Data-driven optimization for automated warehouse operations decarbonization

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Abstract: The rapid development of intelligent warehouse systems is resulting in the realization of automation in warehouse activities and raising awareness of decarbonization, particularly the need to reduce carbon emissions from electricity consumption. Driven by the decarbonization trend, microgrid systems with rooftop photovoltaic panels are becoming more popular in warehouses and are providing zero-carbon electricity for warehouse operations. How to make better use of microgrid systems and reduce the consumption of electricity generated from traditional energy sources is becoming increasingly important in warehouse systems. This paper investigates an operational problem in a warehouse system equipped with a shuttle-based storage and retrieval system, in which a microgrid system acts as the main electricity source. Power-load management is applied to avoid peaks of energy consumption, and a mixed linear programming model is developed to optimize task sequencing and scheduling with decarbonization awareness. To solve the proposed problem, a data-driven variable neighbourhood search algorithm is built. Numerical experiments are conducted to validate the model and algorithm. Sensitivity analysis shows the effectiveness of power-load management and the influence of system configuration on energy consumption.

Keywords: automated warehouse; decarbonization; warehouse operations management; mixed integer linear programming.

1. Introduction

The warehouse industry is devoting itself to the development and application of automated and intelligent warehouse systems (Boysen et al., 2019). On the other hand, warehouse activities are contributing more and more carbon emissions as the result of increasing energy consumption of automated warehouse equipment. The energy consumption of warehouse equipment is raising the decarbonization awareness in the warehouse industry(Ali et al., 2022, Bartolini et al., 2019). The decarbonization in warehouses involves two main measures: promoting the use of renewable energy and energy saving through operations management measures.

In recent years, the rooftop photovoltaic (PV) system is a widely used renewable energy supply system in many green warehouses. Rooftop PV systems install solar PV panels on unused spaces of warehouse rooftops and generate zero-carbon electricity to support warehouse equipment operations. The rooftop PV panels are often combined with energy storage systems to form a microgrid system with rooftop PV panels (MSR). The energy storage system in MSR is used to store the surplus electricity and avoid issues regarding energy instability, enabling warehouses to control, store, and adjust the renewable energy supplies. MSR integrates the generation, supply, and storage of zero-carbon electricity, and provide an environmentally-friendly

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alternative to conventional energy sources. The existing applications of MSR have achieved great economic and environmental benefits. The Guangsheng warehouse of State Grid Yangzhou Power Supply Company, which is used for storage and distribution of power suppliers in Jiangsu, China, is an example of automated warehouse powered by MSR. Recently, the warehouse has obtained the "carbon neutral" certification, becoming the first "zero-carbon warehouse" in the State Grid Corporation of China. According to the certification, the total carbon emission of the warehouse from December 1, 2021 to February 28, 2022 is 69.28 tons, and its PV system generates 108,600 kilowatt hours of electricity. After all the carbon emissions are offset, the carbon emission is reduced by 7.1 tons, reaching the carbon neutrality standard (Guan, 2022). Another example comes from JD.com "Asia No.1" Xi'an Intelligent logistics Park, the exploration of JD logistics in green warehousing. The "Asia NO.1" Logistics Park in Xi'an is equipped with an automated warehouse system like Tianlang shuttle-based storage and retrieval systems (SBS/RS) along with MSR for power supply (see Figure 1). The logistics park has been certified as the first carbon neutral logistics park in China through the optimization of warehouse operations, the usage of MSR-generated electricity and carbon trading (Shaanxi Daily, 2022). The benefits of rooftop PV system and MSR have been demonstrated by scholars. According to the research of Wang et al. (2018), the power generation potential of rooftop PV in Beijing is quite substantial which can largely reduce carbon and air pollutant emissions. The CO2 emission reduction factor of rooftop PV substitution for the local grid power supply in Beijing is estimated to be 919.34 g CO2-eq./kWh. Meanwhile, the deployment of rooftop PV is economically practicable. The research of Zhao and Xie (2019) indicates that the dynamic investment payback period of rooftop PV system is 4.0–8.5 years, and the levelized cost of electricity for the construction of small industrial and commercial rooftop photovoltaic is 0.2727–0.5573CNY/kWh. The application of rooftop PV and MSR can help the production systems including warehouses improve both economic and environmental performance.

Figure 1: SBS/RS and rooftop PV (Source: left: Cao (2020); right: Xiamen Container Terminal Group (2021))

The application of MSR in automated warehouse has two problems, which may limit the performance of MSR. On the one hand, due to the limitation of PV panels' installed capacity, it is often difficult to meet the total electricity demand of warehouse equipment by MSR. Warehouses need to purchase extra electricity from the grid to fill the gap. On the other hand, the mismatch between energy supply and demand often exists since the supply of MSR-generated electricity fluctuates with the change of weather conditions. The mismatch can reduce the utilization of MSR-generated electricity, which may require extra grid-purchased electricity consumption, or result in the waste of excess MSR-generated electricity due to the capacity limit of energy storage system. For the first problem, warehouse can save energy through operation management methods. Warehouses can reduce unnecessary work by operational measures such as task sequencing and scheduling, and thus reduce the electricity consumption (Zhen and Li, 2022). The reduction of unnecessary work can save plenty of electricity, and achieve a win–win situation between operational efficiency and environmental performance. For the second problem, warehouse and production systems can actively adjust the energy demand by energy-efficient scheduling based on the operation of MSR (Kim et al., 2021, Zhang et al., 2022, Luo et al., 2020). One of the main benefits of energy-efficient scheduling is that the utilization of MSR can be significantly improved. Power-load management (PLM) is an operations management strategy used to prevent peaks of energy consumption (Hahn-Woernle and Gunthner, 2018). The implementation of PLM in warehouses limits the amount of warehouse equipment working at the same time and requires delays in task schedules. The tasks will be re-sequenced and rescheduled according to real-time power demand and the electricity demand threshold. The delayed tasks will be completed during the idle time in previous schedule.

The basic concept of PLM provides some insights for operations management in automated warehouses with MSR. The output of MSR-generated electricity is stochastic and affected by the weather. By using some PV power forecasting techniques, warehouse operator can get a forecast of MSR-generated electricity supply in the planning horizon (Ahmed et al., 2020). The forecast can be used as the reference for task scheduling, which provide the threshold of electricity demand in task scheduling with PLM. The task sequencing and scheduling under PLM may help warehouses improve the utilization of the renewable energy provided by the MSR. Given this context, this paper studies the operational problem of warehouse decarbonization based on automated warehouses equipped with SBS/RS and MSR, which is extracted from the previously mentioned JD logistics example. The objective is to reduce the grid-purchased electricity consumption and increase the utilization of MSR-generated electricity through appropriate scheduling and sequencing of tasks. To do this, we construct a mixed-integer linear programming (MILP) model for the comprehensive decision problem. We build a framework for a data-driven solution approach and design a tailored data-driven variable neighborhood search (VNS) algorithm that uses historical data to accelerate the solution procedure. Numerical experiments are conducted to validate the proposed model and show the efficiency of the proposed algorithm in solving large-scale problems, and managerial insights are derived through sensitivity analysis. The model and algorithm can provide essential support for the development of warehouse management systems for automated warehouses with MSR.

The remainder of this paper is organized as follows. The related works are summarized and reviewed in the next section. Problem background and the MILP model are described and proposed in Section 3 and Section 4, respectively. The data-driven VNS solution methodology is elaborated in Section 5. Numerical experiments and some sensitivity analysis are conducted in Section 6. The conclusions are outlined in the last section.

2. Literature review

In recent decades, awareness of climate change and carbon emissions has led to increased concern on decarbonization in industry and production system (Zhang et al., 2021b, Zhang et al., 2021a). Some scholars, such as He Junliang and Chen Gang, contribute meaningful research on decarbonization (He et al., 2021, He, 2016, Chen et al., 2013, Yang et al., 2020). As the research scope of this paper focuses on the operations management and energy saving in automated warehouses with MSR, this section reviews the related works from three perspectives: (1) SBS/RS and energy-efficiency (2) MSR in warehouse and production systems, and (3) operations management measures to improve the utilization of renewable energy. The first two perspectives are mainly related to the system characteristics of the proposed warehouse system. The last perspective aims to conclude the operational measures used in this paper.

SBS/RS are variants of automated storage and retrieval systems (AS/RS) in which the storage and retrieval processes are accomplished by shuttles and lifts instead of traditional S/R machines (Lerher et al., 2015, Ekren, 2017, Roy et al., 2015). Compared with the traditional crane-based AS/RS, SBS/RS can achieve greater flexibility and efficiency in terms of throughput and environmental impacts (Tappia et al., 2015). According to Gruzauskas et al. (2018) and Ekren et al. (2018), SBS/RS can achieve better environmental performance in terms of energy savings and carbon emission reduction. The movement characteristics of shuttles and lifts including velocity and acceleration/deceleration have significant effects on total energy consumption (Liu et al., 2021). Another environmentally friendly aspect of SBS/RS is that the system can realize energy regeneration through the regenerative braking of shuttles and lifts (Ekren and Akpunar, 2021).

