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Multi-objective Optimisation Methods for Minimising Total Weighted Tardiness, Electricity Consumption and Electricity Cost in Job Shops Through Scheduling

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DECLARATION OF ORIGINALITY

Title of Thesis: Multi-objective Optimisation Methods for Minimising Total Weighted Tardiness, Electricity Consumption and Electricity Cost in Job Shops Through Scheduling

I declare that the thesis hereby submitted for the degree of Doctor of Philosophy at the University of Nottingham is my own work except as cited in the references and has not been previously submitted for any degree.

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Abstract

Manufacturing enterprises nowadays face the challenge of increasing energy prices and requirements to reduce their emissions. Most reported work on reducing manufacturing energy consumption focuses on the need to improve the efficiency of resources (machines). The potential for energy reducing at the system-level has been largely ignored. At this level, operational research methods can be employed as the energy saving approach. The advantage is clearly that the scheduling and planning approach can be applied across existing legacy systems and does not require a large investment. For the emission reduction purpose, some electricity usage control policies and tariffs (EPTs) have been promulgated by many governments. The Rolling Blackout policy in China is one of the typical EPTs, which means the government electricity will be cut off several days in every week for a specific manufacturing enterprise. The application of the Rolling Blackout policy results in increasing the manufacturing enterprises' costs since they choose to start to use much more expensive private electricity to maintain their production. Therefore, this thesis develops operational research methods for the minimisation of electricity consumption and the electricity cost of job shop type of manufacturing systems. The job shop is selected as the research environment for the following reasons. From the academic perspective, energy consumption and energy cost reduction have not been well investigated in the multi-objective scheduling approaches to a typical job shop type of manufacturing system. Most of the current energy-conscious scheduling research is focused on single machine, parallel machine and flow shop environments. From the practical perspective, job shops are widely used in the manufacturing industry, especially in the small and medium enterprises (SMEs). Thus, the innovative electricity-conscious scheduling techniques delivered in this research can provide for plant managers a new way to achieve cost reduction.

In this thesis, mathematical models are proposed for two multi-objective job shop scheduling optimisation problems. One of the problems is a bi-objective problem with one objective to minimise the total electricity consumption and the other to minimise the total weighted tardiness (the ECT problem). The other problem is a tri-objective problem which considers reducing total electricity consumption, total electricity cost

and total weighted tardiness in a job shop when the Rolling Blackout policy is applied (the EC2T problem).

Meta-heuristics are developed to approximate the Pareto front for ECT job shop scheduling problem including NSGA-II and a new Multi-objective Genetic Algorithm (GAEJP) based on the NSGA-II. A new heuristic is proposed to adjust scheduling plans when the Rolling Blackout policy is applied, and to help to understand how the policy will influence the performance of existing scheduling plans. NSGA-II is applied to solve the EC2T problem. Six scenarios have been proposed to prove the effectiveness of the aforementioned algorithms.

The performance of all the aforementioned heuristics have been tested on Fisher and Thompson 10×10, Lawrence 15×10, 20×10 and 15×15 job shop scenarios which were extended to incorporate electrical consumption profiles for the machine tools. Based on the tests and comparison experiments, it has been found that by applying NSGA-II, the total non-processing electricity consumption in a job shop can decrease considerably at the expense of the schedules' performance on the total weighted tardiness objective when there are tight due dates for jobs. When the due dates become less tight, the sacrifice of the total weighted tardiness becomes much smaller. By comparing the Pareto fronts obtained by GAEJP and by NSGA-II, it can be observed that GAEJP is more effective in reducing the total non-processing electricity consumption than NSGA-II, while not necessarily sacrificing its performance on total weighted tardiness. Thus, the superiority of the GAEJP in solving the ECT problem has been demonstrated. The scheduling plan adjustment heuristic has been proved to be effective in reducing the total weighted tardiness when the Rolling Blackout policy is applied. Finally, NSGA-II is proved to be effective to generate compromised scheduling plans for using the private electricity. This can help to realise the trade-off between the total weighted tardiness and the total electricity cost. Finally, the effectiveness of GAJEP in reducing the total non-processing electricity consumption has been validated in a real-world job shop case.

Published Papers

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Acronyms

APT	automatic programming tool
CNC	computer numerical control
DO	delayed operation
ECT	the bi-objective total electricity consumption, total weighted tardiness job shop scheduling problem
EC2T	the tri-objective total electricity cost, total electricity consumption and total weighted tardiness job shop scheduling problem
EPTs	electricity usage control policies and tariffs
ESP	electricity supply plan
FIFO	first in first out
FJS	flexible job shop
GAs	genetic algorithms
GAP	government electricity supply available period
GAEJP	multi-objective genetic algorithm for solving the ECT job shop scheduling problem
GSCM	green supply chain management
GUP	the government electricity supply unavailable period
IP	idle period
JPE	job related processing electricity consumption
JSSP	job shop scheduling problem
KERS	kinetic energy recovery system
LMO	left move operation

LSH	local search heuristic
LSO	left shift operation
MMS	machining-based manufacturing system
MRR	material removal rate
NC	numerical control
NPE	non-processing electricity consumption
OBES	operation-based encoding schema
OEMs	original equipment manufacturers
PE	processing electricity consumption
PLMO	permissible left move operation
PLSO	permissible left shift operation
POJ	an operation’s preceding operation within the same job
POM	an operation’s preceding operation on the same machine
PRS	process route selection
PT/TUP	ratio of production time compared to the total up-time of the machines
PVTOU	peak-valley time of use tariff
RB	rolling blackout policy
SBH	shifting bottleneck heuristic
SMEs	the small and medium enterprises
SWP	step-wise power tariff
TWT	total weighted tardiness

Nomenclature

$BS_{F_i}^{min}$	boundary solution in Pareto front F_i with the minimum value in the selected objective function
$BS_{F_i}^{max}$	boundary solution in Pareto front F_i with the maximum value in the selected objective function
B_k	the break-even duration of machine M_k for which Turn Off/Turn On is economically justifiable instead of running the machine idle
$C_i(s)$	completion time of J_i in schedule s (i.e. the completion time of the last operation of J_i, $O_i^{u_i}$)
C_k^r	completion time of m_k^r on M_k
C_{ik}^l	completion time of O_{ik}^l on M_k
$C_{ik'}^{l-1}$	completion time of $O_{ik'}^{l-1}$
$C_{s_{pt}^{v_1}}$	crowding distance of $s_{pt}^{v_1}$
d_i	due date of J_i
$E_{ik}^{lruntime}$	electricity consumption of M_k when it executes the runtime operations for processing O_{ik}^l
$E_{ik}^{lcutting}$	electricity consumption of M_k when it actually executes cutting for O_{ik}^l
E_{ik}^{lbasic}	electricity consumed by M_k with the idle power level during p_{ik}^l
E_{ik}^l	JPE of O_{ik}^l on M_k
E_k^{turn}	electricity consumed by Turn Off/Turn On

$E_k^{turnoff}$	electricity consumed to turn off the machine M_k
E_k^{turnon}	electricity consumed to turn on the machine M_k
E_{2x}	ending time of the $2x$ th period
E_{2x-1}	ending time of the $2x-1$ th period
$E_{2(x-y)-1}$	ending time of the $2(x-y)-1$ th period
eip_k^w	ending time of ip_k^w on M_k
f	tardiness factor
G_{pt}^1	s_{pt}^1's corresponding Gantt chart
I_{pt}	individual p in generation t. $I_{pt} = \left\{I_{pt}^v\right\}_{v=1}^{u_{pt}}$ after the family creation process
I_{pt}^v	v-th family member in I_{pt}
ip_k	a finite set of u_k ordered idle periods on M_k, $ip_k = \{ip_k^w\}_{w=1}^{u_k}$
ip_k^w	w-th idle period on M_k
$ip_{O_{ik}^l}$	a finite set of t idle periods on machine M_k that allow O_{ik}^l to be left shifted, $ip_{O_{ik}^l} = \left\{ip_{O_{ik}^l}^e\right\}_{e=1}^t$
J	a finite set of n jobs, $J = \{J_i\}_{i=1}^n$
M	a finite set of m machines, $M = \{M_k\}_{k=1}^m$
M_k'	a finite set of operations processed on M_k, $M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^n \sum_{l=1}^{u_i} \gamma_{ik}^l}$
m_k^r	r-th operation processed on M_k within a feasible schedule s
m_k^{r-1}	m_k^r's preceding operation on the same machine M_k
$N_{s_{pt}^v}^{l_1}$	first left neighbour of s_{pt}^v
$N_{s_{pt}^v}^{r_1}$	first right neighbour of s_{pt}^v

$N_{s_{pt}^{v}}^{n_1}$	first group of neighbours for s_{pt}^{v}
$N_{s_{pt}^{v}}^{l_2}$	second left neighbour of s_{pt}^{v}
$N_{s_{pt}^{v}}^{r_2}$	second right neighbour of s_{pt}^{v}
$N_{s_{pt}^{v}}^{n_2}$	second group of neighbours
O_i	a finite set of u_i ordered operations of J_i, $O_i = \{O_{ik}^{l}\}_{l=1}^{u_i}$
O_{ik}^{l}	l-th operation of J_i processed on M_k
$O_{ik'}^{l-1}$	preceding operation of O_{ik}^{l} in J_i
O_{pt}	objective function set of chromosome I_{pt}, $O_{pt} = \left\{O_{s_{pt}^{1'}}\right\} \cup \left\{O_{s_{pt}^{n'_v}}\right\}_{v=1}^{h_{pt}}$
p_{ik}^{l}	processing time of O_{ik}^{l}
$P_k(t)$	input power of M_k
P_k^{idle}	idle power of M_k
$P_{ik}^{lruntime}$	power level of M_k when it executes the runtime operations for processing O_{ik}^{l}
$P_{ik}^{lcutting}$	power level of M_k when it actually executes cutting for O_{ik}^{l}
P_k^{turnon}	average power input for M_k during t_k^{turnon}
$P_k^{turnoff}$	average power input of M_k during $t_k^{turnoff}$
P_t	population at generation t with N individuals, $P_t = \{I_{pt}\}_{p=1,t=1}^{N,G}$
r_i	release time of J_i into the system
γ_{ik}^{l}	$\gamma_{ik}^{l} = 1$ if the l-th operation of J_i processed on M_k, 0 otherwise
S_{ik}^{l}	starting time of O_{ik}^{l} on M_k

S_{2x}	starting time of the $2x\ th$ period
S_{2x-1}	starting time of the $2x-1\ th$ period
$S_{2(x-y)-1}$	starting time of the $2(x-y)-1\ th$ period
s	a feasible schedule plan
S	a finite set of all feasible schedule plans, $s \in S$
S_k^r	starting time of m_k^r on M_k
s_{pt}^1	initial semi-active schedule for chromosome I_{pt} decoded by semi-active schedule builder
$s_{pt}^{1'}$	first feasible solution for chromosome I_{pt}. i.e. the Turn Off/Turn On version of s_{pt}^1
S_{pt}	solution set of chromosome I_{pt}, $S_{pt} = \left\{s_{pt}^{1'}\right\} \cup \left\{s_{pt}^{n_v'}\right\}_{v=1}^{h_{pt}}$
$s_{pt}^{n_v'}$	$v+1$-th feasible solution of chromosome I_{pt}
s_{pt}^v	I_{pt}^v's corresponding solution
S_{min}^{DO}	earliest starting time of all the delayed operations related to the $2x\ th$ period
$T_i(s)$	tardiness of J_i, defined as $T_i(s) = max\{0, C_i(s) - d_i\}$
T	the cycle period of the Rolling Blackout policy
t_s	the time point which separates T from Δt_s and Δt_o
Δt_s	government electricity supply available period, GAP
Δt_o	government electricity supply unavailable period, GUP
$t_{ik}^{lcutting}$	cutting time
t_k^{OFF}	time required to turn off M_k and turn on it back on
$t_k^{turnoff}$	time consumed to turn off the machine M_k

t_k^{turnon}	time consumed to turn on the machine M_k
w_i	weighted importance of J_i
$Y_{ii'k}^{ll'}$	$Y_{ii'k}^{ll'} = 1$ if O_{ik}^{l} precedes $O_{i'k}^{l'}$ on M_k, 0 otherwise
Z_k^r	$Z_k^r = 1$ if $S_k^{r+1} - C_k^r \geq max(B_k, t_k^{OFF})$, 0 otherwise

CHAPTER 1 INTRODUCTION

1.1 Background

Manufacturing, as the backbone of modern industry (Jovane et al. 2008), consumes resources, and brings about environmental problems. In recent years, threatened by resource depletion and environmental degradation, increasing numbers of researchers have paid attention to topics related to sustainable manufacturing. Sustainable manufacturing has been defined as:

"Sustainable manufacturing must respond to: Economical challenges, by producing wealth and new services ensuring development and competitiveness through times; Environmental challenges, by promoting minimal use of natural resources (in particular non-renewable) and managing them in the best possible way while reducing environmental impact; Social challenges, by promoting social development and improved quality of life through renewed qualit*y of wealth and jobs"*.

-Jovane et al. (2008)

According to this definition, modern manufacturing enterprises have to guarantee their profitability to keep competitive to survive in the fierce market environment. Meanwhile, they are often under increasing pressure to mitigate the environmental damage caused by their production activities.

Energy is one of the most vital resources for manufacturing. In the last 50 years, the consumption of energy by the industrial sector has more than doubled and industry currently consumes about half of the world's energy (Mouzon et al., 2007), as shown in **Figure 1.1**, The price of energy is escalating as a result of the increasing price of crude oil (Kilian 2008). For example, in 2006, energy costs for U.S.A. manufacturers were $100 billion annually (Mouzon et al. 2007), which today is even higher.

Additionally, energy consumption is one of the most significant factors that lead manufacturing enterprises to become environmentally unfriendly. In the U.S.A., the manufacturing sector consumes about one-third of the energy used and contributes to about 28% of greenhouse gas emissions (Mouzon 2008). One of the most important forms of energy for manufacturing is electricity which is often highly polluting during its production processes. Every year in China, manufacturing consumes around 50% of the entire electricity produced (Tang et al. 2006), and generates at least 26% of the total carbon dioxide emission. A quantity of 900g of carbon dioxide is released into the atmosphere at the production stage of one kilowatt-hour of electricity (Mouzon et al. 2007). Thus, reducing the electricity consumption of manufacturing can significantly improve its environmental performance.

