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ORIGINAL PAPER

An energy-aware optimisation model to minimise energy consumption and carbon footprint in a flexible manufacturing system

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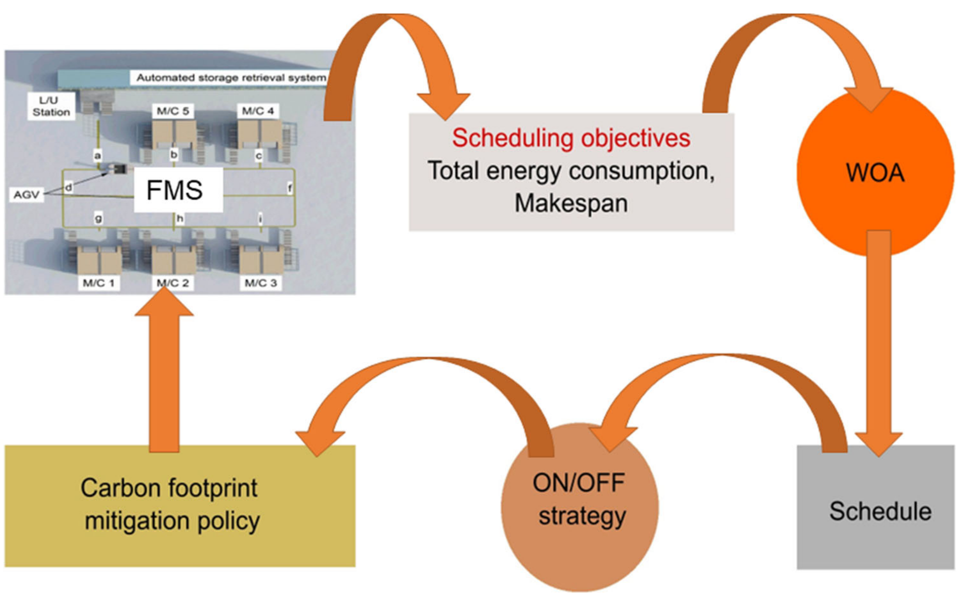
Abstract

This paper proposes an energy-aware production schedule model for flexible manufacturing systems (FMSs) that aims to minimise energy costs and carbon tax while considering rising energy costs and environmental policies motivated by climate change concerns. The model is based on a sequence-dependent five-machine FMS scheduling problem, which is flexible in levels of parts, tools, machines, and routings. The proposed model is solved as a multi-objective problem, with tardiness and energy consumption as primary goals and carbon footprint reduction policies incorporated into the framework as control strategies. The machine ON/OFF strategy is also introduced to reduce idle energy. The study analyses the trade-off between minimising tardiness and carbon emissions to achieve both service level and environmental sustainability of the FMS. The proposed model reduced total energy consumption and carbon emissions by 20% and 21%, respectively, without compromising manufacturing deadlines. Future research may explore the integration of renewable energy sources and storage systems, considering more complex manufacturing scenarios, such as stochastic demands, machine failures, and workforce constraints.

Graphical abstract



Keywords Multi-objective scheduling · Makespan · Energy consumption · Tardiness · Carbon footprint

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1 Introduction

Industrial growth has escalated energy demand and greenhouse gas emissions in recent years. According to Energy Information Administration, USA, 2016, businesses consume 31.8% of the world's energy and 29% of electricity-related CO_2 emissions, Environmental Protection Agency, USA, 2019. International Energy Outlook (2019) predicts that industrial energy use will increase by over 30% from 2018 to 2050, reaching about 315 quadrillion British thermal units by 2050 (EIA) [1]. But the unexpected outbreak of the novel coronavirus disease (COVID-19) in 2019 has changed the economy, energy supply, and demand scenario in 2020 [2], which is expected to make a comeback in these years. Electrical energy consumption and carbon dioxide emissions are known to be intimately connected. Manufacturers can reduce CO_2 emissions by conserving energy, indirectly addressing the current global warming scenario [3].

Many nations, including Sweden, Germany, Finland, and France, have implemented policies such as time-of-use (TOU) tariffs and carbon taxes to focus on rising energy demand and greenhouse gasses. Most typical carbon-reduction strategies, such as emissions taxes, baseline emissions, and emissions trading systems, compel industries to pay the price for each tonne of carbon emissions they emit and compensate them for staying within emission limits. Foumani and Smith-Miles [4] investigated the influence of carbon reduction rules on the industrial sector's economic edge from the standpoint of an environmental policymaker. The research centred on flow shop scheduling in an effort to reduce lead times and carbon emissions. The study of Ding et al. [5] demonstrates a multi-objective optimisation framework for lowering total CO_2 emissions and makespan.

In the manufacturing industry, there are four main types of manufacturing shop facilities: the job shop, the flow shop, the flexible job shop, and the flexible manufacturing system (FMS). An FMS has a high potential for energy-efficient scheduling due to their greater flexibility in the machine, operational, and material handling levels than job-shop, flow-shop, and flexible job-shop. There is very little research in energy-efficient scheduling of the FMS that is primarily oriented on lowering energy consumption and makespan [6–9]. There is room for research on FMS scheduling with energy price and carbon footprint reduction approach. Reducing the use of electricity during the manufacturing process can reduce the total energy consumption of manufacturing enterprises, which can be accomplished through energy-efficient scheduling [10]. Prior to 2011, there was just a few research on the control and scheduling of the production process to reduce environmental effects [11]. Production scheduling was used to decrease energy consumption and overall tardiness in manufacturing, as reported by [12, 13]. Also, methods like the ON/OFF strategy in idle machines for minimising the total energy consumption in production systems and thereby limiting the peak load were introduced [14, 15]. For an FMS-specific case, the earliest work on multi-objective scheduling that takes alternate route options for mitigating tardiness and idleness is addressed in [16]. In order to increase environmental sustainability, Barak et al. [17] researched the energy-efficient scheduling of an FMS.

Lee et al. [18] projected one of the very first works in CO_2 mitigation by comparing three distinct carbon tax scenarios in different industries. In order to regulate total carbon quantity and reduce carbon intensity, Zhu et al. [19] tested a variety of carbon mitigation strategies. Zhang et al. [20] presented a low-carbon scheduling model for a flexible job shop that took into account both production and carbon emission parameters. Other relevant works to lower carbon footprint and makespan can be found in [21–24]. There are strategies to reduce an industry's carbon footprint by replacing old machinery with greater efficiency machines based on low-carbon technologies. On the other hand, modern low-carbon technologies can fail, and the transfer from theory to reality is always lengthy [25]. Scheduling has a significant chance of improving energy efficiency in this circumstance.

