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Research article

Multi-objective optimization for AGV energy efficient scheduling problem with customer satisfaction

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Abstract: In recent years, it has been gradually recognized that efficient scheduling of automated guided vehicles (AGVs) can help companies find the balance between energy consumption and workstation satisfaction. Therefore, the energy consumption of AGVs for the manufacturing environment and the AGV energy efficient scheduling problem with customer satisfaction (AGVEESC) in a flexible manufacturing system are investigated. A new multi-objective non-linear programming model is developed to minimize energy consumption while maximizing workstation satisfaction by optimizing the pick-up and delivery processes of the AGV for material handling. Through the introduction of auxiliary variables, the model is linearized. Then, an interactive fuzzy programming approach is developed to obtain a compromise solution by constructing a membership function for two conflicting objectives. The experimental results show that a good level of energy consumption and workstation satisfaction can be achieved through the proposed model and algorithm.

Keywords: AGV; energy consumption; mixed-integer programming; customer satisfaction; interactive fuzzy programming approach
Mathematics Subject Classification: 90C11, 90C29

1. Introduction

In the modern business landscape, there is growing recognition that the effective scheduling of automated guided vehicles (AGVs) can assist companies in striking a balance between energy conservation and workstation satisfaction. Therefore, the energy consumption of AGVs for the manufacturing environment and the AGV energy efficient scheduling problem with customer satisfaction (AGVEESC) in a flexible manufacturing system are investigated.

A flexible manufacturing system (FMS) typically comprises workstations and computer numerical control (CNC) machines used for manufacturing, along with AGV systems and manufacturing execution systems (MES) that can process a variety of products [1]. Under the command of MES, the AGV moves to the designated pickup location, picks up the semi-finished products and delivers them to the location where the subsequent processing process will be performed, delivers finished products to the depot, updates its status information after completing the transportation task and reverts to the depot to wait for the next task to be performed.

It is necessary to consider time windows in the AGV scheduling problem. For flexible manufacturing workshops, suitable time windows can improve task completion rates, shorten production cycles and optimize the use of workshop resources. Many researchers have applied hard time window constraints to require AGVs to complete their tasks within a specified time [2, 3]. However, it is difficult to schedule the AGVs in flexible manufacturing workshops considering the hard time windows. Hence, in [4], an efficient and feasible AGV scheduling solution is obtained by defining customer satisfaction, representing the degree of AGV time window violation. In addition, the green production model has become a significant trend in today's manufacturing industry with global environmental protection awareness. It has been shown that appropriate scheduling can achieve energy-efficient manufacturing, regardless of the workshop type [5]. However, as far as we know, the AGV energy efficient scheduling problem with customer satisfaction (AGVEESC) still needs to be well studied in the existing literature.

Hence, multi-objective mixed-integer programming considering two conflicting objective functions is studied. The main contributions of this paper are as follows.

(1) An energy consumption model is developed for the AGVs in FMS, which dynamically takes into account the load and varying motion states of the AGVs. The arc energy consumption is a joint nonlinear function of load and velocity;
(2) A Pickup and Delivery Problem (PDP) is also considered in the proposed mixed integer programming, which reflects the real situation in FMS that AGVs are needed to transport the product currently processed in the workshop to its next processing workstation;
(3) A customer satisfaction function is constructed to represent the degree of time window violation. Furthermore, a multiobjective nonlinear model is constructed to balance customer satisfaction and energy consumption. A linearization technique is used to convert the proposed model to be a mixed integer linear programming equivalently;
(4) An interactive fuzzy programming approach is used to obtain a compromise solution by constructing a membership function of two conflicting objectives.

The remainder of the paper is structured as follows: The literature on closely related issues is briefly reviewed in Section 2. Section 3 analyzes the energy consumption of AGVs, develops the AGVEESC model and linearizes the model by introducing some auxiliary variables. Section 4 designs an interactive algorithm to find a compromise solution between customer satisfaction and energy consumption. The experiments, the computational results and the validation of the proposed model are presented in Section 5. Finally, Section 6 concludes the study and suggests further research.

2. Literature review

This section reviews the literature on the problem investigated in this paper, including environmental issues, pickup and delivery, and customer satisfaction in AGV scheduling problems (AGVSP) and VRP. Table 1 summarizes the previous work to make the literature review more understandable.

Table 1. Selective literature review summary.

Author	Manufacturing workshop	Obj		Objective/s				Multi-obj method				Pickup and delivery	Time window		EC model			AGV
		Single objective	Multiple objective	Cost/ Profit	Energy consumption	Customer satisfaction	Others	TH approach	ϵ-constraint	Heuristic	Others		Hard time window	Soft time window	Fuel EC model	Linear to distance/ or mass	AGV real EC model	
Zhang et al. 2021 [5]	✓		✓		✓		✓				✓						✓	✓
Shahparvari et al. 2018 [6]		✓		✓								✓	✓					
Zou et al. 2022 [4]	✓		✓	✓	✓	✓				✓				✓		✓		✓
Tan et al. 2021 [7]	✓		✓		✓		✓				✓	✓				✓		✓
Demir et al. 2014 [8]			✓		✓		✓		✓		✓		✓		✓			
Li et al. 2023 [9]	✓	✓		✓									✓					✓
Li et al. 2020 [10]		✓					✓										✓	✓
Gao et al. 2022 [2]			✓		✓		✓			✓			✓				✓	✓
Wang et al. 2018 [11]		✓			✓							✓	✓		✓			
Zhou et al. 2018 [12]			✓		✓	✓					✓	✓				✓		✓
Ghannadpour et al. 2019 [13]			✓		✓	✓	✓				✓			✓		✓		
This work	✓		✓		✓	✓		✓				✓		✓			✓	✓

2.1. AGV scheduling problem

The integration of AGVs and manufacturing systems is becoming increasingly common among enterprises, primarily due to their various benefits across several dimensions, including economics, environment and safety [14]. Some scholars focused on the AGVSP in a manufacturing workshop to reduce manufacturing costs. Zou et al. [15] proposed a mixed integer linear programming model for the material transportation process, which minimizes the total transportation cost for AGVs. Taking into account the penalty cost for a time violation and the fixed cost of AGVs, Li et al. [9] proposed a new approach to finding a solution with low manufacturing cost.

Also, there are many scholars interested in reducing the makespan of products by optimizing the scheduling of AGVs. A bi-objective mixed-integer programming model was created by Tan et al. [7] to reduce overall carbon emissions and the lifespan of AGVs in a flexible open shop environment. Faced with the challenges of multi-machine co-production and multi-AGV co-scheduling, Fontes et al. [16] presented a new mixed integer linear programming model with two sets of chain decisions to reduce production makespan. A mathematical model was developed by Li et al. [17] to reduce the standard deviation of buffer waiting periods and the overall distance travelled by AGVs.

The literature mentioned above shows how to optimize AGV scheduling in terms of reducing manufacturing costs or makespan, which contributes to the sustainable development of the enterprise.

2.2. Green vehicle route problem

Recently, in reaction to environmental legislation and carbon tax policies, many companies have adopted eco-friendly distribution to promote environmental sustainability. In logistics, fuel vehicles dominate medium- and long-distance transportation due to their range, payload and cost advantages over electric vehicles. Therefore, modeling and analysis of fuel consumption [18–20] to reduce vehicle route energy consumption [8, 21, 22] and total transportation costs, as well as green route planning for heterogeneous fleets [11, 23], is an important research direction for GVRP.

In short-distance transportation, several types of businesses, such as taxi companies, restaurants and courier companies, have switched from fuel vehicles to electric vehicles. However, there are issues such as poor electric vehicle range and low penetration of electric vehicle charging facilities, for which many researchers have studied the green electric vehicles routing problem considering fixed charging [24, 25] and partial charging [26, 27]. In addition, previous GVRP studies generally assume vehicle speed to be fixed, for which Macrina et al. [28] propose an integrated energy consumption model that considers acceleration and brake and provides a more realistic modelling of the charging process.

However, the energy consumption model for electric vehicles cannot be directly applied to AGVs due to the different operating environments, despite AGVs being battery-powered. Only some researchers have studied the energy consumption of AGVs in the context of the production floor. According to Goeke et al. [29], the primary factors determining a vehicle's energy consumption are load, speed and terrain gradient. For the load, Qiu et al. [30] proposed a model of AGV energy consumption considering load and travel distance. For the speed, Li et al. [10] and Zhang et al. [5] proposed new energy consumption models by combining the physical laws to model the motion module of the AGV. Nevertheless, it should be noted that these models were developed based on simplified modeling conditions, such as uniform motion or constant load, and may not be suitable for predicting energy consumption in dynamic FMS environments where AGV speeds and loads are subject to rapid change.

2.3. VRP with customer satisfaction

In reality, numerous companies are prepared to incur higher route expenses to improve customer satisfaction and lifetime value. Stavropoulou et al. [31] studied the consistent vehicle routing problem for heterogeneous fleets to minimize the total transportation cost and consistency of service providers and service times. Wang et al. [32] applied the concept of total time window violations to quantify customer dissatisfaction and developed a soft time window bi-objective model to minimize total customer dissatisfaction and energy consumption. Ghannadpour et al. [13] maximized customer satisfaction with varying priorities by assigning different fuzzy time windows.

The manufacturing process of the workstation will be affected if AGV fails to reach it on time. Therefore, it is essential to consider customer satisfaction when scheduling AGVs in manufacturing workshops, but only a few scholars have studied this issue. For example, Zou et al. [4] constructed a satisfaction function and designed an AGVSP for a matrix manufacturing workshop to maximize customer satisfaction while minimizing distribution costs. Zhou et al. [12] assessed customer satisfaction with the total weighted delay time and devised an energy-efficient scheduling approach to minimize both total delay and energy consumption for the part-feeding task in a mixed-flow assembly line.