To promote sustainable and green issues into warehouse and logistics management, energy saving should be further implemented (Tirkolaee et al., 2021, Ren et al., 2021, Singh et al., 2018). Renewable energy sources such as wind and solar energy can be used to promote sustainable warehousing operations and sustainable supply chain management (Dadhich et al., 2015). The rooftops of warehouses provide an ideal site for the installation of PV systems, which deploy solar panels on the warehouse rooftop to convert solar energy to electricity. Photovoltaic panels not only provide power to the warehouse system, but also lower the temperature of rooftops, which reduce the energy consumption required for cooling on the refrigerated warehouse roof (Dominguez et al., 2011, Luerssen et al., 2019). MSR can provide essential electricity supplies by on-site generation and the discharge of energy storage devices and reduce the consumption of grid-purchased electricity. With the ability to offset emissions from grid-purchased electricity and to provide power during blackouts, on-site solar PVs and battery storage can simultaneously reduce climate, health, and outage damages along with energy costs (Farthing et al., 2021, Iqbal et al., 2021). The application of MSR enables warehouses and other production systems to achieve environmental sustainability (Jin et al., 2022). According to Pham et al. (2019), net-zero energy operations are feasible and affordable in locations where solar or wind energy is abundant. To provide essential supplementary to MSR power supply, conventional energy generation systems, such as diesel generators or grids, can be combined with MSR to form a hybrid microgrid system (Abedini et al., 2016).

The awareness of energy consumption and the related environmental impact has promoted the growth in energy-efficient operations management (Bänsch et al., 2021). Implementing decarbonization by operations management measures can result in significant economic and environmental benefits (Zhen et al., 2020a, Zhen et al., 2020b). Energy-efficient scheduling of production systems is an effective way to improve energy efficiency and to reduce energy cost (Gao et al., 2020). In automated warehouse systems, suitable sequencing and task schedules can reduce the movement of cranes, and thus reduce energy consumption (Tostani et al., 2020, Ene et al., 2016). Meneghetti et al. (2015) investigate the internal relationship among system design, task sequencing and storage assignment, and provide decision support of energy-efficient scheduling as well as system design. Time-of-use, critical-peak, and other types of tariffs can be used to adjust electrical demand by influencing the responses of customers. Warehouses can change the task schedule to accommodate electricity tariffs and avoid extra energy costs (Wang and Li, 2017, Cheng et al., 2017).

The on-site electricity generation from renewable energy is usually volatile because of weather and other factors. A mismatch between supply and demand often occurs, causing extra consumption of traditional energy and wastage of renewable energy. Energy-efficient scheduling can actively adjust demand and accommodate the renewable electricity output. Basso et al. (2019) examine scheduling problems related to charging automated guided vehicle batteries in which several chargers are powered by on-site photovoltaic panels and can be used during a limited time of a day. Meneghetti et al. (2018) investigates the influence of on-site photovoltaic system on the yearly cost of the refrigerated AS/RS. The photovoltaic system can provide electricity supply for warehouse system and reduce the yearly cost as well as grid-purchased electricity consumption. In order to further improve energy efficiency, we introduce the MSR and PLM to the research of warehouse system. The application of energy-efficient scheduling in production systems with MSR is proved to be beneficial in terms of the utilization of renewable energy resources(Cui et al., 2019). PLM is a customer-side operational strategy of energy-efficient operations. The basic principle of PLM is to delay tasks when the instantaneous power exceeds the pre-determined thresholds, and reduce the electricity consumption in peak periods with only a small loss of throughput (Hahn-Woernle and Gunthner, 2018). The MSR and the idea of PLM may enhance the energy-efficient scheduling of production systems including warehouses with on-site renewable energy systems since the electricity demand can be adjusted by PLM to accommodate the output of renewable energy systems. However, there’s little research about task sequencing and scheduling in warehouses or other production systems which applies MSR and PLM together.

To make an in-depth analysis about the research methodologies of energy-efficient scheduling, we summarized the reviewed studies into Table 1. From the table, we can see that the energy-efficient scheduling in warehouses are a research focus, and the scheduling of systems with on-site renewable energy systems is emerging in recent years. The on-site renewable energy systems are usually combined with power grid to form a hybrid energy supply system. The main decision of the energy-efficient scheduling is task scheduling, and the main objective is energy saving. Mathematical programming model is the main models used by researchers, and heuristic algorithms are main solution methods for problem solving. Based on these main research topics and methodologies, we apply PLM into energy-efficient scheduling with MSR in an SBS/RS automated warehouse. We build a mathematical programming model to characterize the internal relationships between sequencing, scheduling and energy consumption, and select variable neighbourhood search algorithm for problem solving. A tailored data-driven method is designed to improve the efficiency of the algorithm. Several works stress the economic efficiency index like time or production rate in their objective. To balance the economic and environmental objective, we set that all tasks should be in a fixed make-span, which is usually specified by their deadlines.

Table 1: the summary of research about energy-efficient scheduling

Article	System	Energy		Decision	Objective			Model	Solution method
		GR	RE		EN	TI	PI		
Cui et al. (2019)	PS	√	√	SC	√		√	MP	Benders decomposition method
Tostani et al. (2020)	AS/RS	√		SA, SC	√	√		MP	A Modified Cooperative Coevolutionary Algorithm
Ene et al. (2016)	Forklift warehouse	√		BA, routing	√			-	Genetic algorithm
Meneghetti et al. (2015)	AS/RS	√		SA, SC, DE	√	√		CP	Large Neighborhood Search, Simulation
Meneghetti et al. (2018)	AS/RS	√	√	DE	√			CP	Simulation
Wang and Li (2017)	PS	√		SC	√	√		AM	Exhaustive search and particle swarm optimization
Cheng et al. (2017)	PS	√		BA, SC	√	√		MP	Heuristic algorithm
Basso et al. (2019)	AGV	√	√	SC	√	√		MP	Greedy heuristic
Hahn-Woernle and Gunthner (2018)	AS/RS	√		PLM, SC	√		√	SI	Simulation
This paper	SBS/RS	√	√	PLM, SC	√			MP	Variable neighbourhood search algorithm Data-driven method

Notes: PS: production system, SC: scheduling, SA: storage assignment, DE: design, BA: batching, MP: mathematical programming, AM: analytical model, SI: simulation, CP: constraints programming,

3. Problem description

This study focuses on the sequencing and scheduling problem of an automated warehouse system equipped with SBS/RS and MSR. The energy-efficient and decarbonization efforts are implemented through the operations management measures for making better use of MSR-generated electricity and energy saving. A typical example of such a warehouse system is illustrated in Figure 2 to clarify the operational process and related principles. The main equipment of SBS/RS includes storage racks for tote storage, buffer conveyors for connecting a lift and shuttles, a lift for accessing tiers and input/output (I/O) points of the rack, and tier-captive shuttles that travel along the aisles. The warehouse needs to perform retrieval operations to retrieve the required totes and storage operations to store the totes in the pre-assigned storage positions. The operation states of shuttles and lift can be classified into two types: empty, which refers to the movement from the dwell point position to the start position of a new task, and loaded, which refers to the movement to handle a tote. When performing retrieval operations, the shuttle moves from the dwell point to the retrieval position to pick up the required tote and then moves to the position of the buffer conveyor for the tier to unload the tote. The tote waits for the lift on the buffer conveyor. At the same time, the lift goes to the tier to load the tote and goes down to the I/O point of the rack. The storage operation travels in the opposite direction of the retrieval operation. The lift goes to the I/O point of the rack first to pick up the tote, then lifts the tote up to the assigned tier and unloads the tote to the buffer conveyor. The shuttle travels to the I/O position of the tier and takes the tote waiting on the buffer conveyor to the assigned storage position. The point of service completion rule is used as the dwell point policy of shuttles and the lift, that is, once a shuttle or the lift finishes a retrieval or storage task, it will stay at the end position of the finished task until moving to the start position of another task. To improve the efficiency of warehouse task processing, warehouse operators need to assign the sequence and schedule of all tasks and make a detailed schedule for equipment including the shuttles and lift.