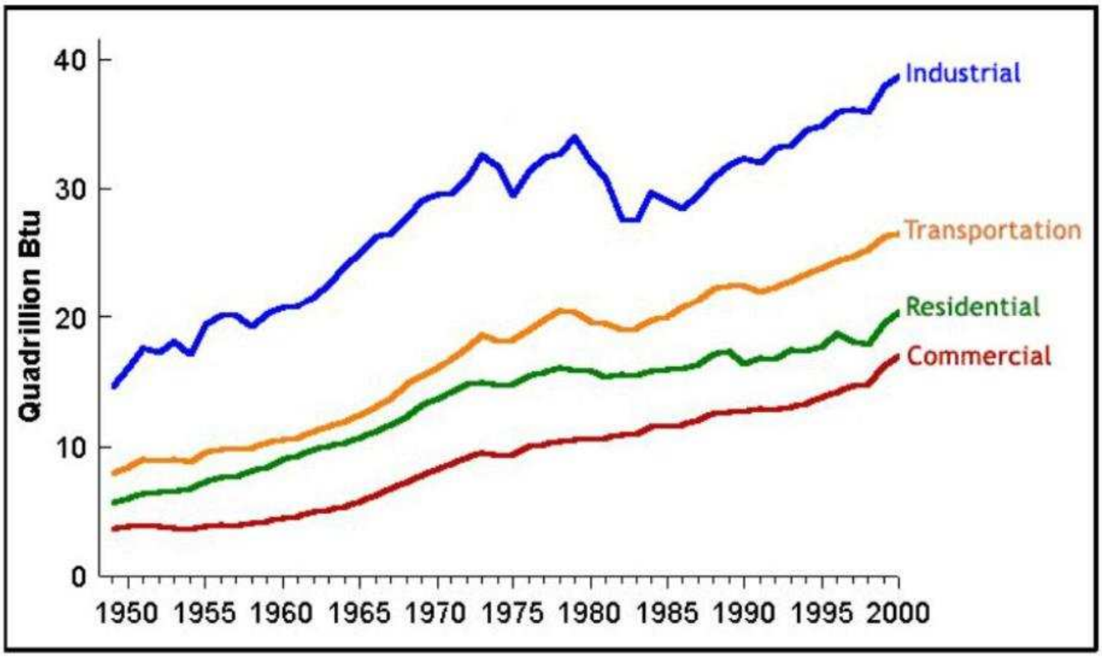


Figure 1.1: U.S.A. energy consumption by market segment from 1950 to 2000 (Mouzon 2008)

Furthermore, there is an increasing trend that manufacturing enterprises across the whole world would be required to pay for their negative environmental impacts. Many enterprises in Europe have begun to pay for their emission since the 1990s (Jeswiet & Kara 2008). A bill for carbon tax has been passed by the Australian parliament in 2011 (BBC, 2011). Designs of tax on greenhouse gas emission have been tabled in the U.S.A, and China (Metcalf & Weisbach, 2009; Stdaily, 2011).

The trend of rising energy prices, together with the growing concern over manufacturing's environmental impact, and the possibility of taxing manufacturing's emissions have become obstacles that manufacturing enterprises need to overcome on the way to achieve sustainability. In other words, there is a new objective for modern manufacturing enterprises. To achieve this, solutions need to be proposed for reducing energy and its related environmental cost during production, as well as ensuring quality and customer satisfaction (Gungor & Gupta 1999).

Many countries including the U.S.A., Australia, Germany, United Kingdom, China and others, have committed to reduce their emission under the Copenhagen Accord in 2009 (Productivity commission, 2011). Based on the fact that the process of generating electricity usually plays the role of the single largest source of carbon dioxide emissions, many countries have proposed new electricity generation and usage control policies to achieve emission reduction.

Some of these new policies are power generation oriented, which are used to decrease carbon intensity in the generation processes, encouraging the electricity generation enterprises to employ clean and low carbon intensive technologies to replace the traditional high carbon intensity ones. (Climatechange, 2011, Epa, 2011, People, 2011). However, as the adoption of these new technologies will cost more than continuing with traditional methods, this would lead to an increased electricity price.

Other policies are electricity consumer focused. For instance, the Chinese government has promulgated corresponding electricity usage control policies and tariffs (EPTs) for emission reduction, which are gathered and shown in **Table 1.1**. The reason for considering EPTs which executed in China is based on the fact that this country overtook the United States in 2011 to become the world's largest producer of manufactured goods, and it has become a key component of global manufacturing supply chains.

All the current EPTs can be divided into two types. One is direct-control and the other is indirect-control. As their names imply, the direct-control type is designed to limit the electricity usage and its related emissions to a certain level; the indirect-control type is supposed to obtain extra incomes from the raising of the electricity price and then devote the extra income to the emission treatment.

Table 1.1: Existing EPTs (Chinahightech, 2011; Sohu, 2011)

Type	Policy
Direct control	Rolling Blackout (RB)
Indirect control	Peak-Valley Time of Use tariff (PVTOU)
	Step-Wise Power tariff (SWP)

The Rolling Blackout policy for industry electricity supply is a typical direct-control policy, which means the government electricity are cut off for one or two days in every week for a specific manufacturing enterprise. For instance, in every week, the government electricity supply would be cut off during Sunday and Monday for company A, it would be resumed from Tuesday to Saturday. In the same week, the government electricity supply for company B would be available from Monday to Friday. Normally, in China, the manufacturing companies work seven days a week. In some other areas, the Rolling Blackout policy executes in a way that the government electricity is cut off for several hours in a day for a specific enterprise.

The indirect-control type includes the Peak-Valley Time of Use tariff (PVTOU) and the Step-Wise Power tariff (SWP). The PVTOU is designed to balance the time-based the unevenness of electricity demand. Implementation of this policy will encourage manufacturing companies to execute production in the electricity usage valley period for cost saving. The PVTOU does not necessarily cut the total electricity consumption. The SWP is used to limit the resident electricity usage, which means the electricity price would increase in steps when electricity usage accumulates to a certain quantity. The extra income from this rise in electricity price is expected to cover the increase of CO_2 emission reduction cost in electricity generation (Nrdc, 2010).

All the aforementioned electricity usage control policies and tariffs will result in increasing costs for manufacturing companies, including electricity costs and other operational costs. The Rolling Blackout policy is the most difficult one for the normal operations of a company within all the existing electricity usage control policies and tariffs, since the production of manufacturing companies can be significantly limited by its implementation. Therefore, the operational cost will be increased. For some companies, up to 1/3 of their production has been lost as a result of the Rolling Blackout policy (Sohu, 2011). To deal with an electricity shortage circumstance, some manufacturing companies are illegally starting their own diesel generators to maintain production which increases their expense on electricity. Private diesel electricity costs twice as much as the government supplied resource. Ironically, the original intention of implementing the Rolling Blackout policy is to reduce emission. However, the policy results in the wide use of diesel generated electricity which is more emission intensive than the government supplied resource. Finally, the implementation of the Rolling Blackout policy results in emission increasing and production deteriorating. Based on the above discussion about electricity usage control policies and tariffs and the power consumption charging method, it is safe to conclude that the way a manufacturing company uses electricity will exert increasing influence on its production cost. Therefore, another new objective for manufacturing enterprises is to reduce electricity cost during production as well as ensure quality and customer satisfaction when electricity usage control policies and tariffs are implemented.

Most of the existing research on reducing manufacturing energy consumption has focused so far on developing more energy (particularly electrical energy) efficient machines or machining processes (Fang et al., 2011). However, compared to the background energy consumed by the manufacturing equipment operations, the energy requirements for the active removal of material can be quite small (Dahmus and Gutowski, 2004). Especially in the mass production environment it takes no more than 15% of the total energy usage. The majority of energy is consumed by functions that are not directly related to the production of components (Gutowski et al., 2005). This implies that efficiency improving efforts focusing solely on the machines or processes may miss a significant energy saving opportunity. In fact, there is a larger energy reducing margin on the system-level where the operational research methods can be employed as the energy saving approach. Additionally, compared to machine or process redesign, implementation of optimised shop floor scheduling and plant operation strategies only requires a modest capital investment and can easily be applied to existing systems (Fang et al., 2011). In addition, research considering the EPTs or other electricity price pattern as constraint is scarce. Only Fang et al. (2011) and Herrmann and Thiede (2009) considered the use of operational research methods to reduce the total energy cost when manufacturing plants are charged based on the peak power demand from the energy provider instead of the actual electricity consumption.

As a result, employing operational research methods can be a feasible and effective approach for manufacturing enterprises to reduce the energy consumption (Mouzon & Yildirim 2008). Approaches to solve the multi-objective scheduling problem with reducing energy consumption and its related cost as part of the objectives need to be developed. This can offer new solutions for any industry which wants to look at an innovative way to decrease its cost and environmental impact.

1.2 Scope, Goals and objective of the thesis

The main goal of this thesis is to address the multi-objective job shop scheduling problems with reducing energy consumption and its related cost as part of the objectives. The job shop type of manufacturing system is selected as the object of study for the following reasons. From the academic perspective, electricity consumption and electricity cost reduction have not been well investigated in the multi-objective scheduling approaches for a typical job shop manufacturing system.. Most of the current energy-conscious scheduling research is focused on single machine, parallel machine and flow shop environments. The lack of a more fundamental energy saving oriented job-shop model and its related scheduling techniques is a significant gap in the current research which needs to be addressed. On the other hand, from the practical perspective, job shops are widely used in the manufacturing industry, especially in small and medium enterprises (SMEs). For instance, original equipment manufacturers (OEMs) in the aerospace industry usually employ the job shop manufacturing system for their capability to satisfy the increasingly diversified customer demands (Harrison et al. 2004).

In this research, all the machines in the job shop are machine tools since they are one of the most important types of equipment in manufacturing industry and highly electricity consuming. Thus, the system can be defined as metalworking and machining-based manufacturing system (MMS). Electrical energy is the only energy resource considered. The Rolling Blackout policy is set as the electricity supply constraint since it is currently the most difficult electricity usage control policy for normal operations of a company. The on time delivery is an important indicator to evaluate the performance of a manufacturing system. Therefore, the total weighted tardiness (TWT) is selected as the scheduling objective to represent the production performance of the job shop. Hence, the two new research problems can be defined as:

- The bi-objective Total Electricity Consumption, Total Weighted Tardiness Job Shop Scheduling problem (Electricity Consumption and Tardiness-ECT).

- The tri-objective Total Electricity Cost, Total Electricity Consumption and Total Weighted Tardiness Job Shop Scheduling problem (Electricity Consumption, Electricity Cost and Tardiness-EC2T).

In the first problem, the electricity price is a constant. In the second problem the Rolling Blackout policy is applied. As mentioned before, the implementation of the Rolling Blackout policy may stimulate manufacturing companies to use private electricity, thereby increasing the cost and emission of the companies. However, only the cost factor will be considered in the EC2T problem. The extra emission caused by using private electricity is currently not included in the scope of this research and should be considered in the future work.

1.3 Contributions

1.3.1 Multi-objective optimisation models

One of the main contributions of this thesis is the consideration of reducing electricity consumption and its related cost together with the scheduling indicator of total weighted tardiness while planning jobs on machines in a job shop. The required mathematical models for the electricity consumption pattern of machine tools and the Rolling Blackout policy have been formalised. The proposed multi-objective optimisation models include two or three objectives. The first model minimises total weighted tardiness and total electricity consumption under a set of constraints in a job shop. The second model minimises total weighted tardiness, total electricity consumption and total electricity cost when the Rolling Blackout policy is applied in a job shop. Both of the problems are NP-hard.

1.3.2 Algorithmic contributions

Meta-heuristics are proposed to find solutions belonging to the near-optimal approximate Pareto front for each model. Firstly, based on the literature research of multi-objective optimisation techniques, the Non-dominant Sorting Genetic Algorithm (NSGA-II) (Deb et al. 2002) is selected and applied to approximate the optimal Pareto front of the ECT problem. Based on the optimisation result of NSGA-II, it can be found that better optimisation technique could be proposed to solve the ECT problem if the Turn off/Turn on method is used. Secondly, a the new Multi-objective Genetic

Algorithm for solving the ECT job shop scheduling problem (GAEJP) based on the NSGA-II and its corresponding scheduling techniques are developed to provide better solutions compared to NSGA-II. In addition, a new heuristic is proposed to adjust existing scheduling plans when the Rolling Blackout policy is applied. This heuristic helps to investigate how the Rolling Blackout policy will influence the performance of existing scheduling plans. Additionally, it is a remedial measurement for manufacturing companies to reduce the deterioration of the total weighted tardiness objective. Finally, the NSGA-II is modified and applied to solve the EC2T problem.

1.4 Outline of thesis

The organisation of this thesis is as follows: Chapter 2 provides the literature review in the area of reducing electricity consumption in metalworking and machining-based manufacturing system (MMS). The state-of-the-art of the related research on different levels of MMS is summarised. Based on this part of the literature review, the research gaps are clarified, which provides the motivation for the research described in this thesis. Then, the state-of-the-art of the multi-objective optimisation techniques for the job shop scheduling problem is reviewed. Based on the review, NSGA-II is selected as the optimisation technique to be applied in this research. Then, procedure of the Genetic Algorithm and how it can be applied to the job shop scheduling problem are introduced. The literature review concludes with the key knowledge gaps.

Chapter 3 focuses on the research methodology, experimental design and optimisation models of the research problems. Six different scenarios and a scenarios comparison experiment are designed. Scenarios 2 and 6 are used to present how developed optimisation solutions based on NSGA-II can be applied to solve ECT and EC2T problems respectively. Scenario 3 is used to present how the proposed new Multi-objective Genetic Algorithm (GAEJP) is effective in solving the ECT problem. Scenarios 4 and 5 are used to investigate the influence that the Rolling Black policy exerts on the performance of scheduling plans produced in Scenarios 2 and 3.. Finally, several scenarios comparison experiments are designed to prove the effectiveness of the aforementioned solutions. The mathematical models for both the ECT and EC2T problems are developed. Based on the models, a modified job shop instance is developed and presented which incorporates electrical consumption profiles for machine tools and the Rolling Blackout policy constraint.

The NSGA-II algorithm is applied to solve the ECT problem as described in Chapter 4 (Scenario 2). In comparison with the optimisation result of a well-established traditional scheduling approach without considering reducing total electricity consumption as an objective (Scenario 1), the NSGA-II is proved to be effective in solving the ECT.

In Chapter 5, the Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) and its corresponding scheduling techniques (Scenario 3) are developed based on NSGA-II to provide better solutions for the ECT problem. A comparison experiment is performed to demonstrate the superiority of the new algorithm to the NSGA-II.

Chapter 6 investigates how the Rolling Blackout policy will affect the performance of the scheduling plans produced in Scenarios 2 and 3 in terms of total weighted tardiness, total electricity consumption and total electricity cost. In this chapter, the performances of scheduling plans in two scenarios are compared (Scenarios 4 and 5). In Scenario 4, there is no private electricity supply during periods when government electricity is unavailable. In this scenario, an new heuristic is proposed to adjust existing scheduling plans when the Rolling Blackout policy is applied. On the contrary, in Scenario 5, private electricity is employed during all the government supply unavailable periods to guarantee the production. Based on the comparison experiment, a compromise plan for using private electricity is proposed where the NSGA-II is applied to deliver the trade-off between the TWT and the total electricity cost.

Chapter 7 serves for verification purpose, where GAEJP has been applied to solve the ECT problem based on a real job shop instance. Only GAEJP is selected to be verified since it is the most innovative algorithm in this research.

The future research work is proposed in Chapter 8.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The general goal of this research is to investigate and develop new methods for decreasing electrical energy waste in a specific manufacturing system, and its unnecessary cost due to the Rolling Blackout policy. To clearly identify the current knowledge gaps which prevent the solution of the aforementioned problems, a literature review has been conducted to explore the area of reducing electricity consumption in a metalworking and machining-based manufacturing system (MMS). The state-of-the-art of this research area will be stated in the following sections. Based on the above, employing operational research methods to reduce the electricity consumption and electricity cost in a job shop by the appropriate scheduling of jobs has been selected as the research topic. Therefore, optimisation techniques for the multi-objective job shop scheduling are reviewed, and the concept and procedure of the Genetic Algorithm are introduced. Then, the application of the Genetic Algorithm to solve the job shop scheduling problem is presented in more detail. The chapter concludes with a clearly defined set of knowledge gaps which underpin this work.