However, due to the wide variety of manufacturing workshops, most existing studies simplify the AGV operating environment by considering only the delayed arrival of AGVs and ignore the impact of the early AGV arrival at the workstation on manufacturing. Also, few scholars have studied the interaction between workstation satisfaction and the energy consumption of AGVs.

2.4. VRP with pickup and delivery

Material transportation and distribution, specifically the pickup and delivery process, has garnered significant scholarly attention in recent decades. Over the past few decades, many models have been developed to coordinate pickups between customers, cross-docking warehouses and suppliers with cross-docking strategy [33–35]. To distribute emergency supplies, Shahparvari et al. [6] proposed a novel emergency pickup and delivery coordination strategy to improve the rapid response to emergency relief distribution in affected areas. Samani et al. proposed a two-stage optimization model considering blood collection and transport to alleviate the shortage of blood products during COVID-19 [36] .

Likewise, in the manufacturing environment, Jun et al. [37] has developed a PDP model that considers the characteristics of autonomous mobile robots with minimal delivery delays to optimize for urgent orders and work-in-process. Adamo et al. [3] and Liu et al. [38] have studied the AGVSP considering pickup and delivery to solve the conflict and collision problems of AGV systems.

The requirement for AGVs to pickup work-in-process or finished products from pickup locations and deliver them to corresponding delivery locations results in heightened route complexity. This subsequently generates a discernible impact on both the energy consumption and customer satisfaction of AGVs. However, this impact is ignored in most existing studies.

2.5. Research gap

AGVSP in manufacturing environments has been studied extensively over the last decades, but the AGVEESC problem, which takes into account pickup and delivery, has yet to be studied extensively. However, it deserves further study for the following reasons. First, as shown in Table 1, Zhang et al. [5], Li et al. [10] and Gao et al. [2] modeled the actual energy consumption of AGVs; however, their model was simplified since considering both the load and speed of AGVs simultaneously would result in a nonlinear model. This simplification renders their model unsuitable for complex FMS where multiple products are produced simultaneously. In addition, while Zou et al. [4], Zhou et. al. [12] and Ghannadpour et al. [13] introduced satisfaction models, they neglected to consider different companies' preferences for early or late arrival of AGVs. Their nonlinear models also add to the difficulty of the problem-solving process. In particular, shahparvari et al. [6], Tan et al. [7] and Wang et al. [11] studied the cost and energy consumption in the pickup and delivery scenario but did not study customer satisfaction in the pickup and delivery scenario.

Therefore, in this research, (i) we develop a more realistic nonlinear energy consumption model that considers both AGV's load and speed; (ii) A new satisfaction function that accounts for early and late arrival preferences is proposed and can be easily linearized; (iii) we examine a comprehensive scenario involving energy consumption, workstation satisfaction and realistic PDP; (iv) A linearization technique is introduced to linearize the nonlinear components of the energy consumption and satisfaction in the model for reducing the difficulty of solving the model; (v) we apply the TH Compromising Programming Approach for the first time to solve this problem, which can interact with the decision maker to obtain more effective compromise solutions that are more satisfactory.

3. Problem description and formulation

3.1. Problem description

A flexible manufacturing workshop that produces multiple products simultaneously, as shown in Figure 1, is divided into different areas based on the functions of the workstations. Each area comprises several workstations that perform similar tasks for producing goods. Each product requires multiple processing stages and needs to be processed in different areas. To illustrate this concept, we consider the processing order of product one in Figure 1: 3→8→11→7. During this process, AGVs depart from the depot and travel through the aisles to pick up semi-finished or finished products. The AGVs then deliver the semi-finished products to the paired delivery locations according to the processing order for each product. Finally, the finished product is delivered to the depot. Consequently, a set of transport requests comprises pickup and delivery of items at paired workstations. The final process of each product corresponds to a depot where the finished products are sent. For ease of modeling, all workstations with transportation requirements are classified into three sets: the pickup workstation set, the delivery workstation set and the final workstation set.

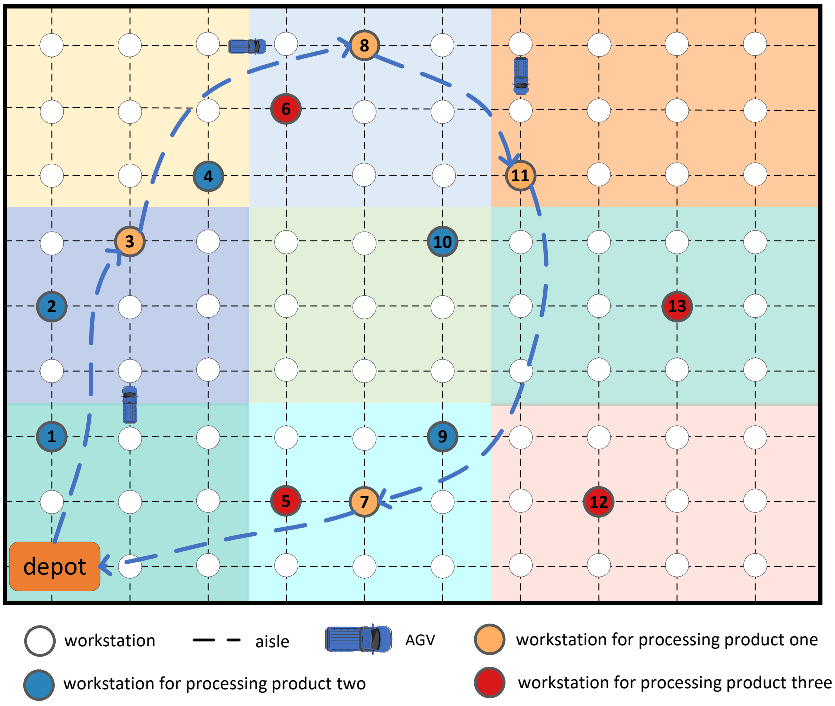

Figure 1. The layout diagram of FMS.

Thus, the problem can be defined on a complete directed graph $G = \{N, A\}$, where $N = P \cup D \cup F \cup \{0, n' + 1\}$ is a set of workstations and $A = \{(i, j)\,|i, j \in N, i \neq j\}$ is a set of edges. Both workstations 0 and $n' + 1$ indicate the depot of the AGVs and finished products. $P = \{1, 2, \ldots, n\}$ denotes the set of pickup workstations, $D = \{n + 1, n + 2, \ldots, 2n\}$ stands for the matching set of delivery workstations, and $F = \{2n + 1, 2n + 2, \ldots, n'\}$ denotes the set of final-workstation workstations.

On arrival at workstation i, the AGV will pickup or deliver the product, increasing the AGV load by q_i (positive for pickup and negative for delivery) and take service time s_i. We define the distance between workstations i and j as d_{ij}, and the time the AGV travels from workstation i to workstation j as t_{ij}. $K = \{1, 2, \ldots, |K|\}$ denotes a homogeneous fleet of AGVs, each AGV has a turning radius of R, the empty mass of the AGV is m and the load weight should not be greater than its load capacity Q. The AGVs depart from the depot and return there after finishing their work. Upon arrival at workstation $i \in P$, the AGV will pick up semi-finished products and then deliver them to the corresponding delivery workstation $i + n$.

3.2. Assumptions

The following assumptions are made in this study:

- AGVs have only straight or turning tracks in transportation, and their acceleration and deceleration occur only in the straight section.
- The equipment in the workshop operated normally, and the AGV ran without any stoppage, collision, or other malfunctions, nor did it stop due to lack of power.
- The floor of the production workshop is flat, with a slope of 0.
- Energy consumption of the AGV stops when it arrives early is neglected in this paper.

3.3. Notations

Sets

K	Set of all AGVs, $K = \{1, 2, \ldots, \lvert K\rvert\}$
P	Set of post-workstations, $P = \{1, 2, \ldots, n\}$
D	Set of pre-workstations, $D = \{1, 2, \ldots, n\}$
F	Set of final-workstations, $F = \{2n + 1, 2n + 2, \ldots, n'\}$
N	Set of all workstations, $N = P \cup D \cup F \cup \{0, n' + 1\}$, where 0 and $n' + 1$ indicate the depot of the AGVs and finished products

Indices

k	Index of AGVs
i, j	Index of workstations
l	Index of acceleration phase
h	Index of deceleration phase

Parameters

a_{acc}	Acceleration of AGVs
a_{dec}	Deceleration of AGVs
v_{0l}	Initial velocity of AGV at the l th acceleration phase
v_{0h}	Initial velocity of AGV at the h th deceleration phase
v_{tl}	Terminal velocity of AGV at the l th acceleration phase
v_{th}	Terminal velocity of AGV at the h th deceleration phase
v_s	Uniform linear motion velocity
v_c	Uniform turning motion velocity
t_{ij}^{total}	Total travel time of AGV from workstation i to j
t_{ij}^{acc}	Acceleration time of AGV from workstation i to j
t_{ij}^{dec}	Deceleration time of AGV from workstation i to j
t_{ij}^{ulm}	Uniform linear motion time of AGV from workstation i to j
t_{ij}^{utm}	Uniform turning motion time of AGV from workstation i to j
s_i	Service time of AGV at workstation i
$[a_i, b_i]$	Time window of workstation i
m	Weight of empty AGV
Q	The load capacity of AGV
q_i	Weight will be added at each workstation (positive for pickup and negative for delivery)

d_{ij}	Straight-line distance between workstation i and j
D_{ij}^{acc}	Acceleration displacement of AGV from workstation i to j
D_{ij}^{dec}	Deceleration displacement of AGV from workstation i to j
D_{ij}^{ulm}	Uniform linear motion displacement of AGV from workstation i to j
D_{ij}^{utm}	Uniform turning motion displacement of AGV from workstation i to j
R	Turning radius of AGV
n_{ij}	The quantity of workstations the AGV turn through from i to j
ρ	The number of acceleration phases of AGVs
υ	The number of deceleration phases of AGVs
P_{sm}	AGV standby power
F_{ij}^{acc}	Motor drive force when AGV accelerates from workstation i to j
F_{ij}^{um}	Motor drive force when AGV uniform motion from workstation i to j
E_{ij}^{total}	Total transport energy consumption of AGV from workstation i to j
E_{ij}^{sm}	Energy used during the standby motion of AGV from workstation i to j
E_{ij}^{acc}	Energy used to propel the AGV from workstation i to j at accelerated motion
E_{ij}^{ulm}	Energy used to propel the AGV from workstation i to j at uniform motion in straight-line sections
E_{ij}^{utm}	Energy used to propel the AGV from workstation i to j at uniform motion in turning sections
η	Power factor overall of driving motors
C_r	Rolling resistance coefficient
g	Gravity acceleration
ω	The degree of importance of the impact on production caused by the early arrival of AGV.
M	A very large number

