



A Robust MILP Model for Energy-Efficient Unrelated Parallel Machines Under Uncertainty to Minimize Makespan, Energy Consumption and Total Tardiness

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Abstract. In sustainable manufacturing, scheduling models must address both operational efficiency and energy consumption under realistic conditions. This paper presents a robust Mixed Integer Linear Programming (MILP) model for the Unrelated Parallel Machine Scheduling Problem with Sequence-Dependent Setup Times (UPMS-SDST), incorporating uncertain processing times. The model simultaneously optimizes three objectives: minimizing makespan, total energy consumption, and total tardiness. Adopting an absolute robustness framework, we model worst-case scenario behaviour to ensure schedule reliability. A new benchmark suite is introduced, reflecting real-world uncertainty through job-machine variability and due-date tightness. Experimental evaluations on small instances demonstrate the MILP model's effectiveness and highlight the computational trade-offs involved in exact optimization.

Keywords: Energy consumption, Unrelated parallel machine scheduling, multi scenario uncertainty, setup time.

1 Introduction

Manufacturing enterprises today encounter intensify pressure to balance operational efficiency with sustainability goal amidst growing environmental concerns and diverse operational conditions [1]. The challenge that associated with this burden are expected to escalate in the course of time due to increasing energy prices, which are anticipated to result from potential carbon taxation and related policies, in addition to the growing energy demands in developing nations [2].

Given that machines play a crucial role in multiple manufacturing processes and considering that the final products are typically handled by machines both directly and indirectly, it can be asserted that machines represent the primary consumers of energy within a factory setting [3]. Consequently, minimizing the

energy consumption associated with these machines would greatly enhance the sustainability of manufacturing practices. Nevertheless, many organizations continue to operate a mix of modern, advanced machinery alongside older, less efficient machine models. Each machine usually operates at different speeds with a slightly diverse energy consumption. Numerous strategies exist for reducing energy usage in manufacturing facilities, including the development of more energy-efficient equipment and processes. In the context of production lines, the efficiency of energy utilization is significantly influenced by production planning and scheduling [4]. Enhancing energy efficiency can be achieved through job sequencing or machine scheduling, as these methods do not necessitate modifications to the machinery, alterations to the facility layout, or substantial financial investments. By considering energy cost, it can reduce 22% electricity cost compared to the classical scheduling [5].

Real operations variability in processing times is a significant source of uncertainty in manufacturing scheduling. This variability can arise from various factors, such as the deterioration of machine performance, and differences in operator skills [6], [7]. This research extends the robust optimization non-identical parallel machine scheduling problem [8], which incorporates sequence-dependent setup times, presents the challenge of effectively assigning a diverse array of jobs to a set of machines that possess varying capabilities, while optimizing conflicting objectives such as energy consumption and operational efficiency. The complexity of this problem is heightened by the heterogeneous nature of machine capabilities, where machines exhibit differences in processing speeds, energy consumption profiles, and compatibility with particular job types. Furthermore, the uncertainty in processing times introduces a multi-scenarios element, influenced by diverse operational conditions. The optimization of makespan, energy efficiency and tardiness as a crucial performance indicator for sustainability goal and manufacture efficiency.

Significant progress was explored in the realm of parallel machine scheduling; however, critical deficiencies remain in effectively addressing the interrelationships among sequence-dependent setup times (SDST), processing-time variability, and energy efficiency within a comprehensive framework. Previous research has largely concentrated on deterministic models involving unrelated machines, neglecting the inherent variability present in real-world systems where processing times can vary due to operational interruptions [9]. Although recent studies have begun to incorporate SDST or energy-aware objectives in isolation, they often overlook the compounded effects of heterogeneous machine capabilities, including differing energy profiles, processing speeds, and job-machine compatibility, which fundamentally influence scheduling dynamics. Furthermore, existing stochastic approaches frequently prioritize traditional metrics like makespan, tardiness, sidestepping the trade-offs

between energy consumption and operational robustness under uncertainty [10]. This fragmentation restricts the practical applicability of previous solutions, as industrial contexts require adaptive, energy-conscious scheduling that considers both machine diversity and unpredictable operational conditions [7]. Our research addresses these deficiencies by proposing an innovative formulation and solution paradigm that concurrently tackles these interconnected complexities, thereby advancing the field towards more realistic and sustainable scheduling systems.

Our primary contribution in this paper is twofold. First we present an extend mathematical model for UPMS-SDST by incorporating uncertain processing time and energy consumption as: $R|S_{ijk}|w_C C_{max} + w_E \sum E_j + w_T \sum T_j$. Second, we introduce a new benchmark suite of UPMS-SDST with Uncertainty scenarios simulating real-world disruptions due to skill variability, machine degradation with energy consumption rate.