2.2 Reducing electricity consumption in a metalworking and machining-based manufacturing system

In order to understand the electricity consumption of MMSs, Vijayaraghavan & Dornfeld (2010) have proposed that the energy consumption of manufacturing systems can be studied at different levels. Levels range from the entire enterprise to the tool-chip interface. As shown in **Figure 2.1**, these levels are not absolutely independent. They overlap each other, filling the whole analysis process for manufacturing systems. The following literature review will be conducted based on these different levels to clarify the knowledge gaps in existing research works and to justify why the manufacturing enterprise level using production planning and scheduling techniques as the energy consumption reducing method is selected as the object of research in this thesis.

2.2.1 Research into the energy consumption at the tool chip interface and sub-component level

At the tool chip interface and sub-component level, research has mainly focused on characterising the energy usage of the specific cutting process. Investigations look at how factors like processing parameters and tool selection affect the cutting energy, or consider approaches to reduce the energy consumption of the individual sub-component in machine tools.

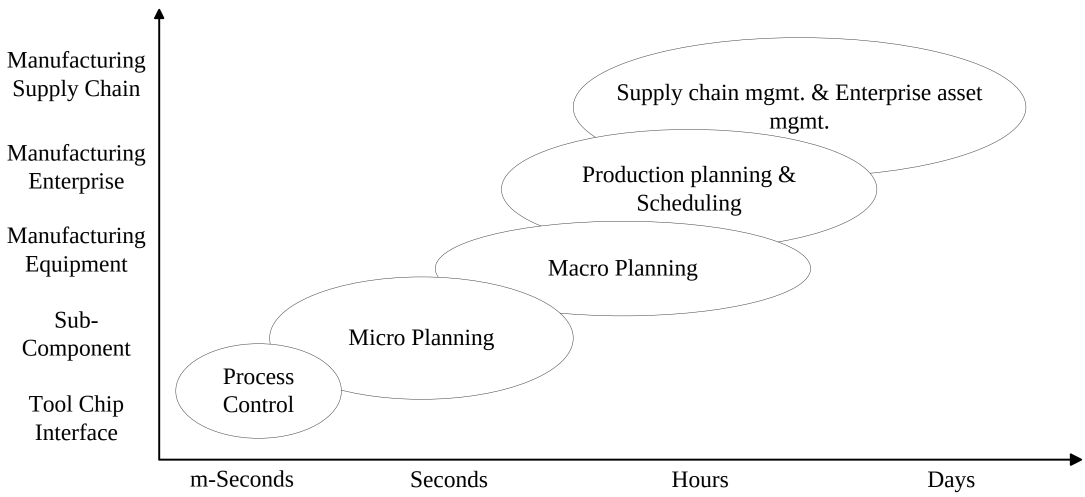


Figure 2.1: Level of analysis of manufacturing with temporal decision scales (Vijayaraghavan & Dornfeld 2010)

Motivated by building a framework for decision-making in environmentally-conscious manufacturing, Munoz & Sheng (1995) have developed an analytical model which integrates aspects of the process mechanics, wear characteristics and lubricant flows. The quantifiable dimensions in this analysis included energy utilisation, process rate, work piece primary mass flow, and secondary flow of process catalysts. According to orthogonal-array analysis, the dominant factors influencing energy utilisation are the geometry of the designed part (dictating the volume of material removed), the work piece material selection (determining the hardness and the shear), and the cutting fluid selection (Munoz & Sheng 1995).

Based on the aforementioned approach for environmentally-conscious machining, Srinivasan & Sheng (1999) have developed a framework towards integrating environmental factors in process planning at both micro and macro levels. At the micro planning level, process, parameters, tooling and cutting fluids are selected for the individual features, while at the macro planning level, interactions between features are examined. Vijayaraghavan & Dornfeld (2010) had defined this work as a very thorough approach for process planning, but the process energy usage was only characterised by the chip removal energy (cutting energy).

Hu et al. (2010) have proposed an additional load loss model based on the power flow model. Theoretically, the additional load losses accounts for 15%-20% of the cutting power. However, in most of the aforementioned research work, this part of the energy loss has been ignored. From the experimental results on a CNC lathe, the author found that the additional load losses is a second order function of the cutting power, and the additional load loss coefficient is a first order function of the cutting power.

A new application of the kinetic energy recovery system (KERS), which is used on F1 racing cars has been proposed by Diaz et al. (2009) for recovering machine tools spindles' energy consumption. By conducting a computer model of a machine tool spindle and a Monte Carlo simulation, the authors showed that the power saving for the whole machine between 5% and 25% could be expected with the KERS. However, the feasibility of this method is currently very low because of the high price of super capacitors used in the KERS. All the aforemetioned research provide methods for modelling the energy consumped by machining processes.

2.2.2 Research into the energy consumption at the manufacturing equipment level

At the manufacturing equipment level, the analysis of energy consumption is expanded to a system level which not only includes energy requirements for the material removal process itself, but also associated processes such as axis feed. The research at this level results in a more complete assessment of machining energy consumption (Dahmus & Gutowski 2004).

Some of the representative works have been developed by researchers in professor Gutowski's group in the Massachusetts Institute of Technology. They have focused a considerable amount of work on exploring characteristics of energy consumption or environmental impact of machining process. These processes includes milling, turning, drilling, sawing, grinding, electrical discharge machining, water jet machining, injection-moulding and iron casting (Kordonowy 2003, Dahmus & Gutowski 2004, Dahmus 2007, Baniszewski 2005, Cho 2004, Kurd 2004, Jones 2007). One of the most important contributions of this group is their approach for breaking down the total energy use of machining processes, as shown in **Table 2.1** and **Figure 2.2**. This modelling approach is employed as the basis for modelling the power input of machine tools at the workshop level for this research. Based on this approach and experiments for measuring energy consumption of machine tools (Kordonowy 2003), they have unveiled the fact that the energy consumed by actual material removal represents only a small amount of the total energy used in machining. For instance, the specific cutting energy accounts for less than 15% of the total energy consumed by a modern automatic machine tool during machining. This finding had been referenced by many authors.

Table 2.1: Classification of power demand of machine tools

Type of energy use	Content
Constant start-up operations	Start-up energy use, for computers, fans, unloaded motors, etc.
Run-time operations	Energy used to position materials and load tools
Material removal operations	Actual energy involved in cutting

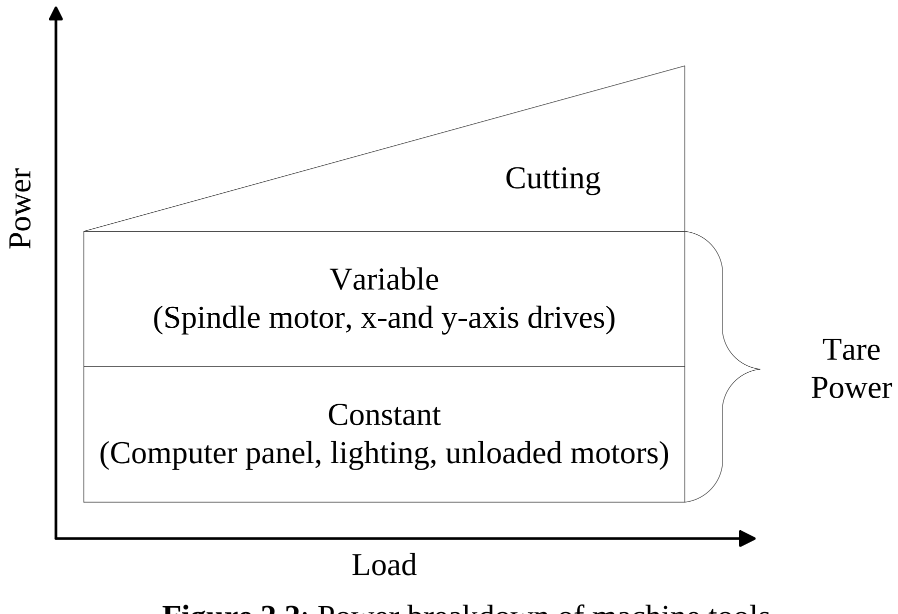


Figure 2.2: Power breakdown of machine tools,
after Dahmus & Gutowski (2004) and Diaz et al. (2010)

Kordonowy (2003) has accomplished power measurement work for milling machines at different automotive levels with various material removal rates (MRR), as shown in **Table 2.2**. This experiment shows the classification of different operations and how much energy they consume. On the other hand, from this experiment, we can find that the machine "tare" energy consumption accounts for a significant part in the total consumption. The more modern the machine, the higher percentage of the tare energy it uses.

Table 2.2: The individual stages of the Cincinnati Milacron 7VC Automated Milling Machine, made in 1988.(Kordonowy 2003)

Type of operations	Process	Power Consumption (W)	Percentage of Total Power (%)
Constant start-up operations	Computer and Fans	1680	13.5
	Servos	>0	>0
	Coolant Pump	1200	9.6
	Spindle Key	140	1.2
	Unloaded Motors	340	2.7
Constant run-time operations	Jog (x/y/z axis translation)	960	7.7
	Tool Change	480	3.8
	Spindle (z axis translation)	1440	11.5
	Carousel Rotation	240	1.9
Material removal operations	Machining MRR: $4.52 \times 10^{-7}\ m^3/s$	2400	19.2
	Machining MRR: $9.03 \times 10^{-7}\ m^3/s$	4800	38.5
	Machining MRR: $12.04 \times 10^{-7}\ m^3/s$	6000	48.1

Methods of estimating machining energy consumption and processing time according to the numerical control (NC) code have been proposed by He et al. (2011). This method provides a potentially faster way to estimate the energy consumption of machining processes. However, the drawbacks of it are obvious. Firstly, the cutting force is one of the main factors in the estimation, but it varies during the cutting process, leading to a poor estimation accuracy for the power consumption of the spindle motor and servo motors. Secondly, this method requires power parameters of the specific machine tools. It requires a considerable amount of work to build the power consumption data base for every machine. Additonally, some of the power parameters would vary with the different materials that are processed by the machine tool.

Avram & Xirouchakis (2011) have developed a methodology to estimate the energy requirements during the use phase of the spindle and feed axis according to an automatic programming tool (APT) file. This method considers the entire machine tool system by taking into account its steady-state and transient regimes, but it is only applicable to milling process plans of 2.5D part geometries.

Dietmair & Verl (2009) have proposed a generic method to model the energy consumption behavior of machines tools based on the conclusion that the power consumption of the machine varies mainly with its operating state. This model can be used in planning processes to predict the actual power drain profile and to optimise the machines for minimal energy consumption.

2.2.3 Research into energy consumption at the work shop level

Based on the review presented above, the energy consumption reduction in a MMS can be realised on different levels. Most existing research on reducing manufacturing energy consumption has focused so far on developing more energy (particularly electrical energy) efficient machines for machining processes (Fang et al., 2011). However, compared to the background energy consumed by the manufacturing equipment operations, the energy requirements for the active removal of material can be quite small (Dahmus and Gutowski, 2004), especially in a mass production environment, it accounts for no more than 15% of the total energy usage. The majority of energy is consumed by functions that are not directly related to the production of components (Gutowski et al., 2005). This implies that efficiency improving efforts focusing solely on the machines or processes may miss a significant energy saving opportunity. In fact, there is a larger energy reducing opportunity at the system-level where operational research methods can be employed as an energy saving approach. Additionally, compared to machine or process redesign, implementation of optimised shop floor scheduling and plant operation strategies only requires a modest capital investment and can easily be applied to existing systems (Fang et al., 2011). As a result, the manufacturing enterprise (work shop) level is selected as the entry point for decreasing energy consumption in this research for the following reasons:

From a practical point of view, a considerable amount of electricity consumption could be saved by using operational research methods in a MMS. case study from Mouzon (2008) further illustrates this potential. In Wichita, Kansas, USA, at an aircraft supplier of small parts, the manufacturing equipment energy and time data were collected at a machine shop that had four CNC machines. Although this machine shop was considered as the bottleneck by the production planning department, it was observed that, in an 8-hour shift, on average a machine stayed idle 16% of the time. Typically, 13% energy saving would have been achieved if proper scheduling plans were applied.

On the other hand, from an academic point of view, apparent knowledge gaps can be identified in this area after analysing the existing research works. A detailed analysis for existing research in this area will be presented in this section. The knowledge gaps identification will be illustrated in **Section 2.4**.

Based on existing works in the area of using operational research methods to reduce electricity consumption in a MMS, a general framework for this topic can be summarised, including models, electricity and its cost (E-cost) saving methods (ESMs) and optimisation methods, as shown in **Figure 2.3**. This framework can not only be employed to analyse the contributions, shortcomings and gaps of the current research works, but also can serve as the foundation for model building, ESMs selection and optimisation methods development.

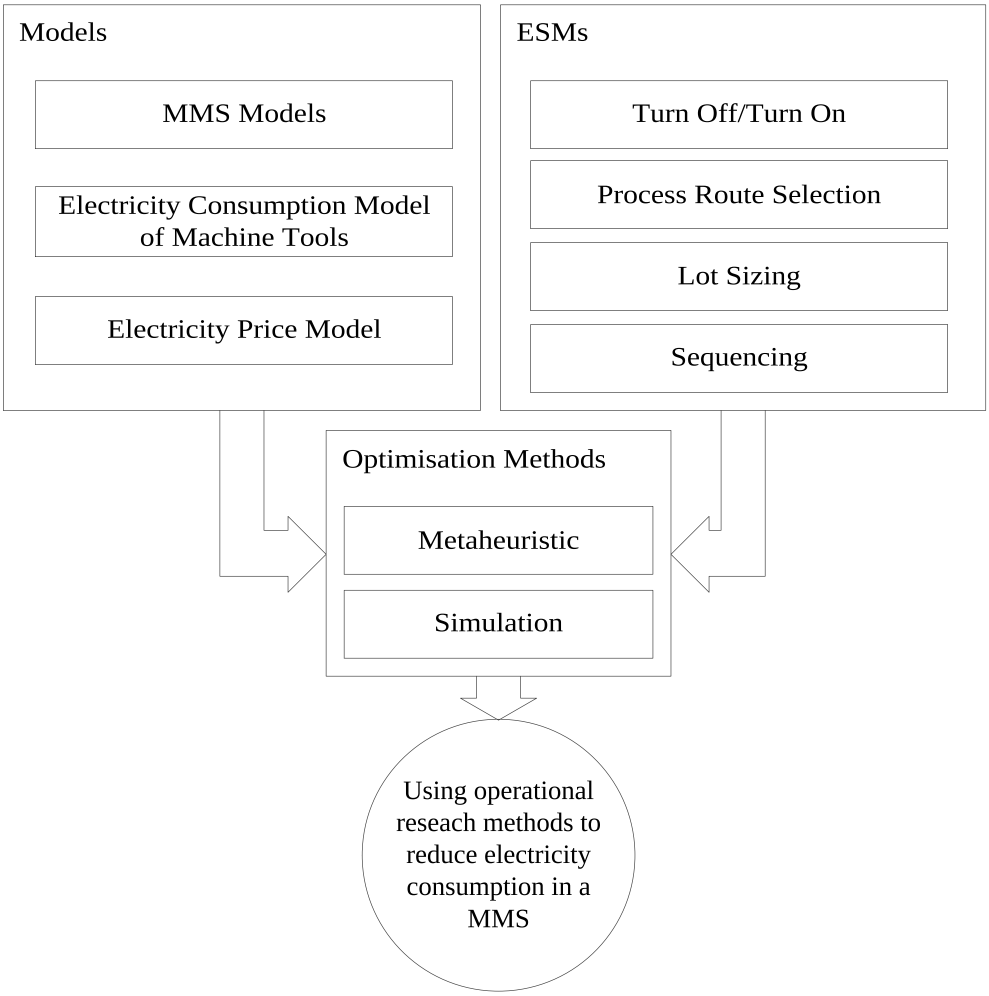


Figure 2.3: The research framework for employing operational research methods to reduce electricity consumption in a MMS

As shown in **Figure 2.3**, the model of a MMS including electricity and E-cost saving consideration should be built first, to provide the base for the research. Secondly, the potential methods for electricity and E-cost saving should be proposed. Finally, the optimisation methods will be developed based on the combination of model and ESMs. The MMS model which incorporates the electricity consumption reduction and electricity cost saving consideration can be divided into three sub-models: the MMS models, machine tools electricity consumption model and the electricity price model.