Decision variables

x_{ij}^k	$x_{ij}^k = \begin{cases} 1, & \text{if AGV } k \text{ travels from workstation } i \text{ to } j \\ 0, & \text{otherwise} \end{cases}$
T_i^k	The arrival time of AGV k at workstation i
Q_i^k	Total load of AGV k before it loads at workstation i

3.4. Energy consumption analysis

We develop an energy consumption model of AGVs based on the ideas put out by Zhang and Wu [5]. In the process of material handling, the motion state of the AGV can be divided into five categories: stop, standby, acceleration, deceleration and uniform velocity. The energy consumption of AGV can be decomposed accordingly. However, the deceleration motion's energy consumption is minuscule since the drive motor's output power reduces noticeably throughout it, even to zero, which is the same as the stop motion.

Standby motion lasts throughout AGV movement. The power of different devices that keep the AGV working regularly, such as sensors and signal lamps, indicated as P_sm, may be added to estimate the standby power of the AGV. For any given route, the acceleration phase ($l = 1, 2, 3, \cdots, \rho$), the deceleration phase ($h = 1, 2, 3, \cdots, \upsilon$) and the number of turns n^t_{ij} that the AGV will undergo while travelling on the route are known. Therefore, the standby energy consumption of AGV from workstation i to j can be calculated as follows:

$$E^{sm}_{ij} = P_{sm}(s_i + t^{total}_{ij}), \tag{3.1}$$

where s_i is the service time of AGV at workstation i, according to the presumptions made before, t^{total}_{ij} is the sum of the acceleration, deceleration and uniform motion times of AGV from workstation i to j.

The acceleration and deceleration time of AGV from workstation i to j are calculated as follows:

$$t^{acc}_{ij} = \sum_{l=1}^{\rho} \frac{v_{tl} - v_{0l}}{a_{acc}}, \tag{3.2}$$

$$t^{dec}_{ij} = \sum_{h=1}^{\upsilon} \frac{v_{th} - v_{0h}}{a_{dec}}. \tag{3.3}$$

The corresponding acceleration and deceleration displacements are calculated as follows:

$$D^{acc}_{ij} = \sum_{l=1}^{\rho} \left[v_{0l} \times \frac{v_{tl} - v_{0l}}{a_{acc}} + \frac{1}{2} a_{acc} \left(\frac{v_{tl} - v_{0l}}{a_{acc}} \right)^2 \right], \tag{3.4}$$

$$D^{dec}_{ij} = \sum_{h=1}^{\upsilon} \left[v_{0h} \times \frac{v_{th} - v_{0h}}{a_{dec}} + \frac{1}{2} a_{dec} \left(\frac{v_{th} - v_{0h}}{a_{dec}} \right)^2 \right]. \tag{3.5}$$

The most common intersection on the AGV driving track is shown in Figure 2. The distance traveled by the AGV straight through the intersection is $2R$, and the distance traveled by the AGV turning through the intersection is $\pi R/2$.

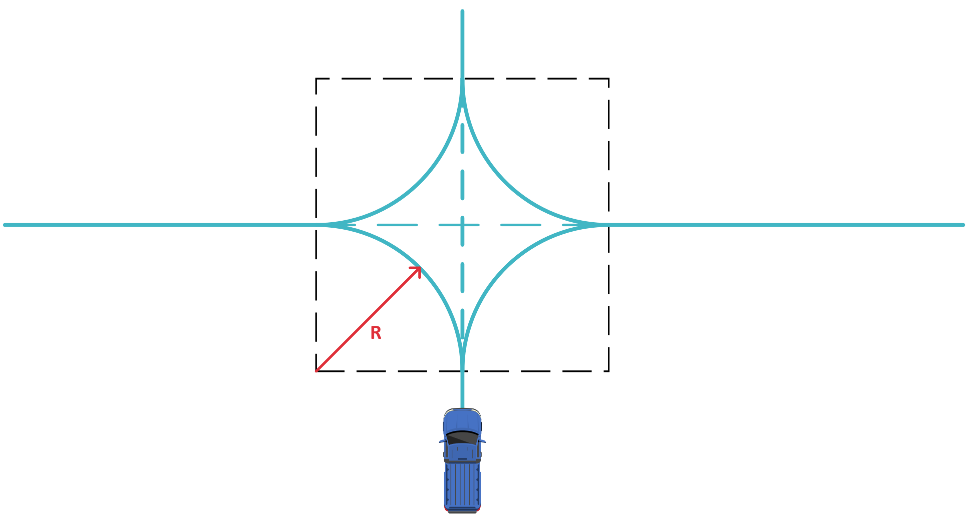

Figure 2. Diagram of the most common intersections on AGV driving tracks.

So, the uniform linear motion displacement of AGV from workstation i to j can be calculted as:

$$D_{ij}^{ulm} = d_{ij} - D_{ij}^{acc} - D_{ij}^{dec} - 2Rn_{ij}. \tag{3.6}$$

The uniform turning motion displacement of AGV from workstation i to j can be calculted as:

$$D_{ij}^{utm} = \frac{1}{2}\pi Rn_{ij}. \tag{3.7}$$

Then, the uniform linear and turning motion time of AGV from workstation i to j can be acquired as:

$$t_{ij}^{ulm} = \frac{D_{ij}^{ulm}}{v_s}, \tag{3.8}$$

$$t_{ij}^{utm} = \frac{D_{ij}^{utm}}{v_c}. \tag{3.9}$$

In the process of AGV driving, the energy consumed by the motor is used to overcome frictional and acceleration resistances that impede the movement of the AGV for work. To simplify the analysis, air resistance and slope resistance are neglected, as the AGV moves at a low speed and the floor of the production workshop is flat.

When the AGV is in the accelerated driving state, its driving force can be presented as:

$$F_{ij}^{acc} = C_r\left(m + Q_i^k\right)g + \left(m + Q_i^k\right)a_{acc}. \tag{3.10}$$

So the acceleration energy consumption of AGV can be acquired as:

$$E_{ij}^{acc} = \frac{F_{ij}^{acc} \times D_{ij}^{acc}}{\eta}. \tag{3.11}$$

When the AGV is in uniform motion, its driving force can be presented as:

$$F_{ij}^{um} = C_r\left(m + Q_i^k\right)g. \tag{3.12}$$

The uniform motion of AGV can be divided into uniform linear motion and uniform turning motion, where the energy used to propel the AGV from workstation i to j at uniform motion in straight sections:

$$E_{ij}^{ulm} = \frac{F_{ij}^{um} D_{ij}^{ulm}}{\eta}. \tag{3.13}$$

And the energy used to propel the AGV from workstation i to j at uniform motion in turning sections can be obtained as:

$$E_{ij}^{utm} = \frac{F_{ij}^{um} \times D_{ij}^{utm}}{\eta}. \tag{3.14}$$

Based on the previous analysis, we can obtain the total energy consumption of AGV between workstation i and j is

$$\begin{aligned} E_{ij}^{total} &= E_{ij}^{sm} + E_{ij}^{acc} + E_{ij}^{ulm} + E_{ij}^{usm} \\ &= P_{sm}\left(s_i + t_{ij}^{total}\right) + \frac{F_{ij}^{acc} \times D_{ij}^{acc}}{\eta} + \frac{F_{ij}^{um}\left(D_{ij}^{ulm} + D_{ij}^{utm}\right)}{\eta} \\ &= P_{sm}\left(s_i + t_{ij}^{total}\right) + \left(Q_i^k + m\right)\left(\frac{(C_r g + a_{acc}) \times D_{ij}^{acc} + C_r g \times \left(D_{ij}^{ulm} + D_{ij}^{utm}\right)}{\eta}\right). \end{aligned} \tag{3.15}$$

3.5. Customer satisfaction analysis

The expected pickup or delivery time window for workstation $i \in N$ is denoted by $[a_i, b_i]$. Workstation dissatisfaction will occur if the vehicle fails to arrive within the given time window. As shown in Figure 3, customer satisfaction would be zero if the AGV failed to arrive within the given time window according to the classical satisfaction function. However, in many practical applications, the AGV may inevitably fail to arrive within the specified time window, resulting in an infeasible model solution. The fuzzy customer satisfaction function allows AGVs to arrive outside a specified time window, improving the feasibility of the solution in real-world situations. Nevertheless, it is difficult for traditional fuzzy customer satisfaction functions to simultaneously satisfy the dual requirements of measuring the extent to which AGVs violate the time window and being linearized to reduce the difficulty of solving the model. Therefore, this study proposes a novel satisfaction function defined as follows:

$$S\left(T_i^k\right) = \begin{cases} \frac{1}{\omega(a_i - T_i^k)}, T_i^k < a_i, \\ \infty, a_i \le T_i^k \le b_i, \\ \frac{1}{(1-\omega)(T_i^k - b_i)}, T_i^k > b_i. \end{cases} \tag{3.16}$$

where T_i^k denotes the arrival time of AGV k at workstation i. In addition, a weighting parameter ω, ranging from 0 to 1, reflects the degree of importance of the impact on production caused by the early arrival of the AGV. If $\omega > 0.5$, early arrival has a greater impact than later arrival, which means that the company expects less waiting time, and the opposite is true if $\omega < 0.5$.

