1560.5/ 175.5	2188.0/ 277.6
		250	25	3156.5/ 159.6	2568.4/ 244.7	2733.2/ 238.2	**2140.3/ 91.2**	2813.0/ 221.8	3347.9/ 297.9	3269.5/ 200.3	2777.5/ 228.5	3146.0/ 279.9	2318.7/ 82.3	2826.6/ 231.8	3881.7/ 393.8
			50	3617.1/ 176.2	2802.7/ 246.5	2743.0/ 232.5	**2168.2/ 106.5**	2834.3/ 210.5	3317.6/ 200.5	3872.4/ 268.7	3058.2/ 235.6	3047.5/ 271.8	2315.2/ 99.7	2834.8/ 228.3	3904.9/ 321.7
			100	3912.5/ 167.5	3046.9/ 175.8	2523.5/ 151.8	**2050.8/ 92.0**	2716.4/ 265.4	3139.0/ 145.2	4284.0/ 262.0	3385.8/ 263.5	2893.6/ 197.7	2207.2/ 83.4	2707.4/ 215.3	3628.7/ 285.6
	15	50	25	1157.1/ 167.5	733.4/ 146.6	758.6/ 180.0	487.0/ 77.5	750.1/ 165.0	814.0/ 134.8	1358.5/ 206.2	867.8/ 162.6	883.1/ 199.6	**479.0/ 44.4**	784.3/ 177.8	1040.4/ 163.7
			50	1234.0/ 223.2	736.2/ 198.1	695.0/ 160.5	493.2/ 80.1	701.7/ 98.1	865.5/ 206.2	1425.6/ 283.9	918.5/ 223.5	871.9/ 198.9	**472.2/ 49.4**	769.2/ 125.4	1036.6/ 254.2
			100	1244.1/ 229.6	732.3/ 127.7	675.2/ 98.7	441.5/ 65.0	711.2/ 100.6	836.8/ 198.7	1437.5/ 227.7	864.1/ 185.1	812.5/ 173.5	**437.4/ 46.8**	719.3/ 129.5	1024.6/ 246.5
		150	25	2863.8/ 224.7	2257.7/ 218.6	2311.9/ 208.7	1424.1/ 96.4	2409.2/ 329.3	2721.1/ 284.3	3099.2/ 257.0	2648.9/ 232.9	2814.9/ 250.7	**1402.9/ 70.4**	2600.2/ 377.4	3361.0/ 360.8
			50	3324.0/ 288.3	2308.7/ 300.6	2234.8/ 270.4	1396.9/ 105.7	2281.3/ 279.3	2696.5/ 330.4	3793.5/ 380.6	2736.0/ 318.4	2769.5/ 371.8	**1365.5/ 79.2**	2503.9/ 307.9	3425.6/ 418.9
			100	3594.7/ 245.3	2627.8/ 188.8	2217.0/ 189.9	**1336.9/ 93.2**	2310.5/ 168.8	2648.8/ 270.1	4074.0/ 295.7	3043.2/ 241.3	2749.1/ 277.5	1337.1/ 68.3	2582.9/ 242.0	3382.2/ 340.3
		250	25	4289.2/ 276.3	3706.3/ 353.2	3915.0/ 411.3	**2283.6/ 109.7**	3953.0/ 321.2	4462.6/ 456.9	4536.0/ 228.0	4340.6/ 381.6	4803.4/ 461.5	2313.6/ 108.4	4430.9/ 334.8	5742.6/ 525.9
			50	5111.5/ 342.8	3902.5/ 279.9	3891.4/ 296.7	**2250.1/ 102.8**	3975.0/ 315.6	4609.6/ 341.1	5614.9/ 394.6	4700.1/ 388.7	4843.3/ 421.6	2332.8/ 76.6	4360.7/ 373.0	5855.5/ 431.0
			100	5811.2/ 379.0	4325.8/ 351.6	3919.2/ 353.4	**2214.5/ 117.2**	3977.4/ 367.9	4509.0/ 330.9	6524.3/ 405.7	5143.3/ 509.4	4808.2/ 458.6	2290.4/ 127.9	4429.6/ 346.2	5510.9/ 469.0
3	5	50	25	262.2/ 37.7	186.7/ 27.0	166.2/ 26.2	154.5/ 26.9	195.2/ 32.9	215.5/ 33.1	228.3/ 34.5	149.3/ 40.7	139.1/ 32.4	242.2/ 31.5	**114.3/ 36.0**	194.6/ 68.1
			50	225.0/ 35.7	154.9/ 22.8	144.7/ 27.5	125.8/ 24.2	160.8/ 25.5	206.4/ 31.7	200.5/ 58.3	125.8/ 34.9	119.6/ 42.4	213.7/ 18.1	**81.6/ 23.6**	145.8/ 35.1
			100	188.0/ 46.8	147.4/ 41.0	121.3/ 25.2	96.1/ 22.0	131.8/ 30.3	185.2/ 35.6	162.7/ 47.6	134.2/ 49.8	83.0/ 23.7	179.9/ 28.0	**74.8/ 31.2**	157.2/ 35.4
		150	25	807.2/ 64.8	577.3/ 52.3	551.5/ 63.7	573.3/ 64.8	620.4/ 69.9	753.5/ 73.2	736.8/ 77.8	529.0/ 61.1	498.3/ 71.9	830.4/ 50.9	**449.5/ 76.2**	631.4/ 86.2
			50	833.3/ 66.0	619.2/ 52.8	529.5/ 53.2	515.0/ 32.2	640.7/ 48.3	737.4/ 58.1	773.6/ 72.5	585.1/ 64.5	497.6/ 56.7	813.5/ 35.5	**446.4/ 55.5**	664.6/ 86.7
			100	791.4/ 64.3	647.4/ 83.5	498.0/ 55.5	462.0/ 62.5	565.0/ 66.0	689.6/ 62.2	731.5/ 104.7	631.6/ 117.9	432.2/ 90.9	734.4/ 46.8	**371.2/ 75.8**	611.6/ 102.5
		250	25	1283.8/ 91.4	985.1/ 70.3	955.2/ 77.5	959.9/ 65.7	1097.4/ 72.5	1266.9/ 67.1	1128.9/ 74.1	896.6/ 60.0	866.4/ 84.2	1429.8/ 50.4	**797.7/ 80.8**	1162.2/ 107.3

(*continued on next page*)

Table 13 (*continued*)