2 Problem Formulation

In this section, we present a mixed integer linier programming (MILP) model for the unrelated parallel machine scheduling that consider sequence dependent setup times (UPMS-SDST) adapted from [8] with extend energy consumption consideration and due dates for each job.

2.1 Assumption

Assumptions of the problems are as follows: Each machine has different processing capabilities. Processing times are uncertain with multi-scenarios, modelled with worst-case values (absolute robustness). The setup time between jobs depends on their processing sequence on the same machine. All jobs are available at time zero. Jobs execution cannot be interrupted. Each job has a predefined due date. Tardiness is allowed but penalized in the objective function. Energy consumption is linearly proportional while the value depends on the machine and the state between processing and setup (idle).

2.2 Mathematical Formulation

The UPMS-SDST described as follows. Let $J = \{1, \dots, n\}$ be the set of Job requests, $M = \{1, \dots, m\}$ be the set of Unrelated Machines, with a subset of machine capabilities $M_j \subseteq M$, and $S = \{1, \dots, o\}$ be the set of Scenarios. The processing times for each job $j \in J$ corresponds to:

$$p_{ijs} = \frac{p_j}{\varepsilon_{ij} * \alpha_{ijl}} \quad (1)$$

In the machine $i \in M$ under scenarios $s \in S$, where p_j is defined as the optimal processing time known for job j , ε_{ij} as the machine i efficiency for job j and op_{ijl} is defined as operator performance while executing job j using machine i under scenario s , each job also has setup times s_{ijk} with a due date d_j , and each machine $i \in M$ corresponds to the energy consumption rates es_i and processing energy consumption rates ep_i . The decision variable x_{ij} equals 1 if job $j \in J$ is assigned to machine $i \in M$ and S_j are the starting times of job $j \in J$ with the completion time C_j for job $j \in J$.

Our mathematical model formulation is using the following the traditional three-field notation for scheduling problems proposed by Graham [11] that reflected by $\alpha|\beta|\gamma$,

$$R|s_{ijk}|w_C C_{max} + w_E \sum E_j + w_T \sum T_j \tag{2}$$

Type:

R : Unrelated Parallel Machine Problem

Sets:

- J = $\{1, 2, 3, \dots, n\}$: Jobs indexed by j, k
- M = $\{1, 2, 3, \dots, m\}$: Machines indexed by i
- S = $\{1, 2, \dots, s\}$: Scenarios indexed by l
- J_0 = $J \cup \{0\}$: Include dummy job 0
- M_j $\subseteq M$: Set of Machines qualified to process job $j \in J_0$
- J_i = $\{j \in J_0 : i \in M_j\}$: Set of jobs qualified on machine $i \in M$

N.b. The set of M_j & J_i represent the same information from different perspectives. This distinction is made to simplify the model and enhance clarity.

Parameters:

- s_{ijk} : Setup time on machine i from job $j \in J_0$ to $k \in J$
- p_{ijl} : Processing times job $j \in J$ machine $i \in M$ under scenario $l \in S$
- \hat{p}_{ij} : Worst processing time job $j \in J$ on machine $i \in M$
- d_j : Due date of job $j \in J$
- ep_i : energy consumption rate processing on machines $i \in M$
- es_i : Energy consumption rate during setup on machine $i \in M$
- \mathcal{M} : A large number
- w_C, w_E, w_T : Weight for Makespan, Energy, and Tardiness, respectively

where $w_C + w_E + w_T = 1$

Decision Variables:

- x_{ij} : 1 if on machine i , job j is assigned, 0 otherwise; defined only if $i \in M_j$
- y_{ijk} : 1 if on machine i , job j is right before job k ; 0 otherwise; defined only if $i \in M_j \cap M_k, j \neq k$
- S_j : Start time of job $j \in J$
- C_j : Completion time of job $j \in J$
- T_j : Tardiness of job $j \in J$
- ES_j : Setup energy of job $j \in J$
- Ep_j : Processing energy of job $j \in J$
- E_j : Total energy of job $j \in J$
- C_{max} : Makespan
- E_{total} : Total Energy consumption