As shown in Figure 3, our proposed function can measure the degree of AGV violation of the time window all within the domain of T_i^k. The closer T_i^k to the given time window, the higher the customer satisfaction will be, and if T_i^k is within the given time window, the customer satisfaction will be infinite. Defining the satisfaction function in this way has the advantage that the function can be easily linearized.

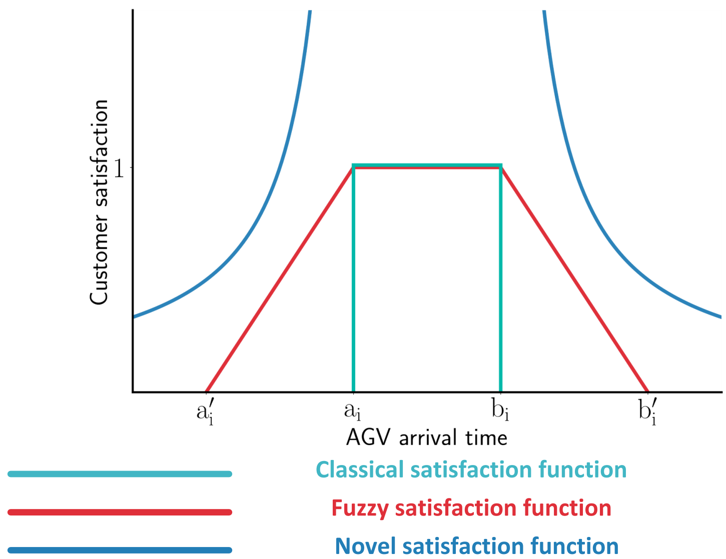

Figure 3. Different satisfaction functions.

The function takes the reciprocal operation, which has the following reciprocal form:

$$S^{-1}\left(T_i^k\right) = \begin{cases} \omega(a_i - T_i^k), T_i^k < a_i \\ 0, a_i \le T_i^k \le b_i \\ (1-\omega)(T_i^k - b_i), T_i^k > b_i \end{cases} \tag{3.17}$$

It is equivalent to $max\{\omega(a_i - T_i^k), 0, (1-\omega)(T_i^k - b_i)\}$ and we can define it as customer dissatisfaction, which can be easily linearized as shown in 3.7. Maximizing customer satisfaction is equivalent to minimizing customer dissatisfaction. Maximizing customer satisfaction is equivalent to minimizing customer dissatisfaction. Thus, to convenience the calculation, we use minimizing the sum of customer dissatisfaction as the model's objective function.

Therefore, the decision maker needs to trade off total energy consumption and total customer dissatisfaction to find an optimal transportation route for the material handling task performed by AGVs.

3.6. Proposed model

From the above analysis, we can get the following model:

$$\min f_1 = \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} E_{ij}^{total} x_{ij}^k, \tag{3.18}$$

$$\min f_2 = \sum_{k\in K}\sum_{i\in N} max\{\omega(a_i - T_i^k), 0, (1-\omega)(T_i^k - b_i)\}, \tag{3.19}$$

s.t.,

$$x_{ii}^k = 0, \quad \forall i \in N, \forall k \in K, \tag{3.20}$$

$$\sum_{j\in N} x_{0,j}^k = 1, \quad k \in K, \tag{3.21}$$

$$\sum_{i\in D\cup C} x_{i,n'+1}^k = 1, \quad k \in K, \tag{3.22}$$

$$\sum_{k\in K}\sum_{j\in N} x_{ij}^k = 1, \quad \forall i \in P \cup D \cup F, \tag{3.23}$$

$$\sum_{j\in N} x_{ij}^k - \sum_{j\in N} x_{ji}^k = 0, \quad \forall i \in P \cup D \cup F, \forall k \in K, \tag{3.24}$$

$$x_{i+n,i}^k = 0, \quad i \in P, k \in K, \tag{3.25}$$

$$x_{0,i+n}^k = 0, \quad \forall i \in P, \forall k \in K, \tag{3.26}$$

$$\sum_{j\in N} x_{ij}^k - \sum_{j\in N} x_{i+n,j}^k = 0, \quad \forall i \in P, \forall k \in K, \tag{3.27}$$

$$T_{i+n}^k \ge T_i^k, \quad \forall i \in P, \forall k \in K, \tag{3.28}$$

$$T_j^k \ge t_{0,j}^{total} - M\left(1 - x_{0,j}^k\right), \quad j \in N, k \in K, \tag{3.29}$$

$$T_j^k \leq t_{0,j}^{total} + M\left(1 - x_{0,j}^k\right), \quad j \in N, k \in K, \tag{3.30}$$

$$T_j^k \geq T_i^k + s_i + t_{ij}^{total} - M\left(1 - x_{ij}^k\right), \quad \forall i, j \in N, \forall k \in K, \tag{3.31}$$

$$T_j^k \leq T_i^k + s_i + t_{ij}^{total} + M(1 - x_{ij}^k), \quad \forall i, j \in N, k \in K, \tag{3.32}$$

$$\max\{0, q_i\} \leq Q_i^k \leq \min\{Q, Q + q_i\}, \quad \forall i \in N, \forall k \in K, \tag{3.33}$$

$$Q_j^k \geq q_j - M(1 - x_{0j}^k), \quad \forall j \in N, \forall k \in K, \tag{3.34}$$

$$Q_j^k \leq q_j + M(1 - x_{0j}^k), \quad \forall j \in N, \forall k \in K, \tag{3.35}$$

$$Q_j^k \geq Q_i^k + q_j - M(1 - x_{ij}^k), \quad \forall i, j \in N, \forall k \in K, \tag{3.36}$$

$$Q_j^k \leq Q_i^k + q_j + M(1 - x_{ij}^k), \quad \forall i, j \in N, \forall k \in K, \tag{3.37}$$

$$x_{ij}^k = \{0, 1\}, \quad \forall i, j \in N, \forall k \in K, \tag{3.38}$$

$$T_i^k \geq 0, Q_i^k \geq 0, \quad \forall i \in N, \forall k \in K. \tag{3.39}$$

Objective. In the model mentioned above, the objective function f_1 is to minimize the total energy consumption, and f_2 is to minimize the workstation dissatisfaction.

VRP constraints. Constraint (3.20) ensures that AGVs cannot go around the same workstation, while constraints (3.21) and (3.22) require that each AGV departs from the depot and arrives back at the depot after completing its task. Constraint (3.23) implies that only one AGV leaves each workstation, and constraint (3.24) represents the balance of incoming and outgoing flows at each workstation. Constraints (3.23) and (3.24) guarantee that each workstation is served by one and only one AGV.

Pickup and delivery constraints. Constraints (3.25) and (3.26) state that the AGV must pick up the product-in-progress before it travels to the delivery point in order to make a successful delivery. Constraint (3.27) imposes that the product-in-progress should be delivered by the same vehicle after pickup, and constraint (3.28) indicates that the delivery cannot occur before the pickup.

Arrival time constraints. Constraints (3.29) and (3.30) indicate that each AGV departs from the depot at time 0. Constraints (3.29)–(3.32) calculate the arrival time of the AGV k at each workstation, which also can be used as sub-tour elimination.

Capacity constraints. Constraint (3.33) limits the feasible range of loads the AGV can carry when leaving the workstation. Constraints (3.34) and (3.35) guarantee that each AGV departs the depot with zero loads. Constraints (3.34)–(3.37) calculate the arrival loads of AGV k at each vertex.

Finally, Constraints (3.38) and (3.39) are the restrictions on decision variables.

3.7. Linearization

From mathematical expressions (3.15), E_{ij}^{total} is a linear function of Q_i^k and the function can be defined as:

$$E_{ij}^{total} = \alpha_{ij} Q_i^k + \beta_{ij}. \tag{3.40}$$

Therefore,

$$f_1 = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} (\alpha_{ij} Q_i^k + \beta_{ij}) x_{ij}^k, \tag{3.41}$$

which is a nonlinear function. Similarly, the objective function f_2 and the constraint (3.33) are nonlinear either. Hence, the proposed model is mixed-integer nonlinear programming which is hard to be solved.

In this paper, some linearization techniques are used to convert the proposed model into mixed-integer linear programming, which is shown as the following theorem:

Theorem 1. *The proposed nonlinear AGVEESC model can be converted into mixed-integer linear programming by introducing auxiliary variables and adding constraints.*

Proof. Introducing the following auxiliary variables:

z_{ij}^k	$z_{ij}^k = \left(\alpha_{ij}Q_i^k + \beta_{ij}\right)x_{ij}^k$, which is the energy consumption of AGV k traveling from workstation i to j.
L_i^k	$L_i^k = max\{\omega(a_i - T_i^k), 0, (1-\omega)(T_i^k - b_i)\}$, which is the dissatisfaction of workstation i caused by AGV k.