			50	1345.6/90.3	1052.8/72.9	896.0/74.4	935.0/58.5	1066.1/73.9	1262.7/68.5	1245.8/103.1	980.9/86.7	836.2/78.6	1407.7/50.2	**778.4/81.2**	1136.7/115.0
			100	1406.4/97.3	1177.5/101.1	916.4/74.4	863.4/77.5	1048.3/91.0	1247.7/86.8	1350.9/136.6	1115.6/99.5	816.1/100.9	1361.4/56.7	**748.1/66.5**	1125.9/110.7
	10	50	25	422.4/83.7	243.2/54.7	243.2/56.8	**189.4/40.6**	242.0/49.3	296.1/63.8	491.8/130.7	274.5/67.2	275.0/77.2	251.4/23.0	212.1/43.4	345.2/99.2
			50	464.0/79.7	274.8/64.0	250.1/57.5	**148.7/42.5**	251.1/44.0	288.3/62.4	512.3/88.3	310.1/76.4	267.1/69.3	238.9/26.5	204.0/44.4	340.8/88.4
			100	430.8/83.2	262.1/49.5	233.3/45.9	**119.0/33.9**	221.2/36.9	270.1/48.6	500.9/96.1	324.7/86.1	267.8/59.0	201.0/25.9	198.4/55.3	306.0/79.6
		150	25	1239.0/99.0	881.0/72.1	871.1/56.1	**604.1/44.8**	939.6/77.0	1062.6/128.0	1299.7/120.7	989.3/100.8	1007.0/129.7	837.5/40.5	863.1/108.6	1276.8/146.6
			50	1315.2/121.2	869.0/94.6	829.0/104.2	**572.5/57.7**	918.1/101.4	1031.1/109.6	1473.9/141.0	1056.2/141.7	973.5/144.5	797.2/48.9	859.8/149.2	1209.6/146.0
			100	1425.5/103.7	1018.1/107.0	821.8/99.9	**507.7/51.1**	878.5/88.5	1006.7/95.9	1620.9/137.1	1174.6/133.1	996.3/137.0	751.2/50.6	797.0/115.7	1187.8/174.4
		250	25	1945.1/124.1	1400.0/129.3	1433.4/138.9	**1015.1/62.1**	1566.7/131.2	1791.4/159.6	1998.6/149.7	1610.3/166.0	1700.9/199.2	1404.6/62.1	1533.0/193.8	2071.5/248.6
			50	2222.0/152.1	1570.0/108.4	1482.3/105.7	**1017.6/41.5**	1618.8/125.4	1849.6/122.1	2382.7/195.1	1789.3/154.2	1776.5/169.2	1405.4/52.4	1636.9/167.9	2211.3/251.9
			100	2308.3/118.7	1758.6/135.1	1466.6/132.8	**948.9/79.0**	1572.5/119.1	1827.4/205.5	2615.0/198.8	2071.2/240.2	1784.8/164.1	1359.3/72.7	1555.1/198.6	2104.8/252.8
	15	50	25	694.1/141.7	362.9/101.3	367.3/80.5	**219.7/35.0**	360.4/86.8	443.7/100.0	778.3/178.4	493.2/92.1	478.5/97.1	300.1/24.3	376.7/97.6	551.7/137.7
			50	641.1/99.1	347.6/79.4	344.6/62.5	**191.5/55.3**	323.7/75.4	395.3/90.3	790.4/149.2	454.1/121.7	433.2/133.1	279.3/35.7	347.2/80.5	513.9/147.5
			100	638.3/163.0	369.1/104.3	335.6/92.2	**152.0/25.7**	336.8/89.9	380.8/91.0	843.9/161.7	493.3/153.9	446.4/140.9	237.7/25.0	373.3/109.6	509.2/166.2
		150	25	1794.4/147.1	1222.7/115.2	1240.7/119.5	**673.1/68.0**	1259.9/131.6	1394.0/168.0	1986.4/136.4	1583.5/191.9	1674.1/211.3	862.7/46.8	1441.8/168.1	1939.6/254.8
			50	1968.6/141.6	1293.9/114.1	1227.7/122.2	**664.1/56.4**	1266.2/122.9	1437.6/119.8	2390.3/219.0	1691.4/139.7	1631.4/148.4	828.0/38.1	1434.4/161.3	1948.5/199.1
			100	2149.5/225.4	1455.7/130.5	1280.0/151.1	**583.4/67.1**	1309.1/116.5	1450.4/142.1	2616.5/221.8	1953.0/184.5	1732.5/213.0	805.9/42.9	1531.1/148.0	1995.1/178.6
		250	25	2704.1/156.3	2048.1/168.2	2087.8/185.7	**1093.2/107.0**	2160.4/144.3	2458.5/182.4	2878.2/211.1	2642.2/250.5	2910.5/312.4	1420.8/72.8	2497.5/243.4	3230.7/345.0
			50	3145.9/226.6	2133.3/203.7	2078.1/186.6	**1107.1/71.7**	2249.8/159.8	2457.9/205.4	3631.9/233.8	2835.4/329.9	2967.3/320.5	1427.0/72.4	2518.2/230.9	3340.5/299.3
			100	3335.4/266.1	2376.7/204.9	2110.1/194.0	**1019.2/82.9**	2198.8/148.6	2459.5/191.9	4074.1/386.4	3087.2/311.4	2893.7/307.1	1401.1/84.9	2539.8/244.9	3294.6/288.3
4	5	50	25	167.8/22.4	112.4/25.1	109.0/22.8	66.7/14.4	114.6/19.6	137.1/19.5	125.9/39.4	73.3/21.8	72.5/23.7	157.8/17.3	**51.5/15.0**	101.7/24.8
			50	158.6/39.7	100.1/27.2	87.9/16.6	52.1/15.3	106.2/32.7	128.4/29.4	105.4/46.0	66.8/32.5	64.8/32.3	137.6/23.1	**45.9/21.0**	97.8/35.7
			100	109.7/27.1	80.1/26.4	75.8/20.4	34.2/10.0	81.4/20.4	99.9/21.0	78.1/38.4	48.9/19.0	51.5/23.1	102.5/17.9	**31.1/11.7**	63.8/25.6
		150	25	561.5/35.5	403.6/26.8	367.4/31.1	306.1/33.2	439.5/33.7	515.3/36.4	457.7/57.7	316.2/41.8	313.9/43.7	587.5/21.3	**262.7/42.9**	404.3/56.5
			50	577.9/60.4	419.6/47.8	354.5/35.1	268.9/25.9	415.1/42.1	485.8/35.0	468.0/62.3	341.6/41.2	284.8/51.9	565.1/25.9	**232.8/37.0**	367.4/37.3
			100	552.6/46.7	436.1/48.4	332.0/34.2	**210.5/24.8**	404.8/56.8	471.5/35.5	480.7/63.5	400.9/67.2	267.8/51.7	524.8/36.9	225.6/38.5	350.3/41.5
		250	25	937.0/73.7	669.6/47.6	643.0/46.3	531.5/35.3	776.3/58.2	883.1/75.5	750.5/72.2	543.7/68.6	543.6/79.3	1033.7/37.2	**473.0/52.4**	722.4/84.1
			50	949.3/56.7	743.7/52.6	631.5/54.4	497.7/34.1	747.7/49.1	890.2/51.2	801.8/60.7	648.7/58.5	537.7/73.9	1010.7/44.2	**491.1/49.8**	731.9/71.7
			100	935.7/47.2	792.1/58.9	611.0/39.3	442.6/39.4	726.7/56.2	823.5/60.9	834.7/73.7	715.3/103.6	491.5/62.3	940.9/38.9	**425.5/61.4**	642.3/77.2
	10	50	25	292.2/54.9	157.1/32.3	165.8/32.4	**80.0/16.5**	162.8/25.3	194.9/49.6	298.8/41.7	175.6/51.6	159.5/48.2	175.4/16.4	114.8/31.7	196.0/75.4
			50	266.9/43.5	146.0/26.9	134.4/22.4	**66.6/15.9**	142.9/32.0	153.7/32.2	311.6/95.8	155.0/37.2	129.3/40.4	155.4/18.7	93.6/28.5	161.3/54.0
			100	250.5/72.0	160.4/37.7	153.6/30.0	**47.5/9.2**	150.3/38.3	171.5/37.3	267.7/82.2	177.5/51.3	143.0/33.4	134.9/12.3	93.6/27.4	174.8/64.3
		150	25	885.4/68.0	551.6/40.4	548.6/42.4	**332.4/38.6**	629.0/63.2	690.3/54.4	892.4/94.6	612.9/63.1	643.7/56.8	582.0/35.2	550.0/64.4	735.6/88.3
			50	930.0/92.4	592.9/62.1	554.5/63.1	**296.7/32.8**	597.3/61.3	693.3/56.1	1044.0/121.8	671.8/85.8	642.8/110.6	552.0/26.9	529.4/127.5	735.5/78.1
			100	914.1/71.3	657.9/75.7	546.7/59.3	**249.7/35.6**	585.2/52.8	655.8/70.6	1037.4/129.1	771.7/106.3	615.6/119.5	518.1/30.3	514.6/86.7	676.7/110.1
		250	25	1406.3/66.9	983.8/67.7	985.0/86.3	**591.4/41.9**	1130.5/86.3	1232.6/94.1	1395.2/137.3	1125.9/116.7	1190.1/120.6	1016.2/49.1	1038.0/132.5	1343.9/133.5
			50	1545.5/102.9	1064.3/108.4	992.9/95.8	**553.4/55.4**	1085.9/100.8	1205.8/101.0	1657.8/153.3	1219.6/131.7	1175.4/163.6	999.2/48.0	990.4/93.1	1374.2/155.3
			100	1599.3/79.5	1235.4/95.4	1033.3/95.3	**493.0/45.7**	1116.6/96.9	1228.2/97.2	1877.0/126.3	1423.3/110.1	1235.5/122.4	953.2/38.4	992.3/76.4	1380.1/150.5

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Table 13 (*continued*)

	15	50	25	422.2/ 95.6	218.3/ 57.3	212.0/ 41.5	**110.1/ 19.7**	214.6/ 42.2	259.7/ 63.1	503.2/ 127.9	273.7/ 102.5	283.0/ 88.6	214.1/ 20.6	190.0/ 69.8	345.4/ 103.3
			50	432.8/ 80.4	221.5/ 54.7	210.6/ 48.7	**91.2/ 19.8**	205.0/ 53.3	240.9/ 39.2	545.8/ 138.1	288.8/ 74.4	294.5/ 72.7	208.9/ 21.8	212.7/ 80.4	325.9/ 85.4
			100	399.5/ 80.9	223.2/ 66.5	215.1/ 53.2	**62.2/ 20.9**	171.0/ 52.3	221.3/ 52.8	513.0/ 129.3	325.4/ 99.2	279.1/ 88.8	163.5/ 25.4	170.8/ 55.2	288.6/ 87.6
		150	25	1273.4/ 112.5	827.1/ 114.8	812.8/ 111.0	**363.0/ 47.9**	860.3/ 118.6	947.2/ 116.6	1442.8/ 155.9	1103.7/ 152.0	1127.3/ 185.1	598.6/ 31.1	975.6/ 191.2	1284.6/ 224.8
			50	1325.6/ 123.3	808.1/ 93.2	779.0/ 87.1	**320.2/ 28.9**	819.3/ 102.4	888.0/ 70.5	1618.9/ 156.8	1059.6/ 138.7	1088.7/ 212.5	572.8/ 34.8	905.3/ 150.6	1170.8/ 133.1
			100	1377.3/ 133.0	855.4/ 98.5	774.9/ 78.6	**282.0/ 36.3**	825.5/ 104.4	894.5/ 100.5	1763.7/ 173.3	1210.0/ 191.5	1100.7/ 151.9	526.7/ 25.5	897.8/ 140.3	1258.7/ 166.8
		250	25	1959.3/ 99.2	1425.2/ 105.4	1417.6/ 108.4	**636.5/ 42.6**	1520.5/ 97.8	1629.3/ 124.9	2121.1/ 102.1	1875.5/ 183.0	2014.2/ 160.8	1035.3/ 46.2	1732.3/ 161.3	2197.3/ 176.5
			50	2204.6/ 94.3	1416.7/ 110.2	1383.2/ 100.5	**594.8/ 39.6**	1486.6/ 121.8	1622.8/ 96.0	2594.5/ 204.0	1862.5/ 167.1	1941.8/ 222.5	1005.6/ 44.5	1712.1/ 196.4	2214.8/ 241.5
			100	2316.1/ 130.4	1551.9/ 119.2	1365.4/ 116.4	**527.7/ 37.5**	1439.6/ 99.5	1576.2/ 150.5	2924.9/ 333.9	2125.5/ 201.7	1882.9/ 183.1	937.8/ 43.6	1575.9/ 141.2	2104.6/ 218.5