The amount of research on scheduling with environmentally-oriented objectives is currently small but increasing. For example, Fang et al. (2011) considered reducing the peak power load in a flow shop. Bruzzone et al. (2012) developed a method to modify the schedule of the jobs in the flexible flow shops in order to adjust to the maximum peak power constraint. Subaï et al. (2006) considered the energy and waste reduction in the hoist scheduling problem for the surface treatment processes without changing the original productivity. Wang et al. (2011) proposed an optimal scheduling procedure to select the appropriate batch and sequence policies to improve the paint quality and decrease repaints, thereby reducing energy and material consumption in an automotive paint shop. Mouzon et al. (2007, 2008) and He et al. (2010, 2012) developed the representative research in this area, thus the following analysis will be based on their work.

2.2.3.1 The contribution of existing work (work shop level)

Manufacturing system models and electricity consumption pattern of machine tools

Both Mouzon et al. (2008a, 2008b, 2007) and He et al. (2012, 2010) have adopted simplified manufacturing system models which are widely used in the scheduling research area. Machines and jobs are the only elements considered in these models. The typical models include single machine, flow shop and job shop. Sometimes, parallel machines are added into these basic models to make them closer to the real manufacturing workshops. The definitions and details of these classical models as well as those including parallel machines can be found in Pinedo (2012). Mouzon's research focuses on the single machine environment and the parallel machine environment. The study of He et al. (2012a) is based on a flexible job shop environment which is a generalisation of the job shop with the parallel machine environment.

According to Dahmus and Gutowski (2004) and Kordonowy (2003), the electricity consumption for a machine tool in a feasible schedule can be divided into two types: the non-processing electricity consumption (NPE) and processing electricity consumption (PE). NPE is associated with machine start-up, shut-down and idling. The electricity consumed when a job is processed on a specific machine can be defined as the job related processing electricity consumption (JPE), including the basic power consumption of the machine tools, i.e. idle power, the runtime operations and the actual cutting power consumption. Thus, PE is the sum of all the JPE on a specific machine, and the total PE is the sum of all PEs in a work shop. Each JPE has been defined as a constant value by both Mouzon (2008) and He et al. (2012a) in their models, since at the workshop level, the main concern is how the scheduling plans affect the total electricity consumption of the manufacturing system. Therefore, the JPE can be seen as a constant for scheduling problems. Additionally, the electricity price in both of the aforementioned research works was considered as a constant.

Electricity and E-cost saving methods

Realising that in the manufacturing environment large quantities of energy are being consumed by non-bottleneck machines as they lie idle, and that whenever a machine is turned on, there is a significant amount of start-up energy consumption (Drake et al., 2006), Mouzon (2008) proposed a Turn Off/Turn On method. The work is based on the assumption that a machine tool could be turned off when it becomes idle for electricity saving purposes. Note that idle time does not include activities considered as set up, part removal or maintenance. A warm-up consumes Start-up (turn on) electricity, i.e. the electricity required to start up the machine. Idle power is the power required per unit time by the machine when staying idle. The machine requires Stop Time to be turned off, which consumes stop (turn off) electricity (Mouzon et al., 2007). According to these characteristics of a machine tool, the value (S) of the break-even duration for which the execution of Turn Off/Turn On is economically justifiable instead of running the machine at idle can be calculated as:

$$S = \frac{Turn\ Off/Turn\ On\ Electricity}{Idle\ power\ consumption\ per\ unit\ time} \tag{2.1}$$

Let γ be the inter-arrival time between jobs and t_{Off} the time required to turn off and then turn on the machine. If $\gamma \geq \max(S, t_{Off})$, then the machine can be turned off for a particular length of time and then turned on to process some other jobs.

The Process Route Selection (PRS) method has been adopted by Mouzon et al. (2008a, 2008b, 2007) to reduce both total PE and total NPE for parallel machine environment. He et al. (2012, 2010) used the same method to decrease both total PE and total NPE for a flexible job shop environment. The limitation for PRS is that it is only effective in systems which have alternative routes with different energy characteristics for the same job, i.e. PRS is not applicable to workshops without alternative routes, or having identical alternative routes for jobs, for instance, the job shop environment.

The Sequencing method has also been adopted by Mouzon (2008). It considers that the order of jobs which are processed on the same machine will affect the total amount of the idle time and the length of each idle period of that machine. This will further influence the decision of whether there should be an execution of Turn Off/Turn On between two consecutive jobs on the same machine. Consequently, the sequencing method could be effective for electricity saving.

Optimisation methods

Mouzon et al. (2008a, 2008b, 2007) have developed operational research methods including dispatching rules, a genetic algorithm and a greedy randomized adaptive search procedure to determine on WHICH machine the job should be scheduled (in the multi-machine), WHEN to start a job on the machine, and WHEN to execute a Turn Off/Turn On to minimise the total NPE (or both of the total NPE and total PE when the parallel machine exists) and classical scheduling objectives including total completion time, total tardiness, load balancing on a single machine and single machine with machine in parallel environments where jobs have unequal release dates.

2.2.3.2 The limitations of existing work at the work shop level

Based on Pinedo's (2012) definition of job shops and the electricity consumption model of machine tools (Mouzon et al., 2008a, 2008b, 2007; He et al., 2012, 2010), the electricity consumption focused job shop models can be defined and classified into several types according to the complexity, as shown in **Figure 2.4**. The term "complexity" here refers to conditions of parallel machines in terms of processing time and electrical characteristics for a specific operation.

As shown in **Figure 2.4**, the basic job shop model includes only the most simplified job shop characteristics, which had been defined as a set of n jobs which are to be processed on m machines following a predefined order or technological path (Pinedo, 2012).

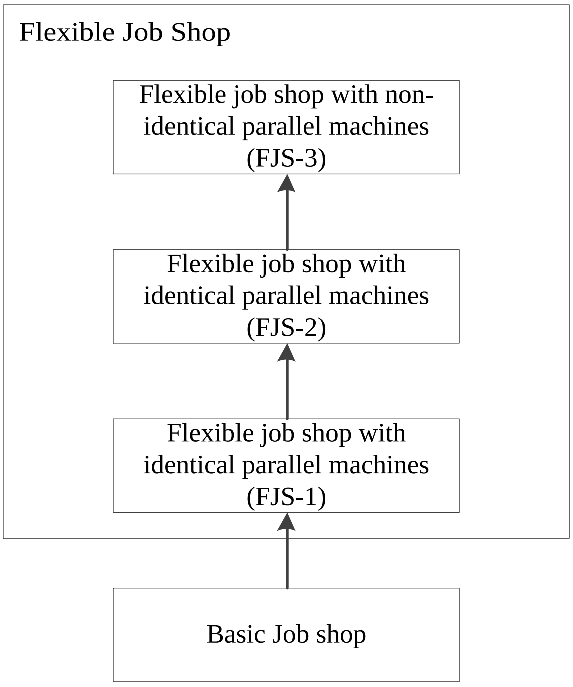


Figure 2.4: Types of job shop

The flexible job shop (FJS) models had been defined by Pinedo (2012) as a generalisation of the job shop allowing for parallel machines. Instead of m machines in series there are c work centres with a number of identical parallel machines in each work centre. Each job has its own route to follow through the shop; job j requires processing on only one machine in each work centre and any machine can do. However, the reality of manufacturing workshops is that, parallel machines belonging to the same work centre are not necessarily always identical. In addition, with the consideration of the electricity consumption of machines, the definition for parallel machines in a FJS could be reasonably expanded in this research. The expanded definitions for parallel machines of the three types of FJS (FJS-1, FJS-2 and FJS-3) shown in **Figure 2.4** are presented in **Table 2.3**.

The aforementioned four types of job shop models can cover nearly all of the job shop circumstances in the real manufacturing world. According to their definitions, in the basic job shop model, no parallel machine exists. In other words, there are no alternative routes for any job. Thus, it is not possible to reduce the total PE in a basic job shop. Hence, two electricity saving methods can be used in a basic job shop to reduce its total NPE, one is the Turn Off/Turn On method, and the other is the Sequencing of jobs. The applicable electricity saving methods for the FJS-1 are the same as the two for the basic job shop as the parallel machines are absolutely identical from both the processing and electricity consumption aspects in FJS-1. For FJS-2, it is possible to find a way to reduce the total PE, if the parallel machines in a specific work centre consume different amounts of electricity for processing the same job. In other words, the alternative routes for each job have different electricity consumption characteristics, which means the electricity saving can be achieved by Process Route Selection for each job in addition to the approaches for the previous two models. For FJS-3, it is reasonable to conclude that the electricity saving can be realised by all the three ESMs proposed for the previous models.

Table 2.3: The expanded definitions for parallel machines of the three types of FJS

Name	Definition expansion on parallel machines	Processing time	Energy consumption
FJS with identical parallel machines (FJS-1)	Following Pinedo's (2012) definition for identical parallel machine.	The time p_{ij} that job j spends on work centre i is a constant which is independent from the machine processing it, since all the parallel machines in a specific work centre are absolutely identical.	The amounts of electricity consumed by any machine in work centre i for processing job j are the same.
FJS with identical parallel machines (FJS-2)	Following Pinedo's (2012) definition for identical parallel machine.	The time p_{ij} that job j spends on work centre i is a constant which is independent from the machine processing it, since all the parallel machines in a specific work centre are identical from the aspect of processing time for job j.	The amounts of electricity consumed by each machine in work centre i for processing job j are different. The difference comes from factors like various levels of wear conditions of the parallel machines.
FJS with non-identical parallel machines (FJS-3)	Following Pinedo's (2012) definition for unrelated parallel machine.	The time p_{ij} that job j spends on work centre i depends on the machine processing it, all the parallel machines in a specific work centre are non-identical from the aspect of processing time for job j.	The amounts of electricity consumed by each machine in work centre i for processing job j are different.

According to the above discussion on different types of job shop models and their potential electricity saving methods, it is easy to see that from the modelling perspective, the applicable range of Mouzon et al.'s (2008a, 2008b, 2007) work is limited in circumstances of a single machine environment and parallel machine environment. It may be argued that a typical job shop can be disassembled into several single machines. Then the optimisation methods developed by Mouzon et al. (2008a, 2008b, 2007) can be applied to each of them to achieve the optimisation of the whole job shop. This is not a reasonable approach since it may result in local optimisation for some machines or jobs, but a deterioration of the performance of the job shop as a whole. He et al. (2010, 2012) only developed modelling methods for minimising the electricity consumption of the FJS-3. Nevertheless, the limitations of this type of model are obvious, since they are based on the assumption that alternative routes with different electricity consumption amounts always exist for jobs. This means these models are not applicable for the basic job shop and FJS-1.

From the electricity saving methods perspective, He et al., (2012, 2010) only considered the Process Route Selection approach. However, the Turn Off/Turn On and Sequencing are also effective electricity saving methods for the FJSs.

From the optimisation methods perspective, He et al., (2012, 2010) have not proposed any effective approaches for the optimisation purpose. The classical First in First out (FIFO) rule has been employed in their research for job dispatching. Therefore, their research work only demonstrates how different process route selection plans affect the total electricity consumption of the FJS-3, but does not effectively optimise them.

According to what has been discussed above, it is clear that employing operational research methods to reduce the total energy consumption in a typical job shop version of MMS without parallel machines has still not been explored very well, i.e. there are research opportunities to develop the electricity saving oriented basic job shop model and its related optimisation techniques. Additionally, both of the aforementioned researchers considered the electricity price as a constant in their research, none of any electricity usage control policies and tariffs have been studied.

In addition, Herrmann et al. (2009, 2011) proposed a concept to integrate the energy consideration into a manufacturing system simulation approach. Besides the machines' energy consumption, energy consumed by other facilities like the technical building services are also taken into account. This is a very general framework which integrates both the manufacturing supply chain level and the manufacturing enterprise level, according to **Figure 2.3**. This approach is different from the research works discussed above since a simulation technique has been employed. It is worth mentioning that in the flow shop case study of this research, an instantaneous power limit tariff and the lot sizing ESM have been considered. The simulation results of 14 different scenarios have demonstrated that the lot size is a factor that can influence the electricity consumption of MMS. For the optimisation part, in this case the authors only tried to use the simulation technique to run several scenarios, and then to find the scenario which gives the most favourable solution compared to the others. However, the solution quality could have been much improved if the appropriate meta-heuristic for optimisation had been applied.

The optimisation methods are very important for this PhD research. It can be seen from above, that the scheduling problems always become multi-objective optimisation problems when the electricity saving objective is added. Thus, based on the knowledge gap identification in **Section 2.4**, the literature survey includes a focus on multi-objective optimisation techniques for the job shop scheduling problem.

2.2.4 Research into energy consumption at the manufacturing enterprise and supply chain level

At the manufacturing enterprise and supply chain level, the associated facilities such as automatic guide vehicles, compressor and lighting would be taken into consideration for the energy consumption analysis.

Herrmann & Thiede (2009) have proposed a simulation approach to realise the integration concept to foster energy efficiency in manufacturing companies at different levels from a single technical production system to technical building services. In their research, the main objective for companies from an economic as well as ecological perspective is to maximise energy efficiency. This means optimising the ratio of the production output (e.g. in terms of quantities with defined quality) to the energy input (electricity, gas, and oil) for technical building services and the production equipment of the system. A case study of an SME producing inner races for the automotive industry was conducted to show the practical applicability of this method.

Herrmann et al. (2011) have also presented an energy oriented simulation model for the planning of manufacturing systems, including consideration of the dynamic interaction of different processes as well as auxiliary equipment such as compressed air generation. The authors tried to build a seamless simulation environment to integrate all the relevant energy flows of a factory, and simulated them in order to identify and select measures for improvement. Aluminum die casting and a weaving mill were set as the case studies to demonstrate the applicability of this method.

Zhu & Sarkis (2004) used emprical results from 186 respondents on the Green supply chain management (GSCM) practice in Chinese manufacturing enterprises to examine the relationships between GSCM practice and environmental and economic performance. Based on a moderated hierarchical regression analysis, they concluded that GSCM practices tended to have a win-win relationship in terms of enviromental and economic performance.

2.3 Multi-objective optimisation techniques for the job shop scheduling problem

The aim of multi-objective optimisation is to help decision-makers to find the best or most suitable solution to a specific problem in which more than one objective is considered. This is an emerging area whereas, unlike single-objective optimisation, no common techniques can be applied to all applications. In multi-objective optimisation, instead of only one solution to the problem, there are a set of solutions, a Pareto optimal set.