With the introduction of auxiliary variables, the objective function f_1 can be expressed as:

$$\min \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} z_{ij}^k. \tag{3.42}$$

And the following constraints should be considered.

$$z_{ij}^k \le \alpha_{ij}Q_i^k + \beta_{ij}, \quad \forall i, j \in N, \forall k \in K, \tag{3.43}$$

$$z_{ij}^k \ge \alpha_{ij}Q_i^k + \beta_{ij} - (\alpha_{ij}Q + \beta_{ij})(1 - x_{ij}^k), \quad \forall i, j \in N, \forall k \in K, \tag{3.44}$$

$$\beta_{ij}x_{ij}^k \le z_{ij}^k \le (\alpha_{ij}Q + \beta_{ij})x_{ij}^k, \quad \forall i, j \in N, \forall k \in K. \tag{3.45}$$

Similarly, the objective function f_2 can be expressed as:

$$\min \sum_{k\in K}\sum_{i\in N} L_i^k. \tag{3.46}$$

And the following constraints should be considered.

$$L_i^k \ge (1-\omega)(T_i^k - b_i), \quad i \in N, k \in K, \tag{3.47}$$

$$L_i^k \ge \omega(a_i - T_i^k), \quad i \in N, k \in K, \tag{3.48}$$

$$L_i^k \ge 0, \quad i \in N, k \in K. \tag{3.49}$$

Finally, the constraint (3.33) is equivalent to the following constraints:

$$Q_i^k \ge q_i, \forall i \in N, \forall k \in K, \tag{3.50}$$

$$Q_i^k \le Q, \forall i \in N, \forall k \in K, \tag{3.51}$$

$$Q_i^k \le Q + q_i, \forall i \in N, \forall k \in K. \tag{3.52}$$

From the above analysis, the nonlinear objective function f_1 and f_2 are equivalent to (3.42)–(3.45) and (3.46)–(3.49), respectivelly. Constraint (3.33) is equivalent to (3.50) to (3.52). All the reformulated objectives and constraints are linear. Hence, the proposed nonlinear AGVEESC model is converted into mixed-integer linear programming. □

4. Interactive fuzzy programming approach

In past decades, many practical approaches for multiple objective optimization problems have been proposed by different researchers, including goal programming, scalarizing method, ϵ-constraint method and so on. These approaches can be grouped into three categories: methods without or with a priori preference articulation, interactive methods and methods with a posteriori preference articulation [39]. Among them, the interactive fuzzy solution approaches allow decision-makers to specify the degree of satisfaction and preferences for every objective function separately, which helps decision-makers select a solution that matches their expectations. Torabi and Hassini [40] proposed an efficient interactive fuzzy programming approach for multi-objective referred to as the TH approach by combining Lai and Hwang's method [41] and Selim and Ozkarahanl's method [42]. They experimentally demonstrate that the TH approach improves the quality of solutions, allows decision-makers to choose balanced or unbalanced solutions based on their preferences, and decreases computational complexity. Consequently, the TH approach is applied to solve the multi-objective optimization problem in this paper, and we can obtain the theorem as follows:

Theorem 2. *The multi-objective AGVEESC model proposed in this paper can be transformed into a single-objective model by the TH approach in [40].*

Proof. According to [40], the positive ideal solution (PIS) and negative ideal solution (NIS) of each objective function should be determined first. The PIS for each objective function can be obtained by solving the corresponding model as follows:

$$f_1^{PIS} = min f_1, f_2^{PIS} = min f_2, \tag{4.1}$$

s.t.,

$$v \in F. \tag{4.2}$$

where F is the feasible region by considering constraints (3.20)–(3.32), (3.34)–(3.39), (3.43)–(3.45) and (3.47)–(3.52).

Denote v_i^* and $Z_i(v_i^*)$ as the PIS of the i-th objective function and its corresponding value of the objective function, respectively. Then, its associated NIS can be estimated as follows:

$$f_1^{NIS} = Z_1(v_2^*), f_2^{NIS} = Z_2(v_1^*). \tag{4.3}$$

Next, the linear membership function of each objective function is presented as follows:

$$\mu_1(v) = \begin{cases} 1, & f_1 < f_1^{PIS}, \\ \frac{f_1^{NIS} - f_1}{f_1^{NIS} - f_1^{PIS}}, & f_1^{PIS} \le f_1 \le f_1^{NIS}, \\ 0, & f_1 > f_1^{NIS}, \end{cases} \tag{4.4}$$

$$\mu_2(v) = \begin{cases} 1, & f_2 < f_1^{PIS} \\ \frac{f_2^{NIS} - f_2}{f_2^{NIS} - f_2^{PIS}}, & f_2^{PIS} \le f_2 \le f_2^{NIS}, \\ 0, & f_2 > f_2^{NIS}, \end{cases} \tag{4.5}$$

where $\mu_i(v)$ denotes the degree of satisfaction for the i-th objective function.

Therefore, the proposed multi-objective AGVEESC model can be transformed into a single-objective model as follow:

$$\max \lambda (v) = \gamma\lambda_0 + (1 - \gamma) \sum_i \theta_i \mu_i (v), \tag{4.6}$$

s.t.,

$$\lambda_0 \leq \mu_i (v), \quad i = 1, 2, \quad v \in F, \quad \lambda_0, \gamma \in [0, 1], \tag{4.7}$$

where γ indicates the compensation coefficient, which implicitly controls the minimum level of objectives' satisfaction and the degree of compromise among the objectives. Parameter $\theta_i > 0$ satisfies $\sum_i \theta_i = 1$ and denotes the relative importance of the i-th objective function, which is determined by the preferences of decision-makers. In addition, $\lambda_0 = \min_i \{\mu_i(v)\}$ donates the minimum degree of objectives' satisfaction. □

The following steps are the basic tuning strategy of the compensation coefficient γ and the weight θ_i to solve this single objective model:

Step1: Specify the value of relative importance weight for each objective.

Step2: Specify the value of the compensation coefficient γ. It is noteworthy that if the decision maker intends to obtain an unbalanced compromising solution based on the weights, corresponding γ should be selected as a small value (e.g., smaller than 0.3).

Step3: Solve the proposed model. If the compromising solution does not satisfies the decision maker, adjust the parameters γ by $\gamma = \gamma + \Delta\gamma$ (e.g., 0.1) and return to Step 2.

5. Case study

To support the proposed model and solution method, some numerical tests are implemented into practice. Because no benchmark instances match the AGVEESC model, we design a new instance for the AGVEESC: a small-size instance where 2 AGVs are responsible for 12 workstations consisting of 2 pickup and delivery tasks and 8 single transport tasks.

Each workstation has the following properties: identity, location (x, y-axis), time window and the number of materials. The instance is designed based on the test benchmark collected from practical instances by Zou et al. [43]. The parameters of AGV in the model are derived from Zhang et al. [5]. The technical parameters of AGV are shown in Table 2. In addition, the degree of importance of the impact on production caused by the early arrival of AGV is considered 0.5.

The numerical results are generated in the following environment: the model is coded using Docplex 2.11.176 within Python 3.8.1 and solved by Cplex 12.10 on Windows 10 with 16 GB RAM and an AMD Ryzen 5 4600H processor, and the run-time was limited to 7200s. The model has 1,905 equations, 449 continuous variables and 392 binary variables.

Table 2. AGV technical parameters.

Parameter	Value	Parameter	Value
Acceleration of the accelerated motion a_{acc}	1 m^2	Number of wheels	4
Acceleration of the decelerated motion a_{dec}	1 m^2	Power source	Lithium iron phosphate battery
Battery capacity	40 $A\Delta h$	Rated power of each driving motor	80 W
Battery voltage	24 V	Rolling friction coefficient C_r	0.03
Length $L \times$ Width $W \times$ Height H	800 mm $\times$ 600 mm $\times$ 400 mm	Standby Power P_{sm}	25 W
Deadweight m_0	60 kg	Steering mode	Differential control
Driving motor efficiency	0.9	Turning radius R	0.85 m
Maximum load Q	100 kg	Turning speed v_c	0.5 m/s
Number of driving motors	4	Uniform linear motion speed v_s	1 m/s

5.1. Performance analysis

To verify the performance of the proposed method, a common method for solving multi-objective optimization, namely the Pareto front obtained by the weighting method, is used as a comparison in this paper.

The process of obtaining the Pareto front by the weighting method is as follows. The original objective functions are first normalized to obtain g_1 and g_2, after which the bi-objective problem is transformed into a single-objective problem by defining different weight vectors as follows:

$$\max \varpi g_1 + (1 - \varpi) g_2. \tag{5.1}$$

A step size δ is set so that $\varpi = \delta * k$, where $k \in [0, \frac{1}{\delta}]$, and the approximate Pareto front is obtained by solving single-objective optimization problems of various weights.

Setting the step size too large may result in missing some significant points on the Pareto front. However, setting the step size too small will increase the scale of optimization problems and be computationally inefficient. Therefore, the step size is set to 0.05, making the times of the optimization problems to be 20, and the approximate Pareto front obtained is shown below:

As shown in the Figure 4, there is a conflict between these two objectives: increasing the desire for lower energy consumption requires sacrificing customer satisfaction. From the above figure, point A compromises lower energy consumption and lower workstation dissatisfaction, making it the best solution from a trade-off perspective.

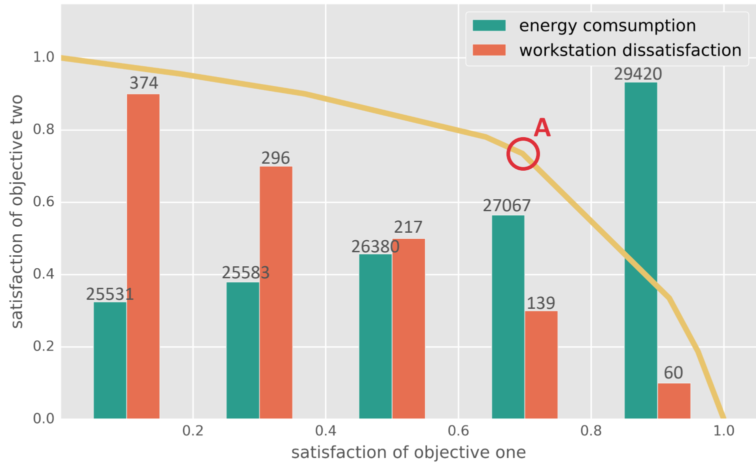

Figure 4. The approximate Pareto front.

Obtain compromise solutions according to the interactive fuzzy programming approach in Section 4, and the details of the approach are not listed here due to the limited space. The procedure of iteration to obtain the compromise solution using the TH approach is shown in the following figure:

As shown in Figure 5, since the interactive fuzzy programming approach can find the optimal solution by adjusting the weights between different objectives and limiting the size of tolerance, it usually takes only a few iterations to obtain a compromise solution that satisfies the decision maker, and the process does not require solving all the boundary solutions to obtain the Pareto front, which is more efficient than the traditional weighted method to find the Pareto front.