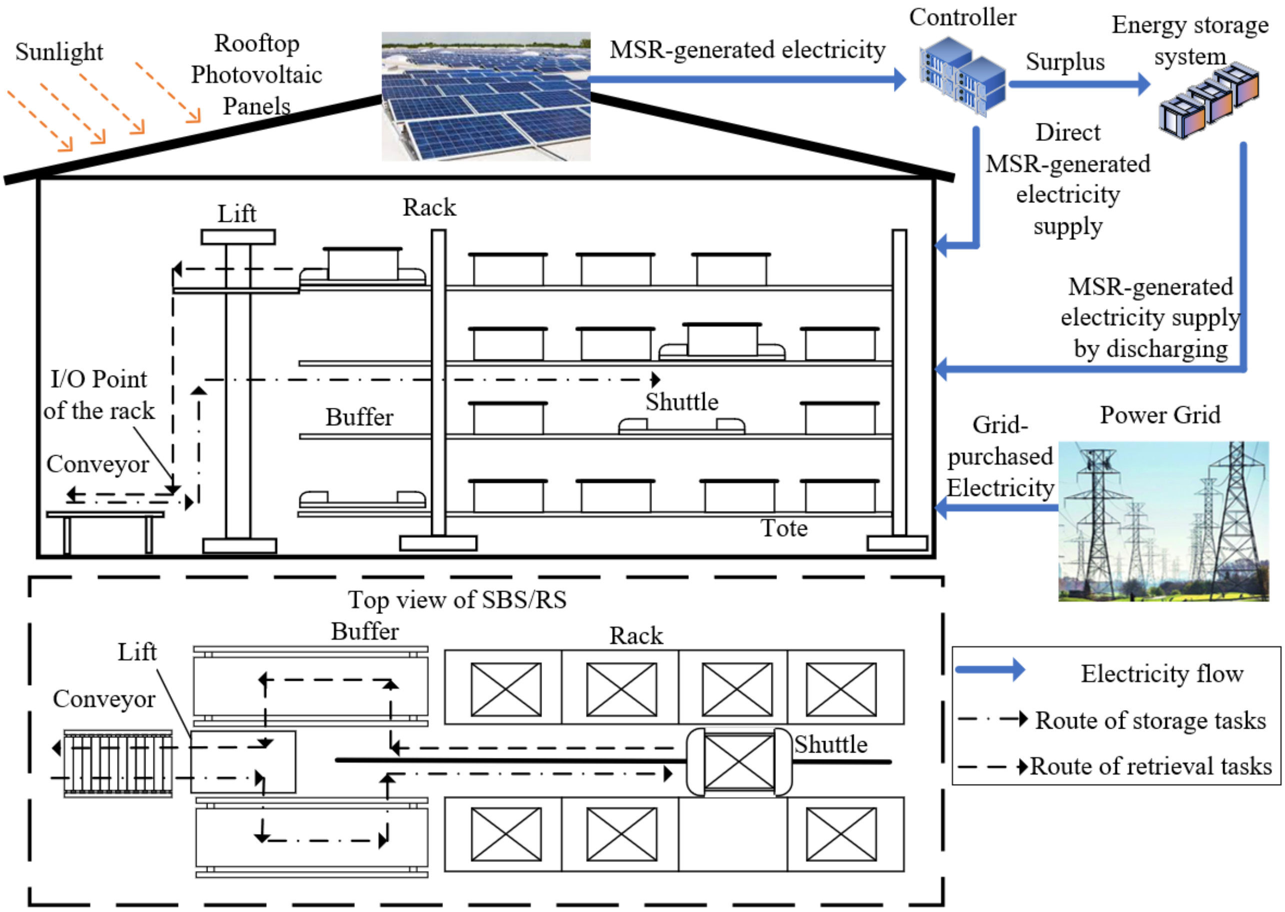


Figure 2: A sketch map of SBS/RS and the electricity supply of MSR

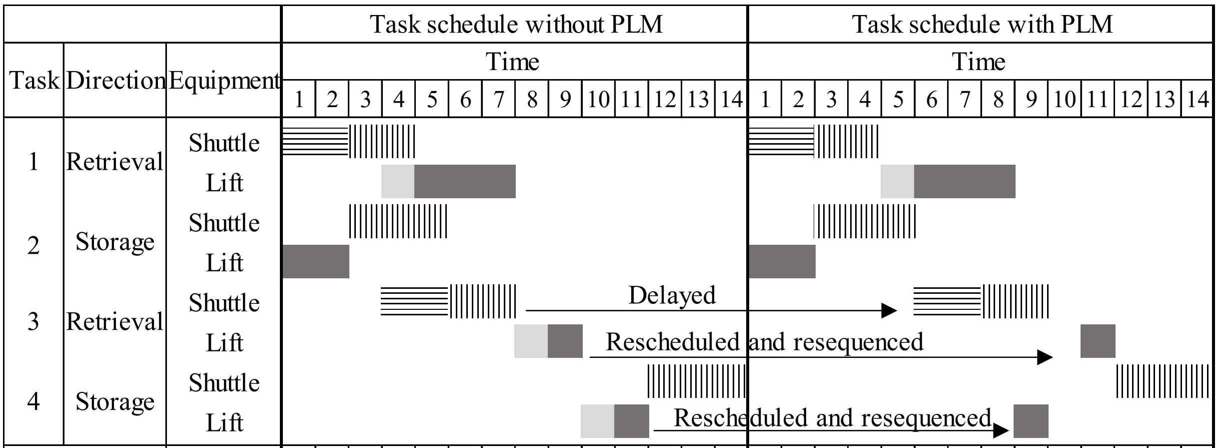
The operation of the shuttles and lift consumes electricity, which is a key source of warehouse carbon emissions. In our problem setting, we illustrate a hybrid electricity supply system that consists of MSR and power grid. The electricity generated by MSR is preferentially used in the system as its zero-carbon emission feature, and the grid-purchased electricity is used as the supplement when the supply of MSR-generated electricity cannot meet the electricity demand. The operation of the MSR is a dynamic process which is controlled by the controller. The on-site PV panels generate electricity to supply the demand of the warehouse system via the controller. If the supply of electricity generated by the PV panels exceeds the demand, the unconsumed electricity can be stored in the energy storage system until the system is full. Once the energy storage system is full, the excessive electricity cannot be stored and has to be wasted. Although the MSR can realize net-zero energy operations in some cases (Pham et al., 2019), the unstable supply of renewable energy resources generally leads to the mismatch between supply and demand, especially at peak times. Therefore, the system needs to purchase electricity from grids to meet the gap in electricity supply. The electricity purchased from the grids is usually generated from fossil fuels such as coal, diesel, or natural gas, and it incurs extra energy costs and leads to carbon emissions. It is not economically or environmentally friendly to purchase electricity from the grid. Based on the characteristics of the hybrid energy supply system, the warehouse should overcome the following two operations management problems to achieve its decarbonization objective:

1. How to prevent the unnecessary use of grid-purchased electricity. The basic concept behind this problem is that the MSR should act as the main electricity supplier, and the grid should act as an auxiliary electricity source to fill the gap between the MSR supply and demand. Measures concerning warehouse operations management, such as sequencing and scheduling, can be taken so that both the total electricity consumption and the grid-purchased electricity consumption at peak times can be reduced.

2. How to reduce the waste and make full use of MSR-generated electricity. In addition to expanding the capacity of energy storage systems, the improvement of warehouse task sequencing and scheduling can adjust the electricity demand when the supply of MSR-generated electricity is sufficient.

Based on the above two challenges, the importance of operations management for the decarbonization objective is evident. By forecasting the supply of MSR-generated electricity within the planning horizon, the warehouse can develop an electrical supply-based schedule to make better use of MSR-generated electricity as well as to avoid possible energy consumption peaks. The concept of PLM may provide the basis for further improvement beyond traditional time-based or energy-based optimization objectives. The implementation of PLM in warehouses will limit the amount of warehouse equipment working at the same time, delaying the start time of some tasks to be processed or changing the sequence of tasks to avoid peak demand issues. In our problem setting, once an equipment starts to move to process tasks, the moving should not to be interrupted since the additional starts and stops will increase the equipment wears and energy depletion. Figure 3 illustrates two warehouse task scheduling examples to explain the effectiveness of PLM. The total grid-purchased electricity consumption of the task schedule without PLM is six units. The grid-purchased electricity is used at time 5, 6, and 7, when the task workload is relatively high and the supply of MSR-generated electricity is insufficient. The PLM delays the empty movement and loaded movement of the shuttle processing task 3 to reduce the workload of the peak time. Moreover, the PLM re-sequences the lift's movement of task 3 and 4 so that the empty movement before handling the tote of the two tasks is eliminated, resulting in the reduction of electricity consumption. The application of PLM achieves net-zero energy operations of the example.

PLM can reduce the consumption of grid-purchased electricity and improve the utilization of renewable energy-generated electricity by avoiding the peak demand and make better use of the MSR generated electricity in off-peak times. The PLM may cause the unlimited delay in some cases, especially when the supply of MSR-generated electricity is relatively insufficient. To prevent the unlimited delay of tasks, we set that all tasks should be completed within a pre-defined planning horizon. The start time of the planning horizon can be now or sometime later, and the end time of the planning horizon should be the deadline or the latest delivery time of all tasks. To make sure that all tasks can be finished in the planning horizon, we can select some tasks that should be processed now by priority, deadline and other factors.



		Without PLM														With PLM													
	Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Energy Consumption (unit)	Shuttles	1	1	4	5	3	2	2					2	2	2	1	1	4	4	2	1	1	2	2			2	2	2
	Lift	3	3		2	3	3	3	2	3	2	3				3	3			2	3	3	3	3		3			
	Total	4	4	4	7	6	5	5	2	3	2	3	2	2	2	4	4	4	4	4	4	4	5	5	0	3	2	2	2
Electricity Supply (unit)	MSR	3	3	4	4	4	3	3	4	5	5	4	4	5	3	3	3	4	4	4	3	3	4	5	5	4	4	5	3
	Stored	5	4	3	3	0	0	0	0	2	4	7	8	8	8	5	4	3	3	3	3	2	1	0	0	5	6	8	8
	Grid	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Electricity stored (unit)		4	3	3	0	0	0	0	2	4	7	8	8	8	8	4	3	3	3	3	2	1	0	0	5	6	8	8	8
Total Grid-Purchased Electricity Consumption		**6**														**0**													

Shuttles' loaded movement
Shuttles' empty movement
lift's loaded movement
Lift's idle movement

Figure 3: An example of task scheduling with PLM

Based on the description above, we tackle the operational problem of warehouse decarbonization in the proposed warehouse system. The decarbonization objective can be interpreted as reducing the consumption of grid-purchased electricity because it has higher unit carbon emissions than MSR-generated electricity (close to zero emissions). The operational measures for controlling the consumption of grid-purchased electricity include task sequencing and scheduling as well as PLM. We need to determine a detailed schedule based on PLM for both storage and retrieval tasks and adjust the schedule according to the forecast MSR-generated electricity supply. All of the tasks should be completed within the planning horizon. Before addressing the proposed model, some assumptions need to be clarified:

1. There is enough space in the buffer.

2. The supply of MSR-generated electricity is known in advance.

3. To simplify the problem, we discretize the planning horizon into a set of time units. The length of a time unit is very short, usually about 1-3 seconds to ensure the accuracy of the decision.

3. The position of both retrieval tasks and storage tasks is predetermined, and the travel time of the lift and shuttles between different positions is known in advance.