Table 14
Mean values and standard deviations of mean tardiness attained by twelve new PDRs ($DDT = 1.5$).

f	mq	n_{new}	Î»$_{job}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
2	5	50	25	435.8/ 68.8	267.3/ 41.2	271.6/ 48.2	331.8/ 49.0	315.9/ 52.0	367.7/ 48.2	421.8/ 94.8	227.6/ 37.1	233.6/ 45.2	360.7/ 36.8	**217.0/ 41.5**	362.8/ 63.2
			50	438.1/ 72.6	282.9/ 59.0	255.5/ 52.6	287.5/ 46.2	267.3/ 33.7	354.1/ 67.9	376.1/ 56.0	244.5/ 58.0	230.9/ 55.8	333.8/ 33.4	**195.8/ 48.2**	354.7/ 71.3
			100	346.2/ 80.3	251.3/ 70.3	211.2/ 52.4	232.2/ 36.9	213.0/ 41.0	309.2/ 59.8	320.9/ 88.8	229.3/ 63.5	192.5/ 62.9	286.1/ 40.5	**151.5/ 38.1**	302.5/ 75.3
		150	25	1215.4/ 63.3	866.7/ 61.5	865.0/ 65.4	1112.4/ 76.1	976.5/ 71.8	1234.4/ 90.0	1188.1/ 101.4	838.2/ 87.0	858.6/ 74.5	1262.8/ 41.8	**770.6/ 100.0**	1228.8/ 133.2
			50	1300.5/ 113.4	952.5/ 101.1	876.4/ 109.5	1095.3/ 104.6	984.8/ 114.6	1241.9/ 138.3	1307.1/ 145.9	944.1/ 125.3	854.4/ 122.9	1250.9/ 100.8	**829.0/ 85.5**	1198.3/ 142.1
			100	1365.3/ 125.3	1033.4/ 113.3	847.7/ 94.2	1025.2/ 86.1	947.2/ 100.4	1203.3/ 108.9	1330.5/ 127.6	1063.7/ 138.7	829.7/ 104.2	1201.0/ 67.0	**788.8/ 80.9**	1189.4/ 135.5
		250	25	1953.4/ 111.7	1499.7/ 121.9	1507.2/ 130.6	1926.5/ 106.7	1672.4/ 121.2	2130.9/ 138.2	1894.1/ 165.6	**1427.9/ 127.3**	1448.5/ 150.7	2190.7/ 88.1	1430.1/ 108.1	2099.4/ 128.3
			50	2120.9/ 118.4	1599.9/ 112.5	1515.8/ 127.5	1884.9/ 104.1	1644.3/ 123.7	2078.3/ 139.6	2068.5/ 132.1	1526.9/ 118.7	1467.8/ 126.7	2161.4/ 95.7	**1398.8/ 125.8**	2097.0/ 220.8
			100	2203.9/ 156.8	1801.3/ 150.5	1440.4/ 124.8	1865.2/ 132.0	1666.5/ 103.0	2096.1/ 146.1	2207.0/ 182.9	1768.2/ 132.4	1439.3/ 125.6	2127.4/ 86.1	**1363.6/ 119.6**	2090.2/ 209.8
	10	50	25	749.4/ 117.0	423.8/ 95.7	419.7/ 89.1	**341.8/ 51.4**	427.4/ 86.4	527.2/ 141.2	794.1/ 136.2	456.4/ 111.9	464.9/ 90.5	368.1/ 45.9	448.6/ 96.6	596.7/ 137.1
			50	725.3/ 104.8	411.7/ 75.4	404.7/ 89.1	**311.1/ 53.6**	425.1/ 73.6	518.2/ 84.3	829.2/ 148.6	464.1/ 107.8	437.8/ 113.5	320.8/ 40.1	414.8/ 99.3	606.7/ 114.2
			100	639.0/ 118.7	423.1/ 108.6	369.0/ 99.5	**263.5/ 49.7**	364.6/ 75.7	458.8/ 105.6	713.8/ 184.2	465.8/ 110.8	393.7/ 95.7	301.1/ 41.4	339.2/ 84.1	525.2/ 121.9
		150	25	2021.6/ 161.7	1488.1/ 166.8	1516.3/ 179.2	**1227.5/ 116.1**	1591.2/ 122.4	1851.7/ 195.3	2117.9/ 171.7	1680.6/ 174.2	1720.4/ 156.0	1298.6/ 83.6	1631.8/ 181.1	2146.3/ 230.9
			50	2234.4/ 194.4	1530.4/ 170.7	1515.7/ 201.5	**1203.7/ 102.1**	1545.9/ 171.6	1847.5/ 219.0	2418.3/ 198.5	1671.6/ 217.2	1685.3/ 233.2	1273.3/ 79.4	1595.1/ 171.9	2186.6/ 298.9
			100	2378.2/ 199.0	1660.8/ 169.7	1441.4/ 147.6	**1083.9/ 67.9**	1526.1/ 117.6	1865.8/ 195.6	2559.1/ 226.4	1864.6/ 170.9	1631.4/ 133.6	1193.0/ 71.7	1516.1/ 138.9	2138.4/ 236.5
		250	25	3044.5/ 148.9	2522.3/ 179.5	2607.1/ 226.2	**2026.8/ 131.7**	2730.4/ 179.0	3178.3/ 203.4	3132.6/ 243.8	2734.3/ 206.3	3007.4/ 229.9	2184.2/ 87.0	2750.1/ 187.6	3652.2/ 288.9
			50	3548.3/ 190.1	2593.3/ 167.0	2615.4/ 139.1	**2009.7/ 97.8**	2788.3/ 239.9	3267.9/ 262.1	3769.8/ 278.3	2922.4/ 161.2	3026.6/ 212.3	2233.9/ 81.2	2844.3/ 225.7	3733.0/ 444.7
			100	3868.6/ 178.8	2862.6/ 234.9	2641.8/ 177.2	**1969.0/ 118.9**	2756.7/ 148.5	3235.2/ 206.5	4247.2/ 231.7	3257.0/ 287.0	3003.6/ 262.7	2172.7/ 107.4	2832.4/ 228.3	3730.5/ 239.4
	15	50	25	1054.1/ 175.2	639.3/ 155.9	649.8/ 176.5	393.0/ 74.9	659.8/ 170.9	783.1/ 197.7	1162.5/ 177.6	786.5/ 160.9	782.6/ 209.2	**370.4/ 50.5**	678.8/ 171.8	964.1/ 192.8
			50	1098.0/ 191.5	592.6/ 143.6	615.4/ 155.2	**334.1/ 55.6**	605.7/ 169.9	748.8/ 232.5	1274.1/ 201.6	760.3/ 155.1	719.3/ 156.7	341.9/ 38.2	684.8/ 167.3	939.1/ 224.0
			100	1145.8/ 216.7	670.5/ 182.8	635.0/ 138.1	**285.9/ 58.6**	600.9/ 116.4	728.2/ 193.4	1344.8/ 250.1	818.3/ 174.2	766.7/ 154.0	311.8/ 33.8	636.9/ 139.2	968.4/ 266.6
		150	25	2849.5/ 250.1	2150.8/ 291.2	2215.8/ 288.0	**1271.1/ 104.6**	2217.1/ 232.7	2604.9/ 324.0	3072.8/ 272.6	2605.9/ 359.8	2746.2/ 419.0	1296.3/ 83.1	2488.5/ 306.4	3295.3/ 392.3
			50	3310.0/ 227.8	2184.3/ 224.8	2164.6/ 175.8	**1244.0/ 78.5**	2252.3/ 258.2	2577.3/ 266.4	3761.7/ 311.1	2617.5/ 269.6	2646.6/ 312.4	1268.9/ 67.7	2491.5/ 297.0	3262.8/ 256.9
			100	3571.0/ 356.9	2394.2/ 255.0	2275.0/ 247.5	**1192.8/ 111.1**	2301.1/ 211.6	2628.9/ 317.9	4087.9/ 440.5	2903.5/ 290.7	2790.9/ 295.8	1222.6/ 83.2	2535.3/ 233.8	3430.6/ 373.8
		250	25	4185.3/ 208.8	3579.5/ 289.4	3728.1/ 365.2	**2125.6/ 99.4**	3867.3/ 420.0	4463.5/ 393.8	4369.6/ 244.4	4291.8/ 375.8	4651.0/ 449.4	2209.9/ 106.5	4229.8/ 471.0	5601.2/ 493.3
			50	5005.8/ 326.7	3678.3/ 227.7	3758.0/ 255.4	**2089.4/ 90.0**	3806.3/ 301.3	4425.3/ 319.9	5417.2/ 409.6	4407.1/ 357.3	4689.3/ 404.7	2155.6/ 67.7	4328.0/ 373.4	5551.7/ 370.7