In recent years, several studies have been conducted to address energy-efficient scheduling in the manufacturing industry. Guo et al. [26] proposed a novel approach for flow-shop scheduling that incorporates an ultra-low idle status for machine tools and a hybrid genetic algorithm with energy-saving strategies. Tian et al. [27] proposed an integrated optimisation model for flexible job shop scheduling that considers machining power and tool life prediction and an energy-saving strategy to minimise production cost and energy consumption while accounting for cutting-tool degradation. Duan et al. [28] presented a collaborative scheduling model for large metallic components manufacturing, aiming to minimise makespan and carbon emissions, which showed significant improvements over non-collaborative workshops.

However, a research gap remains in integrating time-based scheduling objectives with energy-environmental policies such as emission taxes and carbon trading in a flexible route scheduling framework. The relationship between the order and scheduling of tasks and energy use is rarely investigated, and further investigation is required into the feasibility of using the ON/OFF technique at the machine level to reduce idling energy usage. To address this gap, this paper proposes an integrated approach that optimises both scheduling and energy consumption, taking into account environmental policies and the impact of machine ON/OFF strategy. This approach contributes to the field by highlighting the importance of incorporating carbon emission cost leverage points

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for energy efficiency and green production while ensuring on-time delivery and service standards in a practical industrial setting.

This paper provides a practical production scheduling framework for a five-machine flexible manufacturing system in order to address the challenges mentioned above. The model considers the reduction of total tardiness and energy consumption as the primary scheduling objectives, with carbon footprint reduction strategies acting as the scheduling control strategy. Production plans are created by identifying alternative routes and machinery for every manufacturing operation. The optimal solution developed by the framework is used with an ON/OFF approach to reduce further total energy consumption, and consequently, the carbon footprint. The proposed method is founded on the fact that the retrieved solution is highly compliant with time, energy, and environmental-based parameters. The study shows how energy and environmental regulations influence a production system's time, cost, and energy-based performance. The contributions of this paper are outlined as follows:

1. A multiple-objective strategy to lower tardiness and high energy requirements in an FMS.
2. Carbon footprint regulations, such as emissions taxes and carbon trading, are implemented into the framework to achieve a cost-effective and environmentally responsible solution.
3. A multi-objective whale optimisation algorithm (WOA) to generate Pareto optimal solutions at an opportune time for the proposed model.
4. The effectiveness of the suggested approach in meeting consumer and environmental restrictions is evaluated and depicted in terms of makespan, energy cost, emission tax, and carbon trading.

The paper is structured as follows: Section 2 gives an overview of the methodology and algorithm used. Section 3 presents the FMS model. Section 4 describes the proposed model evaluation and discussion. Section 4.3 Conclusion and future insights.

2 Methodology

2.1 Notation.

The following input parameters and decision variables are used across the whole text to represent the adaptive framework in detail.

CE_T Total carbon emissions of a given sequence. λ CO_2 conversion factor

TEC The total energy consumption of a given sequence

CT_i Completion time of job i.

DD_i Due date for the job i.

UPC_i Unit penalty cost for the job i.

BS_i Batch size of job i.

X_P Total penalty costs paid to complete all delayed jobs after their target date.

MPP Maximum Permissible Penalty.

PT_{ji} Processing time of i^{th} job with J^{th} machine.

E_{mPj} Energy use for operation p on machine J.

$E_{w,j}$Idle power E_w of machine $J_j t_{w,j}$ Idle time t_w on machine J_j

W_1 Weightage factor for tardiness.

W_2 Weightage factor for energy consumption.

F_1 The objective function for reducing tardiness.

F_2 The objective function for reducing energy consumption.

TCE Total carbon emissions of a given sequence.

Q_{max} Carbon emission baseline.θ Carbon credit price

This work presents an adaptive energy-aware multi-objective scheduling optimisation model that can be employed to lower carbon footprint through effective machine scheduling. The suggested approach is based on a five-machine route-dependent FMS scheduling model. The model balances customer needs and environmental constraints by managing production floor-level scheduling objectives such as makespan and energy consumption. The framework's scheduling decisions are affected by the organisation's carbon footprint reduction efforts, which include a carbon price. The proposed model uses a Whale Optimisation Algorithm (WOA) to optimise the objectives mentioned above to create a Pareto solution. The generated solution is examined critically in terms of time, total energy cost, and carbon footprint parameters. The framework searches for alternate solutions if the best one falls short of the standards set by the customer or manufacturer for makespan, peak load, and carbon footprint. Whenever the machine is idle for more than 60 min, the model's ON/OFF strategy kicks in. Figure 1 depicts the proposed framework's model.

2.1 Mathematical model

An FMS scheduling event consists of J = 1, 2…, j machines and N = 1, 2…, n jobs. P = 1, 2…, p operations are necessary to complete each job. As long as the requirement for alternative routes is met, an operation P_{NJ} on a job, N is processed by many machine types. Because of the uniqueness of each machine, the identical operation on different machines may require different processing times and energy consumption (EC). This study considers two levels of machine energy usage (Idle EC and Processing EC). AGV is used to transfer a job from a machine J_x to the following machine J_z when a job N's operation P_{NJ} ends on machine J_x. The solution to the problem is to allocate machines to each operation simultaneously. The order of tasks for each machine is chosen to reduce tardiness and energy consumption. One or more

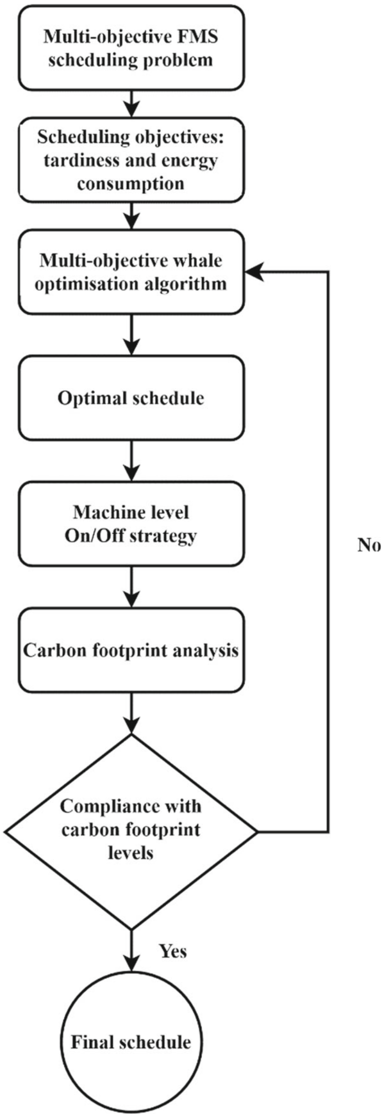

Fig. 1 Overview of the proposed model

machines can perform four operations for each job. As illustrated below, some restrictions must be met to simplify the problem at hand [29, 30].