4. The energy consumption of both shuttles and lift per unit of time is constant and varies according to the working state and tasks.

5. By pre-selecting some tasks, all tasks can be processed within the planning horizon.

4. Mathematical model

This section formulates a mixed-integer linear programming model for optimization problem on sequencing and scheduling warehouse retrieving and storage tasks in SBS/RS with MSR.

4.1 Notations

This section defines the parameters and decision variables used in the model. For better clarification and understanding, we use the Roman letters to denote the parameters and the Greek letters to denote the variables, respectively.

Indices and sets

I	set of all equipment. $I = \{S, L\}$, in which S represents shuttles, and L represents the lift.
E	set of all tiers, which are indexed by e.
K	set of all tasks, which are indexed by k.
$e^K, e^{K'}$	dummy tasks which represent the start and end points of tasks. $k_0 = K \cup \{e^K\}$, $K_T = K \cup \{e^{K'}\}$
K^{re}	set of all retrieval tasks.
K^{st}	set of all storage tasks.
K_e	set of all tasks processed by the shuttle of tier e.
T	set of planning horizon, which are indexed by t. $T' = T - \{0\}$.

Parameters

a	the capacity of energy storage system.
n_t	forecasted MSR-generated electricity supply at time t.
$c_{i,k}^1$	electricity consumption per unit time of equipment i to move from the dwell point to the start position of task k.
$c_{i,k}^2$	electricity consumption per unit time of equipment i to handle the tote of task k.
$m_{i,k}$	equipment i's travel time to handle the tote of task k.
$\widehat{m}_{i,k_1,k_2}$	equipment i's travel time from the dwell point after finishing task k_1 to the start position of task k_2.
M	a sufficiently large number.

Decision variables

α_t	total available quantity MSR-generated electricity at time t.
α_t^+	grid-purchased electricity at time t.
α_t^-	remained MSR-generated electricity stored in energy storage system at the end of time t.
$\beta_{i,k,t}^1$	binary, equals one if equipment i is travelling from the dwell point to the start position of task k at time t, otherwise zero.
$\beta_{i,k,t}^2$	binary, equals one if equipment i is handling the tote of task k at time t, otherwise zero.
$\epsilon_{i,k}$	the start time of equipment i moving from the dwell point to the start position of task k.
$\zeta_{i,k}$	the start time of equipment i handling the tote of task k.
θ_{i,k_1,k_2}	binary, equals one if equipment i processes task k_2 after k_1, otherwise zero.

4.2 Mathematical model

$$min \sum_{t \in T} \alpha_t^+ \tag{1}$$

s.t.

$$\epsilon_{i,k} + \sum_{k_1 \in K} \theta_{i,k_1,k} \cdot \widehat{m}_{i,k_1,k} \leq \zeta_{i,k} \qquad \forall i \in I, k \in K \tag{2}$$

$$\zeta_{S,k} + m_{S,k} \leq \zeta_{L,k} \qquad \forall k \in K^{re} \tag{3}$$

$$\zeta_{L,k} + m_{L,k} \leq \zeta_{S,k} \qquad \forall k \in K^{st} \tag{4}$$

$$\sum_{k_1 \in K^0} \theta_{i,k_1,k} = \sum_{k_1 \in K^T} \theta_{i,k,k_1} = 1 \qquad \forall i \in I, k \in K \tag{5}$$

$$\sum_{k \in K_e} \theta_{S,0,k} = \sum_{k \in K_e} \theta_{S,k,T} = 1 \qquad \forall e \in E \tag{6}$$

$$\sum_{k \in K} \theta_{L,0,k} = \sum_{k \in K} \theta_{L,k,T} = 1 \tag{7}$$

$$\epsilon_{i,k_2} \geq \zeta_{i,k_1} + m_{i,k_1} + M\left(\theta_{i,k_1,k_2} - 1\right) \qquad \forall i \in I, k_1, k_2 \in K \tag{8}$$

$$\zeta_{L,k_2} \geq \zeta_{L,k_1} + M\left(\theta_{S,k_1,k_2} - 1\right) \qquad \forall i \in I, k_1, k_2 \in K^{re} \tag{9}$$

$$\zeta_{S,k_2} \geq \zeta_{S,k_1} + M\left(\theta_{L,k_1,k_2} - 1\right) \qquad \forall i \in I, k_1, k_2 \in K^{st} \tag{10}$$

$$\epsilon_{i,k} - t \leq M(1 - \beta_{i,k,t}^1) \qquad \forall i \in I, k \in K, t \in T \tag{11}$$

$$\epsilon_{i,k} + \sum_{k_1 \in K} \theta_{i,k_1,k} \cdot \widehat{m}_{i,k_1,k} - t - 1 \geq M(\beta_{i,k,t}^1 - 1) \qquad \forall i \in I, k \in K, t \in T \tag{12}$$

$$\sum_{t \in T} \beta_{i,k,t}^1 \geq \sum_{k_1 \in K_e} \theta_{i,k_1,k} \cdot \widehat{m}_{i,k_1,k} \qquad \forall i \in I, k \in K \tag{13}$$

$$\zeta_{i,k} - t \leq M(1 - \beta_{i,k,t}^2) \qquad \forall i \in I, k \in K, t \in T \tag{14}$$

$$\zeta_{i,k} + m_{i,k} - t - 1 \geq M(\beta_{i,k,t}^2 - 1) \qquad \forall i \in I, k \in K, t \in T \tag{15}$$

$$\sum_{t \in T} \beta_{i,k,t}^2 \geq m_{i,k} \qquad \forall i \in I, k \in K \tag{16}$$

$$\alpha_0 = n_0 \tag{17}$$

$$\alpha_t = n_t + \alpha_{t-1}^- \qquad \forall t \in T - \{0\} \tag{18}$$

$$\left(\sum_{k \in K} \sum_{i \in I} \left(c_{i,k}^1 \cdot \beta_{i,k,t}^1 + c_{i,k}^2 \cdot \beta_{i,k,t}^2\right)\right) - \alpha_t \leq \alpha_t^+ - \alpha_t^- \qquad \forall t \in T \tag{19}$$

$$\alpha_t, \alpha_t^+ \geq 0 \qquad \forall t \in T \tag{20}$$

$$0 \leq \alpha_t^- \leq a \qquad \forall t \in T \tag{21}$$

$$\beta_{i,k,t}^1, \beta_{i,k,t}^2 \in \{0,1\} \qquad \forall i \in I, k \in K, t \in T \tag{22}$$

$$\epsilon_{i,k}, \zeta_{i,k} \geq 0 \qquad \forall i \in I, k \in K \tag{23}$$

$$\theta_{i,k_1,k_2} \in \{0,1\} \qquad \forall i \in I, k_1, k_2 \in K \tag{24}$$

Objective (1) minimizes the total grid-purchased electricity consumption of the planning horizon. Constraints (2) define the start time of an equipment handling a tote should be later than the time that the equipment arrives at the start position from the dwell point. Constraints (3) make sure that for a retrieval task, the start time of the lift handling the tote of task k should be later than the finish time of the shuttle handling the tote. Constraints (4) make sure for a storage task, the start time of the shuttle handling the tote of task k should be later than the finish time of the lift handling the tote. Constraints (5)– (7) guarantee the consecutiveness of two tasks handled by the lift and shuttles. Constraints (8) define the time relationship for two consecutive tasks. Constraints (9) and (10) ensure that the task sequence between shuttles and lift is consistent. Constraints (11)- (13) are used to decide whether equipment i is moving to the start position of task k at time t. Constraints (14)- (16) are used to decide whether equipment i is handling the tote of task

k at time t. Constraints (17) and (18) calculate the available MSR-generated electricity supply at time t. Constraints (19) calculate the grid-purchased energy consumption and the remained electricity in energy storage system at time t. Constraints (20)- (24) define the decision variables.

5. The framework of data-driven solution approach

Warehouse systems are not only storage places for various products, but important nodes of logistics information flows. Intelligent warehouses can process and utilize information and data to improve the efficiency of the warehouse and the logistics network. Various data-driven technologies, such as the Internet of Things, machine learning, artificial intelligence, and intelligent algorithms, are used to enhance the efficiency of warehouse operations. To improve solving efficiency and make full use of warehouse information flow to assist decision making, this paper establishes the framework of data-driven solution approach, which includes a method for data set generation and application, and a tailored VNS algorithm.

The data-driven solution approach aims to discover a novel solution method by analysing, mining, and utilizing historical operational data (Yu et al., 2019, Cai et al., 2021). In the proposed warehouse system, historical operational data contain task information, MSR-generated electricity supply, basic parameter of system configurations, and the operation status of shuttles and lift during storage and retrieval process. By analysing historical operational data, system operational efficiency can be evaluated in terms of travel time and cost. Motivated by the travel time-related energy-efficiency objective of the proposed model, the data-driven solution framework selects the total empty movement time of shuttles and lifts as the mainly concerned index in historical data. Moreover, we set up a simple criterion based on historical data to determine whether the total empty movement time of a given solution is satisfactory from the perspective of energy-efficiency and practical feasibility, and utilize the criterion to mathematical models and optimization algorithms. Additional constraints are added to the proposed mathematical model, and a variable neighbourhood search-based solution approach is designed for further optimization.