Objective Function:

$$\min Z = w_C C_{max} + w_E E_{total} + w_T T_{total} \quad (3)$$

Constraints:

$$\sum_{i \in M_j} x_{ij} = 1, \quad \forall j \in J \quad (4)$$

$$\sum_{k \in J_i} y_{i0k} = 1, \quad \forall i \in M \quad (5)$$

$$\sum_{i \in M_k, j \in J_i \setminus \{0, k\}} y_{ijk} = x_{ij}, \quad \forall k \in J \quad (6)$$

$$\sum_{i \in M_j, k \in J_i \setminus \{0, j\}} y_{ijk} \leq x_{ij}, \quad \forall j \in J \quad (7)$$

$$S_k \geq s_{i0k} - \mathcal{M}(1 - y_{i0k}), \quad \forall i \in M, k \in J_i \quad (8)$$

$$S_k \geq S_j + \hat{p}_{ij} + s_{ijk} - \mathcal{M}(1 - y_{ijk}), \quad \forall i \in M, \forall j, k \in J_i, j \neq k \neq 0 \quad (9)$$

$$C_j = S_j + \sum_{i \in M_j} \hat{p}_{ij} x_{ij}, \quad \forall j \in J \quad (10)$$

$$C_{max} \geq C_j, \quad \forall j \in J \quad (11)$$

$$T_j \geq C_j - d_j, \quad \forall j \in J \quad (12)$$

$$T_j \geq 0, \quad \forall j \in J \quad (13)$$

$$T_{total} = \sum_{j \in J} T_j \quad (14)$$

$$Ep_j = \sum_{i \in M_j} \hat{p}_{ij} ep_i x_{ij}, \quad \forall j \in J \quad (15)$$

$$ES_k = \sum_{i \in M_k} \sum_{j \in J_0 \cap J_i \setminus \{k\}} s_{ijk} e s_i y_{ijk}, \quad \forall k \in J \tag{16}$$

$$E_j = Ep_j + ES_j, \quad \forall j \in J \tag{17}$$

$$E_{total} = \sum_{j \in J} E_j, \quad \forall j \in J \tag{18}$$

$$S_j, C_j, T_j, E_j, Ep_j, ES_j \geq 0, \quad \forall j \in J \tag{19}$$

$$C_{max}, T_{total}, E_{total} \geq 0 \tag{20}$$

$$x_{ij}, y_{ijk} \in \{0,1\}, \quad \forall j \in J_0, k \in J \setminus \{j\} \text{ and } i \in M_j \cap M_k \tag{21}$$

Constraint (2) Each job $j \in J$ is assigned to exactly one qualified machine $i \in M_j$
 (3) Dummy as the first job for each machine $i \in M$ (4) Each job $k \in J$ must has one predecessor (5) Each job $j \in J$ has one successor at most (6) Start time sequencing if job $k \in J$ right after Dummy job (7) Start time sequencing if job $k \in J_i$ right after job $j \in J_i$ if $j \neq k \neq 0$ (8) Define Completion time job $j \in J$ (9) Define Makespan (10) Define the tardiness (11) Ensure tardiness not less than 0 (12) Define total tardiness (13) Define energy consumption processing job $j \in J$ (14) Define energy consumption setup job $j \in J$ (15) Define energy consumption job $j \in J$ (16) Define total energy consumption (17-18) Variable domains (19) Ensure the binary of variable domains x and y .

2.3 Example Problem

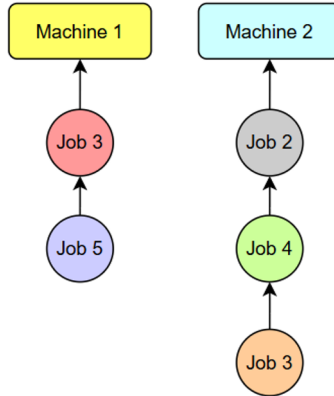


Fig. 1. Problem illustration

An example with two scenarios two machines and 5 jobs. Machine capability $M1 = [1,3,4,5]$, $M2 = [1,2,4,5]$. Matrix of the processing time each machine each scenario as Table 1, and setup times machine 1 as the table 2, and for setup times machine 2 as the table 3, respectively matrix ep is the energy consumption rate

when processing, matrix es is the energy consumption rate when setup and matrix d is the due dates for each job.

Table 1. processing time with multi-scenario

Scenario	M/J	$J1$	$J2$	$J3$	$J4$	$J5$
S1	$M1$	15	-	18	12	17
	$M2$	14	13	-	16	20
S2	$M1$	14	-	17	13	19
	$M2$	16	12	-	15	18

Table 2. setup time machine 1

$j \backslash k$	1	2	3	4	5
0	3	-	4	3	4
1	-	-	3	4	5
2	-	-	-	-	-
3	4	-	-	4	2
4	3	-	4	-	2
5	5	-	2	4	-

Table 3. Setup time machine 2

$j \backslash k$	1	2	3	4	5
0	3	4	-	3	4
1	-	3	-	3	4
2	2	-	-	2	5
3	-	-	-	-	-
4	5	4	-	-	4
5	3	4	-	3	-