1. A machine can only execute one process at a time.
2. There are no machine breakdowns or production interruptions.
3. Each part type has a specific processing sequence, due date, and penalty cost for missing the target date.
4. Since computers control all operations, each part's processing time is known deterministically.
5. All machines are available at time 0.
6. The time required to set up the machine is avoided.

The basic contextual definitions of the electricity price, carbon footprint, and FMS shop-level scheduling objectives are described ahead.

The delay in finishing a task prior to its due date is measured by tardiness in scheduling. Machines are scheduled for a set of jobs with specific due dates. If a job is finished beyond the deadline, it is subjected to tardiness costs. Penalties for tardiness are proportional to processing delays. In addition to financial liabilities, the delay substantially influences customer satisfaction [30, 31].

The first manufacturing objective of this study is to reduce tardiness, as stated by the equation below [32]:

$$\text{Tardiness, T} = X_P = \sum_{j=1}^{J}\left[\max\left\{0,\ T_j - DD\right\}\right] \tag{1}$$

$$\mathrm{F}_1 = \min(\mathrm{T}) \tag{2}$$

The second manufacturing objective is to reduce overall energy consumption (kWh), which is influenced by machining energy E_m of the working machines and energy EI_m, which is the energy used by machines when they are not machining or waiting for work to arrive. Equation 4 determines the Total Energy Consumption (TEC) for a schedule in an FMS that includes 'm' machines, 'n' jobs, and 'i' activities.

$$E_m = \sum_{j=1}^{J} E_{mj} \times X_{mj} \tag{3}$$

$$\text{Total energy consumption TEC} = \sum_{m=1}^{M} E_m + \sum_{m=1}^{m} EI_m \times t_m \tag{4}$$

$$\mathrm{F}_2 = \min(\mathrm{TEC}) \tag{5}$$

According to Mouzon et al. [12], an idle machine wastes 13% of the total energy consumed by the schedule. An ON/OFF strategy can aid in the reduction of total idle energy consumption. The FMS schedule optimisation problem for mitigating tardiness and total energy consumption is classified as an NP-hard problem [33].

2.2 Flat price electricity tariff structure

A flat rate energy tariff is a type of energy tariff where the customer pays a fixed rate for each unit of energy they use. The customer pays the same price per unit of energy regardless of how much energy is consumed under a flat rate tariff. The advantage of this type of tariff is that it is easy to budget for and can provide a more predictable energy bill. Flat price electricity tariff is computed by multiplying energy consumption with the price of electricity over time, Eq. 6.

$$\text{Total energy price,}\quad CE = B_C \times TEC \tag{6}$$

Electricity retail prices for industrial clients are often close to wholesale prices. In this study, the energy base price (B_C) was fixed at \$0.0726 \$/kWh [34].

2.3 Carbon footprint reduction structure

The carbon footprint may be explicated as "*the quantity of greenhouse gases expressed in terms of* CO_2*, emitted into the atmosphere by an individual, organisation, process, product, or event from within a specified boundary*" [35]. The carbon footprint restrictions are classified into three broad categories. The "Scope 1" boundary includes the organisation's direct emissions from activities like burning fuel. In contrast, the 'Scope 2' boundary stretches to the carbon emissions on the energy supplier side created by the purchased energy. Scope 3 comprises any further indirect emissions inside an enterprise's value chain. Our research focuses on the Scope 2 emissions induced by the consumption of electricity by machines.

Reducing the carbon footprint of operations and processes in the global industrial sector is becoming increasingly critical. This study investigates three typical carbon reduction strategies for FMS scheduling: "taxes on emissions, baselines on emissions, and emissions trading schemes" [4]. Such initiatives can replace conventional scheduling strategies with environmentally responsible scheduling methods. The economic performance of the industrial sector may be affected by pollution abatement policies. A tax on emissions for each tonne of carbon produced could pressure large emitters to pay or limit emissions below the consented baseline.

2.3.1 Tax on emissions (ToE) policy

The government taxes manufacturing systems based on the quantity of carbon dioxide generated throughout the manufacturing process [4]. In this study, the emission fee is \$ 33.55/tonne CO_2 [36]. As CO_2 generation is essentially determined by the energy consumption of industrial systems, and Eq. (7) can compute it. In this work λ (CO_2 conversion factor) is assigned as 0.785 kg CO_2/kWh [3].

$$CE_T = \lambda \times TEC \tag{7}$$

2.3.2 Baseline on emissions (BoE) policy

The production schedules are bound by strict baselines (upper limits) for the amount of carbon emitted during production. The boundaries may well aid in controlling the emission at a specific instant in time [4].

2.3.3 Emissions trading (ET) policy

The schedules under consideration that fall below the carbon baselines may get a credit for carbon emissions throughout the schedule rather than a penalty to reach or exceed the baseline, as appropriate. It can be determined using Eq. 8 [4].

$$ET = \theta.(TCE - Q_{max}) \tag{8}$$

If the schedules don't comply with the emission baseline, emission trading can have a positive value, but if they do, it can have a negative value. Positive values may start the penalty, while negative values may start the industry a reward. The carbon credit cost in this study is \$0.050 per kilogramme of CO_2 [4].

2.4 Whale optimisation algorithm (WOA)

WOA is a swarm intelligence algorithm based on population that has been presented for continuous optimisation problems. The social behaviour of humpback whales, the giant creatures on the planet, inspires the WOA technique. It has been demonstrated that this method outperforms or is comparable to specific existing algorithmic strategies [37]. The hunting behaviour of humpback whales inspired WOA. Each solution is regarded as a whale in WOA. In this solution, a whale tries to occupy a new location in the search space by utilising the best member of the group as a reference. Whales use two procedures to locate prey and attack. The prey is encircled in the initial step, and bubble nets are created in the second. In terms of optimisation, as whales look for prey, they explore the search space, and exploitation occurs in the attack behaviour.