Marler & Arora (2004) define multi-objective optimisation as the process of optimising systematically and simultaneously a collection of objective functions. The general mathematical representation of a multi-objective optimisation problem is as follows:

$$minimise\ F(s) = \left(f_1(s), \dots, f_{nObj}(s)\right) \quad s \in S \tag{2.2}$$

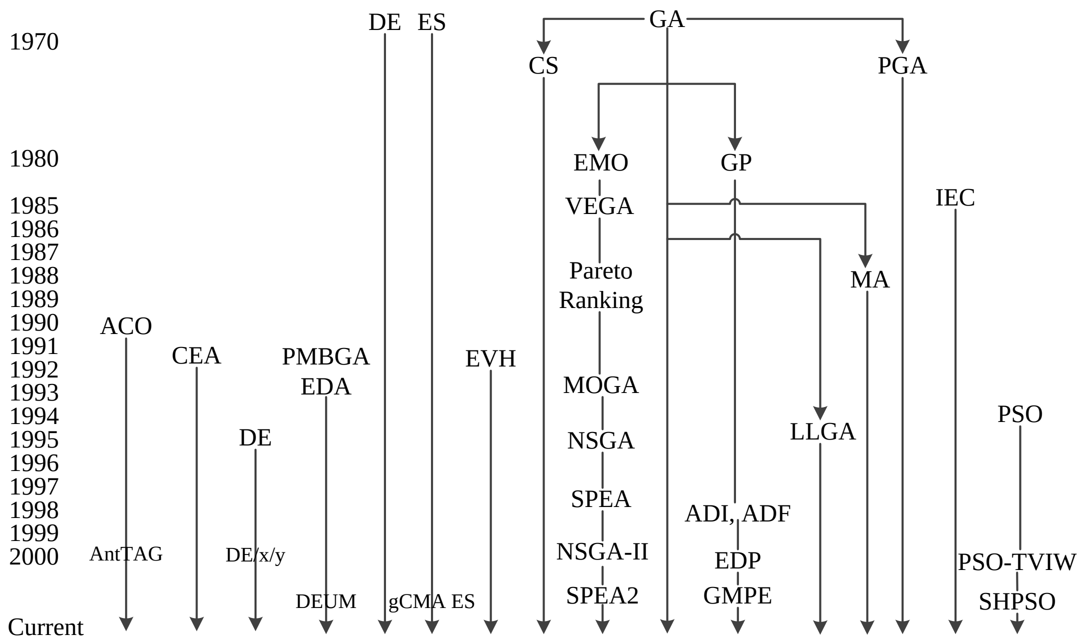
$$g_i(s) \leq 0 \;\; \forall i = 1 \dots n \tag{2.3}$$

$$h_j(s) = 0 \;\; \forall j = 1 \dots p \tag{2.4}$$

where $f_k\colon S \longmapsto \mathbb{R}$ is the k–th objective function and $nObj$ is the number of objectives. **Equation 2.3** is the inequality constraints for the multi-objective optimisation problem where n is the total number of inequality constraints. **Equation 2.4** is the equality constraints for the multi-objective optimisation problem, where p is the number of equality constraints. These two types of constraints can be linear or non-linear. Elements of vector F are objective functions. The quality of a schedule is measured according to $nObj$ criteria. The goal is to find the set of non-dominated solutions optimising the $nObj$ objectives over the constraint set. Usually in multi-objective optimisation, there is no single optimal solution but a set of non-dominated solutions. For instance, in the multi-objective scheduling problem, for any two schedules s and s', s is said to dominate s', if $f_i(s) \leq f_i(s')$ for $i \in \{1, \dots, nObj\}$ with at least one strict inequality. A schedule s^* is called Pareto optimal or a non-dominated solution if no $s' \in S$ dominates s^*, i.e. if it is not possible to improve any of the $f_i(s^*)$ values without increasing the $f_q(s^*)$ value for at least one q. The set of Pareto optimal solutions is known as the Pareto set and its image in the objective function space is known as the Pareto front. The task is to find a set of solutions that lie on and are well spread along the Pareto front. It is the task of the decision-makers in practice to choose the solution that best suits their needs.

2.3.1 Multi-objective job shop scheduling optimisation techniques

The job shop used in this research is the static one. In the static type of environment, the number of jobs and the arrival times are already known in advance (Metta 2008). Most of the research during the last three decades has concentrated on the deterministic job shop problem making it one of the well-developed models in the scheduling theory. The solution of any optimisation problem is evaluated by objective functions (Metta 2008). Normally, in a manufacturing company, one or more objectives, such as completion time, tardiness, and throughput, may be considered simultaneously important when a scheduling decision needs to be made. When more than one criterion is considered, usually, a multi-objective scheduling approach is utilised. Often, it is hard to find the optimal Pareto front for these multi-criteria scheduling problems. Jain & Meeran (1998) provide a review on job shop scheduling techniques, Parveen & Ullah (2010) and Bakuli (2006) delivered a state-of-the-art review on multi-objective job shop scheduling optimisation techniques. Within this review, lexicographical approaches, weighted objectives approaches, Pareto approaches and goal programming approaches are introduced and compared. Meta-heuristics are semi-stochastic methods. For complex real world problems, meta-heuristics are often applied with some other approaches to enhance the problem solving ability. Tabu Search, Simulated Annealing and Evolutionary algorithms are the representative meta-heuristic methods. The success of these methods is defined by their capability in producing near optimal solutions in less computational time (Metta 2008). Based on the above, it has been identified that currently methods based on the evolutionary algorithms have been widely used for solving multi-objective job shop scheduling optimisation problems. A comprehensive overview of recent advances of evolutionary computation (EC) studies is provided by Gen & Lin (2013), as shown in **Figure 2.5**. Evolutionary Algorithms differ in the implementation details and the nature of the particular applied problem.



ACO	Ant Colony Optimisation	GA	Genetic Algorithm
CEA	Coevolutionary Algorithm	GP	Genetic Programming
CS	Classifier System	IEC	Interactive Evolutionary Computation
DE	Differential Evolution	LLGA	Linkage Learning GA
EDA	Estimation of Distribution Algorithms	MA	Memetic Algorithm
EMO	Evolutionary Multiobjective Optimisation	PGA	Parallel GA
EP	Evolutionary Programming	PMBGA	Probalilisti Model Building GA
ES	Evolution Strategies	PSO	Perticle Swarm Optimisation
EVH	Evolvable Hardware		

Figure 2.5: Evolution of evolutionary algorithms (Gen & Lin 2013)

Genetic algorithms are part of the evolutionary methods family. Many authors have studied the application of the multi-objective genetic algorithm in solving the job shop scheduling problem in order to obtain an approximate Pareto front. Veldhuizen & Lamont (2000) and Zhou et al. (2011) provide detailed literature reviews on multi-objective evolutionary algorithms. Dahal et al. (2007) and Hart et al. (2005) introduced the state-of-the-art of how multi-objective genetic algorithms can be applied to the job shop scheduling problem. Chen & Ho (2005) developed an efficient multi-objective genetic algorithm to solve the problems of production planning of flexible manufacturing systems, considering four objectives: minimising total flow time, machine workload unbalance, greatest machine workload and total tool cost. Rabiee et al. (2012) apply the Non-dominant Sorting Genetic Algorithm (NSGA-II), the non-dominated ranked genetic algorithm, the multi-objective genetic algorithm and the Pareto archive evolutionary strategy to solve a problem of partial flexible job shop with the objectives of minimising the makespan and total operation cost. Vilcot & Billaut (2008) propose a genetic algorithm based on the NSGA-II to minimise the makespan and maximum lateness in a general job shop which is abstracted from the printing and boarding industry. Based on the aforementioned research works, the NSGA-II (Deb et al., 2002) has been identified particularly suitable for solving a 2 or 3 objective optimisation problem with high efficiency (computationally speaking). This algorithm does not use any external memory as the other multi-objective evolutionary algorithms do. Instead, the elitist mechanism of it consists of combining the best parents with the best offspring. Because of the good performance, it is becoming a benchmark against which other multi-objective evolutionary algorithms have to be compared (Coello 2006). The multi-objective optimisation problems addressed in this research have 2 or 3 objectives. Thus, the NSGA-II is adopted for this research as the optimisation technique. In the following, the basic concept and procedure of the Genetic Algorithm and NSGA-II are introduced.

2.3.2 Genetic Algorithms

Genetic Algorithms (GAs) are adaptive heuristic search algorithms inspired by the evolutionary ideas of natural selection and natural genetics to optimise highly complex objective functions. GAs have been successfully applied to solve optimisation problems including scheduling. Based on Yamada (2003), Dahal et al. (2007), Liu &

Wu (2008); Mukhopadhyay et al. (2009), Eiben & Smith (2008) and Sivanandam & Deepa (2007), the basic concepts and the procedure of GAs are introduced in the following section.

Basic Concepts

In GAs, the set of individuals, defined as population, is used to represent solutions. There are two representations for each individual: genotype and phenotype. The genotype, gives an encoded representation of a potential solution in the form of a chromosome. A chromosome is made of genes arranged in a linear succession and every gene controls the inheritance of one or several characters or features. The phenotype represents a potential solution to the problem in a straightforward way. The phenotype can be obtained by decoding the genotype.

Each individual has its fitness value, which measures how suitable the individual is for the local environment. The Evolution Theory tells us that among individuals in a population, the one that is the most suitable for the local environment is most likely to survive and to have greater numbers of offspring. This is called the rule of "survival of the fittest."

The objective function f of the target optimisation problem plays the role of the environment. The fitness F measures an individual's survivability in terms of the original optimisation criteria. When the target is to minimise, an individual with smaller objective function value has a higher fitness. The most straightforward way to calculate an individual's fitness is to define it as the difference between the maximum of objective function over the current population and the individual's own objective function value:

$$F(x) = max_{y \in P}\{f(y)\} - f(x) \tag{2.5}$$

where x is an individual in the current population P.

The Procedure of a Simple Genetic Algorithm

The main procedure of a GA includes Population initialisation, Evaluation, Selection, Crossover, Mutation and Replacement, as shown in **Figure 2.6**. The algorithm starts from a random initial population P_0. P_t is a population at generation t with N individuals. Then the fitness value of each individual is calculated based on the value of its objective function. As seen from **Figure 2.6**, the transition from one generation to the next consists of four basic components: selection, crossover, mutation and replacement.

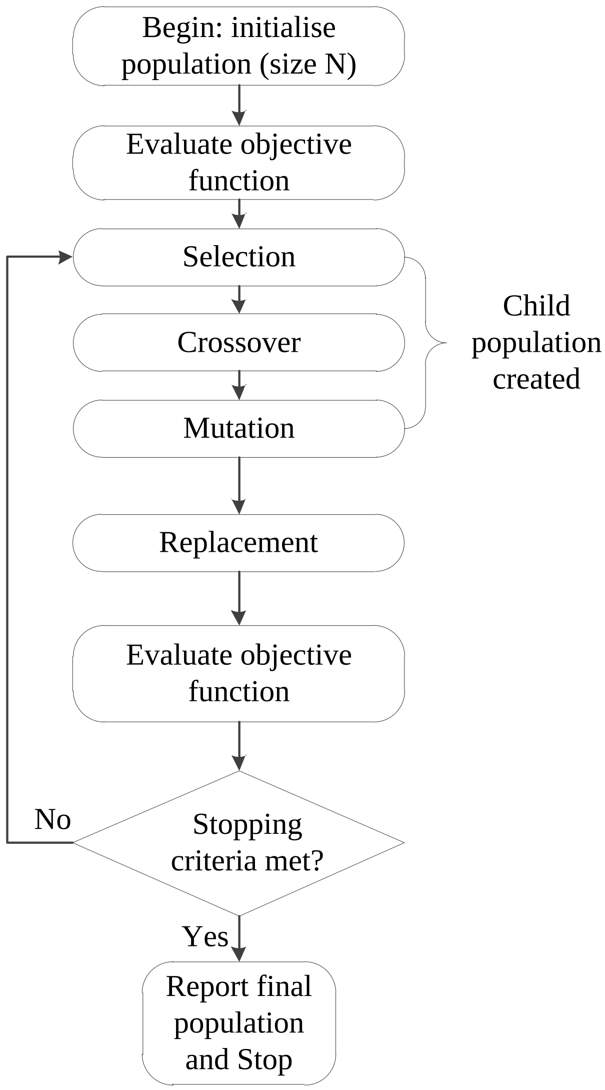


Figure 2.6: The procedure of GA

Selection: Mechanism for selecting individuals for reproduction according to their fitness. The higher fitness value an individual has, the higher probability it has to be selected as the parent into the mating pool. The population size of the mating pool is N. Selection is accomplished by the selection operator. For instance, when employing the binary tournament selection operator, two solutions from the original population are randomly selected and then the one with the higher fitness value is chosen.

Crossover: Method of merging the genetic information of two individuals to produce the next generation. The crossover rate p_c needs to be defined first, which means the crossover operation will be applied to $p_c \times N$ individuals from the mating pool. The procedure can be depicted as follows: firstly, randomly pair the N individuals to create $N/2$ parents; then allocate a random number r in interval $(0, 1]$ for each pair of parents. If $r < p_c$, then crossover the corresponding parents. Typically, p_c is in interval $[0.6, 0.9]$. After the crossover, the initial offspring with N individuals are produced. The crossover is accomplished by the crossover operator. For instance, assume that the chromosome is a bit string of length n. The one point crossover operator sets one crossover point on a string at random and takes a section before the point from one parent and takes another section after the point from the other parent and recombines the two sections to form a new bit string. For example, considering A_1 and A_2 being a bit string of length $n = 5$ as parents as follows:

$$A_1 = 0000 \vdots 0$$

$$A_2 = 1111 \vdots 1$$

The symbol $\vdots$ indicates the crossover point, and in this case it is set after the fourth bit. The one point crossover yields two initial offspring=s A_1' and A_2' as follows:

$$A_1' = 1111 \vdots 0$$

$$A_2' = 0000 \vdots 1$$

Mutation: Randomly deform the chromosomes after the crossover operation with a certain probability. The purpose of mutation is to avoid local optimisation (i.e. being stuck in a local optimum) by preventing the population of chromosomes from becoming too similar to each other and slowing the evolution process. The mutation rate p_m needs to be defined first, which means the mutation operation will be applied to $p_m \times N$ individuals from the initial offspring. The procedure can be depicted as: allocate a random number r in interval $(0, 1]$ for each individual. If $r < p_m$, then mutate the corresponding individual. Typically, p_m is in interval $[0.01, 0.1]$. After the mutation, the new generation P_{t+1} is obtained. The mutation is accomplished by the mutation operator. For instance, a bit-flip mutation operator is shown below, where the third gene from the left in $A_1'$is selected with a small probability and its bit is flipped resulting in A_1'' which is the final offspring of A_1:

$$A_1' = 11110$$

$$A_1'' = 11010$$

Replacement: A replacement strategy is used to decide if offspring will replace parents, and which parents to replace. Based on the replacement strategy used, two main classes of Genetic Algorithms can be identified. One of them is the generational genetic algorithms (CGA). In this category, the replacement strategy replaces all parents with their offspring after all the offspring have been created and mutated, no overlap between populations of different generations. The other is the steady state genetic algorithms (SSGA). In this category, immediately after an offspring is created and mutated, a replacement strategy is executed. Some overlap exists between populations of different generations. The amount of overlap between the current and new populations is referred to as the generation gap. A replacement rate which specifies the fraction of the population that is replaced by its offspring needs to be defined.

Finally, the objective function and fitness values need to be calculated for individuals in the new generation. Then, if the stopping criteria are satisfied, the algorithm stops and reports the final generation, if not, the algorithm goes back to the selection operation and continues until the stopping criteria are satisfied.

2.3.3 GAs and the job shop scheduling problem (JSSP)

The chromosome encoding and decoding procedures are very important when applying GAs to the JSSP. The key factors include chromosome, schedule builder and schedule. The relationships among them are depicted in **Figure 2.7**.