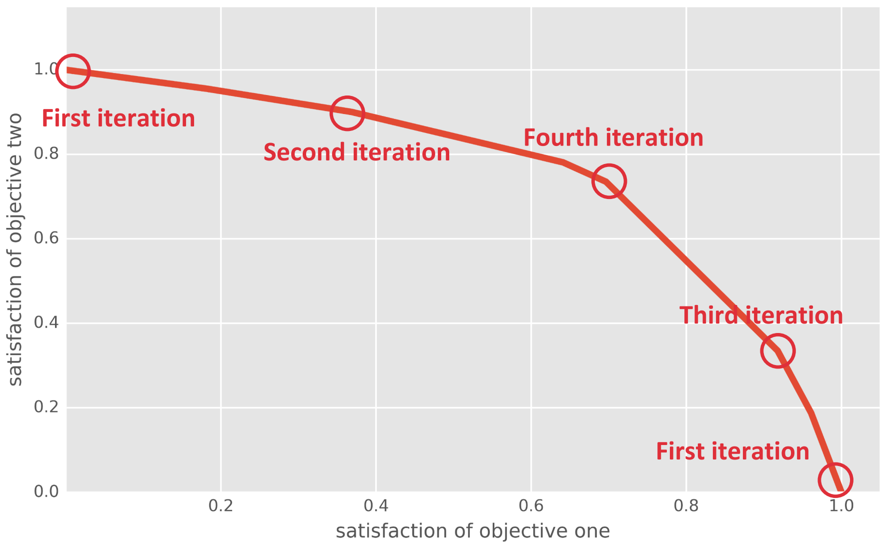

Figure 5. Representation of each iterative step on the Pareto front.

5.2. *Result analysis*

To intuitively illustrate the advantages of the compromise solution, the corresponding roadmaps of the solutions obtained by considering only one objective and the compromise solution are compared in Figure 6.

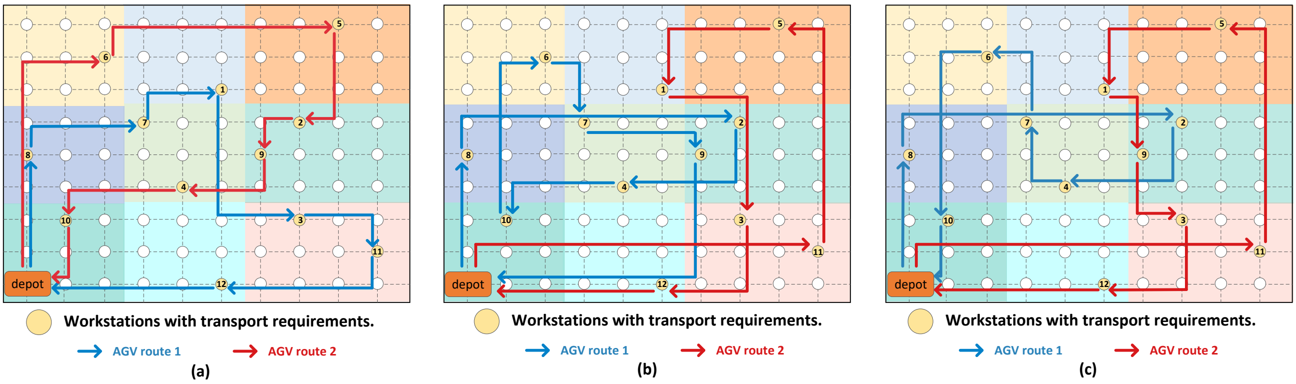

Figure 6. The route followed by each model.

As shown in Figure 6(a), when only minimizing the objective of energy consumption, the optimal routes of two AGVs are as follows: Route 1: $N_0 \to N_8 \to N_7 \to N_1 \to N_3 \to N_{11} \to N_{12} \to N_0$; Route 2: $N_0 \to N_6 \to N_5 \to N_2 \to N_9 \to N_4 \to N_{10} \to N_0$. These two routes end with an energy consumption of 25374.7 J and a workstation dissatisfaction of 414. This solution only focuses on minimizing energy consumption, which is in line with the current objectives of many companies for environmental protection and carbon emission reduction, and this solution is referred to as an energy-friendly solution in this paper.

As shown in Figure 6(b), when only minimizing the objective of workstation dissatisfaction, the optimal routes of two AGVs are as follows: Route 1: $N_0 \to N_8 \to N_2 \to N_4 \to N_{10} \to N_6 \to N_7 \to N_9 \to N_0$; Route 2: $N_0 \to N_{11} \to N_5 \to N_1 \to N_3 \to N_{12} \to N_0$. Compared to the solution of Figure 6(a), these solutions yield a total workstation dissatisfaction of 21.2 and energy consumption of 31766.8 J, which is 94.8% lower and 25.2% higher, respectively. Hence, this solution is referred to as a customer-first solution in this paper.

As shown in Figure 6(c), when minimizing the single-objective model to obtain the compromise solution, the optimal routes of two AGVs are as follows: Route 1: $N_0 \to N_8 \to N_2 \to N_4 \to N_7 \to N_6 \to N_{10} \to N_0$; Route 2: $N_0 \to N_{11} \to N_5 \to N_1 \to N_9 \to N_3 \to N_{12} \to N_0$. Obviously, the solution compromises energy consumption and workstation dissatisfaction, in which the total workstation dissatisfaction increases by 104 compared to the result in Figure 6(b), but the energy consumption decreases by 4451 J. Therefore, this solution is referred to as a compromise solution.

The energy-friendly solution needs to pay attention to customer satisfaction. It uses each sub-route between customer nodes by avoiding unnecessary turns and backtracking. The customer-first solution only considers customer satisfaction. However, it may create some backtracking in the route due to disregarding the relative positions between customer nodes. For example, the turning back from N_{10} to N_6 and N_7 to N_9 in Figure 6(b) will increase the energy consumption.

Compared to the customer-first solution, the compromise solution has less backtracking, which can reduce energy consumption. Compared to the energy-friendly solution, the compromise solution has more consideration for customers with tight time window constraints. For example, arranging N_4 and N_{11} in the front part of the route will decrease workstation dissatisfaction.

5.3. Applicability of the proposed model

To validate the applicability of the proposed model, this section expands the scale of the instance and designs medium-size and large-size instances to conduct simulation experiments. The medium-size instance adds two pairs of pickup and delivery nodes, two general task nodes and one AGV based on the small-size instance. The large-size instance adds four pairs of pickup and delivery nodes, four general task nodes and two AGVs based on the small-size instance. The experimental results for problems of different sizes are shown in the following table.

According to Table 3, as the number of workstations on the manufacturing workshop and the number of AGVs increased, the average energy consumption of AGVs and the average workstation dissatisfaction caused by AGVs decreased. There are two main reasons for this.

Table 3. Comparison of results for different size problems.

		small-size	medium-size	large-size
AGV number		2	3	4
number of Pickup and Delivery nodes		2	4	6
number of general task nodes		8	10	12
number of binary valuables		392	1200	2704
number of continuous valuables		449	1321	2913
number of constraints		1905	5526	12080
solution from optimize f_1	Z_1	25374.66	33666.95	36561.12
	Z_2	414	409.79	366.4
solution from optimize f_2	Z_1	31766.78	43752.89	63824.26
	Z_2	21.22	67.6	126
compromise solution	Z_1	27315.24	35393.96	46949.69
	Z_2	125.26	165.96	157.12
compromise solution	Average Z_1	13657.62	11646.93	11737.42
	Average Z_2	62.63	55.32	39.28
number of iterations		4	5	4

First, since the area of the manufacturing workshop does not expand, the number of demand workstations increases, which also means that the number of workstations to be served on the same route increases, making AGV operation more efficient and reducing AGV backtracking.

Second, as the number of assignable AGVs increases, more AGVs cooperate to make task assignment more flexible, reduce the pressure on individual AGVs to a certain extent and reduce the arrival delay and backtracking that would otherwise be unavoidable due to an insufficient number of AGVs, making the arrival time of AGVs more stable and reliable.

As can be seen from Table 3, the compromise solutions obtained by solving the model proposed in this paper at different scales of instances have good performance. On the small-size instance, workstation dissatisfaction can be reduced by 69.7% by sacrificing 7.6% of energy consumption. On the medium-size instance, workstation dissatisfaction can be reduced by 59.5% by sacrificing 5.1% of energy consumption. Finally, on the large-size instance, workstation dissatisfaction can be reduced by 57.1% by sacrificing 28.4%. On the other hand, even as the problem scale increases, a satisfactory compromise solution can still be obtained with a relatively small number of iterations using the interactive algorithm proposed in this paper.

5.4. *Sensitivity analysis*

5.4.1. Impact of the weights of objective functions

The compensation coefficient γ reflects the importance of the lowest satisfaction level of the model, and the decision maker needs to choose an appropriate compensation coefficient. The solution obtained with a larger compensation coefficient γ is more optimal for the lower satisfaction bound λ_0.

To investigate the effect of the compensation coefficient on satisfaction, this section solves the model by varying the value of the compensation coefficient with a step size of 0.1. The results are shown in the following tables.

Table 4 illustrates that for small-size instances, the TH method can provide a unique compromise solution if $\gamma \geq 0.4$, whereas for medium- and large-size instances, as shown in Tables 5 and 6, a unique compromise solution is obtained when $\gamma \geq 0.7$.

Table 4. Computational results for small-size instances.

	$\theta_1 = 0.2$			$\theta_1 = 0.5$			$\theta_1 = 0.8$		
γ	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2
0	0.181	0.181	0.955	0.696	0.696	0.735	0.188	0.961	0.188
0.1	0.369	0.369	0.90	0.696	0.696	0.735	0.335	0.918	0.335
0.2	0.641	0.641	0.781	0.696	0.696	0.735	0.335	0.918	0.335
0.3	0.641	0.641	0.781	0.696	0.696	0.735	0.696	0.696	0.735
≥ 0.4	0.696	0.696	0.735	0.696	0.696	0.735	0.696	0.696	0.735

Table 5. Computational results for medium-size instance.