2.4.1 A mathematical-based model and optimisation algorithm

In the first phase of this section, a mathematically oriented model is offered from encircling prey, searching for prey, and spiral bubble-net feeding operations. The WOA heuristic, like other swarm-based heuristics, begins by arbitrarily generating a set of NP potential solutions, as shown below:

$$x_{i,j}^{t=0} = X_{i,min} + rand_{i,j}(0,1) \times (x_{i,mix} - x_{i,min}) \tag{9}$$

where t represents the generation or iteration number, j = 1, …, NP, i = 1,…, D (D, the size of the problem), $x_{i,\,min}$ and $x_{i,\,max}$ is the lowest and highest values of the ith design variable, individually.

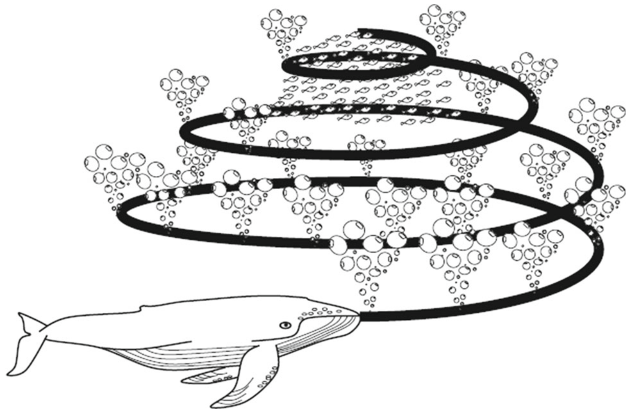

Fig. 2 Humpback whales' bubble-net feeding behaviour [37]

The WOA also includes (1) the encircling mechanism around the prey, (2) the development of the bubble net for trapping the prey, and (3) the approach for searching for the prey. The various stages are detailed below.

Encircling prey mechanism The first step in hunting is to encircle the prey. Clearly, the detected candidate is presumed to be the present strong candidate. Then, its position is iteratively adjusted to the optimal global solution. This behaviour is described by Eqs. (10) and (11) below:

$$D = \left|C.x^{*}(t) - x \geq (t)\right| \tag{10}$$

$$x(t+1) = x * (t) - A.D \tag{11}$$

where t represents the present iteration, x^* is the optimal solution, and x is the actual solution. Equations (12) and (13) provide the coefficient vectors A and C.

$$A = 2 \times a.r - a \tag{12}$$

$$C = 2 \times r \tag{13}$$

where a is decreased linearly from 2 to 0, and r is randomly distributed within the interval [0,1].

Bubble-net attacking method (exploitation phase) The approach adopted by humpback whales to capture prey involves the formation of a spiralling, shrinking bubble net, as depicted in Fig. 2. The first process is modelled mathematically by lowering the value of 'a' in Eq. (14) over time as described below:

$$a = 2 - \frac{2t}{t_{max}} \tag{14}$$

where t represents the present iteration count, and t_{max} is the one given by the criterion. Similarly, the spiral updating position is expressed as:

$$D' = \left|x^{*}(t) - x(t)\right| \tag{15}$$

$$x(t = 1) = D'.e^{bl}.\cos(2\pi l) + x^{*}(t) \tag{16}$$

where b is the constant that governs the shape of the logarithmic spiral, and l is a random number between − 1 and 1. During the optimisation process, shrinking encircling is given a 50% probability, and the spiral-shaped route is given a 50% chance, as represented in the equations below [37]:

$$x(t+1) = \begin{cases} x^{*}(t) - A.D, & if p < 0.5 \\ D'.e^{bl}.\cos(2\pi l) + x^{*}(t), & if p \geq 0.5 \end{cases} \tag{17}$$

Search for prey During the exploration stage, a strategy is used to divert a solution away from the most well-known search agent using vector A, which has random values in the interval [−1, 1]. This is expressed as follows [37]:

$$x(t+1) = x_{rand} - A.D \tag{18}$$

where x_{rand} is a random whale selected from the current population.

The WOA-based energy-aware model in this article is compared to the NSGA II [38] model with the same scheduling goals and carbon footprint policy in order to validate efficiency.

3 Description of the FMS model

The FMS under consideration consists of two AGVs, an automated storage retrieval system (AS/RS), five computer numerical control machines (CNCMs), an input buffer (I/B), and an output buffer (O/B) at each machine [39]. The input/output buffer serves as a short-term repository for unfinished components and raw materials. The material handling between the CNCMs is accomplished by AGVs, transporting the finished product from any CNCM to the unloading station and the loaded pallets from the L/U station to any CNC machines. AGVs offer directional flexibility and can move one pallet at a time. The AGVs start at the loading/unloading station, and after staring at the schedule, they park at their last delivery station. The loading station gets parts for manufacturing, while the unloading station receives components that have been manufactured [29, 39]. The FMS layout is portrayed in Fig. 3, drawn in Blender 2.80.

Fig. 3 FMS layout [29]