A. Energy processing rate:

$$ep_j = \begin{bmatrix} 0.8 \\ 0.9 \end{bmatrix} \tag{20}$$

B. Energy setup rate:

$$es_j = \begin{bmatrix} 0.4 \\ 0.5 \end{bmatrix} \tag{21}$$

C. Due Date:

$$d_j = \begin{bmatrix} 30 & 35 & 40 & 47 & 50 \end{bmatrix} \tag{22}$$

2.4 Solution Representation

The solution of the UPMS-SDST consists of a string of machines and jobs. It is denoted by m machines $\{1, 2, \dots, m\}$ and n jobs $\{1, 2, \dots, n\}$ as displayed in the Figure 1 and Figure 2, the solution representation of Energy efficient UPMS-SDST describe 2 schedules: the first schedule is the initial schedule solution that come up before the improvement and the second schedule showing the final schedule after the improvement. The first column of each row in the schedule contains the machine number that will execute the job, and the next column of each row is a sequence of jobs that will be executed sequentially.

Initial Schedule	
1	3 5
2	2 4 1

Fig. 2. Initial Solution Representation

Final Schedule	
1	4 3 5
2	1 2

Fig. 3. Final Solution Representation

For example, under the Figure 1, there is 2 machine that will execute the jobs, and the first machine sequentially executing job 3 and job 5, while the second machine sequentially executing job 2, job 4 and job 1. After the improvement, the first machine should sequentially execute the job 4, job 3 and job 5. Meanwhile the second machine should sequentially execute the job 1 and job 2.

3 Computational Experiments

MILP models was primarily implemented under Gurobi Solver 12.0.1. using python programming language, running with Intel® Core™ i7-11700 processor, on a 64-bit platform at 2.50 GHz processor speed, and using 96.0 GB of RAM under Windows 11 Pro operating system. with 3600 s as the time limit we used for the models.

The data we used to generate instances involving processing times, setup times, due dates, machine capability probability, and energy consumption rate are similar with the literature [12], [13], [14], [15], [16]. Two instance type were generated as Small, and Large. There is 10 replication each combination and to ensure reproducibility, a random seed is applied.

3.1 Experiment Protocol

320 small instances dataset of difference combination were generated similar to Vallada instances [17], systematically evaluate jobs each machine and each scenario by varying digit of machines $M \in \{2,3,4,5\}$, jobs $N \in \{6,8,10,12\}$, and machine-operator performance scenarios $S \in \{2,3\}$.

Base processing times for jobs (p_j) are sampled uniformly from $U[10,100]$, while machine efficiency me_{ij} and operator performance level op_{ijl} are drawn from $U[0.80,1.00]$ and $U[0.75,0.95]$, respectively, to model heterogeneous processing times for each machine in each scenario. Minimal machine capability probability rate = 0.8. Let M_j denote the matrix representing the machines capable of performing job j and from difference perspective J_i denote the matrix representing the jobs that can be processed by machine i . For each job j processing times on each machine i under scenario l are computed as $p_{ijk} = p_j / (\varepsilon_{ij} * op_{ijl})$, introducing uncertainty through operator variability. Deadlines (d) are assigned uniformly between $\max(p)$ and $\max(p)*n/m - U[\max(p), \max(p)*n/m]$ to reflect workload-dependent constraints. Additional parameters include job-specific setup times $s_{ijk} \sim U[5,25]$, machine energy consumption processing rates $ep_i \sim U[0.8,1.2]$, and machine consumption setup rates $es_i \sim U[0.4,0.6]$. The objective function in this study is constructed as a single weighted objective that integrates makespan, total energy consumption, and total tardiness, with each objective assigned an equal weight of 1/3.

3.2 Performance Metrics

Our proposed absolute robust energy efficient UPMS-SDST MILP model result presented in Table 4. First column consists of instance ID, "The first column lists the instance IDs in the format " $J_x_My_Sz$," indicating a problem with x jobs, y machines, and z uncertainty scenarios. The #Opt column shows the number of runs (out of 10 replications) in which Gurobi found the optimal solution within the predefined time limit. The CPU column presents the average solving time (in seconds) across these runs, providing insight into the computational effort required. The Gap column denotes the maximum deviation from optimality, representing the worst-case percentage difference between the best objective value found and the best lower bound obtained during the solving process. Since MILP solvers like Gurobi continuously improve the lower bound during optimization, it is possible that the solution found is indeed optimal, but this cannot be formally proven within the time limit [18]. The LB (lower bound) and Obj (objective function value) columns report the average values obtained during the replications, where the objective value represents the tri-objective function

combining makespan, total tardiness, and total energy consumption equally (0.33 weight each). A gap of 0.00% indicates that the optimal solution has been reached.