	$\theta_1 = 0.2$			$\theta_1 = 0.5$			$\theta_1 = 0.8$		
γ	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2
0	0.495	0.495	0.925	0.712	0.829	0.712	0.383	0.974	0.383
0.1	0.495	0.495	0.925	0.712	0.829	0.712	0.383	0.974	0.383
0.2	0.558	0.558	0.899	0.712	0.829	0.712	0.712	0.829	0.712
0.3	0.558	0.558	0.899	0.712	0.829	0.712	0.712	0.829	0.712
0.4	0.738	0.77	0.738	0.738	0.77	0.738	0.712	0.829	0.712
0.5	0.738	0.77	0.738	0.738	0.77	0.738	0.712	0.829	0.712
0.6	0.738	0.77	0.738	0.738	0.77	0.738	0.712	0.829	0.712
≥ 0.7	0.738	0.77	0.738	0.738	0.77	0.738	0.738	0.77	0.738

Table 6. Computational results for large-size instance.

	$\theta_1 = 0.2$			$\theta_1 = 0.5$			$\theta_1 = 0.8$		
γ	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2	λ_0	μ_1	μ_2
0	0.442	0.442	0.969	0.619	0.619	0.871	0.219	0.954	0.219
0.1	0.527	0.527	0.945	0.619	0.619	0.871	0.219	0.954	0.219
0.2	0.527	0.527	0.945	0.619	0.619	0.871	0.328	0.895	0.328
0.3	0.527	0.527	0.945	0.619	0.619	0.871	0.328	0.895	0.328
0.4	0.619	0.619	0.871	0.671	0.671	0.758	0.671	0.671	0.758
0.5	0.619	0.619	0.871	0.671	0.671	0.758	0.671	0.671	0.758
0.6	0.619	0.619	0.871	0.671	0.671	0.758	0.671	0.671	0.758
≥ 0.7	0.671	0.671	0.758	0.671	0.671	0.758	0.671	0.671	0.758

The TH method accommodates different effective solutions by assigning varying weights to a specific problem based on the decision maker's preference. For small values of γ (≤ 0.2), the model prioritizes optimization of the weighted objectives to obtain higher satisfaction in line with the decision maker's preferences. For larger values of γ (> 0.2), the model places greater emphasis on optimizing the lowest satisfaction among multiple objectives.

The maximum value of λ_0 is achieved when the compensation coefficient γ is large (0.4 for small-size, 0.7 for medium- and large-size). Once the compensation coefficient reaches this threshold, altering the weights has no impact on λ_0 since a larger gamma automatically increases the significance of both objectives. On the other hand, when θ_1 value is fixed, increasing the compensation coefficient increases λ_0. Additionally, a more consistent weighting of objectives leads to a larger λ_0.

Therefore, if a decision maker does not have a specific objective preference or aims to achieve high satisfaction scores for multiple goals simultaneously, a larger γ can be selected to optimize the minimum satisfaction. Conversely, a smaller value of γ would be more appropriate if a decision maker prefers a particular objective.

5.4.2. Impact of the weights of time violation

Companies that manufacture different products may experience varying impacts from material delays on their manufacturing operations. To explore optimal solutions for different cases, we adjust the value of the parameter ω to modify the relative importance of waiting time and delay time (with γ set to 0.1 and θ_1 set to 0.5), and the results are shown in the following tables.

The results presented in Tables 7 and 8 illustrate that, for small and medium-size instances, if ω is greater than or equal to 0.7, late arrivals have minimal impact on production compared to early arrivals. As a result, the model prioritizes late-arriving workstations to optimize waiting time, even if it means sacrificing some delay time. However, this trade-off may lead to increased energy consumption, which needs to be considered to meet customer preferences. Conversely, when ω is less than 0.7, the solutions are consistent with the compromise solutions shown in Table 3.

Table 7. Computational results for small-size instance.

ω	energy consumption	workstation satisfaction	waiting time	delay time	violate time
0	27315.24	150.87	150.87	99.65	250.52
0.1	27315.24	145.75	150.87	99.65	250.52
0.2	27315.24	140.63	150.87	99.65	250.52
0.3	27315.24	135.51	150.87	99.65	250.52
0.4	27315.24	130.38	150.87	99.65	250.52
0.5	27315.24	125.26	150.87	99.65	250.52
0.6	27315.24	120.14	150.87	99.65	250.52
0.7	27668.97	106.62	108.87	105.65	214.52
0.8	27668.97	106.29	108.87	105.65	214.52
0.9	27668.97	105.96	108.87	105.65	214.52

Table 8. Computational results for medium-size instance.

ω	energy consumption	workstation satisfaction	waiting time	delay time	violate time
0	35393.96	134.2	191.72	140.2	331.92
0.1	35393.96	145.35	191.72	140.2	331.92
0.2	35393.96	150.5	191.72	140.2	331.92
0.3	35393.96	155.66	191.72	140.2	331.92
0.4	35393.96	160.81	191.72	140.2	331.92
0.5	35393.96	165.96	191.72	140.2	331.92
0.6	35393.96	171.11	191.72	140.2	331.92
0.7	37032.79	110.84	67.72	211.41	289.12
0.8	37032.79	96.56	67.72	211.41	289.12
0.9	37032.79	82.09	67.72	211.41	289.12

When dealing with large-size instance, Table 9 indicates that delayed arrivals significantly affect production if ω is less than or equal to 0.1. In this case, the model prioritizes early workstation arrival to optimize delay time, with lower energy consumption compared to the compromise solution obtained from Table 3. Nevertheless, if ω is greater than or equal to 0.7, the model prioritizes late-arriving workstations to optimize waiting time, even if it means sacrificing some delay time. This trade-off necessitates businesses to sacrifice energy consumption to satisfy specific preferences for early or delayed arrival. When ω takes values between 0.2 and 0.7, the final results are compromise solutions.

Table 9. Computational results for small-size instance.

ω	energy consumption	workstation satisfaction	waiting time	delay time	violate time
0	46274.23	41.52	522.31	41.52	563.83
0.1	46274.23	89.6	522.31	41.52	563.83
0.2	46949.69	123	213.99	100.25	314.24
0.3	46949.69	134.37	213.99	100.25	314.24
0.4	46949.69	145.75	213.99	100.25	314.24
0.5	46949.69	157.12	213.99	100.25	314.24
0.6	46949.69	168.49	213.99	100.25	314.24
0.7	47115.98	150.67	25.8	442.02	467.81
0.8	47115.98	109.04	25.8	442.02	467.81
0.9	47115.98	67.42	25.8	442.02	467.81

Overall, the model solutions ensure low energy consumption and customer dissatisfaction, even when companies have distinct preferences for early or delayed arrival.

6. Conclusions

This paper proposes a multi-objective mixed integer programming for the AGV scheduling problem in FMS. To reflect the energy consumption of AGVs more accurately and objectively, an energy consumption model is established, taking into account the structure and motion of AGVs as well as the load. The proposed mixed integer programming takes into account a PDP problem since, in practice, AGVs are required to transport the product being processed in the workshop to its subsequent processing workstation. A customer dissatisfaction function is constructed to measure the degree of the time windows violation. To trade-off customer dissatisfaction and energy consumption, An interactive fuzzy programming approach is used to obtain a compromise solution for decision-makers.

Numerical experiments demonstrate the application and validity of the proposed model. The results show that the two objective functions conflict with each other. The energy-friendly solution needs to pay attention to customer satisfaction. It uses each sub-route between customer nodes by avoiding unnecessary turns and backtracking. The customer-first solution only considers customer satisfaction. Nevertheless, it may create some backtracking in the route due to disregarding the relative positions between customer nodes. The TH approach can efficiently compromise two conflicting objective functions and obtain a satisfactory solution.

In future studies, the proposed model can consider multiple vehicles and warehouses. Additionally, taking into account how AGVs are charged can bring the proposed model closer to the actual production environment.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there is no conflict of interest.

References

1. X. Wang, W. Wu, Z. Xing, X. Chen, T. Zhang, H. Niu, A neural network based multi-state scheduling algorithm for multi-AGV system in FMS, *J. Manuf. Syst.*, **64** (2022), 344–355. http://dx.doi.org/10.1016/j.jmsy.2022.06.017
2. J. Gao, X. Zheng, F. Gao, X. Tong, Q. Han, Heterogeneous multitype fleet green vehicle path planning of automated guided vehicle with time windows in flexible manufacturing system, *Machines*, **10** (2022), 197. http://dx.doi.org/10.3390/machines10030197
3. T. Adamo, T. Bektaş, G. Ghiani, E. Guerriero, E. Manni, Path and speed optimization for conflict-free pickup and delivery under time windows, *Transport. Sci.*, **52** (2018), 739–755. http://dx.doi.org/10.1287/trsc.2017.0816
4. W. Zou, Q. Pan, L. Wang, Z. Miao, C. Peng, Efficient multiobjective optimization for an AGV energy-efficient scheduling problem with release time, *Knowl.-Based Syst.*, **242** (2022), 108334. http://dx.doi.org/10.1016/j.knosys.2022.108334
5. Z. Zhang, L. Wu, W. Zhang, T. Peng, J. Zheng, Energy-efficient path planning for a single-load automated guided vehicle in a manufacturing workshop, *Comput. Ind. Eng.*, **158** (2021), 107397. http://dx.doi.org/10.1016/j.cie.2021.107397
6. S. Shahparvari, B. Bodaghi, Risk reduction for distribution of the perishable rescue items; a possibilistic programming approach, *Int. J. Disast. Risk Re.*, **31** (2018), 886–901. http://dx.doi.org/10.1016/j.ijdrr.2018.07.018
7. W. Tan, X. Yuan, G. Huang, Z. Liu, Low-carbon joint scheduling in flexible open-shop environment with constrained automatic guided vehicle by multi-objective particle swarm optimization, *Appl. Soft Comput.*, **111** (2021), 107695. http://dx.doi.org/10.1016/j.asoc.2021.107695
8. E. Demir, T. Bektaş, G. Laporte, The bi-objective pollution-routing problem, *Eur. J. Oper. Res.*, **232** (2014), 464–478. http://dx.doi.org/10.1016/j.ejor.2013.08.002
9. Z. Li, H. Sang, J. Li, Y. Han, K. Gao, Z. Zheng, et al., Invasive weed optimization for multi-AGVs dispatching problem in a matrix manufacturing workshop, *Swarm Evol. Comput.*, **77** (2023), 101227. http://dx.doi.org/10.1016/j.swevo.2023.101227
10. X. Li, G. Hua, A. Huang, J. Sheu, T. Cheng, F. Huang, Storage assignment policy with awareness of energy consumption in the kiva mobile fulfilment system, *Transport. Res. E-Log.*, **144** (2020), 102158. http://dx.doi.org/10.1016/j.tre.2020.102158