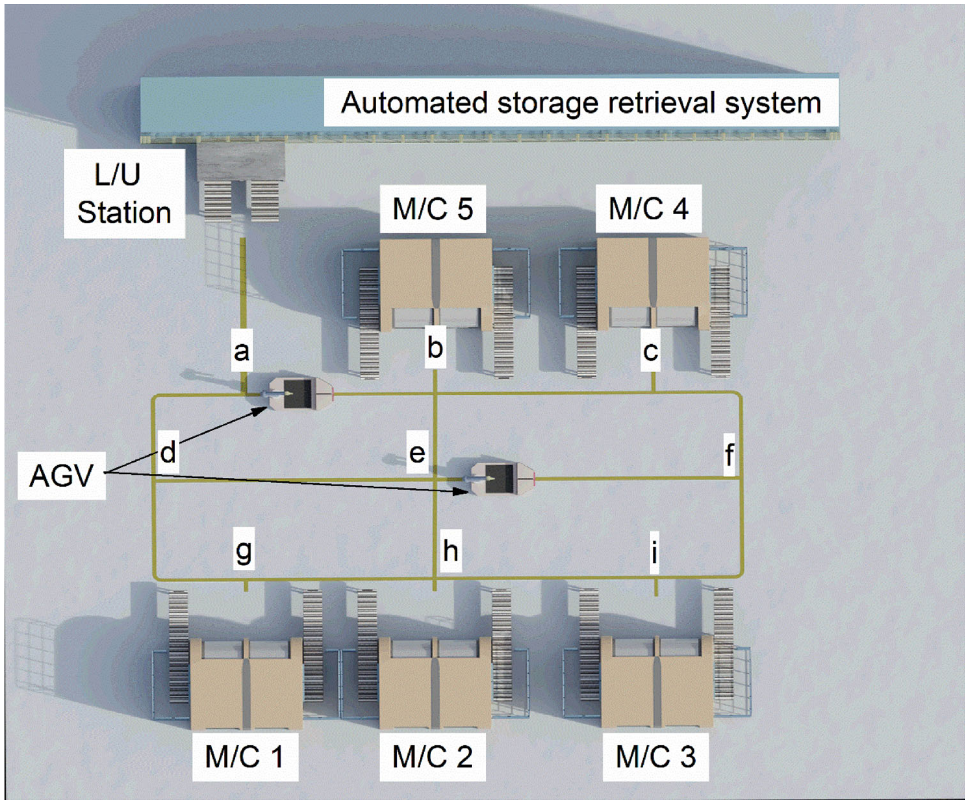

Table 1 Power consumption of each machine

Machine number	Idle power(W)	Machining power (W)
1	1000	2260
2	1100	1680
3	1220	1360
4	800	1970
5	700	1200

4 Model evaluation and discussion

4.1 Base case introduction

MATLAB® R2019a solves the WOA algorithm and optimisation model. Hewlett-Packard Notebook PC with Intel Core i5(R) 6200, 2.80 GHz processor with 8 GB,1600 MHz memory, and NVIDIA GeForce940M, 2 GB GPU are used for all experiments.

4.2 Problem parameters

The idle and machining power of machines is given in Table 1. The FMS can handle eight-part verities with four operations per part. Table 6 (Appendix) demonstrates various routing plans for each part type and their process times. Table 1 depicts idle and machining power. The route data matrix for the distance between each machine tool is shown in Table 7 (Appendix). Table 2 depicts the part mix of eight different parts with a batch size of 100, which is used to test the proposed model.

The suitability of the optimal schedule is analysed for makespan, energy price and carbon footprint reduction policies. Table 3 shows the maximum allowable limits for makespan (Cmax), energy price, the baseline of emission, and maximum permissible ToE for this model's testing.

4.3 Model results

The production schedule selected by the presented model is portrayed in Table 4. Table 5 displays the comparative scheduling outcomes and cost breakdown based on the Makespan, total energy consumption, Total energy cost ($), Carbon tax, and Carbon trading. The solution space is extensive, as the makespan extends from 3200 to 3420 min for WOA and NSGA II, respectively. The range of total energy usage values is 232.13 kWh to 278.91 kWh. As demonstrated in Table 5, the proposed framework with an ON/OFF strategy output solution has the lowest total cost. The framework assigns jobs to machines so that the schedule's total energy consumption and carbon footprint may be below the baseline of emission constraints, as shown in Fig. 4. As shown in Table 1, M/C 1 is the highest energy-consuming machine

Table 2 The demand for part types for different production volumes Chan [39]

Production volume (Nos.)/part variety	The demand of part (Nos.)							
	1	2	3	4	5	6	7	8
100	14	14	10	10	10	14	14	14

Table 3 Time-energy and carbon footprint-based limiting constraints

Parameter	Maximum permissible limit
C_{max}	4000 min
Energy price	20$
BoE	0.101 kg CO_2/kWh
ToE	10 $

Table 4 Part order and alternate route selected by the model

Part number (alternate route no.)	5(1), 6(3),4(1),2(2),1(2),3(1),8(3),7(2)

in the FMS model, which is managed by the framework in periods of time to idle to minimise the total energy consumption (Fig. 4a). At the same time, the ON/OFF strategy further reduces energy consumption by turning the machines off Fig. 4b. As shown in Fig. 4b, machine M_2, the model, kept the machine in the ON state despite being idle at the 184th minute since the idle duration was less than 60 min. This limitation is imposed because regularly switching the machines ON and OFF can harm the system. Heavy machinery can take a long time to power up and configure.

In Fig. 5, the Pareto solution with and without an ON/OFF strategy is examined for electrical load and makespan. The graphical representation clearly shows that the ON/OFF method has significantly decreased energy use at a single point in time by lowering the idle energy consumption of the machines. As a result, when the schedule with an ON/OFF strategy is compared to the usual schedule, there is a − 20.41% optimality gap in total energy consumption, resulting in a 21.23% savings in total energy cost. Figure 4 demonstrates how the framework has configured the machines to turn off after 60 min of inactivity.

The carbon footprint is highly proportionate to energy consumption. The optimal schedule is analysed for carbon footprint and makespan with an upper bound for carbon footprint called Baseline on Emissions (BoE) for the presented strategies. The following observations are made from the carbon footprint analysis graph; Fig. 6b with the ON/OFF strategy, carbon emission levels followed the Baseline on Emissions with a minor violation compared with Fig. 6a. The model with WOA and ON/OFF strategy performed better than the model with NSGA II, demonstrating the effectiveness of the suggested framework. The analysis of the results indicates that the suggested framework can make existing facilities more energy-efficient and environmentally friendly without requiring substantial capital expenditures. The model has a broad scope for fulfilling the anticipated increase in energy demand in the near future.

Table 5 Scheduling results for WOA and NSGA II with and without ON/OFF strategy

Parameter	Whale optimisation algorithm (WOA)			NSGA II		
	Without an ON/OFF strategy	With an ON/OFF strategy	Optimality gap (%)	Without an ON/OFF strategy	With an ON/OFF strategy	Optimality gap (%)
Running time of the algorithm (sec.)	12.42	13.12	5.64	14.26	15.23	6.80
C_{max} (min.)	3200	3200	0	3420	3420	0
TEC (kWh.)	294.68	232.13	− 20.41	316.18	278.91	11.79
Total energy cost ($)	21.39	16.85	− 21.23	22.95	20.25	11.79
TCE (tonCO_2)	0.23	0.18	− 21.23	0.25	0.22	11.79
Carbon tax ($)	7.75	6.10	− 21.23	8.31	7.33	11.79
Carbon trading ($)	− 3.89	− 6.35	− 63.08	− 2.41	− 4.62	91.70
Overall cost ($)	25.25	16.6	34.26	28.85	22.96	20.42