(*continued on next page*)

Table 14 (*continued*)

f	mq	n_{new}	Î»$_{job}$	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
			100	5469.0/317.1	3793.0/393.9	3638.4/407.9	**2023.5/134.8**	3753.0/379.7	4289.7/373.1	6228.4/435.7	4568.3/474.1	4511.4/506.8	2122.9/127.3	4167.1/376.1	5356.6/552.0
3	5	50	25	226.6/39.8	122.3/30.0	114.7/27.8	98.3/26.8	134.0/28.2	182.8/43.7	186.2/55.2	107.0/33.7	100.3/46.4	190.7/28.9	**78.7/29.1**	146.3/44.6
			50	199.5/44.7	121.1/35.5	111.6/28.0	77.3/16.7	131.5/23.3	160.2/46.1	174.0/55.7	89.6/30.8	85.9/33.5	162.9/15.9	**74.6/23.0**	122.6/39.6
			100	159.7/48.3	100.2/41.7	102.4/28.2	66.8/19.9	116.7/29.4	141.4/32.1	152.8/70.2	87.9/31.7	82.4/26.9	135.4/23.6	**62.8/26.2**	117.6/39.2
		150	25	771.3/53.9	533.8/50.4	533.1/50.4	519.7/48.7	621.5/54.4	748.9/66.3	731.5/64.6	501.3/68.8	500.4/63.0	813.3/41.2	**427.3/67.1**	678.2/99.6
			50	790.9/70.7	565.9/56.9	509.5/45.5	461.4/38.9	593.0/50.9	691.4/50.9	752.8/79.7	494.3/55.2	453.1/59.1	760.5/42.1	**413.4/80.1**	611.5/81.9
			100	763.2/84.3	578.0/49.3	464.5/36.6	392.8/43.4	559.3/50.0	653.3/68.0	712.0/74.1	539.8/56.9	418.3/44.5	704.9/38.4	**355.6/51.8**	577.9/82.7
		250	25	1247.3/89.2	905.4/84.6	890.0/76.3	872.0/66.1	1065.4/65.6	1230.8/75.1	1127.8/89.8	787.5/110.2	796.6/81.7	1377.2/76.2	**748.8/74.5**	1133.3/118.0
			50	1334.5/87.6	974.9/65.4	878.3/62.0	852.3/55.9	1047.7/58.0	1219.0/86.3	1211.3/107.0	884.5/91.4	796.8/80.3	1350.5/57.6	**720.4/81.9**	1106.8/74.2
			100	1351.2/107.5	1060.8/91.4	862.5/58.3	801.1/60.5	1005.9/57.7	1208.7/69.6	1351.2/103.3	990.2/107.9	752.4/79.9	1299.6/41.4	**715.1/75.1**	1052.2/85.4
	10	50	25	372.9/85.1	183.1/40.5	191.6/47.4	**109.6/23.5**	187.4/40.2	243.2/30.0	437.4/104.0	238.1/76.1	236.4/56.5	174.5/29.2	169.1/48.8	287.9/54.1
			50	363.2/68.0	170.6/46.5	182.1/52.1	**101.6/26.7**	173.9/49.6	213.4/52.6	451.6/115.2	201.5/69.1	208.9/84.6	162.8/16.6	140.8/47.2	262.0/85.0
			100	339.2/66.9	177.9/58.8	165.8/48.8	**73.7/20.3**	162.4/43.7	215.0/43.8	382.2/109.9	241.6/92.5	207.2/65.5	137.9/20.4	141.6/53.9	252.9/78.5
		150	25	1199.6/94.0	798.3/105.0	793.7/117.1	**528.3/59.3**	872.4/122.5	1024.5/114.6	1295.2/107.3	943.8/94.3	992.9/160.8	745.9/51.7	829.7/127.3	1181.2/181.8
			50	1333.2/134.9	834.6/67.9	797.3/83.5	**475.3/61.1**	870.1/84.7	1000.3/114.0	1476.9/159.8	962.7/90.1	966.8/117.5	725.5/48.6	824.2/99.2	1216.2/151.8
			100	1295.5/121.6	848.4/122.0	767.5/87.5	**440.0/57.8**	823.2/103.1	955.1/120.7	1562.3/198.0	1017.2/149.1	921.6/156.5	671.3/47.4	760.3/123.7	1161.3/165.4
		250	25	1934.6/142.8	1419.2/151.7	1464.3/157.9	**939.7/60.2**	1588.6/162.2	1796.8/187.5	1970.7/154.9	1653.1/202.3	1785.9/178.5	1346.3/66.6	1525.1/158.0	2103.7/242.4
			50	2156.2/113.6	1427.1/123.2	1418.8/117.2	**910.7/73.7**	1526.7/120.8	1808.2/133.0	2328.6/141.8	1668.7/119.3	1678.7/138.6	1321.1/53.7	1495.8/179.6	2122.2/214.4
			100	2235.6/136.0	1559.2/120.6	1385.7/111.7	**825.1/52.5**	1499.7/104.2	1717.0/105.9	2555.0/182.8	1878.2/141.4	1709.9/156.5	1240.5/42.9	1445.8/136.5	2023.4/189.2
	15	50	25	632.6/118.2	309.1/88.0	299.1/76.1	**138.9/36.8**	287.1/81.4	338.4/80.6	714.0/141.2	435.3/140.2	434.2/135.2	201.7/18.7	320.0/102.9	495.4/125.4
			50	555.1/125.8	258.4/72.6	256.5/73.7	**124.8/28.1**	248.8/67.7	308.5/81.1	741.7/137.5	387.4/124.7	348.9/98.8	185.9/21.7	255.1/67.4	408.9/79.5
			100	515.0/94.4	272.2/82.4	268.4/74.1	**86.7/19.7**	275.5/79.1	303.7/82.1	686.7/143.8	399.6/139.7	382.0/114.6	153.7/18.1	304.0/72.8	446.2/127.2
		150	25	1716.1/138.7	1145.1/128.6	1143.8/131.8	**522.9/51.7**	1177.3/129.0	1372.1/145.5	1969.1/199.7	1551.2/190.0	1593.3/189.7	725.9/34.8	1373.4/215.5	1911.8/241.6
			50	1885.4/154.6	1143.8/123.4	1109.8/139.7	**487.7/49.6**	1164.4/110.0	1294.7/138.9	2323.4/221.9	1546.8/168.6	1548.4/202.9	705.2/44.2	1345.6/167.6	1885.8/268.8
			100	1887.7/156.2	1182.4/162.9	1119.3/130.7	**441.9/68.2**	1149.1/127.1	1281.7/193.3	2435.1/256.1	1614.6/195.7	1521.8/190.5	658.5/50.3	1319.5/249.9	1819.7/310.6
		250	25	2632.8/191.0	1989.8/165.9	2027.0/210.2	**951.0/74.8**	2102.3/174.0	2372.1/197.3	2880.4/212.8	2645.6/250.3	2906.1/264.0	1318.3/52.4	2517.6/304.2	3307.4/342.6
			50	3095.7/166.9	2085.0/136.4	2074.0/148.9	**914.6/62.4**	2197.6/121.0	2420.5/148.9	3597.1/235.7	2776.0/233.1	2890.6/294.0	1303.5/38.6	2536.8/262.2	3278.5/321.9
			100	3192.4/232.5	2132.9/153.5	1985.3/166.5	**868.8/70.3**	2054.6/143.8	2249.7/188.4	4038.8/293.8	2942.1/251.4	2745.7/233.1	1242.6/53.6	2418.2/224.5	3059.6/274.7
4	5	50	25	130.8/21.6	69.3/15.6	69.0/15.8	42.3/8.9	78.7/17.6	98.5/23.9	96.3/26.2	42.9/16.9	44.7/17.7	112.2/15.3	**31.7/15.2**	67.3/31.4
			50	113.4/26.6	57.6/16.2	57.6/15.3	29.3/11.2	68.8/14.1	89.2/23.4	86.2/41.6	31.5/20.0	34.4/16.9	89.2/11.1	**18.3/7.5**	53.7/28.3
			100	82.0/33.9	46.9/21.5	55.4/14.7	22.2/5.7	62.4/16.7	81.3/18.1	50.4/33.0	28.5/27.8	28.3/10.5	80.1/14.4	**20.0/10.5**	50.0/17.4
		150	25	542.6/41.8	343.9/37.4	336.2/43.8	242.0/37.9	405.6/49.0	486.1/45.5	438.0/63.7	280.1/60.3	272.1/64.0	546.7/33.0	**229.0/53.7**	380.1/57.0
			50	539.6/41.7	371.2/40.3	323.6/28.5	**210.7/21.6**	407.8/41.2	475.3/50.3	443.4/67.1	302.2/54.7	250.5/36.0	514.5/29.0	217.5/37.1	357.1/64.1
			100	522.0/50.3	384.6/41.6	324.1/45.8	**169.8/23.3**	377.3/40.0	438.9/35.4	426.2/73.9	308.4/55.0	251.8/47.1	469.9/30.4	195.0/39.0	326.2/46.9
		250	25	917.1/39.7	642.4/46.2	628.3/30.4	480.7/33.9	756.7/40.1	873.0/45.3	736.5/70.2	501.8/54.4	513.1/48.2	999.3/29.7	**465.0/38.2**	696.8/79.6
			50	930.3/62.0	675.2/51.8	610.9/42.3	467.9/38.2	734.9/52.4	853.1/58.5	812.2/84.2	561.7/61.2	529.2/73.4	974.2/39.2	**445.1/60.8**	704.7/75.6
			100	934.4/60.1	728.4/42.5	588.5/34.6	**380.0/25.3**	710.1/46.9	812.7/59.2	802.5/84.8	622.2/47.4	486.7/49.5	922.0/35.1	413.7/38.0	645.4/78.7
	10	50	25	260.4/40.8	116.3/27.2	117.2/27.6	**48.4/14.5**	109.1/26.5	149.8/34.7	273.6/66.4	125.7/44.1	128.1/50.2	111.7/17.1	89.4/30.0	167.4/46.9