5.1 Data set generation and application

This subsection demonstrates the basic process of data-driven method to generate data sets from historical data, and the application of data sets in mathematical model and optimization algorithm. The basic processes are shown in Figure 4. By selecting appropriate historical data, we can generate the index for further processing, i.e. the empty/loaded ratios of historical tasks. The generated index from historical data can be classified into data sets by the number of tasks, and obtain data sets for large and real-scale problem by data fitting method. The data sets are applied into the model by adding additional constraints which can reduce the solution search space, and the application of data sets in the data-driven variable neighbourhood search algorithms are mainly focuses on the evaluation of solution quality in neighbourhood search procedure, and add extra triggering conditions in the diversification method.

(1) Index selection and data set generation from historical data

The electricity consumption of the warehouse system is related to the equipment's movement. According to the proposed model, equipment i 's total empty travel time can be calculated by $m_i^{empty} = \sum_{k_1 \in K} \sum_{k_2 \in K} \theta_{i,k_1,k} \cdot \widehat{m}_{i,k_1,k}$, and equipment i's total loaded travel time of all tasks can be calculated by

$m_i^{loaded} = \sum_{k \in K} m_{i,k}$. The empty travel time is directly related to the decision of task sequence. A proper task sequence will reduce the empty travel time as well as the energy consumption, so the empty travel time can be used to evaluate the efficiency of a task sequence. Meanwhile, the empty travel time can be influenced by the start/end positions of different tasks. The loaded travel time is pre-determined by the start/end positions of tasks to be processed, which could be used as a reference of task workload. Based on the fact and characteristics of historical data, we use the empty/loaded ratio $b_i = m_i^{empty}/m_i^{loaded}$ as the key index of the data-driven solution framework, and generate data sets used for data-driven algorithms in the following steps.

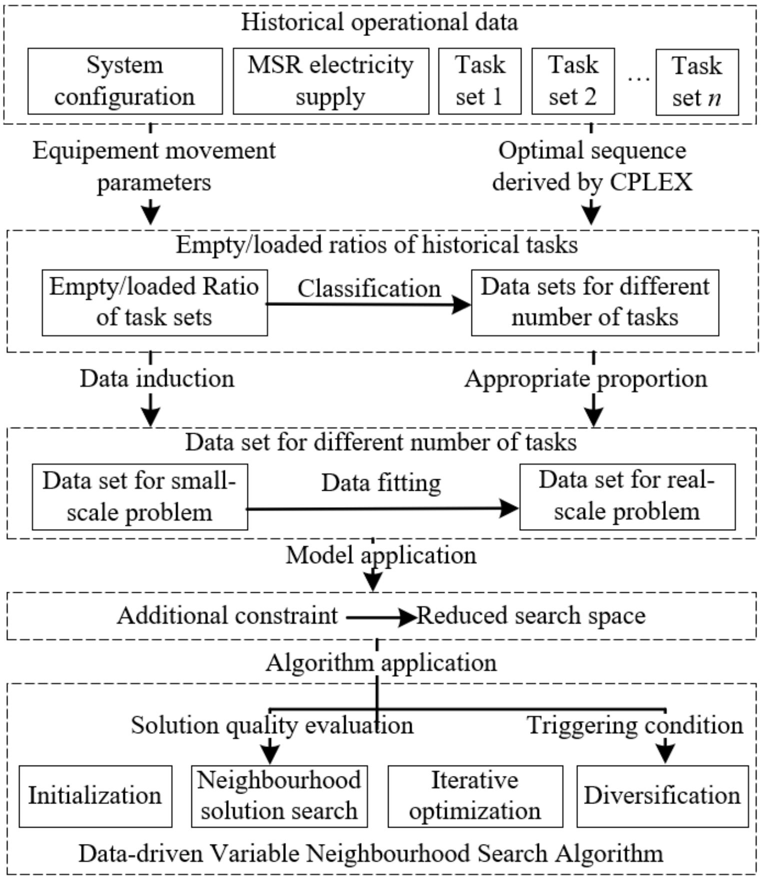


Figure 4: The basic process of data-driven solution methodology

Step 1: collect historical operational data. The data to be collected includes rack configuration data (number of tiers, totes per tier, storage positions), operating data of shuttles and lift (travel time and electricity consumption for different tasks under different working conditions), historical task sets (the direction and the totes to be handled), and the supply of MSR-generated electricity.

Step 2: obtain optimal task sequence and the empty/loaded ratio of different sets of historical tasks. The optimal task sequencing solutions should be obtained as the benchmark for further optimization. Commercial solver like CPLEX can be used to generate optimal task sequence by solving the proposed model. The optimal empty/loaded ratio for each task set should be generated with the optimal sequence instead of historical sequences based on experience and expertise.

Step 3: classify data into different data sets, and analyse the data characteristics. The empty/loaded ratio of the historical tasks varies with the number of tasks. We classify the optimal empty/loaded ratio according to the number of tasks in task sets, and obtain an upper bound of empty/loaded ratio $b_{|K|}^{i}$ for task sets with $|K|$ tasks. To ensure the tightness of the upper bound and eliminate the influence of unexpected maximum value, we can also obtain a value ${b_{|K|}^{i}}^{*}$ which is greater than a certain percent of the empty/loaded ratio for the given task sets, for example, 90% or 95%.

Note that we apply the commercial solver to obtain the optimal solutions in the data set generation process. The commercial solver can only solve small-scale historical tasks, and can hardly obtain a feasible solution of a real-scale problem with hundreds of storage and retrieval tasks. To deal with the problem, we can use the fitting method to generate the data set for real-scale instances according to small-scale instances. The historical data used in the fitting method should be under the same system configuration and electricity supply. We can use the historical data with different small-scale tasks, or randomly generate some small-scale instances if the small-scale historical data is not enough, as the basic data for the fitting process. A fitting probability distribution function can be obtained by these small-scale instances, which can be used to estimate ${b_{|K|}^{i}}^{*}$ of real-scale problem. The data set generation is the preparation work which should be taken in the idle time of computing power before problem-solving. The historical data sets of ${b_{|K|}^{i}}^{*}$ are then used in the solution procedure to determine whether the index is satisfactory.

(2) Applicating data-driven method in problem solving

The data set generated in 5.1 is used as the benchmark for optimization. According to the data set generation process, ${b_{|K|}^{i}}^{*}$ is a more precise upper bound value after excluding some extreme value in historical data. If the empty/loaded ratio of a specific solution is greater than ${b_{|K|}^{i}}^{*}$, we believe that this solution is usually unsatisfactory in terms of empty travel time in the most cases. So, we can use the data set to exclude some unsatisfactory solutions in the problem-solving process. To be specific, we add the following additional constraints to the model.

$$b_i \leq {b_{|K|}^{i}}^{*} \qquad \forall i \in I \tag{25}$$

The additional constraints can reduce the solution search space and accelerate the solution procedure. In a few cases, the model with the additional constraints cannot get a feasible solution since all feasible solutions has been excluded by the additional constraints. The solution characteristics of these cases are too rare to be characterized by the historical data, so the additional constraints should be excluded from the model to obtain the solution. In the data-driven neighbourhood search algorithm, the additional constraints can be used to determine if a candidate solution is a satisfactory solution in neighbourhood search procedure and diversification method. For the neighbourhood search procedure, if enough satisfactory solution has been obtained, the generation of neighbourhood search in an iteration can be stopped. The additional constraints are also used as a trigger condition for diversification method. If a satisfactory solution has not been obtained as the current best solution for several iterations, we can believe that the current solution can hardly obtain a satisfactory solution in the current neighbourhood search space. The diversification method will run to generate new current solutions for the next iteration.

5.2 Data-driven variable neighbourhood search algorithm

Due to the NP-hard feature of task sequencing problem, the proposed model cannot be solved by commercial solver for real-scale instances. The VNS has been widely used in the optimization problem of warehouse operation management. We therefore developed a VNS-based solution approach which applies the proposed data-driven method for acceleration.

(1) Solution representation

In the proposed warehouse system, all tasks should be handled by the lift. The lift is usually the bottleneck resource in SBS/RS. On the other hand, the vertical movement of lifts consumes much more energy than the horizontal movement of shuttles. So we choose the variables θ_{L,k_1,k_2} which indicate the lift's task sequence of tasks as the core variables for further iterations. A vector L is defined to represent the lift's task sequence with $|K|$ elements, where each element represents the index of a task.

The shuttles should process tasks in the same order as the lift in most cases. According to constraints (9) and (10), the sequence of two tasks for the same direction goes the same for both lift and shuttles. For the case that a storage task is processed right after a retrieval task, the shuttle's sequence should be the same as the lift's sequence to reduce the empty movement between tasks. For the case that a retrieval task processed right after a storage task, we should compare the empty travel time in two different sequences, and select the sequence with the shortest empty time. Other variables, including the variables indicating the start time of tasks, and the variables for energy consumption, are determined by the method to derive fitness value in this subsection.

(2) Initialization

We design a three-step Clarke and Wright (C-W) algorithm to generate an initial solution for further iteration. The first step is to generate the sequences of shuttles. For those tasks performed in the same tier, we use the principle of the C-W algorithm to determine the sequence of each shuttle. The second step is to generate a preliminary sequence of the lift by C-W algorithm. The preliminary sequence describes the inter-tier movement sequence but not to determine the actual task sequence. The elements of preliminary sequences represent only the moving direction (retrieving/storage) and the start/end tiers. The elements can be replaced by other tasks with same direction in the same tier without incurring more lift's electricity consumption. The third step is to assign the actual task to the preliminary sequence of lift. For elements representing a specific tier in the preliminary sequence, the actual task is assigned according to the sequence of the shuttle on that tier should follow the rule mentioned in solution representation. If there is any inconsistency between two sequences, the shuttle's sequence should be changed based on the lift's sequence.