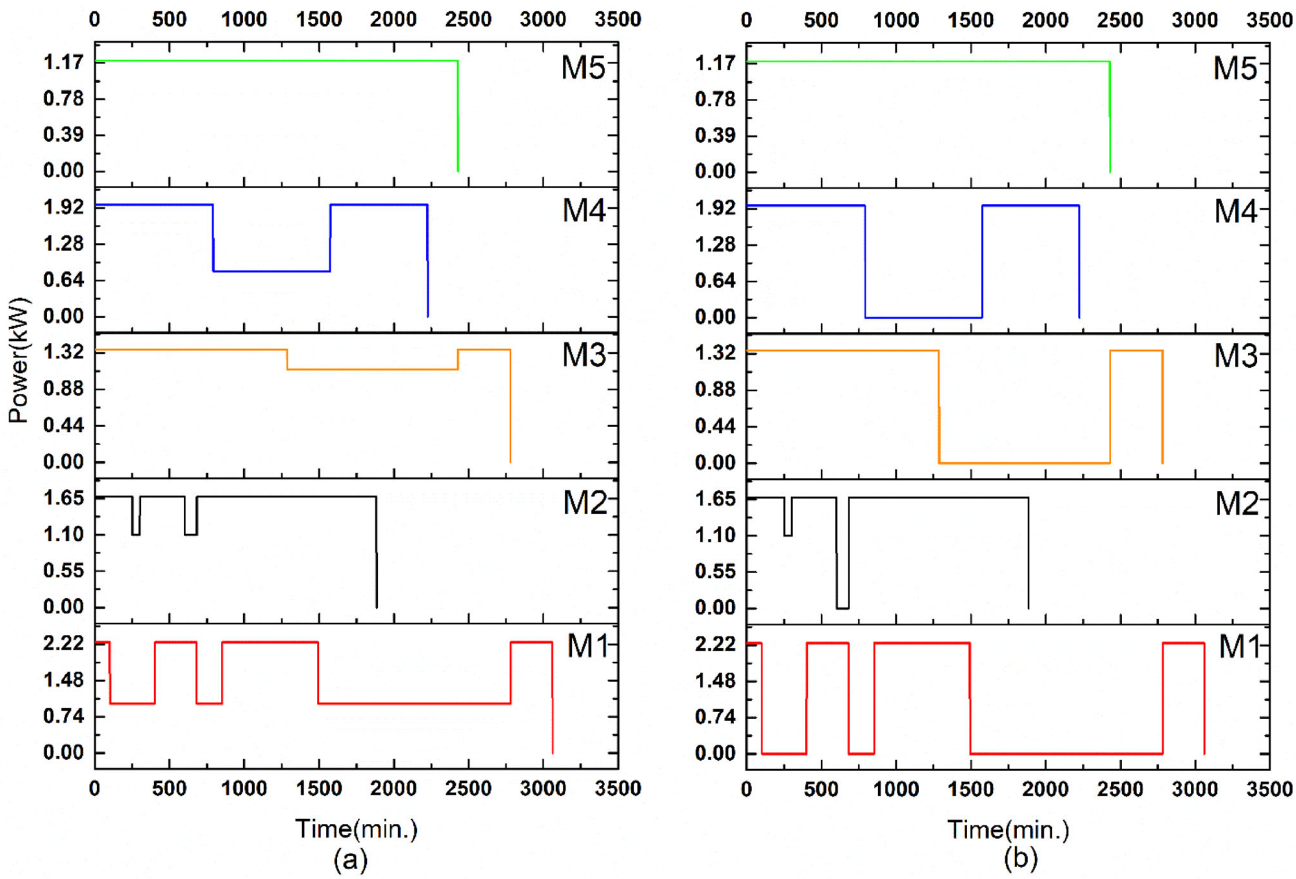

Fig. 4 Analysis of machine-level energy consumption for optimal schedule with (**b**) and without (**a**) ON/OFF strategy

5 Conclusion and future insights

Industries face significant challenges due to the rising energy costs and global warming policies. In this study, we propose an adaptive energy optimal production scheduling model for flexible manufacturing systems (FMS) that aims to reduce energy costs and carbon footprint emissions while accounting for the flexibility of routes in FMS scheduling problems. We emphasise the importance of considering carbon footprint policies, whether imposed by corporate or governmental organisations, in manufacturing scheduling decisions. Our proposed model is formulated as a multi-objective optimisation problem and solved using metaheuristics, demonstrating superior performance over existing scheduling optimisation algorithms such as NSGA II.

Our study highlights the significance of incorporating environmental policies and energy costs in manufacturing scheduling decisions to achieve sustainable and efficient production. While the proposed adaptive energy optimal production scheduling model can lower production costs by reducing energy consumption and carbon footprint, it may require compromises on traditional time-based targets such as makespan, which can impact customer satisfaction. However, our case study shows that the energyaware adap- tive model can meet makespan, energy price, and carbon tax objectives, while avoiding additional expenses related to missing the deadlines.

We compare the optimal schedule from the adaptive model using the whale optimisation algorithm (WOA) and ON/OFF

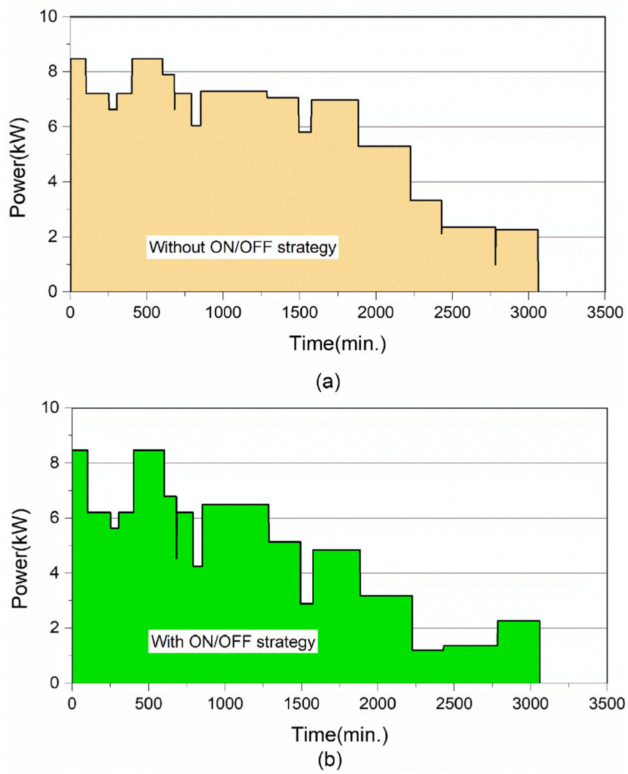

Fig. 5 Electric load analysis of optimal schedule with (**b**) and without (**a**) ON/OFF strategy