Table 4. Computational results

Instance ID	MILP Gurobi				
	#Opt	CPU	Gap	LB	Obj
J6_M2_S2	10	0.11	0,00%	288,83	288.83
J6_M2_S3	10	0.11	0,00%	312,07	312.07
J6_M3_S2	10	0.14	0,00%	249,60	249.60
J6_M3_S3	10	0.11	0,00%	218,97	218.97
J6_M4_S2	10	0.14	0,00%	211,40	211.40
J6_M4_S3	10	0.12	0,00%	213,53	213.53
J6_M5_S2	10	0.13	0,00%	182,10	182.10
J6_M5_S3	10	0.13	0,00%	195,73	195.73
J8_M2_S2	10	4.27	0,00%	417,73	417.73
J8_M2_S3	10	1.92	0,00%	401,93	401.93
J8_M3_S2	10	1.01	0,00%	309,10	309.10
J8_M3_S3	10	1.67	0,00%	334,93	334.93
J8_M4_S2	10	0.85	0,00%	283,43	283.43
J8_M4_S3	10	0.82	0,00%	329,67	329.67
J8_M5_S2	10	0.92	0,00%	257,10	257.10
J8_M5_S3	10	1.25	0,00%	260,63	260.63
J10_M2_S2	10	78.12	0,00%	631,57	631.57
J10_M2_S3	10	249.24	0,00%	594,83	594.83
J10_M3_S2	10	34.61	0,00%	449,37	449.37
J10_M3_S3	10	42.29	0,00%	461,63	461.63
J10_M4_S2	10	11.54	0,00%	348,27	348.27
J10_M4_S3	10	20.46	0,00%	411,80	411.80
J10_M5_S2	10	14.27	0,00%	319,87	319.87
J10_M5_S3	10	2.72	0,00%	334,10	334.10
J12_M2_S2	0	3600.0	26,67%	564,49	767.93
J12_M2_S3	2	3391.02	22,20%	570,15	745.37
J12_M3_S2	2	2944.34	12,01%	509,59	579.60
J12_M3_S3	6	2309.74	5,13%	517,62	544.63
J12_M4_S2	9	510.12	0,39%	431,86	433.77
J12_M4_S3	7	1764.10	0,71%	452,98	457.43
J12_M5_S2	10	78.46	0,00%	381,47	381.47
J12_M5_S3	10	263.05	0,00%	433,23	433.23

3.3 Result and Analysis

Across all 320 benchmark instances, a total of 320 runs were executed. Out of these, the MILP model achieved 286 optimal solutions, resulting in a high overall optimality rate of 89.38%. The model successfully solved all instances in the J6, J8, and J10 groups to optimality, regardless of the number of machines or uncertainty scenarios, which demonstrates its strong performance and efficiency for small- to medium-sized problems. The average computation times for these groups remain under 250 seconds for even the largest J10 instances, and often below 5 seconds for smaller sets, confirming that the solver can efficiently handle low to moderate levels of complexity.

However, the optimality rate decreases for J12 instances, where increased problem size and scenario complexity introduce significant computational challenges. For example, instances like J12_M2_S2 and J12_M2_S3 achieved no or few optimal solutions, with high gaps of 26.67% and 22.20%, respectively, despite long run times nearing the 3600-second time limit. In contrast, J12_M5_S2 and J12_M5_S3, which involve more machines, were solved optimally in significantly less time, suggesting that increased machine availability helps reduce solution complexity. This performance degradation highlights the NP-hard nature of the UPMS-SDST problem under uncertainty and underscores the limitations of exact methods like MILP in large-scale settings.

Overall, the MILP model effectively balances robustness and sustainability through its tri-objective formulation. While it performs exceptionally well on small to medium-scale instances by generating reliable and energy-efficient schedules under worst-case uncertainty, future work should explore scalable heuristic or metaheuristic algorithms to address the growing complexity in larger instances.

4 Conclusion

This study addressed the challenge of scheduling on unrelated parallel machines with uncertain processing times and sequence-dependent setup durations, emphasizing energy efficiency. A Mixed-Integer Linear Programming (MILP) formulation was developed and demonstrated strong performance on smaller problem instances, consistently reaching optimal solutions. Nonetheless, its limited scalability for larger cases highlights the importance of exploring heuristic or hybrid methods for more complex, real-world scenarios. The results establish the MILP model as a valuable reference point for evaluating future optimization strategies.

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