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Table 14 (*continued*)

		50	204.8/51.6	87.1/31.5	90.9/30.0	**40.9/10.8**	89.9/31.2	107.9/26.1	248.9/85.4	94.3/38.5	86.3/39.1	99.3/13.5	68.0/36.1	95.4/34.8
		100	165.0/48.5	75.1/30.9	79.3/27.0	**29.4/11.1**	73.8/19.5	105.6/32.3	188.6/64.9	99.3/60.9	78.4/41.9	83.1/10.2	43.6/21.5	94.4/43.1
	150	25	834.1/79.8	498.5/63.1	504.0/59.8	**244.3/28.5**	583.9/62.5	633.4/62.3	883.6/89.8	579.6/80.7	592.1/76.7	497.4/23.7	495.1/85.7	688.0/95.9
		50	877.8/63.5	514.9/47.2	498.8/56.5	**214.0/33.1**	558.8/60.2	631.5/70.6	963.6/104.6	613.6/76.8	589.9/83.7	485.2/33.1	489.5/97.5	720.3/105.1
		100	862.6/90.6	542.4/79.0	497.0/68.9	**165.5/21.8**	547.9/64.1	607.8/71.4	1003.2/165.7	671.0/138.9	577.5/109.6	434.7/33.6	489.5/95.2	690.7/117.5
	250	25	1352.1/78.3	921.7/77.8	941.0/77.7	**492.1/44.8**	1046.2/85.4	1181.5/68.8	1387.4/118.1	1068.8/96.3	1123.2/135.8	941.2/57.6	962.2/105.3	1323.3/128.1
		50	1466.2/91.0	955.6/77.6	922.5/79.9	**442.0/43.6**	1038.3/73.1	1140.3/103.5	1555.6/135.0	1109.0/122.9	1105.5/125.2	921.0/52.2	957.1/88.6	1259.8/182.6
		100	1519.3/126.4	1016.2/72.0	894.3/76.3	**375.8/43.2**	1009.9/64.7	1101.5/85.4	1742.4/155.4	1240.0/153.0	1082.9/103.9	849.8/40.6	908.8/108.5	1245.8/140.5
15	50	25	349.2/63.9	150.1/44.8	151.7/40.6	**65.3/12.9**	140.9/33.4	174.0/36.4	423.1/91.6	228.0/64.7	221.9/66.5	142.7/14.0	134.1/63.2	269.7/84.2
		50	338.6/61.8	144.0/45.9	136.7/46.5	**55.6/13.1**	128.8/38.3	169.2/48.7	466.6/114.1	218.1/69.7	211.5/70.9	121.5/12.7	138.5/63.0	233.3/87.5
		100	291.9/71.3	127.5/40.9	138.8/52.4	**45.3/14.9**	121.4/40.7	155.5/53.5	439.3/119.6	193.4/79.4	173.7/77.8	110.9/16.0	121.2/65.2	206.8/72.7
	150	25	1180.4/96.3	691.2/113.1	698.6/111.2	**236.4/32.4**	760.8/96.8	825.2/88.3	1359.2/148.5	971.5/159.6	1012.2/156.9	463.6/20.9	883.9/144.6	1122.9/139.3
		50	1240.7/80.2	720.0/83.4	692.2/84.3	**207.4/37.2**	722.6/65.6	811.2/73.1	1535.9/123.3	1016.9/131.4	998.7/149.1	448.4/25.0	809.6/114.7	1128.6/131.9
		100	1276.8/108.2	715.5/78.5	691.3/102.3	**173.5/18.5**	695.2/84.4	775.8/75.7	1689.3/206.5	1074.9/151.8	1004.6/157.0	401.7/29.7	799.3/133.8	1076.5/160.3
	250	25	1827.6/113.3	1268.3/110.9	1285.5/108.7	**473.0/33.7**	1406.8/112.4	1477.5/122.3	1936.8/173.5	1729.8/174.8	1893.1/177.2	890.6/42.3	1613.6/170.4	2062.8/270.7
		50	2031.2/136.1	1264.2/142.2	1266.1/128.5	**435.7/29.5**	1364.0/135.9	1478.4/142.2	2479.6/236.0	1754.9/205.5	1854.2/230.8	858.0/44.7	1525.1/175.1	1964.4/237.5
		100	2182.1/112.6	1363.4/140.2	1267.8/98.3	**399.2/30.1**	1348.9/100.3	1502.7/99.3	2781.6/205.1	1915.8/110.0	1811.7/153.6	827.9/38.2	1549.9/202.9	2066.6/170.9

Appendix D

Table 15
Mean values and standard deviations of mean tardiness attained by the IGA and PSO.

f	mq	n_{new}	Î»$_{job}$	$DDT = 0.5$		$DDT = 1.0$		$DDT = 1.5$	
				IGA	PSO	IGA	PSO	IGA	PSO
2	5	50	25	258.4/26.5	264.8/25.5	238.3/23.0	237.7/23.9	186.6/19.1	183.2/17.6
			50	252.2/25.8	249.3/25.4	208.8/21.4	211.3/21.5	149.8/13.9	154.0/15.5
			100	230.1/23.7	231.2/22.9	182.3/18.0	180.3/18.4	131.4/13.7	130.1/13.1
		150	25	835.9/81.9	840.4/82.9	762.9/74.0	773.4/77.9	724.0/72.9	724.6/72.2
			50	744.0/73.6	749.4/75.4	685.6/67.4	687.1/69.4	657.5/65.1	652.5/65.4
			100	688.6/68.6	687.3/67.7	653.3/66.6	650.5/65.2	593.3/58.9	594.7/59.2
		250	25	1409.7/82.7	1434.7/85.7	1329.3/83.8	1340.2/85.0	1140.2/86.1	1151.3/86.7
			50	1278.4/82.2	1267.1/83.5	1189.5/81.1	1176.1/84.1	1106.2/84.5	1110.6/83.8
			100	1171.4/79.8	1189.3/85.0	1031.2/85.6	1036.6/84.9	951.5/80.9	945.2/82.5
	10	50	25	367.1/36.3	369.1/37.4	283.3/28.6	292.0/28.4	268.4/27.1	264.0/27.1
			50	334.1/33.9	336.5/34.3	272.4/26.5	268.2/27.9	230.9/22.4	231.2/22.9
			100	280.9/29.0	282.4/27.8	232.8/24.1	231.7/22.4	171.4/16.9	171.1/17.6
		150	25	940.6/82.4	939.3/81.8	885.8/80.1	886.5/83.8	829.8/83.8	835.1/83.0
			50	907.0/80.2	917.0/79.9	798.2/79.3	797.7/80.6	760.2/76.4	765.1/77.9
			100	851.5/76.0	854.4/79.2	743.1/73.2	746.3/76.3	716.4/71.0	712.7/70.2
		250	25	1435.5/85.1	1442.5/86.1	1356.6/84.9	1357.0/86.7	1244.2/86.5	1246.3/86.1
			50	1352.9/83.5	1349.1/85.3	1304.0/84.5	1300.2/86.0	1203.4/83.4	1211.6/85.5
			100	1300.5/80.0	1306.0/84.0	1115.0/82.1	1128.9/82.5	1117.9/84.9	1115.9/84.5
	15	50	25	490.0/49.1	487.6/49.7	368.8/36.7	366.8/36.0	334.2/35.1	337.5/33.0
			50	432.7/42.9	434.0/43.9	332.5/32.5	333.5/34.4	285.4/28.2	285.0/29.6
			100	362.2/38.7	362.8/36.0	266.4/26.5	267.7/27.4	237.1/24.8	240.9/23.5
		150	25	1057.1/82.7	1076.0/83.5	894.8/83.4	897.0/82.1	854.4/84.6	850.1/81.0
			50	953.6/81.8	949.9/82.4	848.7/83.1	844.8/83.3	780.3/77.3	785.2/77.5
			100	878.7/85.9	886.1/84.6	772.2/78.0	77.9/77.2	747.2/75.4	742.4/72.8
		250	25	1580.0/88.6	1598.5/84.3	1419.0/85.7	1430.8/86.8	1381.9/86.5	1389.3/85.7
			50	1509.3/87.6	1524.9/88.9	1372.0/85.7	1367.6/84.9	1314.0/80.8	1322.2/84.6
			100	1470.3/85.8	1472.9/85.8	1286.4/87.1	1289.9/81.3	1207.3/83.7	1201.5/82.1
3	5	50	25	152.1/16.6	153.6/15.7	105.0/11.2	103.9/11.4	99.2/12.0	97.6/12.1
			50	130.0/12.9	127.7/13.9	89.0/10.5	87.9/10.3	62.3/9.4	62.8/9.8
			100	106.2/11.5	100.7/11.4	71.8/9.8	73.7/9.7	58.5/8.6	56.0/9.2
		150	25	460.3/45.3	459.9/47.1	382.2/38.1	383.5/39.3	353.5/36.2	350.6/33.9
			50	380.4/39.1	393.7/38.8	342.2/35.8	341.7/35.0	296.0/28.3	292.9/29.1
			100	342.9/34.6	352.3/34.9	297.2/30.3	291.7/29.0	245.9/25.2	244.9/24.6