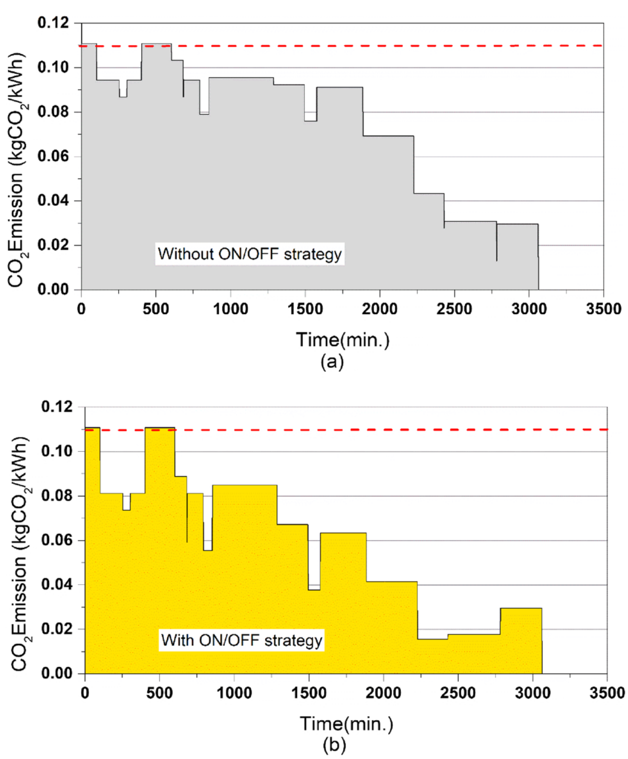

Fig. 6 Carbon footprint analysis of the optimal schedule with (**b**) and without (**a**) ON/OFF strategy

approach to a model incorporating NSGA II with the same objectives and control strategies. Results show that the adaptive model with WOA and ON/OFF approach effectively reduces makespan, energy cost, and carbon costs to 3200 min, \$16.85, and \$6.10, respectively, while meeting all mandated scheduling parameters. Moreover, the model can earn \$6.35 for carbon trading, encouraging industries to implement the developed framework and benefit from its sustainability. This study concludes that integrating an adaptive energy-efficient scheduling framework can effectively reduce demand-side energy and carbon emissions without halting production, as activities on a job can still be performed on other machines in the FMS. This research contributes to ongoing efforts to mitigate the impact of manufacturing on the environment and supports the transition towards sustainable production practices in the industry.

The future scope of the model could include multi-level peak load (Time-of-Use energy Scheme) and varying carbon footprint control strategies, as [4] proposed. Besides, it can also include scheduling under a dynamic production environment with new part addition and machine breakdown. The proposed approach can also be adapted to different production systems, such as flexible job shops with inherent routing and operational flexibility. In addition, future studies could investigate the economic and social impacts of carbon footprint reduction policies on manufacturing operations. This would provide a more comprehensive understanding of the potential benefits and challenges of implementing sustainable production practices in the industry.

Declarations

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

Appendix

See Tables 6 and 7

Table 6 All possible alternative routes and processing times for each part Chan [1]

Part type	Alternate route no.	Operation no. 1 M/c no.)	Processing time (min.)	Operation no. 2 (M/c no.)	Processing time (min.)	Operation no. 3 (M/c no.)	Processing time (min.)	Operation no. 4 (M/c no.)	Processing time (min.)
1	1	1	15	3	24	5	10	2	30
	2	2	18	3	24	5	10	2	30
	3	1	15	3	24	5	10	1	25
	4	2	18	3	24	5	10	1	25
2	1	2	20	3	10	5	35	4	25
	2	2	20	2	16	5	35	4	25
	3	3	24	3	10	5	35	4	25
	4	3	24	2	16	5	35	4	25
3	1	5	40	1	25	4	30	2	15
	2	5	40	1	25	3	27	2	15
4	1	4	30	2	30	5	20	3	25
	2	4	30	2	30	5	20	1	15
5	1	1	10	3	20	2	15	4	30
	2	1	10	3	20	5	20	4	30
6	1	3	25	2	12	1	25	5	10
	2	3	25	2	12	1	25	3	23
	3	5	20	2	12	1	25	5	10
	4	5	20	2	12	1	25	3	23
7	1	4	35	5	10	1	10	2	15
	2	4	35	5	10	4	15	2	15
	3	1	38	5	10	1	10	2	15
	4	1	38	5	10	4	15	2	15
8	1	5	15	4	40	3	25	1	20
	2	5	15	5	30	3	25	1	20
	3	4	10	4	40	3	25	1	20
	4	4	10	5	30	3	25	1	20

Table 7 Route data matrix for distance in meters

Machine	1	2	3	4	5	I/O
1	0	5	11	15	9	6
2	5	0	6	10	4	9
3	11	6	0	6	10	15
4	15	10	6	0	6	11
5	9	4	10	6	0	5
I/O	6	9	15	11	5	0

References

1. (EIA) EIA.: Annual Energy Outlook 2020. In: Department of Energy U, editor. (2020).
2. Vakil TLB.: Coronavirus Is Proving We Need More Resilient Supply Chains. Harvard Business Review (2020).
3. Liu, C.G., Yang, J., Lian, J., Li, W.J., Evans, S., Yin, Y.: Sustainable performance oriented operational decision-making of single machine systems with deterministic product arrival time. J. Clean. Prod. **85**, 318–330 (2014)
4. Foumani, M., Smith-Miles, K.: The impact of various carbon reduction policies on green flowshop scheduling. Appl. Energy **249**, 300–315 (2019)
5. Ding, J.-Y., Song, S., Wu, C.: Carbon-efficient scheduling of flow shops by multi-objective optimisation. Eur. J. Oper. Res. **248**, 758–771 (2016)
6. Sadeghian, R., Sadeghian, M.R.: A decision support system based on artificial neural network and fuzzy analytic network process for