Chromosome encoding and decoding

As shown in **Figure 2.7**, referring to Dahal et al. (2007), Essafi et al. (2008), Cheng et al. (1996), in the JSSP, the chromosome formulation methods are classified into two major approaches: the direct encoding and indirect encoding. In direct encoding, a chromosome completely represents a solution. In indirect encoding, the chromosome represents a sequence of preferences. These decision preferences can be heuristic rules or simple ordering of jobs on a machine. Then, a schedule builder is required to decode the chromosome into a schedule. Applying simple genetic operators on direct representation string often results in infeasible schedule solutions. Thus, the indirect encoding is usually preferable for the JSSP.

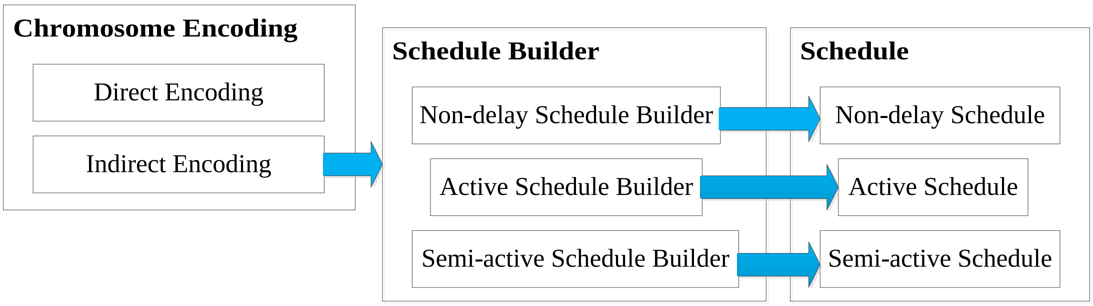


Figure 2.7: The relationships among chromosome, schedule builder and schedule, based on Dahal et al. (2007), Essafi et al. (2008), Cheng et al. (1996)

Schedule builder and schedule

In the indirect encoding schema, the chromosome contains an encoded schedule. A scheduler builder is used to transform the chromosomes into a feasible schedule. The schedule builder is a module of the evaluation procedure and should be chosen with respect to the performance-measure of optimisation (Essafi et al. 2008). The following three types of schedule are normally considered in the JSSP: semi-active, active and non-delayed.

Referring to Pinedo (2009), Yamada (2003) and Essafi et al. (2008), a feasible non-pre-emptive schedule is called semi-active if no operation can be completed earlier without changing the order of processing on any one of the machines. The makespan of a semi-active schedule may often be reduced by shifting an operation to the left without delaying other jobs, which is called the permissible left shift. A feasible non-pre-emptive schedule is called active if it is not possible to construct another schedule, through changes in the order of processing on the machines, with at least one operation finishing earlier and no operation finishing later. In other words, a schedule is active if no operation can be put into an empty hole earlier in the schedule while preserving feasibility. Referring to Özgüven et al. (2010), in a typical job shop, $J = \{J_i\}_{i=1}^{n}$ is a finite set of n jobs are to be processed on a finite set of m machines $M = \{M_k\}_{k=1}^{m}$, following a predefined order; $O_i = \{O_{ik}^{l}\}_{l=1}^{u_i}$ is a finite set of u_i ordered operations of J_i; O_{ik}^{l} is the l-th operation of J_i processed on M_k.

Figure 2.8 depicts how a semi-active schedule becomes an active schedule, where in the upper picture (part A), O_{12}^{2} is a permissible left shift operation which can be shifted to the front of O_{22}^{3} without delaying any other operation. After the left shifting, both of O_{13}^{3} and O_{33}^{3} are permissible left move operations which can be moved forward. All the above actions result in a much improved schedule given in the lower part (part B) of **Figure 2.8**.

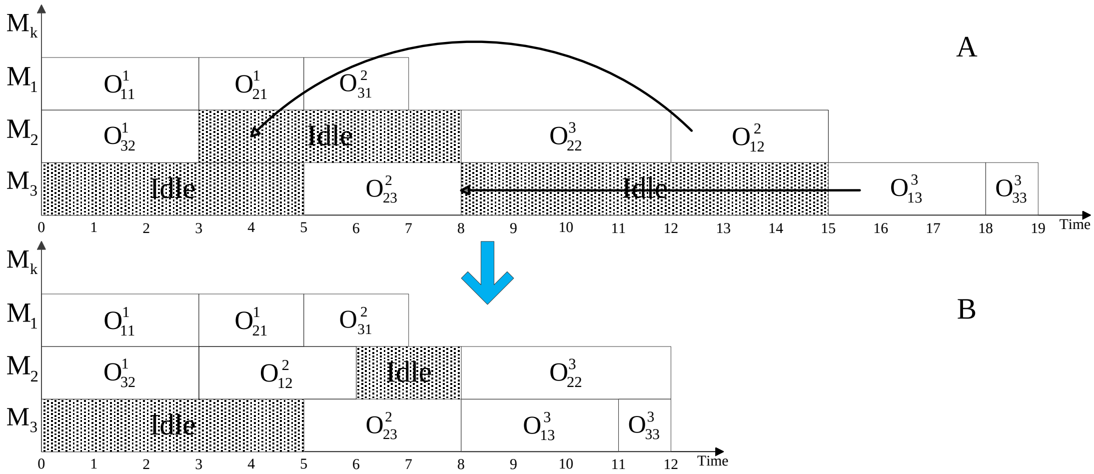


Figure 2.8: An example of a permissible left shift (Yamada 2003)

A feasible schedule is called a non-delay schedule, in which no machine is idle, if an operation is ready to be processed. As shown in **Figure 2.9**, the set of non-delay schedules is a subset of the active schedule. The active schedule is the subset of the semi-active schedule. Correspondingly, there are three types of schedule builders: the semi-active schedule builder, the active schedule builder and the non-delay schedule builder which respectively produce the above three kinds of schedules.

Referring to Essafi et al. (2008), in the traditional searching procedure for the optimal schedule of regular performance measures, the set of active schedules are selected as the search space since it has been demonstrated that some problems have no optimal non-delay schedule, thereby reducing the search space while still ensuring that an optimal schedule can be found. Thus, the active schedule builder is usually employed for decoding the chromosomes to active schedules.

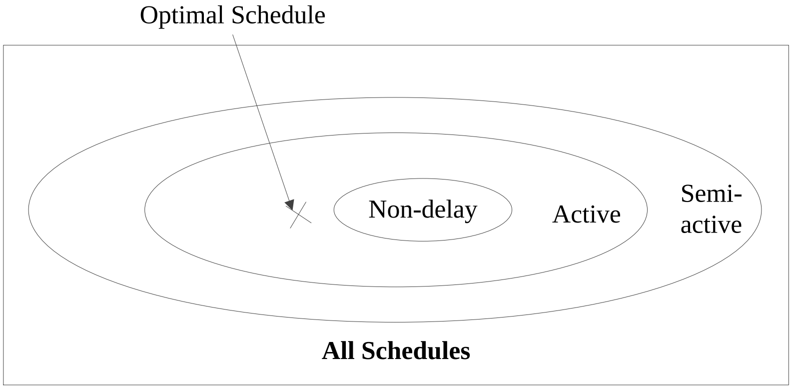


Figure 2.9: Venn diagram of classes of non-preemptive schedules for job shops (Pinedo 2009)

Encoding schema and schedule building process

The operation-based encoding schema (OBES), which is a type of the indirect encoding schemas, is adopted for this research. The OBES incorporates with the schedule builders to develop feasible schedules. OBES is mathematically known as "permutation with repetition" (Dahal et al. 2007), where each job's index number is repeated u_i times (u_i is the number of operations of J_i). By scanning the permutation from left to right, the l-th occurrence of a job's index number refers to the l-th operation in the technological sequence of this job. According to an example provided by Liu & Wu (2008), [321123321] is a feasible chromosome for a 3×3 job shop, 3 on the first gene position stands for O_{32}^1; 2 on the second gene position stands for O_{23}^1; 3 on the sixth gene position stands for O_{31}^2; 1 on the third gene position stands for O_{11}^1; 3 on the seventh gene position stands for O_{33}^3. Thus, the chromosome can be translated to a list of ordered operations as $[O_{32}^1 O_{23}^1 O_{11}^1 O_{12}^2 O_{22}^2 O_{31}^2 O_{33}^3 O_{21}^3 O_{13}^3]$. Decoded by the active schedule builder, the chromosome [321123321] can be transformed into a feasible schedule as depicted in **Figure 2.10**. The advantage of such an encoding scheme is that all the generated schedules are feasible (Dahal et al. 2007).

Table 2.4: The parameters of the 3×3 job shop (Liu & Wu 2008)

O_{ik}^l / J_i	O_{ik}^1	O_{ik}^2	O_{ik}^3	Release time	Due date
J_1	$M_1(2)$	$M_2(2)$	$M_3(3)$	0	The 10th time unit
J_2	$M_3(3)$	$M_2(1)$	$M_1(4)$	0	The 10th time unit
J_3	$M_2(1)$	$M_1(3)$	$M_3(2)$	0	The 10th time unit

In the above example, a schedule is decoded from a chromosome with the following steps by employing the active schedule builder: (1) firstly translate the chromosome to a list of ordered operations, (2) then generate the schedule by a one-pass heuristic based on the list. The first operation in the list is scheduled first, then the second operation, and so on. Each operation under treatment is allocated in the best available processing time for the corresponding machine that the operation requires. The process is repeated until all operations are scheduled. A schedule generated by the procedure can be guaranteed to be an active schedule (Wang et al. 2009).

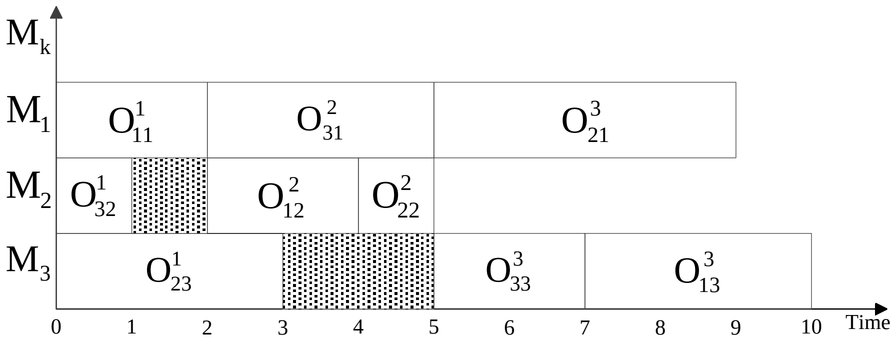


Figure 2.10: Gantt chart of chromosome [321123321], transformed by the active schedule builder (Liu & Wu 2008)

The active schedule builder and the semi-active schedule builder are employed in this research. The reason for adopting the active schedule builder and the working principle of it has been presented in **Section 2.3.3**. The reason for adopting the semi-active schedule builder and how it works will be explained in CHAPTER 5.

2.4 Knowledge gaps

Based on the aforementioned review of the existing research work, one knowledge gap can be identified that the jobs shop scheduling optimisation problem considering electricity saving has not been well explored. In addition, the problem of saving the electricity cost when the Rolling Blackout policy is applied has not been investigated. The further justifications for the knowledge gap are presented as follows:

Firstly, from the optimisation model perspective, the mathematical model of the electricity consumption pattern of machine tools has not been formalised. On the other hand, a typical multi-objective job shop scheduling problem without parallel machines has still not been explored very well when considering reducing the total electricity consumption and electricity cost as part of the objectives.

The basic job shop is the basis for the other flexible job shop models described in **Section 2.2.3.2**. Complexities like parallel machines can be added to the basic job shop to achieve other models.

Secondly, from the perspective of electricity consumption and its related cost saving methods, the Turn Off/ Turn On method combined with the Sequencing method has not yet been applied in a job shop.

The Turn Off/Turn On approach combined with the Sequencing approach has been applied to reduce the electricity consumption in a single machine environment. For reducing electricity consumption in the flexible job shop environment, the Sequencing method and the Process Route Selection method have been applied, but not the Turn off/Turn on approach. Based on the analysis in **Section 2.2.3.2**, the Turn Off/Turn On approach combined with the Sequencing approach can be employed in the basic job shop environment. This could maximally reduce the non-processing electricity consumption in job shops.

Finally, from the perspective of the optimisation methods, there is no algorithm which enables both of the Sequencing and Turn Off/Turn On approaches to be optimally applied in solving the multi-objective job shop scheduling problem which considers reducing the total electricity consumption and electricity cost as part of the objectives.

There is no specific multi-objective optimisation approach for the basic job shop model, which considers maximising the benefit of applying both the Turn Off/Turn On and the Sequencing methods. This is a very important knowledge gap that needs to be addressed. A successful approach can become the reference for developing new solutions for more holistic models, or be directly applied to solve them.

Based on the identified knowledge gaps, the two new research problems can be defined in the following way. The reason for choosing total weighted tardiness as one of the objectives is explained in **Section 3.3**.

- The bi-objective Total Electricity Consumption Total Weighted Tardiness Job Shop Scheduling problem (Electricity Consumption and Tardiness-ECT).

- The tri-objective Total Electricity Cost, Total Electricity Consumption and Total Weighted Tardiness Job Shop Scheduling problem (Electricity Consumption, Electricity Cost and Tardiness-EC2T).

2.5 Summary

This chapter provides the literature review on the area of reducing electricity consumption in metalworking and machining-based manufacturing system (MMS) and the multi-objective optimisation techniques for the job shop scheduling problem. . The state-of-the-art of the related research at different levels of the MMSs are summarised and presented. The concept of Genetic Algorithm and its procedure have been introduced. How GAs can be applied to solve the job shop scheduling problems has been presented. Based on the literature, the knowledge gaps have been identified which provide the evidence to support the contributions of this thesis.

CHAPTER 3 RESEARCH METHODOLOGY, EXPERIMENTAL DESIGN AND OPTIMISATION MODELS OF THE ECT AND EC2T PROBLEMS

3.1 Introduction

The applied research methodology, optimisation model and experimental design are described in this chapter. An experimental environment which includes six different scenarios and a series scenarios comparison experiment are designed for this research. Two Scenarios (Scenario 2 and 6) are developed to present how optimisation solutions developed based on NSGA-II can be applied to solve ECT and EC2T problems respectively. Based on the literature research, NSGA-II has been proved to solve optimisation problems with two or three objectives efficiently. Thus the aforementioned two scenarios, which are part of the innovation points in this research, have to demonstrate the application of the algorithm for solving the new bi-objective (ECT) and tri-objective (EC2T) problems. Besides the aforementioned two scenarios, another new scenario (Scenario 3) is used to introduce the Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP). GAEJP is another important innovation point of this research. It is based on NSGA-II and aims at solving ECT effectively by combining the semi-active schedule builder and Turn off/Turn On method. Finally, the other two scenarios are developed (Scenario 4 and 5) to investigate the influence that the Rolling Blackout policy exerts on the performance of existing scheduling plans (Scenario 2 and 3) in terms of the objective values of the total weighted tardiness, total non-processing electricity consumption and total electricity cost. A new heuristic is proposed to help the manufacturing plant manager to adjust the scheduling plans to reduce the TWT as much as possible when the Rolling Blackout policy is applied. The comparison between Scenario 2 and Scenario 1 (the baseline scenario which represents the traditional single objective scheduling method to achieve minimum TWT) is used to prove the hypothesis that NSGA-II is effective in solving the ECT problem. The comparison between Scenario 3, 2 and 1 is used to prove the hypothesis that GAEJP is superior to NSGA-II in solving ECT. Finally, the comparison between Scenario 6, 5 and 4 is used to prove the hypothesis that NSGA-II is effective in solving the EC2T problem. Finally, based on the proposed model a job shop instance and a Rolling Blackout policy instance are presented.