(*continued on next page*)

Table 15 (*continued*)

f	mq	n_{new}	Î»$_{job}$	*DDT* = 0.5		*DDT* = 1.0		*DDT* = 1.5	
				IGA	PSO	IGA	PSO	IGA	PSO
		250	25	655.0/64.6	658.5/66.4	584.3/57.6	591.2/57.9	526.4/54.1	528.0/52.2
			50	595.2/60.8	595.3/58.9	544.4/56.1	542.4/54.8	482.4/47.8	479.9/48.4
			100	544.3/54.3	554.0/57.2	463.2/46.4	468.7/46.7	433.4/42.9	429.2/44.0
	10	50	25	231.9/22.9	234.8/23.3	143.2/13.8	140.8/14.3	111.5/12.4	114.0/12.7
			50	178.3/17.7	176.3/17.1	119.0/12.1	113.1/12.8	82.8/10.6	82.2/9.6
			100	130.5/13.4	134.5/14.6	81.1/9.3	83.2/10.5	58.3/8.7	61.2/9.8
		150	25	558.0/54.3	559.7/56.6	494.7/48.5	491.0/49.3	378.7/37.3	379.3/37.7
			50	496.3/48.4	493.1/49.1	449.3/45.4	450.2/45.1	321.5/31.4	314.2/32.2
			100	439.1/44.8	442.3/43.9	363.6/35.8	367.0/36.0	284.1/27.7	281.9/28.0
		250	25	938.3/79.0	935.1/81.8	857.5/81.3	858.4/82.7	732.9/72.2	739.1/74.5
			50	868.4/84.1	871.2/84.5	774.0/77.2	775.2/79.0	684.8/67.6	685.9/68.1
			100	815.3/80.6	810.2/79.8	713.3/72.7	720.1/71.3	644.2/65.5	643.9/65.6
	15	50	25	262.7/26.6	263.6/27.1	173.9/17.3	180.3/18.1	136.4/15.0	134.2/14.0
			50	235.9/22.4	234.7/24.2	120.0/12.6	121.9/12.3	95.9/11.7	100.1/10.5
			100	171.7/16.9	174.7/17.0	100.0/11.5	99.8/10.6	67.0/8.1	67.1/9.5
		150	25	637.3/63.8	643.5/64.8	535.4/53.4	537.5/55.0	448.7/44.9	449.3/45.2
			50	610.3/59.9	611.1/62.0	494.4/46.5	492.0/48.3	382.5/38.1	377.5/37.3
			100	580.3/58.5	578.9/57.7	427.8/43.2	431.8/43.6	333.8/30.7	335.1/33.1
		250	25	997.5/84.1	998.5/83.0	952.3/80.2	951.6/83.6	746.5/75.4	748.0/75.2
			50	947.6/82.8	945.4/82.3	881.9/83.8	883.8/85.0	687.9/67.6	690.9/69.5
			100	884.8/81.4	887.8/85.2	836.3/84.9	838.7/80.7	654.3/65.2	650.8/65.3
4	5	50	25	88.5/9.5	90.6/10.6	56.6/8.7	57.4/9.8	42.7/9.7	41.9/8.1
			50	72.9/11.1	76.0/11.0	45.2/9.2	43.9/8.5	35.3/8.1	36.2/8.7
			100	66.0/11.0	60.6/9.4	36.0/8.4	36.4/8.3	14.6/7.2	14.8/8.0
		150	25	232.8/22.4	231.8/23.2	179.9/17.6	183.4/18.7	153.8/15.5	154.0/14.5
			50	205.1/19.5	202.7/21.6	178.5/17.0	176.3/17.2	141.2/14.4	143.2/14.8
			100	172.3/18.4	176.4/17.9	139.9/14.8	141.5/14.8	103.1/11.9	106.4/11.4
		250	25	464.2/45.9	463.2/47.3	388.4/39.6	390.1/38.7	348.4/35.3	346.5/35.3
			50	395.4/37.4	394.1/38.6	333.8/32.2	338.6/34.7	291.9/29.4	292.5/29.0
			100	355.0/34.2	354.3/35.0	288.4/27.2	289.8/28.0	243.2/23.5	244.4/24.6
	10	50	25	143.2/13.4	144.4/15.0	106.4/11.3	107.2/11.4	15.8/7.9	15.7/8.4
			50	100.9/9.8	108.1/11.3	88.9/9.7	87.5/8.9	10.3/8.0	11.8/7.8
			100	84.1/13.3	84.3/12.7	67.3/10.5	66.5/8.7	6.4/5.8	6.2/6.1
		150	25	358.8/36.1	362.6/35.9	289.1/27.7	289.8/29.1	245.5/25.2	247.0/25.1
			50	301.3/28.7	298.0/28.5	235.8/24.1	231.7/23.0	181.8/19.3	180.4/18.4
			100	268.9/25.2	265.6/26.1	200.2/18.5	205.7/20.4	141.2/13.7	140.1/14.2
		250	25	620.9/62.6	623.2/62.1	556.2/55.0	564.0/57.4	523.3/53.6	529.3/52.2
			50	566.2/56.0	564.5/56.8	516.4/51.2	512.1/49.7	465.1/47.3	463.6/46.0
			100	524.3/53.9	516.8/51.2	472.7/46.7	470.6/47.3	414.8/42.7	412.2/42.5
	15	50	25	187.8/17.1	188.5/19.2	130.3/12.5	134.4/13.3	7.9/8.0	7.5/8.6
			50	150.5/14.0	154.2/15.3	101.0/9.8	99.9/10.7	4.5/3.7	4.6/4.1
			100	118.1/10.1	112.0/12.4	80.4/8.6	82.2/9.0	2.6/3.0	2.7/2.8
		150	25	471.5/46.0	480.2/47.7	386.3/39.2	387.1/38.1	274.8/28.6	278.8/28.1
			50	448.1/45.5	443.5/45.2	332.8/31.4	332.4/33.0	242.5/24.0	244.7/24.4
			100	403.7/40.0	398.9/40.4	286.4/29.8	291.7/30.6	183.0/18.8	185.5/17.6
		250	25	772.1/70.6	770.3/78.3	674.8/67.1	679.3/68.4	545.7/53.4	543.4/54.3
			50	702.0/70.0	698.7/69.0	632.4/62.7	636.6/64.0	474.9/46.2	473.3/47.6
			100	635.2/64.8	636.3/64.9	579.5/57.2	580.7/57.2	417.4/42.0	420.3/41.1

Table 16
Average computation time obtained by the DRLs, IGA, and PSO (*DDT* = 0.5).

f	mq	n_{new}	Î»$_{job}$	PPO	TRPO	DlDQN	DDQN	DQN	IGA	PSO
2	5	50	25	0.2	0.2	0.2	0.2	0.2	232.7	183.7
			50	0.2	0.2	0.2	0.2	0.2	192.2	145.5
			100	0.2	0.2	0.2	0.2	0.2	120.8	111.3
		150	25	1.0	1.0	1.0	1.0	1.0	4546.5	1111.4
			50	1.0	1.0	1.0	1.0	1.0	3757.8	846.7
			100	1.0	1.0	1.0	1.0	1.0	3054.1	688.6
		250	25	2.3	2.3	2.3	2.4	2.3	15599.9	2250.5
			50	2.3	2.3	2.4	2.3	2.4	14466.3	2136.6
			100	2.4	2.4	2.3	2.4	2.4	15618.1	2847.3
	10	50	25	0.5	0.5	0.5	0.5	0.5	579.0	301.2
			50	0.5	0.5	0.5	0.5	0.5	609.3	270.8
			100	0.5	0.5	0.5	0.5	0.5	285.1	239.1
		150	25	2.7	2.6	2.6	2.6	2.5	9545.8	2363.7
			50	2.8	2.6	2.6	2.7	2.8	9661.9	2050.7
			100	2.9	2.7	2.7	2.8	2.8	8814.3	1276.3
		250	25	6.2	6.0	6.0	6.1	6.3	45505.4	5404.2
			50	6.6	6.3	6.4	6.5	6.1	37681.2	6047.9
			100	6.7	6.4	6.5	6.3	7.0	29792.8	5380.1
	15	50	25	1.0	1.0	1.0	1.0	1.0	970.9	572.9
			50	1.1	1.0	1.0	1.0	1.1	793.2	706.2
			100	1.1	1.1	1.1	1.1	1.0	455.7	530.1

(*continued on next page*)