(3) Data-driven neighbourhood search procedure

Three neighbourhood search methods are randomly used for generating candidate neighbourhood solutions by equal probability, namely 2-opt method, swap method, and insert method. These neighbourhood structures are inspired by the previous research of travelling salesman problem and vehicle routing problem problem (Meng et al., 2020, Derbel et al., 2019). In our research problem, the decision lift's sequence is similar to the main decisions of these problems, so we apply these neighbourhood structures in the algorithm design. In 2-opt method, the 2-opt operator randomly selects a part of sequence list with more than three elements and then inverts the selected sequence. In the swap method, the swap operator randomly selects two elements in the sequence list and swaps the position of the two elements. The insert method randomly selects an element from the sequence, and insert it to a randomly selected position. Figure 5 shows the neighbourhood search process by examples. By randomly selecting the three neighbourhood structures, the algorithm can obtain diversified neighbourhood solutions, and select the best solution as the historical best solution.

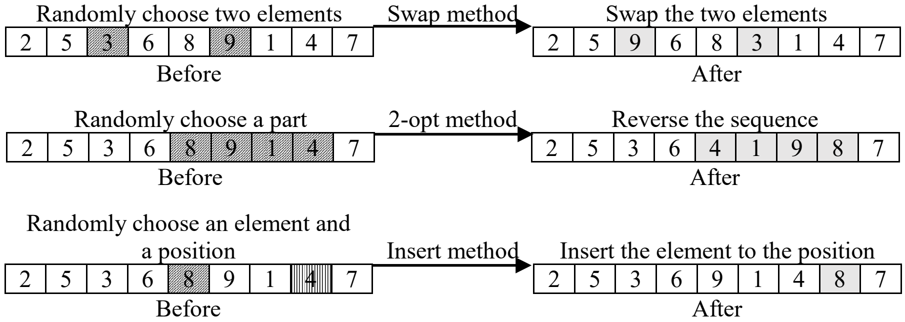


Figure 5: Examples for swap, 2- opt, and insert method

The generation process of candidate solutions in an iteration is stopped after obtaining sufficient candidate solutions. To reduce the effort for generating candidate solutions, we establish a data-driven stop rule which employs the data set generated in section 5.1. Every time a candidate is generated, it is necessary to determine whether the solution satisfies the constraint (25). If a sufficient number of candidate solutions satisfying the requirements of constraints (25) are obtained, the generation process of new candidate solutions can be stopped. The required number of satisfactory solutions should be less than the number to stop the neighbourhood solution generation in an iteration so that less effort in the solution generation process is needed and the search procedure can be stopped in advance. The candidate solution with the lowest fitness value among the existing candidate solutions is selected as the best solution for the next iteration.

(4) Tabu search method

To avoid the neighbourhood search trapped into local optimum, we employ tabu search method in the solution procedure. A tabu list is built to record the moves of the previous search procedure and prevent the repetition of those tabu solutions. The aspiration criterion is employed in the tabu search procedure, that is, if the fitness value of a current neighbourhood solution is better than the best solution found before, the current solution can override the tabu status, and is accepted to as the solution for the next iteration and replaces the best-known solution. The solutions in the tabu list can be unblocked according to “first in first out” principle when the tabu list is full. The solutions can also be unblocked with a certain probability in each iteration.

(5) Diversification

The diversification method is another method employed in our algorithm to ensure the global search ability of the algorithm. If the historical best solution has not been improved for a certain number of iterations, or the algorithm cannot obtain a candidate solution that satisfies the requirement of constraints (25) after several iterations, the diversification method will be triggered. The triggering condition for historical best solution not improved is used to jump out from the local optimum and enlarge the searching space. The triggering condition about satisfactory solution is used to reduce the searching effort for the “unsatisfactory” solution space. A new current solution will be generated by choosing the best solution among several randomly generated solutions.

(6) The method to derive fitness value

We develop a method to schedule the tasks and derive fitness value according to the solution. Before implementing the method, we need to calculate the lower bound of grid-purchased electricity consumption:

$$\underline{a}^+ = max\{\sum_{k\in K}\sum_{i\in I}(c^1_{i,k}\cdot\sum_{k_1\in K}\theta_{i,k_1,k}\cdot\widehat{m}_{i,k_1,k}+c^2_{i,k}\cdot m_{i,k})-\sum_{t\in T}n_t\,,0\} \quad (26)$$

The basic steps of the method are listed as follows:

Step 1: Estimate the shortest completion time of all tasks based on the given sequence and constraints (2)–(4), (9), and (10) ignoring the time limit of the planning horizon. By applying these constraints, the start time of each task can be determined in the order of the task. If the shortest completion time exceeds the planning horizon, the sequence is infeasible to complete all tasks, and the output of energy consumption should be set to M. The infeasible sequence needn't to go for the next steps. If the tasks can be completed in the planning horizon, go to step 2.

Step 2: Schedule all tasks. The start time of all tasks should be set to the latest start time to make sure the completion time of all tasks is at the end of the planning horizon.

Step 3: Calculate the energy consumption of all time points based on the current schedule, and calculate the grid-purchased electricity consumption. If the total grid-purchased electricity consumption equals to $\underline{a}^+$, output the task schedule. If the total grid-purchased electricity exceeds the lower bound, go to step 4.

Step 4: Use the following rules to determine whether a task can start earlier and derive the possible earliest start time.

a) The current start time of the task is later than its earliest start time.

b) The task can start earlier without incurring additional grid-purchased electricity consumption.

c) The possible earliest start time of a task should be the earlier one between its earliest start time and the earliest time that satisfies rule b).

If there are tasks that can be started earlier, select the earliest task among the tasks that can be started earlier. The start time of the selected task should be moved earlier to its possible earliest start time. Then go to step 3. If no tasks can be started earlier, output the task schedule.

6. Numerical experiment

We conduct extensive numerical experiments to validate the effectiveness of the proposed model and the efficiency of the data-driven VNS algorithm. The experiments are performed on a computer equipped with Intel i7-6500U CPU @2.50GHz and 8GB RAM. The proposed model and algorithm are programmed in C# (VS2015) with the solver IBM ILOG CPLEX 12.6.1. The time limit for all of the experiments is set to 7200 seconds.

6.1 Experimental settings

In the experiments, we generate seven different-scale instance groups (ISGs). Each ISG contains five randomly generated instances. The information in Table 2 lists the key parameters for the seven ISGs generated for the experiments. The retrieving tasks are randomly generated with different directions and totes. The length of the planning horizon varies from 50 time units to 1800 time units. The system configuration is also pre-determined by the parameter settings.

Table 2: Key parameter settings for different instance groups

Number of / Group ID	Tasks $\|K\|$	Time $\|T\|$	Tiers $\|E\|$	Totes	Totes per tier	Decision variables	Constraints

ISG1	5	50	5	100	20	1×10^3	2×10^3
ISG2	10	100	5	100	20	5×10^3	9×10^3
ISG3	15	150	5	100	20	1×10^4	2×10^4
ISG4	20	200	5	100	20	2×10^4	3×10^4
ISG5	50	600	6	300	50	1×10^5	3×10^5
ISG6	80	720	6	300	50	2×10^5	5×10^5
ISG7	100	1800	10	1000	100	7×10^5	1×10^6

The parameter setting of electricity supply and consumption in Table 3 is used to create the circumstance that can highlight the importance of PLM. The supply of MSR generated electricity depends on various factors. Here we set the supply as a case, that the energy supply can only satisfy the consumption of only one or two equipment simultaneously. We set the capacity of energy storage system at a low level. The energy storage system can provide electricity for equipment working simultaneously in a short time, but the storage capacity of MSR-generated electricity is relatively low requiring the timely consumption of MSR-generated. Meanwhile, lower capacity reduces the investment of energy storage system, creating more possibilities for the widely adoption.

Table 3: Parameters of electricity supply and consumption

Parameter	Value/range	Parameter	Value/range
a	20	n_t	[3,8]
$c_{L,k}^1$	2	$c_{S,k}^1$	1
$c_{L,k}^2$	[4,6]	$c_{S,k}^2$	[2,4]

The parameter setting of equipment's travel time is set according to the storage position of the task's corresponding totes and the direction of tasks. We set the travelling speed of shuttles to 1, that means the shuttle travels a unit distance in a unit time. The lift's travelling speed is also set to 1, that is, the lift travels a tier in a unit time. So the $m_{L,k}$ can be calculated as the number of tier where the corresponding tote stored, and the $m_{S,k}$ can be calculated by the distance between the storage position and the I/O point of the rack.

6.2 Experimental results

This section tests the effectiveness and efficiency of the proposed data-driven VNS algorithm through comparative experiments. The first experiment is conducted to verify the performance of the proposed algorithm, and the second experiment is to show the efficiency of the data-driven algorithm.

(1) Algorithm performance

To verify algorithm performance, we conduct extensive experiments performed by CPLEX and the proposed algorithm. We firstly conduct the small-scale experiments to compare the results obtained by CPLEX solver and the data-driven VNS algorithm. The difference of the objective value obtained by the two methods is measured by GAP_1, in which the objective value obtained by CPLEX is used as the benchmark. Table 2 shows that the solution obtained by data-driven VNS algorithm is the same as the solution of CPLEX solver for all instances of ISG1, ISG2, which is showed by the column "GAP_1" from the optimality gap is zero. In terms of computation time, although the VNS based method takes longer time to obtain a result, the VNS based method spends much shorter time than CPLEX for all the instances of ISG2 and ISG3. The CPLEX can only find the optimal solution for 10 tasks within 7200 seconds. When the number of tasks increases to 15, CPLEX can only obtain feasible solutions that are not better than the solutions obtained by the VNS algorithm. The VNS algorithm maintains its high efficiency, where the average computing time is only 34 seconds.