The mathematical models for both of the ECT and EC2T problems are proposed. These models are one of the main contributions of this thesis, since they consider reducing electricity consumption and its related cost together with the scheduling indicator of total weighted tardiness in a job shop. The job shop model is introduced. Then the electricity consumption and the electricity cost models are formalised. Objective functions related to the aforementioned models are explained respectively. Finally, a modified job shop instance is developed and presented which incorporates electrical consumption profiles for machine tools and the Rolling Black policy constraints.

3.2 Research methodology and experiment design

The research methodology can be split into three modules, as shown in **Figure 3.1**. The first one is to develop mathematical models for both ECT and EC2T problems. The second part is to propose methods for solving the two problems and the last one is to validate the effectiveness of the new solutions. In addition, there are two submodules for the solution method module. Firstly, to select electricity and its cost (E-cost) saving methods (ESMs) for solving the specific problem (ECT and EC2T) . Secondly, to develop meta-heuristics which enable the selected ESMs to be optimally applied, thereby eventually achieving better Pareto-front. . The aim of this research is to provide potential solutions to manufacturing plant manager to help them reduce the electricity consumption and its related cost. Based on this practical and manufacturing oriented aim, the effectiveness of the proposed meta-heuristics needs to be proved. Normally, indicators like hyper-volume and computational time are employed to evaluate the performance of newly proposed meta-heuristics. However, from a practical perspective, the plant manager could expect a single better solution which can be obtained in a reasonable time instead of a Pareto front which has many solutions and a good value in hyper-volume. It is possible that all solutions from a good Pareto front could be dominated by a single solution from a comparatively worse front (in terms of the hyper-volume value). However the specific solution could be more beneficial to the manager than the general good front. Thus, the effectiveness of the proposed meta-heuristics is evaluated by their electricity consumption reduction potential. Hence, the classical indicators may still not be suitable in this research, and a new method to prove the effectiveness of the proposed solutions for both of the ECT and EC2T problem needs to be developed.

Traditionally, manufacturing plant managers produce the scheduling plans which try to achieve single objective optimisation such as minimising the total completion time or total weighted tardiness. However, considering reducing the electricity consumption as a new objective, the managers need to adopt new methods to improve their scheduling plans from the electricity saving perspective (the ECT problem). Nevertheless, when the Rolling Blackout policy is applied, the aforementioned new methods may still not be ideal for the new problem (the EC2T problem), therefore, further new solutions need to be proposed.

Hence, based on the above background, the effectiveness of the new solutions proposed in this research can be proved if the optimisation results delivered by them, i.e. the values of objective functions, are superior to the results of existing solutions. For instance, the proposed approach for solving the ECT problem is defined as effective if it can provide scheduling plans which have lower electricity consumption and similar value in total weighted tardiness to plans which are produced by the traditional single objective optimisation approach. In ideal circumstances, the newly developed scheduling plans' performance on total weighted tardiness is not worse than the traditional ones. However, deterioration in total weighted tardiness in a reasonable range can still be acceptable if the electricity has been saved. Whether the new solutions are acceptable is decided by the managers. Based on the discussion above, a new experimental environment is proposed for developing new approaches to solve the ECT and EC2T, and proving their effectiveness. Within the environment, six scenarios are designed based on the solution proposing part, as depicted in **Figure 3.1**. There are two sub-modules in each scenario, which are ESMs selection and Meta-heuristics development. The other part of the experimental environment is the scenario comparison which corresponds to the Effectiveness validation part as depicted in **Figure 3.1**. The details of the experiment environment are explained below.

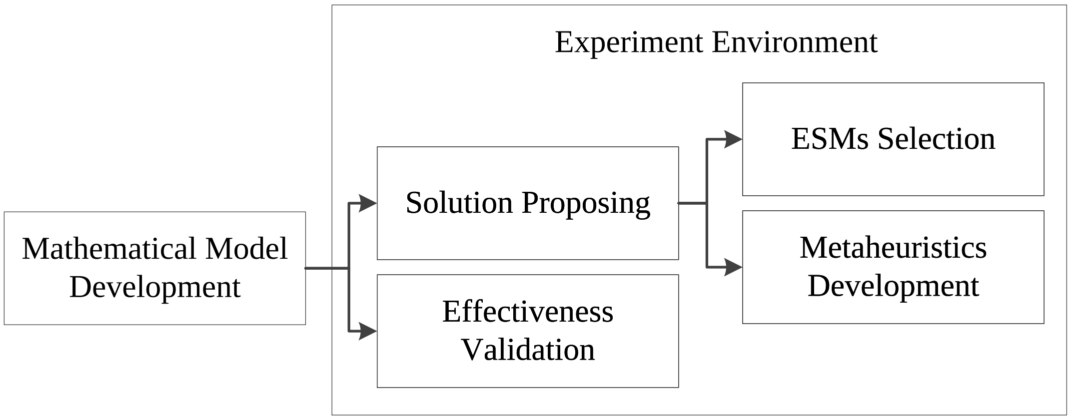


Figure 3.1: The structure of research methodology

3.2.1 Methods for optimisation model and instance development

The structure of this research and the scenarios and their internal relations within the experimental environment are described in **Figure 3.2**. The main characteristics and the relationships of six scenarios are shown in **Table 3.1** while details are given in **Section 3.2.2**.

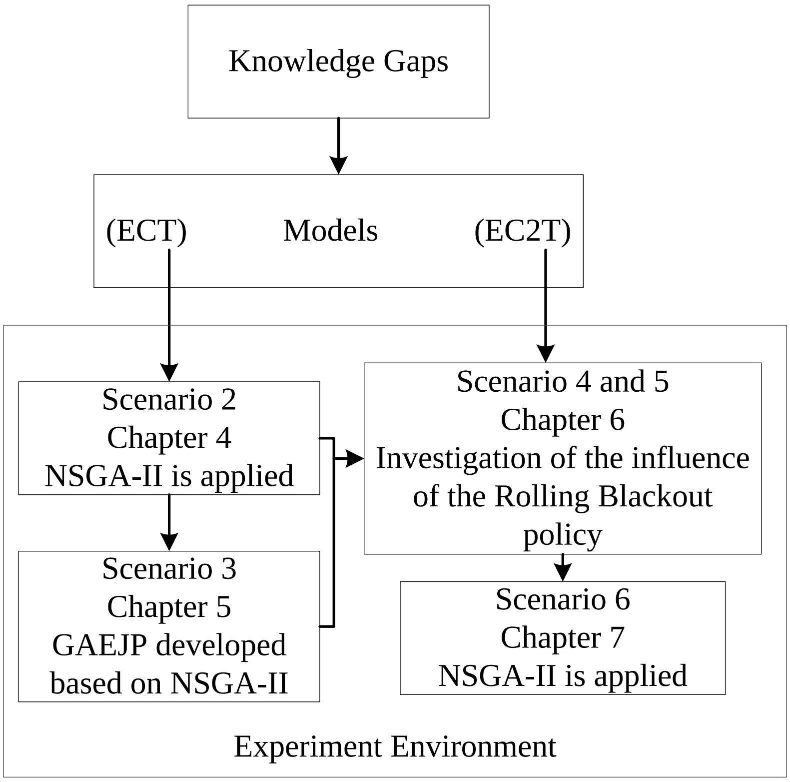


Figure 3.2: The internal relations between scenarios

As shown in **Figure 3.2**, the mathematical models for the ECT and EC2T problems should be developed first as the basis for this research. Thus, the electricity consumption pattern of machine tools when they continuously process different jobs and the

Rolling Blackout policy should be mathematically formalised. The optimisation model for the ECT problem is the combination of the classical job shop model and the newly developed electricity consumption model. Adding the Rolling Blackout policy model to the ECT optimisation model will lead to the model of the EC2T problem. The details of the mathematical model for these two multi-objective optimisation problems will be presented in the following sections.

After the mathematical model development step, job shop instances and the Rolling Blackout policy instances need to be formulated as the test cases. The job shop incorporates electrical consumption profiles for machine tools and the Rolling Blackout policy constraint can be separated into four parts: the job shop and its related parameters; the machine tools' electrical characteristics which correspond to the non-processing electricity consumption; the job-machine related electricity consumption which correspond to job related processing electricity consumption; and finally the pattern of electricity supply.

Four job shop cases are selected from the job shop instances provided by the OR-library (Beasley 1990) which are usually used as the benchmark for testing the performance of algorithms. The selected instances include: Fisher and Thompson 10×10 job shop instance (F&T 10×10), Lawrence 15×10, Lawrence 20×10 and Lawrence 15×15 job shop instances. These job shop instances are selected since they are large and require a comparatively long time to complete all the jobs. Therefore, the effectiveness of the proposed algorithms in reducing the electricity consumption and electricity cost is more evident by using these large job shop instances instead of the smaller ones (with number of jobs and number of machines smaller than 10, respectively).

To satisfy the requirements of this research, the due date and weight for each job and the time unit of the job shop problem need to be defined. The weight of each job J_i is randomly generated integer among 1, 2 and 3. The release time for each job is 0. The time unit is defined as minutes. According to the TWK due date assignment method (Sabuncuoglu & Bayiz 1999; Shi et al. 2007), the due date for a job can be defined as $Due = f \times total\ processing\ time\ of\ the\ job$, where f is the tardiness factor. The due date is decided by the tardiness factor f, where, for instance, $f = 1.5$, this value of f represents a tight due date case (corresponds to 50% tardy jobs). Thus, the value of f is gradually increased for each job shop instance until $f = 1.9$ during the experiments. When $f = 1.9$, in most of the job shop instances the value of total weighted tardiness reaches 0, which means the due date is loose enough so that all the jobs can be delivered before the deadline. The aim is to investigate the performance of the newly proposed solutions under different delivery requirement conditions by using different values in tardiness factor ($f = 1.5, 1.6, 1.7, 1.8, 1.9$). In other words, it can be expected that, when the due date is tight, the new solution may deteriorate the schedules' performance on total weighted tardiness though it can effectively reduce the electricity consumption. When the due date becomes loose, the potential to reduce the electricity consumption while guaranteeing an acceptable value in the total weighted tardiness becomes higher. This can inform the manufacturing plant manager that, the less busy the job shop is, the more opportunity there is to reduce the electricity consumption without deteriorating the delivery.

To perform the optimisation, the electrical characteristics for each machine in the job shop are needed. It can be supposed that all the machine tools in this research are automated ones, meaning that they have a high value of idle power. Thus, more significant optimisation results can be shown. Based on the research developed by Avram & Xirouchakis (2011), Baniszewski (2005), Dahmus (2007), Diaz et al. (2010), Drake et al. (2006), Kalla et al. (2009), Li et al. (2011) and Rajemi (2010), the electricity characteristics for the aforementioned four job shops are generated. All the values are presumed based on the literature. Therefore, they are actually random values located within reasonably defined ranges. The benefits for using random values are as follows. Firstly, the optimisation methods can be defined as generally applicable if they work well with random values. If the electrical consumption profiles for the machine tools are drawn from a real machining-based manufacturing system, and are used as the base for optimisation methods evaluation, then there is a danger that the proposed optimisation methods only work for that specific case. Secondly, if we would like to test more job shop instances in future with electrical characteristics, such as the total 82 job shop instances provided by the OR-library, it would be very time consuming to input the actual electricity characteristics for all the machines. Thus, randomly generating data for electrical characteristics of machines is a feasible method, as long as the values are in reasonable ranges. An example for generating the electricity profile for machines in the F&T 10×10 job shop is given in **Section**

3.7. The method for generating the electricity supply pattern can also be seen in this section.

3.2.2 Methods for experimental design

The main characteristics and the relationships of six scenarios are shown in **Table 3.1**.

Table 3.1: Scenario Design

Scenario	Content and ESMs selected	Function	Chapter
Scenario 1	The classic job shop scheduling problem with the single optimisation objective of minimising the total weighted tardiness. Corresponds to manufacturing companies that do not consider minimising electricity consumption as an objective for producing scheduling plans. None electricity and E-cost saving method is used in this scenario.	Baseline and Control group for Scenario 2 and Scenario 3	Chapter 4
Scenario 2	Minimising the total non-processing electricity consumption is considered as one of the objectives for proposing a job shop scheduling plan. NSGA-II is applied for solving the ECT. Only Sequencing is used as the electricity and E-cost saving method.	Control group for Scenario 3	Chapter 4
Scenario 3	Minimising the non-processing electricity consumption is considered as one of the objectives for proposing a job shop scheduling plan. A Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) is proposed based on the NSGA-II. The hypothesis that the new solution is superior to NSGA-II for the ECT problem will be tested. Turn Off/Turn On and Sequencing are used as the electricity and E-cost saving methods.	Proposing GAEJP and validation	Chapter 5
Scenario 4	The Rolling Blackout policy is applied; no private electricity is provided during the government resource unavailable periods; scheduling plans from Scenario 2 and Scenario 3 are executed. A new heuristic is proposed to help the manufacturing plant manager to adjust the scheduling plans to reduce the TWT as much as possible.	Control group for Scenario 6	Chapter 6
Scenario 5	The Rolling Blackout policy is applied; private electricity is provided during all the government resource unavailable periods; Execute the same scheduling plans as that in Scenario 4.	Control group for Scenario 6	Chapter 6
Scenario 6	The Rolling Blackout policy is applied; private electricity supply is available during all of the government resource unavailable periods. The optimisation solution for the EC2T is proposed.	Proposing new solution and validation	Chapter 7

Scenario 1

This scenario is the baseline which represents the circumstance that a manufacturing company develops its scheduling plans without considering reducing electricity consumption as an objective. As the benchmark, this scenario corresponds to a job shop scheduling problem with the single optimisation objective of minimising total weighted tardiness. Because the weight for each job and the electrical profile for all machines in the job shop instances are originally generated in this research, there is no available optimal solution in terms of minimising total weighted tardiness in the current literature to be used as the benchmark. Thus, the optimal solution for the single objective optimisation problem needs to be firstly found. The Shifting Bottleneck Heuristic and Local Search Heuristic (Pinedo, 2012) approaches will be used as the optimisation techniques in this scenario, since it has already been studied by many researchers and proven to be effective for the job shop scheduling problems. The software LEKIN developed by researchers at New York University (Pinedo, 2009) will be used for delivering the optimisation result in Scenario 1. An optimal scheduling plan and its corresponding Gantt chart will be obtained after the optimisation process. Then, based on the Gantt chart, the value of the total weighted tardiness and total electricity consumption can be obtained. Scenario 1 is the control group and benchmark for Scenarios 2 and 3 to demonstrate the effectiveness of NSGA-II and the new algorithm in solving the ECT problem and to explore the opportunity for them to reduce the electricity consumption in job shops. A control group in a scientific experiment is a group separated from the rest of the experiment where the independent variable being tested cannot influence the results. This isolates the independent variable's effects on the experiment and can help in ruling out alternate explanations of the experimental results (McBurney & White 2009). For instance, take identical growing plants and giving fertiliser to half of them; if there are differences between the fertilised plant group and the unfertilised "control" group, these differences may be due to the fertiliser. The algorithm plays the role of the "fertiliser" in this research.