Table 16 (*continued*)

f	mq	n_{new}	Î»$_{job}$	PPO	TRPO	DlDQN	DDQN	DQN	IGA	PSO
		150	25	5.5	5.2	5.3	5.2	5.6	16602.7	4466.8
			50	5.8	5.3	5.4	5.6	5.9	14219.9	4514.8
			100	5.6	6.0	5.7	5.8	6.3	13102.7	3910.6
		250	25	13.1	12.5	12.7	12.4	13.5	70800.6	9892.1
			50	13.9	12.6	12.6	12.8	13.3	65361.1	10077.8
			100	14.1	13.3	13.5	14.7	13.3	61039.9	11263.3
3	5	50	25	0.2	0.2	0.2	0.2	0.2	166.0	175.6
			50	0.2	0.2	0.2	0.2	0.2	129.9	124.7
			100	0.2	0.2	0.2	0.2	0.2	86.8	132.7
		150	25	1.2	1.2	1.2	1.1	1.2	4129.6	1109.0
			50	1.2	1.3	1.2	1.2	1.3	3328.7	1004.8
			100	1.3	1.2	1.2	1.2	1.3	2715.2	1139.8
		250	25	2.9	2.8	2.8	2.9	2.8	14896.1	2552.4
			50	3.0	2.8	2.8	2.9	3.0	14825.1	2564.5
			100	3.0	3.0	3.0	2.8	3.1	11490.4	2421.6
	10	50	25	0.6	0.7	0.7	0.7	0.7	561.4	323.3
			50	0.7	0.7	0.7	0.7	0.6	376.3	270.1
			100	0.7	0.7	0.7	0.7	0.7	192.4	240.4
		150	25	4.1	3.7	3.7	3.7	4.1	9166.3	2665.1
			50	3.7	4.2	3.8	3.8	4.2	9076.5	2066.4
			100	4.4	4.0	4.0	3.9	4.4	6802.8	1892.0
		250	25	9.2	8.6	8.5	8.5	9.7	41596.1	6537.9
			50	9.7	8.7	8.8	8.9	9.8	40521.5	6127.1
			100	9.2	10.2	9.4	9.2	10.6	29114.0	4653.1
	15	50	25	1.7	1.5	1.5	1.6	1.7	861.1	643.9
			50	1.7	1.6	1.6	1.7	1.6	824.2	595.8
			100	1.6	1.7	1.6	1.6	1.8	485.7	636.0
		150	25	9.5	8.6	8.7	10.0	8.6	16259.6	4778.2
			50	9.7	8.9	8.8	8.7	10.1	17261.9	5604.6
			100	9.5	9.4	10.4	9.8	11.1	11206.0	3709.2
		250	25	21.0	19.9	19.0	22.7	18.9	73297.9	13570.2
			50	22.5	20.1	20.1	20.2	23.0	72349.7	10611.1
			100	24.2	21.8	21.7	21.5	25.1	54271.6	16321.2
4	5	50	25	0.3	0.2	0.3	0.3	0.3	179.9	199.6
			50	0.3	0.3	0.3	0.3	0.2	119.8	175.4
			100	0.3	0.3	0.3	0.3	0.3	48.8	132.2
		150	25	1.6	1.4	1.4	1.5	1.5	3674.7	1253.4
			50	1.4	1.5	1.4	1.5	1.4	2519.5	922.3
			100	1.6	1.4	1.5	1.5	1.6	2023.0	647.6
		250	25	3.3	3.6	3.3	3.3	3.6	17592.3	3002.9
			50	3.6	3.4	3.3	3.4	3.7	13652.8	3243.5
			100	3.8	3.5	3.6	3.7	3.5	10161.8	2854.9
	10	50	25	0.9	0.9	0.9	0.9	0.9	481.5	343.2
			50	1.0	0.9	0.9	1.0	1.0	289.3	383.4
			100	1.0	1.0	1.0	0.9	1.0	198.3	308.8
		150	25	5.0	5.7	5.0	5.1	5.6	10424.8	1974.8
			50	5.9	5.3	5.9	5.2	5.2	8175.0	2514.9
			100	6.3	5.5	5.5	5.6	6.1	4926.1	1995.5
		250	25	13.6	11.4	11.7	11.7	13.3	40308.2	6483.1
			50	11.8	14.2	12.3	12.3	13.4	35063.6	7702.8
			100	14.7	12.7	12.8	14.2	12.7	24898.6	4769.8
	15	50	25	2.2	2.2	2.1	2.2	2.3	831.4	579.2
			50	2.3	2.3	2.3	2.2	2.4	682.3	614.2
			100	2.3	2.3	2.3	2.3	2.3	444.9	425.0
		150	25	15.1	13.5	13.2	13.5	15.2	17043.3	6397.8
			50	15.8	14.0	14.1	15.7	13.9	16103.4	4349.5
			100	16.4	14.9	14.5	14.8	16.4	10644.3	3182.7
		250	25	35.3	30.4	30.3	29.5	34.2	71141.4	13523.5
			50	36.4	30.3	31.0	31.1	35.3	67345.0	13838.5
			100	31.9	39.1	33.4	33.5	37.6	56711.0	8157.9

Table 17

Average computation time obtained by the DRLs, IGA, and PSO ($DDT = 1.0$).

f	mq	n_{new}	Î»$_{job}$	PPO	TRPO	DlDQN	DDQN	DQN	IGA	PSO
2	5	50	25	0.2	0.2	0.2	0.2	0.2	230.8	140.9
			50	0.2	0.2	0.2	0.2	0.2	200.6	138.1
			100	0.2	0.2	0.2	0.2	0.2	140.9	115.5
		150	25	1.0	1.0	1.0	1.1	1.0	3745.9	1405.6
			50	1.0	1.1	1.0	1.1	1.0	3684.5	919.6
			100	1.1	1.0	1.1	1.0	1.0	2636.4	1178.1
		250	25	2.4	2.3	2.4	2.4	2.3	16011.8	2839.7
			50	2.5	2.3	2.4	2.5	2.4	15677.7	1859.4
			100	2.5	2.4	2.4	2.5	2.5	14553.4	2238.6
	10	50	25	0.6	0.6	0.6	0.6	0.6	593.8	330.4

(*continued on next page*)

Table 17 (*continued*)

f	mq	n_{new}	Î»$_{job}$	PPO	TRPO	DlDQN	DDQN	DQN	IGA	PSO
			50	0.6	0.6	0.6	0.6	0.6	487.6	223.0
			100	0.6	0.6	0.6	0.6	0.6	322.5	182.4
		150	25	3.2	3.1	3.1	2.9	3.2	11236.0	2777.3
			50	3.3	3.2	3.3	3.3	3.0	9045.5	1356.5
			100	3.4	3.1	3.3	3.3	3.4	7465.3	1587.1
		250	25	7.4	7.0	7.2	7.3	6.6	42191.4	4949.6
			50	6.8	7.4	7.1	7.3	7.5	40490.4	6168.2
			100	7.8	6.8	7.4	7.6	7.5	31451.4	5904.8
	15	50	25	1.4	1.4	1.4	1.3	1.4	1016.7	471.5
			50	1.4	1.4	1.3	1.4	1.4	938.5	551.3
			100	1.4	1.4	1.4	1.4	1.3	670.7	461.1
		150	25	7.0	7.6	7.5	7.5	8.1	15527.9	4301.8
			50	7.8	7.6	7.6	8.0	7.0	15020.9	4336.2
			100	7.8	7.7	7.8	7.1	8.1	13934.0	3286.7
		250	25	17.0	14.7	16.3	16.5	17.3	64752.6	10834.5
			50	17.6	17.1	17.2	18.0	15.1	68582.8	12470.4
			100	17.9	17.4	17.4	15.7	18.7	57637.9	9585.4
3	5	50	25	0.2	0.2	0.2	0.2	0.2	219.1	152.3
			50	0.2	0.2	0.2	0.2	0.2	159.5	136.4
			100	0.2	0.2	0.2	0.3	0.2	96.2	157.3
		150	25	1.2	1.3	1.3	1.3	1.3	3634.3	1148.0
			50	1.3	1.2	1.3	1.3	1.3	3294.6	1227.9
			100	1.3	1.4	1.3	1.4	1.4	2253.2	888.7
		250	25	3.1	2.9	2.9	3.0	3.1	16552.7	2240.4
			50	3.2	3.0	3.1	2.9	3.2	16124.8	2964.6
			100	3.2	3.0	3.1	3.2	3.0	11679.7	2509.9
	10	50	25	0.8	0.8	0.8	0.7	0.8	581.2	403.7
			50	0.8	0.8	0.8	0.9	0.8	360.5	368.7
			100	0.8	0.8	0.8	0.8	0.8	203.8	200.4
		150	25	4.5	5.2	4.9	4.9	5.1	10734.5	2561.9
			50	5.2	5.0	5.0	5.2	4.6	8423.3	2400.7
			100	5.4	5.2	5.4	4.9	5.1	5962.3	1935.0
		250	25	10.0	11.9	10.8	11.1	11.9	36270.1	5441.1
			50	12.1	11.1	10.1	11.2	12.2	40399.0	6491.5
			100	12.7	10.5	11.6	11.7	12.4	29943.7	5476.7
	15	50	25	1.9	1.8	1.9	1.9	1.8	1068.5	332.8
			50	1.9	1.9	1.9	2.0	1.9	637.5	449.9
			100	1.9	1.7	1.9	2.0	1.8	408.2	484.0
		150	25	13.8	13.8	13.5	12.4	15.0	17239.2	5144.9
			50	14.2	14.3	13.9	15.9	13.0	17308.6	3153.7
			100	13.3	14.1	14.3	13.8	15.9	12687.2	2153.8
		250	25	32.0	29.9	26.3	29.6	31.1	78586.8	16366.6
			50	32.5	26.9	30.5	29.9	31.4	68620.4	14854.4
			100	33.3	31.6	28.7	30.4	33.8	53502.9	8379.7
4	5	50	25	0.3	0.3	0.3	0.3	0.3	157.9	197.6
			50	0.3	0.3	0.3	0.3	0.3	109.3	192.3
			100	0.3	0.3	0.3	0.3	0.3	48.1	127.5
		150	25	1.6	1.7	1.6	1.6	1.7	4022.0	1045.9
			50	1.7	1.6	1.6	1.6	1.8	3317.4	925.2
			100	1.6	1.6	1.6	1.6	1.8	1551.8	811.5
		250	25	3.9	3.7	3.5	3.6	3.9	16402.4	2901.4
			50	3.6	4.1	3.7	3.8	4.0	11661.9	2497.7
			100	4.1	3.7	3.8	3.8	4.1	8931.8	2707.9
	10	50	25	0.9	0.9	0.9	1.0	1.0	511.6	357.6
			50	0.9	0.9	1.0	1.0	0.9	367.3	307.4
			100	0.9	1.0	0.9	1.0	0.9	178.1	237.3
		150	25	7.1	6.7	7.1	6.9	7.4	11693.3	2308.6
			50	7.0	6.9	7.0	6.7	7.6	8661.2	2730.3
			100	7.1	7.2	7.3	7.1	7.5	4998.3	1489.4
		250	25	17.6	16.0	14.8	15.6	17.7	42317.2	8274.3
			50	15.4	17.9	16.5	15.9	18.1	34675.7	5821.0
			100	18.3	15.9	17.2	16.6	18.3	22645.2	6211.8
	15	50	25	2.3	2.3	2.4	2.3	2.3	923.2	578.1
			50	2.3	2.4	2.4	2.5	2.5	704.2	448.5
			100	2.4	2.4	2.5	2.5	2.4	398.6	396.3
		150	25	19.4	19.2	18.7	19.4	18.5	18867.9	4903.8
			50	18.7	18.7	19.2	19.3	19.2	15328.0	4501.6
			100	19.5	18.8	19.3	18.3	18.3	9904.3	3752.1
		250	25	49.8	47.9	44.4	45.4	55.5	82577.2	13892.2
			50	49.9	48.8	46.0	56.4	45.5	73877.9	15904.2
			100	47.1	50.1	48.5	50.3	57.6	46642.1	12871.6