According to Table 4, CPLEX solver cannot obtain the optimal solution within a reasonable time. This makes it improper to act as a benchmark for the evaluation of the data-driven VNS algorithm. In warehouse practice, hundreds of totes need to be retrieved or storage at peak times. To evaluate algorithm's efficiency in solving real-scale problems, we conduct the large-scale experiments by comparing the solutions obtained by the VNS algorithm with the solution obtained by C-W saving method which is elaborated in section 5.2(2). The difference of the objective value obtained by the two methods is measured by GAP_2. The average value of GAP_2 in small-scale problem is used as the benchmark to measure the average value of GAP_2 in large-scale problem. Table 5 shows that the average gap between the two methods is about 43.8%. The VNS algorithm can always make further optimization comparing with the C-W saving method. Moreover, we can observe that the VNS algorithm maintains high efficiency in solving large-scale instances with the average computing time 116 seconds.

Table 4: Algorithm performance for small-scale instances

Instances		CPLEX		Algorithm				
Group	ID	Z_c	t_c	Z_i	Z_a	t_a	GAP_1	GAP_2
ISG1	1	12	1	18	12	13	0.0%	50.0%
	2	25	2	28	25	16	0.0%	12.0%
	3	0	2	0	0	5	—	—
	4	0	1	5	0	9	—	—
	5	3	2	4	3	20	0.0%	33.3%
ISG2	1	9	281	13	9	12	0.0%	44.4%
	2	42	195	42	42	18	0.0%	0.0%
	3	5	697	8	5	27	0.0%	60.0%
	4	0	614	0	0	26	—	—
	5	0	104	10	0	5	—	—
ISG3	1	0	698	0	0	10	—	—
	2	0	1058	5	0	32	—	—
	3	5	2300	8	5	34	0.0%	60.0%
	4	67	4230	85	67	42	0.0%	26.9%
	5	52	>7200	60	42	66	-19.2%	42.9%
ISG4	1	13	>7200	29	10	65	-23.1%	190.0%
	2	38	>7200	42	38	87	0.0%	10.5%
	3	15	>7200	21	0	19	—	—
	4	85	>7200	85	72	97	-15.3%	18.1%
	5	37	>7200	45	31	90	-16.2%	45.2%
Average						34	-5.7%	45.6%

Notes: (1) Z_c represents the objective value of optimal solution obtained by CPLEX in 7200 seconds. If CPLEX cannot obtain the optimal solution within 7200 seconds, Z_c represents the objective value of feasible solution obtained by CPLEX at 7200 seconds. Z_i represents the solution obtained by C-W saving method. Z_a represents the global best solution obtained by the algorithm. (2) t_c and t_a represents the computation time of CPLEX and the algorithm in seconds, respectively. (3) $GAP_1 = (Z_a - Z_c)/Z_c$, $GAP_2 = (Z_i - Z_a)/Z_a$.

Table 5: Algorithm performance for large-scale instances

Instances Group	ID	Z_i	Z_a	t_a	GAP
ISG5	1	157	104	62	50.96%
	2	138	99	100	39.39%
	3	10	0	121	—
	4	60	15	115	300.00%
	5	282	200	138	41.00%
ISG6	1	46	34	75	35.29%
	2	69	58	127	18.97%
	3	133	129	103	3.10%
	4	30	11	132	172.73%
	5	42	24	110	75.00%
ISG7	1	26	0	96	—
	2	167	112	127	49.11%
	3	132	98	148	34.69%
	4	245	207	159	18.36%
	5	167	140	130	19.29%
Average				116	66.0%

Notes: (1) Z_i represents the solution obtained by C-W saving method. Z_a represents the global best solution obtained by the algorithm. (2) t_a represents the computation time of the algorithm in seconds. (3) $GAP = (Z_i - Z_a)/Z_a$.

(2) The efficiency of data-driven algorithm

Table 6: The performance of data-driven VNS algorithm and basic VNS algorithm

Instances Group	ID	Z_b	Z_a	t_b	t_a	GAP_t
ISG3	1	0	0	15	10	33.3%
	2	0	0	32	32	0%
	3	5	5	43	34	20.9%
	4	67	67	64	42	34.4%
	5	42	42	75	66	12.0%
ISG4	1	10	10	80	65	18.8%
	2	42	38	89	87	2.2%
	3	0	0	28	19	32.1%
	4	78	72	121	97	19.8%
	5	32	31	115	90	21.7%
ISG5	1	104	104	78	62	20.5%
	2	99	99	127	100	21.3%
	3	0	0	132	121	8.3%
	4	15	15	146	115	21.2%
	5	200	200	165	138	16.4%
Average				87	72	18.9%

Notes: (1) Z_b represents the global best solution obtained by basic VNS algorithm. Z_a represents the global best solution obtained by the data-driven VNS algorithm. (2) t_b represents the computation time of the basic VNS algorithm in seconds. t_a represents the computation time of the data-driven VNS algorithm in seconds. (3) $GAP_t = (t_b - t_a)/t_b$.

To show the efficiency of the data-driven VNS algorithm, we conduct experiments performed by the data-driven algorithm and the basic VNS algorithm which runs without data-driven acceleration approach. The instances of ISG3, ISG4, and ISG5 is involved in the experiment. According to the result of Table 6, the data-driven VNS algorithm outperforms basic VNS algorithm in terms of computation time. The data-driven VNS algorithm can reduce 18.9% computation time comparing with the basic VNS algorithm. Some solutions obtained by data-driven VNS algorithm are better than the solutions obtained by the basic VNS algorithm. This proves the effectiveness of additional rules.

6.3 Managerial insights

This subsection discusses managerial insights about the system configuration of the SBS/RS as well as the effectiveness of PLM by performing a sensitivity analysis and comparative experiments. The influence of different SBS/RS configurations is analysed through experiments on different equipment operating speeds and different rack configurations. The effectiveness of PLM is derived by comparing the grid-purchased electricity consumption with and without PLM.

(1) The effectiveness of PLM

According to Hahn-Woernle and Gunthner (2018), PLM can avoid the peaks in energy consumption with a slight loss of system throughput. In our research, PLM is used to avoid peak demand to improve the utilization of MSR-generated electricity and reduce the unnecessary consumption of grid-purchased electricity. We conduct comparative experiments to further investigate the effect of PLM in reducing grid-purchased electricity consumption.

Most warehouse research concerns the time objective and focuses on minimizing the total completion time for all tasks. In contrast, our research introduces PLM into task scheduling and pays more attention to energy consumption, given the growing awareness of the need for decarbonization. In the experiments, we use electricity consumption under the traditional time objective as a comparison to show the effectiveness of PLM. Figure 6 shows the result of the comparative experiment. PLM can help the warehouse system realize net-zero energy operations in some instances, whereas net-zero energy operations rarely realizes under the time objective. Moreover, the effectiveness of PLM in reducing grid-purchased energy consumption is relevant to different instances and the supply of MSR-generated electricity. Among the proposed instances, on average, PLM can reduce about 66% of grid-purchased electricity consumption. Based on the SBS/RS energy consumption model of Ekren et al. (2018) and Ekren and Akpunar (2021), we can estimate that the mean energy consumption of a transaction in a similar system is about 3.5×10^{-3} kWh. The application of PLM can reduce about 2.3×10^{-3} kWh per transaction. Based on the carbon reduction factor 919.34 g CO^2-eq./kWh used in the research of Wang et al. (2018), PLM can reduce about 2.1 g carbon dioxide emissions per transaction. A large SBS/RS system processes thousands of transactions a day will reduce about 5 tons carbon dioxide emissions and per year.

The reduction of grid-purchased electricity consumption is partly because the delayed schedule allows the tasks to use more MSR-generated electricity or to wait for sufficient MSR-generated electricity. If the planning horizon is shortened, the task delays brought by PLM will be limited, and the grid-purchased electricity consumption will be closer to the consumption with the time objective. Therefore, the effectiveness of PLM in warehouse decarbonization is related to scheduling flexibility. A longer planning horizon with fewer tasks to be processed can increase scheduling flexibility and provide more suitable application scenarios for PLM.

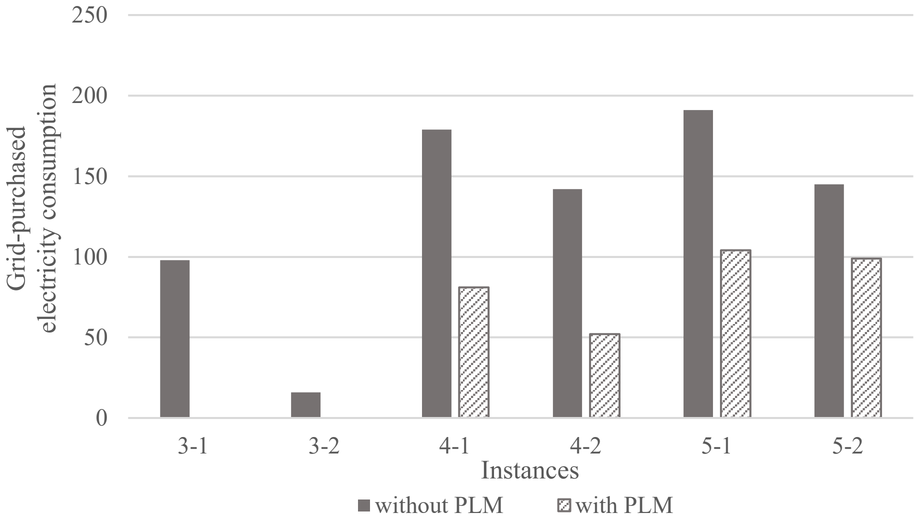


Figure 6: The comparison of grid-purchased electricity consumption with PLM and without PLM

(2) Sensitivity analysis on system configuration of SBS/RS

The energy-efficient design of automated warehouse systems is a hot topic in warehouse decarbonization research. The aim of such research is to determine the optimal system configuration to reduce the total energy consumption of the warehouse system, which could contribute to warehouse decarbonization.