11. J. Wang, Y. Yu, J. Tang, Compensation and profit distribution for cooperative green pickup and delivery problem, *Transport. Res. B-Meth.*, **113** (2018), 54–69. http://dx.doi.org/10.1016/j.trb.2018.05.003
12. B. Zhou, C. Shen, Multi-objective optimization of material delivery for mixed model assembly lines with energy consideration, *J. Clean. Prod.*, **192** (2018), 293–305. http://dx.doi.org/10.1016/j.jclepro.2018.04.251
13. S. Ghannadpour, A. Zarrabi, Multi-objective heterogeneous vehicle routing and scheduling problem with energy minimizing, *Swarm Evol. Comput.*, **44** (2019), 728–747. http://dx.doi.org/10.1016/j.swevo.2018.08.012
14. N. Sivarami Reddy, D. Ramamurthy, K. Prahlada Rao, M. Padma Lalitha, Practical simultaneous scheduling of machines, AGVs, tool transporter and tools in a multi machine fms using symbiotic organisms search algorithm, *Int. J. Comput. Integ. M.*, **34** (2021), 153–174. http://dx.doi.org/10.1080/0951192X.2020.1858503
15. W. Zou, Q. Pan, T. Meng, L. Gao, Y. Wang, An effective discrete artificial bee colony algorithm for multi-AGVs dispatching problem in a matrix manufacturing workshop, *Expert Syst. Appl.*, **161** (2020), 113675. http://dx.doi.org/10.1016/j.eswa.2020.113675
16. D. Fontes, S. Homayouni, Joint production and transportation scheduling in flexible manufacturing systems, *J. Glob. Optim.*, **74** (2019), 879–908. http://dx.doi.org/10.1007/s10898-018-0681-7
17. G. Li, B. Zeng, W. Liao, X. Li, L. Gao, A new AGV scheduling algorithm based on harmony search for material transfer in a real-world manufacturing system, *Adv. Mech. Eng.*, **10** (2018), 1–13. http://dx.doi.org/10.1177/1687814018765560
18. T. Bektaş, G. Laporte, The pollution-routing problem, *Transport. Res. B-Meth.*, **45** (2011), 1232–1250. http://dx.doi.org/10.1016/j.trb.2011.02.004
19. X. Pu, X. Lu, G. Han, An improved optimization algorithm for a multi-depot vehicle routing problem considering carbon emissions, *Environ. Sci. Pollut. Res. Int.*, **29** (2022), 54940–54955. http://dx.doi.org/10.1007/s11356-022-19370-0
20. B. Olgun, Ç. Koç, F. Altıparmak, A hyper heuristic for the green vehicle routing problem with simultaneous pickup and delivery, *Comput. Ind. Eng.*, **153** (2021), 107010. http://dx.doi.org/10.1016/j.cie.2020.107010
21. V. Yu, P. Jodiawan, A. Gunawan, An adaptive large neighborhood search for the green mixed fleet vehicle routing problem with realistic energy consumption and partial recharges, *Appl. Soft Comput.*, **105** (2021), 107251. http://dx.doi.org/10.1016/j.asoc.2021.107251
22. F. Tamke, U. Buscher, The vehicle routing problem with drones and drone speed selection, *Comput. Oper. Res.*, **152** (2023), 106112. http://dx.doi.org/10.1016/j.cor.2022.106112
23. S. Umar Sherif, P. Asokan, P. Sasikumar, K. Mathiyazhagan, J. Jerald, Integrated optimization of transportation, inventory and vehicle routing with simultaneous pickup and delivery in two-echelon green supply chain network, *J. Clean. Prod.*, **287** (2020), 125434. http://dx.doi.org/10.1016/j.jclepro.2020.125434

24. T. Simolin, K. Rauma, R. Viri, J. Mäkinen, A. Rautiainen, P. Järventausta, Charging powers of the electric vehicle fleet: evolution and implications at commercial charging sites, *Appl. Energ.*, **303** (2021), 117651. http://dx.doi.org/10.1016/j.apenergy.2021.117651

25. S. Erdoğan, E. Miller-Hooks, A green vehicle routing problem, *Transport. Res. E-Log.*, **48** (2012), 100–114. http://dx.doi.org/10.1016/j.tre.2011.08.001

26. G. Macrina, L. Di Puglia Pugliese, F. Guerriero, G. Laporte, The green mixed fleet vehicle routing problem with partial battery recharging and time windows, *Comput. Oper. Res.*, **101** (2019), 183–199. http://dx.doi.org/10.1016/j.cor.2018.07.012

27. Y. Xiao, Y. Zhang, I. Kaku, R. Kang, X. Pan, Electric vehicle routing problem: a systematic review and a new comprehensive model with nonlinear energy recharging and consumption, *Renew. Sust. Energ. Rev.*, **151** (2021), 111567. http://dx.doi.org/10.1016/j.rser.2021.111567

28. G. Macrina, G. Laporte, F. Guerriero, L. Di Puglia Pugliese, An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows, *Eur. J. Oper. Res.*, **276** (2019), 971–982. http://dx.doi.org/10.1016/j.ejor.2019.01.067

29. D. Goeke, M. Schneider, Routing a mixed fleet of electric and conventional vehicles, *Eur. J. Oper. Res.*, **245** (2015), 81–99. http://dx.doi.org/10.1016/j.ejor.2015.01.049

30. L. Qiu, J. Wang, W. Chen, H. Wang, Heterogeneous AGV routing problem considering energy consumption, *Proceedings of IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2015, 1894–1899. http://dx.doi.org/10.1109/ROBIO.2015.7419049

31. F. Stavropoulou, The consistent vehicle routing problem with heterogeneous fleet, *Comput. Oper. Res.*, **140** (2022), 105644. http://dx.doi.org/10.1016/j.cor.2021.105644

32. S. Wang, X. Wang, X. Liu, J. Yu, A bi-objective vehicle-routing problem with soft time windows and multiple depots to minimize the total energy consumption and customer dissatisfaction, *Sustainability*, **10** (2018), 4257. http://dx.doi.org/10.3390/su10114257

33. H. Kargari Esfand Abad, B. Vahdani, M. Sharifi, F. Etebari, A bi-objective model for pickup and delivery pollution-routing problem with integration and consolidation shipments in cross-docking system, *J. Clean. Prod.*, **193** (2018), 784–801. http://dx.doi.org/10.1016/j.jclepro.2018.05.046

34. T. Liao, Integrated inbound vehicle routing and scheduling under a fixed outbound schedule at a multi-door cross-dock terminal, *IEEE T. Intell. Transp.*, **23** (2022), 13217–13229. http://dx.doi.org/10.1109/TITS.2021.3122396

35. S. Javanmard, B. Vahdani, R. Tavakkoli-Moghaddam, Solving a multi-product distribution planning problem in cross docking networks: an imperialist competitive algorithm, *Int. J. Adv. Manuf. Technol.*, **70** (2014), 1709–1720. http://dx.doi.org/10.1007/s00170-013-5355-5

36. M. Samani, S. Hosseini-Motlagh, A novel capacity sharing mechanism to collaborative activities in the blood collection process during the covid-19 outbreak, *Appl. Soft Comput.*, **112** (2021), 107821. http://dx.doi.org/10.1016/j.asoc.2021.107821

37. S. Jun, S. Lee, Y. Yih, Pickup and delivery problem with recharging for material handling systems utilising autonomous mobile robots, *Eur. J. Oper. Res.*, **289** (2021), 1153–1168. http://dx.doi.org/10.1016/j.ejor.2020.07.049

38. C. Liu, J. Tan, H. Zhao, Y. Li, X. Bai, Path planning and intelligent scheduling of multi-AGV systems in workshop, *Proceedings of 36th Chinese Control Conference (CCC)*, 2017, 2735–2739. http://dx.doi.org/10.23919/ChiCC.2017.8027778
39. C. Hwang, A. Masud, *Multiple objective decision making-methods and applications*, Berlin: Springer-Verlag, 1979. http://dx.doi.org/10.1007/978-3-642-45511-7
40. S. Torabi, E. Hassini, An interactive possibilistic programming approach for multiple objective supply chain master planning, *Fuzzy Set. Syst.*, **159** (2008), 193–214. http://dx.doi.org/10.1016/j.fss.2007.08.010
41. Y. Lai, C. Hwang, Possibilistic linear programming for managing interest rate risk, *Fuzzy Set. Syst.*, **54** (1993), 135–146. http://dx.doi.org/10.1016/0165-0114(93)90271-I
42. H. Selim, I. Ozkarahan, A supply chain distribution network design model: an interactive fuzzy goal programming-based solution approach, *Int. J. Adv. Manuf. Technol.*, **36** (2008), 401–418. http://dx.doi.org/10.1007/s00170-006-0842-6
43. W. Zou, Q. Pan, L. Wang, An effective multi-objective evolutionary algorithm for solving the AGV scheduling problem with pickup and delivery, *Knowl.-Based Syst.*, **218** (2021), 106881. http://dx.doi.org/10.1016/j.knosys.2021.106881