Table 18
Average computation time obtained by the DRLs, IGA, and PSO ($DDT = 1.5$).

f	mq	n_{new}	Î»$_{job}$	PPO	TRPO	DlDQN	DDQN	DQN	IGA	PSO
2	5	50	25	0.2	0.2	0.2	0.2	0.2	245.9	167.5
			50	0.2	0.2	0.2	0.2	0.2	185.0	188.9
			100	0.2	0.2	0.2	0.2	0.2	126.4	107.8
		150	25	1.1	1.1	1.0	1.0	1.1	4332.0	917.7
			50	1.0	1.0	1.0	1.0	1.0	4059.7	1014.1
			100	1.1	1.1	1.1	1.1	1.1	3200.2	789.4
		250	25	2.5	2.4	2.4	2.4	2.4	15540.9	1950.0
			50	2.5	2.4	2.4	2.5	2.5	14260.6	2189.7
			100	2.5	2.5	2.5	2.5	2.5	14804.0	1969.0
	10	50	25	0.6	0.6	0.6	0.6	0.6	502.8	273.2
			50	0.6	0.6	0.6	0.6	0.6	484.9	307.9
			100	0.6	0.6	0.6	0.6	0.6	373.6	225.5
		150	25	3.6	3.5	3.5	3.5	3.8	9126.0	2486.4
			50	3.7	3.6	3.3	3.5	3.7	9423.4	2359.7
			100	3.7	3.6	3.6	3.6	3.9	8135.2	1514.3
		250	25	7.4	8.2	7.9	7.8	8.2	42671.9	5672.9
			50	8.4	8.1	8.0	8.3	7.4	35922.8	7070.5
			100	8.4	7.6	8.3	8.2	8.5	31287.7	6422.9
	15	50	25	1.3	1.4	1.3	1.4	1.4	920.9	505.3
			50	1.4	1.4	1.5	1.5	1.4	791.6	484.2
			100	1.4	1.5	1.4	1.4	1.5	696.0	448.1
		150	25	9.1	8.7	9.0	8.7	9.5	16062.4	4501.7
			50	9.4	9.4	8.9	9.0	9.8	16946.9	4343.5
			100	9.3	9.1	9.4	8.8	10.3	13135.2	2548.2
		250	25	21.5	18.0	20.4	19.7	20.8	70587.4	11639.4
			50	21.9	21.2	21.1	20.1	18.3	68290.7	13960.2
			100	22.5	21.5	19.0	20.8	22.0	59564.8	9760.4
3	5	50	25	0.2	0.2	0.2	0.3	0.2	247.0	161.0
			50	0.2	0.2	0.2	0.3	0.2	161.7	154.0
			100	0.2	0.2	0.2	0.2	0.2	58.7	134.5
		150	25	1.4	1.3	1.3	1.4	1.4	4088.4	1153.0
			50	1.4	1.4	1.4	1.4	1.5	3669.3	1026.5
			100	1.5	1.4	1.4	1.5	1.4	2902.4	685.8
		250	25	3.4	3.1	3.2	3.3	3.3	16461.1	2070.4
			50	3.4	3.1	3.1	3.2	3.4	14797.8	2987.8
			100	3.4	3.2	3.3	3.2	3.5	12340.6	2341.5
	10	50	25	0.8	0.8	0.8	0.9	0.8	506.9	304.3
			50	0.8	0.8	0.8	0.8	0.8	385.6	321.4
			100	0.8	0.8	0.8	0.8	0.8	231.5	245.3
		150	25	5.7	5.4	5.6	5.5	6.1	12138.1	1748.3
			50	5.9	5.7	5.7	5.5	6.2	8674.8	1479.3
			100	5.6	5.8	5.8	5.7	6.0	6758.9	1795.3
		250	25	14.0	11.7	12.8	12.8	14.0	43365.6	7189.7
			50	12.5	14.1	13.1	13.0	14.4	39717.8	5209.6
			100	14.2	13.3	13.1	14.4	12.6	26755.0	7423.5
	15	50	25	1.9	1.9	1.9	2.0	1.9	880.9	618.1
			50	2.0	1.8	1.9	2.0	1.9	859.3	603.3
			100	1.8	2.0	1.9	2.1	1.9	631.3	399.0
		150	25	14.9	15.2	15.0	14.8	15.3	17856.7	4536.9
			50	15.1	15.2	15.2	15.2	15.1	15905.0	5370.9
			100	15.2	15.9	15.2	15.1	15.8	11831.3	2691.7
		250	25	38.6	35.2	37.3	35.8	45.3	75275.5	9624.7
			50	39.3	38.0	36.5	45.5	36.1	73750.6	11443.0
			100	39.4	38.7	36.4	37.3	44.4	52664.2	10041.5
4	5	50	25	0.3	0.3	0.3	0.3	0.3	131.7	162.9
			50	0.3	0.3	0.3	0.3	0.3	128.7	158.6
			100	0.3	0.3	0.3	0.3	0.3	50.0	133.9
		150	25	1.7	1.7	1.7	1.7	1.8	4074.3	1328.1
			50	1.8	1.7	1.7	1.8	1.8	2696.2	1370.8
			100	1.8	1.8	1.8	1.8	1.8	2141.4	885.8
		250	25	3.9	4.4	4.0	4.1	4.4	16756.3	2921.5
			50	4.4	4.0	4.2	4.0	4.5	13845.3	2829.7
			100	4.5	4.0	4.1	4.2	4.7	9576.2	2754.6
	10	50	25	0.9	1.0	0.9	1.0	1.0	460.1	318.4
			50	0.9	1.0	0.9	1.0	1.0	379.3	314.9
			100	1.0	1.0	1.0	1.0	1.0	125.2	232.0
		150	25	7.6	7.7	7.6	7.4	7.6	11962.5	2538.4
			50	7.9	7.3	7.4	7.4	7.4	8953.6	1627.8
			100	7.5	7.6	7.6	7.6	7.1	5733.8	2616.5
		250	25	18.0	20.1	19.1	19.1	20.4	45096.4	8647.0
			50	20.0	18.4	19.2	19.1	20.5	38359.4	6050.6
			100	19.1	20.1	19.6	19.4	20.4	24891.7	5788.5
	15	50	25	2.4	2.4	2.3	2.5	2.4	876.4	526.9
			50	2.4	2.3	2.4	2.5	2.3	568.1	477.1

(*continued on next page*)

Table 18 (*continued*)

	100	2.4	2.3	2.4	2.3	2.5	451.8	351.2
150	25	19.7	20.8	19.7	19.9	19.5	19290.5	6474.7
	50	19.8	21.1	19.6	19.6	20.0	15740.8	4057.4
	100	19.9	21.0	19.8	20.3	20.1	8781.9	3274.0
250	25	52.6	53.6	54.3	53.9	54.3	79102.2	15460.5
	50	53.6	54.5	53.5	52.4	53.8	69999.8	11832.2
	100	54.4	53.8	54.5	53.7	52.7	47694.0	10534.4

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