According to Liu et al. (2021), the velocity of the lift is a leading factor for energy consumption, and the velocity of shuttles can also influence the total energy consumption. Reducing equipment velocity, especially the lift's speed, can reduce the energy consumption at the cost of longer throughput time and lower system efficiency. In our problem background, the reduction of total energy consumption may contribute to the saving of grid-purchased electricity to some extent. However, the prolonged task schedule reduces the flexibility of PLM, which may increase the total grid-purchased electricity consumption. To demonstrate the trade-off relationship between velocity, system efficiency, and grid-purchased electricity consumption, we conduct experiments by adjusting the velocity parameters of shuttles and the lift.

The velocity parameter represents a multiple of the default velocity. We conduct experiments with the velocity parameter ranging from 0.5 to 1.5; in other words, the velocity can be adjusted within a range of 0.5 to 1.5 times the default velocity. The parameter of electricity consumption per of unit time varies with the velocity and can be calculated with the model of Liu et al. (2021). We conduct experiments with three randomly generated instances in ISG4 and calculate the average grid-purchased electricity consumption for different velocities. Figure 7 shows the results of the experiments. Increasing velocity will increase the total electricity consumption and thus increase the grid-purchased energy consumption. The velocity of the lift has a more significant effect on grid-purchased electricity consumption than shuttle velocity because the vertical movement, especially vertical movement with loads, consumes more electricity than the shuttles. Moreover, higher velocity of both types of equipment will result in higher electricity consumption per unit of time, which the real-time MSR-generated electricity may not be able to satisfy. The grid-purchased electricity consumption of the shuttles and the lift remains at a relatively low level, within the range of 0.6 to 1. The lower velocity can save electricity, but it increases the total travel time of equipment and reduces the flexibility of PLM. Our research provides a new perspective on the trade-off between system efficiency and energy consumption; that is, we argue that reduced equipment velocity does not always reduce the consumption of grid-purchased energy.

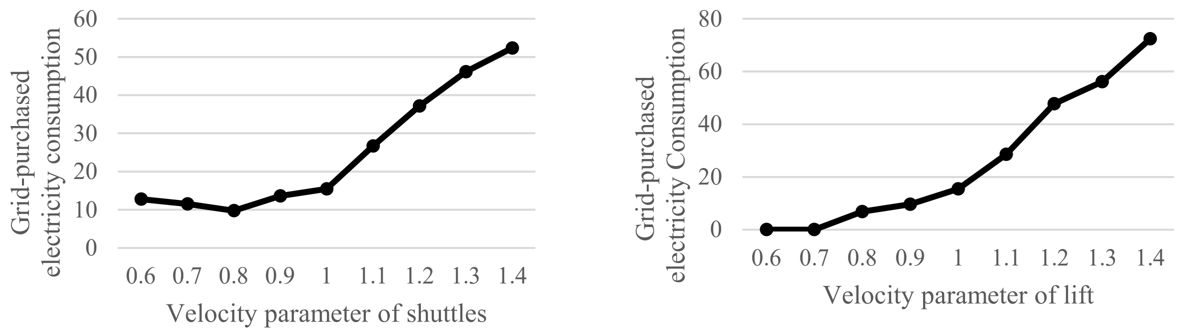


Figure 7: Sensitivity analysis on the velocity of equipment

The rack configuration is a common focus on energy-efficient warehouse design. In general, to store a certain number of totes, a trade-off between the number of tiers and the aisle depth exists in warehouse systems with high-rise racks. Meneghetti et al. (2015) prove that by changing the tiers of rack and the number of totes in one tier, the change of energy consumption forms a U-shaped curve, but the energy saving has very little variations among different rack shapes for the same optimization objective. In our study, based on the energy-efficient scheduling and the application of PLM, different rack configurations will influence the workload of equipment and thus influence the flexibility of PLM. More tiers will increase the vertical movement distance as well as the total energy consumption because the vertical movement of the lift consumes more electricity than the horizontal movement of shuttles for the same distance and speed. The workload of lift will increase the workload of shuttles will decrease in the configuration with more tiers and less storage positions in a tier. The configuration with fewer tiers and more storage positions will result in longer aisles and longer horizontal movement distances and will increase the workload of shuttles. To uncover the internal relationship between rack configuration and grid-purchased electricity consumption, we carry out experiments and obtain the results shown in Figure 8. The rack configuration is expressed in tier-storage position form, for example, the 2-50 means the configuration with 2 tiers and 50 storage position in a tier. In the experiments, we test a rack configuration that stores at least 100 totes, and we vary the number of tiers from 2 to 16. The result is similar to Meneghetti et al. (2015) with the similar U-shaped curve. However, the variance of our experiment is greater. The 6-17 configuration can save more than 70% energy compared to the 2-50 configuration with highest grid-purchased energy consumption. The higher variance of experiment results among different configurations is because the use of MSR-generated electricity reduces the base of grid-purchased electricity consumption, and the PLM in some configurations further reduces the grid-purchased electricity consumption. The 6-17 configuration since it balances the moving distance as well as the workload of equipment, which provides more flexibility for PLM. The operation of can be delayed by the PLM with more flexibility, while the energy consumption of vertical travel doesn't consume much more energy.

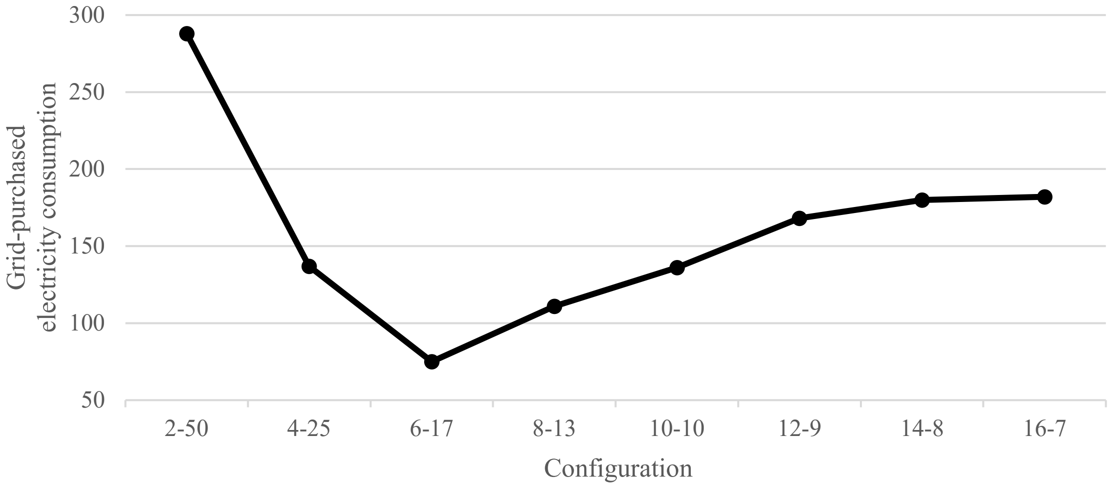


Figure 8: Sensitivity analysis on the tiers of the rack

7. Conclusions

This paper develops a MILP model for a task sequencing and scheduling problem in an automated warehouse with MSR and a concern for decarbonization. PLM is used in the task sequencing and scheduling process to reduce grid-purchased electricity consumption at peak times. A data-driven VNS algorithm is developed to solve the problem, and numerical experiments are conducted to validate the proposed model and algorithm. The major contributions of this study are summarized as follows:

(1) From a modelling perspective, the proposed MILP model integrates task scheduling and scheduling decisions with energy consumption considerations and provides a way to model the work status of warehouse equipment, MSR, and the power grid. Based on the model, warehouse operators can obtain detailed task schedules for warehouse equipment and the operation reference for MSR. To the best of our knowledge, few papers take all of these issues into account.

(2) From an algorithmic perspective, this study designs a data-driven VNS solution method. Data sets generated from historical data are used to reduce the solution search space and accelerate the solution process. The proposed data-driven VNS algorithm provides a way to utilize historical data and improve the solution process of meta-heuristic algorithms. The efficiency of the algorithm is validated by extensive experiments. For some large-scale instances with hundreds of tasks, the proposed algorithm can provide a solution within two minutes.

(3) From a management perspective, some potentially useful managerial insights are obtained. PLM can reduce the consumption of grid-purchased electricity and achieve net-zero energy operations in some cases. The relationship between grid-purchased electricity consumption and system configuration is analysed. Higher equipment velocity will increase the energy consumption, while lower equipment velocity may limit the flexibility of the task schedule and limit the performance of PLM. Rack configuration influences the energy performance by influencing travel distances and workloads.

In future research, we may investigate the robust optimization problem in which the MSR-generated electricity supply is uncertain. In addition, the dynamic task sequencing and scheduling problem needs to be taken into account to provide decision support for responses to real-time order arrivals and disruptions, as well as for changes in the MSR-generated electricity supply.

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