selection of machine tools in a flexible manufacturing system. Int. J. Adv. Manuf. Technol. **82**, 1795–1803 (2016)
7. Dai, M., Ji, Z.C., Wang, Y.: Energy-aware integrated optimisation of process planning and scheduling considering transportation. Mod. Phys. Lett. B. **32**, 7 (2018)
8. Le, C.V., Pang, C.K.: Robust total energy optimization of flexible manufacturing systems based on renyi mean-entropy criterion. IEEE Trans. Autom. Sci. Eng. **13**, 355–367 (2016)
9. Pach, C., Berger, T., Sallez, Y., Trentesaux, D.: Reactive control of overall power consumption in flexible manufacturing systems scheduling: a potential fields model. Control Eng. Pract. **44**, 193–208 (2015)
10. Rajemi, M., Mativenga, P., Aramcharoen, A.: Sustainable machining: selection of optimum turning conditions based on minimum energy considerations. J. Clean. Prod. **18**, 1059–1065 (2010)
11. Fang, K., Uhan, N., Zhao, F., Sutherland, J.W.: A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. J. Manuf. Syst. **30**, 234–240 (2011)
12. Mouzon, G., Yildirim, M.B., Twomey, J.: Operational methods for minimisation of energy consumption of manufacturing equipment. Int. J. Prod. Res. **45**, 4247–4271 (2007)
13. Mouzon, G., Yildirim, M.B.: A framework to minimise total energy consumption and total tardiness on a single machine. Int. J. Sustain. Eng. **1**, 105–116 (2008)
14. Dai, M., Tang, D., Giret, A., Salido, M.A., Li, W.D.: Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm. Robot. Comput. Integr. Manuf. **29**, 418–429 (2013)
15. Shrouf, F., Ordieres-Meré, J., García-Sánchez, A., Ortega-Mier, M.: Optimising the production scheduling of a single machine to minimise total energy consumption costs. J. Clean. Prod. **67**, 197–207 (2014)
16. Jawahar, N., Aravindan, P., Ponnambalam, S.G.: A genetic algorithm for scheduling flexible manufacturing systems. Int. J. Adv. Manuf. Technol. **14**, 588–607 (1998)
17. Barak, S., Moghdani, R., Maghsoudlou, H.: Energy-efficient multi-objective flexible manufacturing scheduling. J. Clean. Prod. **283**, 14 (2021)
18. Lee, C.F., Lin, S.J., Lewis, C., Chang, Y.F.: Effects of carbon taxes on different industries by fuzzy goal programming: a case study of the petrochemical-related industries, Taiwan. Energy Policy **35**, 4051–4058 (2007)
19. Zhu, Z.-S., Liao, H., Cao, H.-S., Wang, L., Wei, Y.-M., Yan, J.: The differences of carbon intensity reduction rate across 89 countries in recent three decades. Appl. Energy **113**, 808–815 (2014)
20. Zhang, C.Y., Gu, P.H., Jiang, P.Y.: Low-carbon scheduling and estimating for a flexible job shop based on carbon footprint and carbon efficiency of multi-job processing. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. **229**, 328–342 (2015)
21. Lin, W.W., Yu, D.Y., Zhang, C.Y., Liu, X., Zhang, S.Q., Tian, Y.H., et al.: A multi-objective teaching-learning-based optimisation algorithm to scheduling in turning processes for minimising makespan and carbon footprint. J. Clean. Prod. **101**, 337–347 (2015)
22. Liu, Q.O., Zhan, M.M., Chekem, F.O., Shao, X.Y., Ying, B.S., Sutherland, J.W.: A hybrid fruit fly algorithm for solving flexible job-shop scheduling to reduce manufacturing carbon footprint. J. Clean. Prod. **168**, 668–678 (2017)
23. Shao, C., Ding, Y., Wang, J.: A low-carbon economic dispatch model incorporated with consumption-side emission penalty scheme. Appl. Energy **238**, 1084–1092 (2019)
24. Abikarram, J.B., McConky, K., Proano, R.: Energy cost minimisation for unrelated parallel machine scheduling under real time and demand charge pricing. J. Clean. Prod. **208**, 232–242 (2019)
25. He, S., Yin, J., Zhang, B., Wang, Z.: How to upgrade an enterprise's low-carbon technologies under a carbon tax: the trade-off between tax and upgrade fee. Appl. Energy **227**, 564–573 (2018)
26. Guo, J., Wang, L.M., Kong, L., Lv, X.T.: Energy-efficient flowshop scheduling with the strategy of switching the power statuses of machines. Sustain. Energy Technol. Assess. **53**, 102649 (2022)
27. Tian, Y., Gao, Z.X., Zhang, L., Chen, Y.J., Wang, T.Y.: A multi-objective optimisation method for flexible job shop scheduling considering cutting-tool degradation with energy-saving measures. Mathematics **11**, 31 (2023)
28. Duan, J.G., Feng, M.Y., Zhang, Q.L.: Energy-efficient collaborative scheduling of heterogeneous multi-stage hybrid flowshop for large metallic component manufacturing. J. Clean. Prod. **375**, 14 (2022)
29. Chan, F.T.S.: Effects of dispatching and routeing decisions on the performance of a flexible manufacturing system. Int. J. Adv. Manuf. Technol. **21**, 328–338 (2003)
30. Jerald, J., Asokan, P., Saravanan, R., Rani, A.D.C.: Simultaneous scheduling of parts and automated guided vehicles in an FMS environment using adaptive genetic algorithm. Int. J. Adv. Manuf. Technol. **29**, 584–589 (2006)
31. Jerald, J., Asokan, P., Prabaharan, G., Saravanan, R.: Scheduling optimisation of flexible manufacturing systems using particle swarm optimisation algorithm. Int. J. Adv. Manuf. Technol. **25**, 964–971 (2005)
32. Kim, D.W., Kim, K.H., Jang, W., Chen, F.F.: Unrelated parallel machine scheduling with setup times using simulated annealing. Robot. Comput. Integr. Manuf. **18**, 223–231 (2002)
33. Lenstra, J.K., Kan, A.R., Brucker, P.: Complexity of machine scheduling problems. J Stud. Integer Program. **1**, 343–362 (1977)
34. EIA.: Electric Power Monthly. In: Administration USEI, editor. US Energy Information Administration, USA, (2022)
35. Pandey, D., Agrawal, M., Pandey, J.S.: Carbon footprint: current methods of estimation. Environ. Monit. Assess **178**, 135–160 (2011)
36. OECD SG.: Effective Carbon Rates. Pricing CO2 through Taxes and Emissions Trading Systems. OECD, Paris (2016).
37. Mirjalili, S., Lewis, A.: The whale optimisation algorithm. Adv. Eng. Softw. **95**, 51–67 (2016)
38. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.A.M.T.: A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Tran. Evol. Comput. **6**, 182–197 (2002)
39. Chan, F.T.S.: Evaluation of combined dispatching and routeing strategies for a flexible manufacturing system. Proc. Inst. Mech. Eng. Part B J. Eng. Manuf. **216**, 1033–1046 (2002)