Scenario 2

In Scenario 2, minimising the electricity consumption is considered as one of the objectives for proposing a job shop scheduling plan (ECT). Only the Sequencing method is applied in this scenario, but not Turn Off/Turn On yet. A large amount of research work has been carried out to employ meta-heuristics to minimise the total idle time of a scheduling plan, which can be seen as the reference for developing the optimisation approach in this scenario. The only difference is that the optimisation objective in this scenario is minimising the total “weighted” idle time of a schedule, the weight is actually the idle power level of each machine tool. NSGA-II will be used as the optimisation approach. The Pareto-front formed by p non-dominated solutions (a group of scheduling plans) will be obtained after the optimisation process. To demonstrate the electricity reduction potential of NSGA-II in solving the ECT problem, the solutions delivered by this algorithm will be compared with the benchmark solution in Scenario 1. The NSGA-II used here is provided by the Jmetal framework (Nebro and Durillo, 2011) since its object-oriented framework allows others to integrate their own algorithms and problems into it. The computational facility used in this research is Dell Latitude E6410 laptop with Intel Core i5 processor (2.67GHz) and 4 GB RAM.

Scenario 3

After observing the electricity consumption reduction performance of NSGA-II, it can be supposed that employing both the Turn Off/Turn On and sequencing method should produce better solutions for the ECT problem.. Electricity saving can be achieved by grouping the idle periods to create the new idles which are long enough to execute Turn Off/Turn On. Thus, in Scenario 3, GAEJP is developed based on NSGA-II aiming at solving ECT more effectively. In this algorithm, a new heuristic is developed to promote the aforementioned idle periods grouping. The solutions obtained by GAEJP will be compared with the benchmark solution to prove its electricity consumption reduction potential in solving the ECT problem. Then, the new solutions will be compared with the NSGA-II solutions to prove the hypothesis that it is superior to NSGA-II in solving the ECT problem. The algorithm has been developed based on the Jmetal framework (Nebro and Durillo, 2011).

Scenario 4, 5 and 6

The scheduling plans produced in Scenario 2 and 3 are used as the baseline for Scenarios 4 and 5 to investigate the influence that the Rolling Black policy exerts on the performance of these scheduling plans in terms of the objective values of the total weighted tardiness, total non-processing electricity consumption and total electricity cost. A new heuristic is proposed in Scenario 4 to help the manufacturing plant manager to adjust the scheduling plans to reduce the total weighted tardiness as much as possible when the Rolling Blackout policy is applied.

Scenario 4 is used to analyse how the manufacturing company's delivery deteriorates as a result of the Rolling Blackout policy. Therefore, in this scenario, the manufacturing company will not use any private electricity supply, such as a diesel generator, when the government supplied resource is unavailable. The job shop will stop working during the blackout periods. The scheduling plans produced in Scenario 2 and Scenario 3 will be adjusted in Scenario 4 to allocate the operations to government electricity available periods. The operations that initially would execute during the blackout periods should be postponed to the closest electricity supply available period, thereby constructing the new scheduling plan for Scenario 4. The comparison between the performance of scheduling plans in Scenario 4 and their original plans, for instance, scheduling plans in Scenario 3, will be used to show how the Rolling Blackout policy cause the schedules' performance on the total weighted tardiness to deteriorate when the use of private electricity is not allowed.

Scenario 5 is used to investigate the influence of employing private electricity on the total electricity cost when the Rolling Blackout is applied. Therefore, in this scenario, private electricity is used to provide power for the manufacturing company during all the blackout periods. The scheduling plans produced in Scenarios 2 and 3 will be performed in Scenario 5. Finally, the comparison between the performance of scheduling plans in Scenario 5 and their original plans, for instance, scheduling plans in Scenario 3, will be used to show that the aforementioned influence that the total electricity cost will increase in Scenario 5.Based on the investigation, it will be found that there is a requirement for proposing an approach to optimally use the private electricity supply, which is the EC2T problem. Finally, NSGA-II is applied to solve the EC2T in Scenario 6. The developed GAEJP is not used in this scenario. Since the main aim to build a schedule is not to achieve longer idle periods and then execute the Turn off/Turn on. Because in this scenario, long idle periods may result in wasting the government supplied electricity resource, and then increase the use of private electricity. Comparing the objective functions' values in Scenario 6 to those in Scenario 4, a better performance on total weighted tardiness should be observed. When comparing the objective functions' values in Scenario 6 to those in Scenario 5, a better performance on total electricity cost should be observed. The details of each scenario and the comparisons among them will be described in the following chapters. The mathematical models for the ECT and EC2T problems and an example for the job shop instance generation will be introduced in the remainder of this chapter.

3.3 Job shop model

Job shops are prevalent in industry. Normally, there are several jobs and each job will visit a number of machines following a predetermined route. As shown in **Figure 3.3**, component A and B are processed in a job shop with four machines, the processing routine for them are Machine $1-3-2-4$ and Machine $3-1-4-2$ respectively. The job shop model used in this research is the deterministic (static) one which means the number of jobs is fixed and all jobs are ready to be processed at time 0. The recirculation circumstance is not considered in this model which means a job only visits any given machine no more than once. The aim of this research is to reduce both TWT and NPE in an aforementioned static job shop. The formal mathematical definition of the problem will be described in detail in the following sections.

Referring to Özgüven et al. (2010), Jain & Meeran (1998) and Vázquez-Rodríguez & Petrovic (2010), in a job shop scheduling problem, $J = \{J_i\}_{i=1}^{n}$, a finite set of n jobs are to be processed on a finite set of m machines $M = \{M_k\}_{k=1}^{m}$, following a predefined order; $O_i = \left\{O_{ik}^{l}\right\}_{l=1}^{u_i}$ is a finite set of u_i ordered operations of J_i; O_{ik}^{l} is the l-th operation of J_i processed on M_k and it requires a processing time denoted p_{ik}^{l}. S_{ik}^{l} indicates the time that O_{ik}^{l} begins to be processed on M_k, while C_{ik}^{l} is the corresponding completion time of the process. $Y_{ii'k}^{ll'}$ is a decision variable such that $Y_{ii'k}^{ll'} = 1$ if O_{ik}^{l} precedes $O_{i'k}^{l'}$ on M_k, 0 otherwise. Each J_i has a release time into the system r_i and a due date d_i, w_i is the weighted importance of J_i.

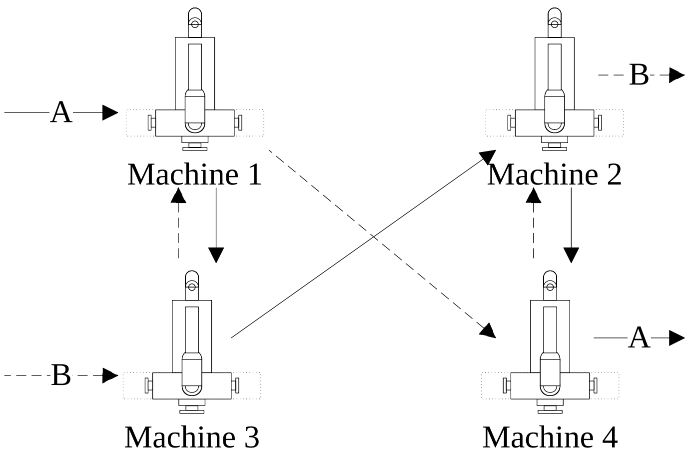


Figure 3.3: A typical job shop

Constraints:

$$S_{ik}^{l} \geq r_i \quad \forall J_i \in J, \forall O_{ik}^{l} \in O_i, \forall M_k \in M \tag{3.1}$$

$$C_{ik}^{l+1} - C_{ik'}^{l} \geq p_{ik}^{l+1} \quad 1 \leq l < l+1 \leq u_i,$$

$$k \neq k', \ \forall J_i \in J, \ \forall O_{ik}^{l+1}, O_{ik'}^{l} \in O_i, \ \forall M_k, M_{k'} \in M \tag{3.2}$$

$$S_{ik}^{l+1} - C_{ik'}^{l} \geq 0 \quad 1 \leq l < l+1 \leq u_i,$$

$$k \neq k', \ \forall J_i \in J, \ \forall O_{ik}^{l+1}, O_{ik'}^{l} \in O_i, \ \forall M_k, M_{k'} \in M \tag{3.3}$$

$$C_{i'k}^{l'} - C_{ik}^{l} \geq p_{i'k}^{l'} \quad Y_{ii'}^{ll'} = 1,$$

$$i \neq i', \forall J_i, J_{i'} \in J, \forall O_{ik}^{l} \in O_i, \forall O_{i'k}^{l'} \in O_{i'}, \forall M_k \in M \tag{3.4}$$

Where

$$Y_{ii'k}^{ll'} \in \{0,1\} \quad i \neq i', \forall J_i, J_{i'} \in J, \forall O_{ik}^{l} \in O_i, \forall O_{i'k}^{l'} \in O_{i'}, \forall M_k \in M$$

$$S_{ik}^{l} \geq 0, C_{ik}^{l} \geq 0 \quad \forall J_i \in J, \forall O_{ik}^{l} \in O_i, \forall M_k \in M$$

$$C_{ik'}^{l} \geq 0 \quad \forall J_i \in J, \forall O_{ik'}^{l} \in O_i, \forall M_{k'} \in M$$

Constraint (3.1) makes sure that the starting time of any job must be greater than its release time. Constraint (3.2) and (3.3) ensure that the precedence relationships between the operations of a job are not violated, i.e. O_{ik}^{l+1} is not started before the $O_{ik'}^{l}$ has been completed and no job can be processed by more than one machine at a time. Constraint (3.4) takes care of the requirement that no machine can process more than one operation at a time. A schedule s that complies with constraints (3.1) to (3.4) is said to be a feasible schedule. The 3×3 job shop instance and its related scheduling plan (Gantt chart) are presented in **Section 2.2.3**, which is a typical job shop instance.

Set S is a finite set of all feasible schedules such that $s \in S$. Given a feasible schedule s, let $C_i(s)$ indicates the completion time of J_i in schedule s. The tardiness of J_i can be denoted as $T_i(s) = max\{0, C_i(s) - d_i\}$.The objective is to minimise the total weighted tardiness of all jobs. This objective is chosen since it is a more general version of a due date related objective function. Minimising the total weighted tardiness is one of the objectives in the multi-objective optimisation for this research. The other two objective functions will be explained in **Section 3.4** and **Section 3.5**, respectively, and the concept of multi-objective optimisation was explained in **Section 2.3**.

$$minimise\left(\sum_{i=1}^{n} w_i \times T_i(s)\right) \tag{3.5}$$

3.4 Electricity consumption model

A very important basis is formalising the mathematical model of the electricity consumption of machine tools when they continuously process different jobs, thereby getting the total electricity consumption of the whole job shop. Without this model, it is not possible to carry out the optimisation in this research. Dietmair & Verl (2009) have shown the structure of a typical machine power input measurement for a simple aluminum milling operation. In **Figure 3.4**, a number of events can be seen to change the power intake between a number of clear cut levels. The time points that the events start are denoted by number 1 to 8 as shown in the figure. The content of the events and their sequence in the milling operation is described in the following. First, the coolant is switched on (1) and the machine executes a rapid motion to its starting position (2). Then the spindle speeds up (3) and the tool enters the work piece (4). Upon termination of the cut (5), the spindle (6) and the coolant (7) are switched off. A substantial idle power intake remains after that (8) (Dietmair & Verl 2009). The optimisation in this research is focused on the work shop level, thus there are two requirements for the machine's electricity consumption model building, one is simplification, and the other is distinguishing the processing electricity consumption and non-processing electricity consumption. Therefore, based on the existing research work on environmental analysis of machining (Dietmair & Verl, 2009; Kordonowy, 2003; Dahmus, 2007; Diaz et al., 2010; He et al., 2012), the simplified power input model for M_k while it is working on O_{ik}^{l} is shown in **Figure 3.5**.

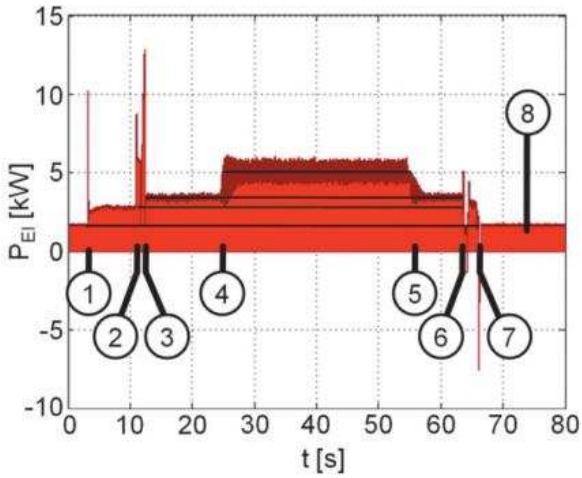


Figure 3.4: Actual power input at machine main connection over time (integral area= consumed energy)(Dietmair & Verl 2009)

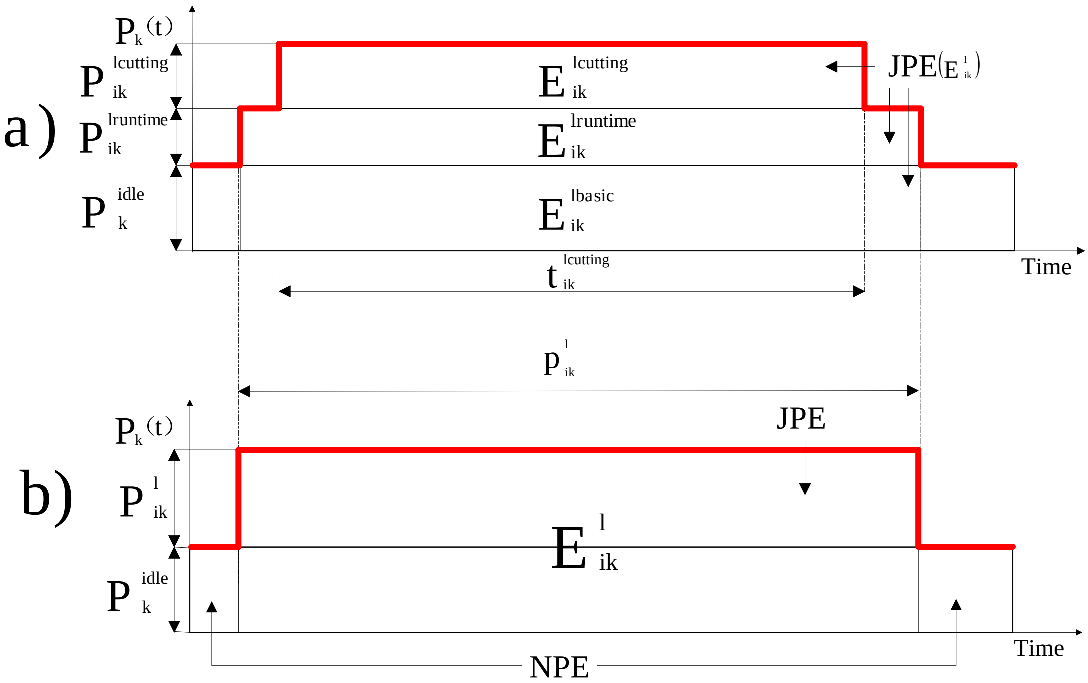


Figure 3.5: The simplified power input of a machine tool when it is working on one operation O_{ik}^{l}, (a) is the first step simplified version, (b) is the further simplified version)

The notations used are as follows:

The input power $P_k(t)$ a machine M_k requires over time is defined as a stepped function represented by the red line in **Figure 3.5**. The idle power level of a machine M_k is defined by P_k^{idle}, the increase in power during runtime operations for processing O_{ik}^l on machine $M_k$is defined by $P_{ik}^{lruntime}$, where the subscript i, k and superscript l have the same meaning with O_{ik}^l.The further additional power requirement for the actual cutting of O_{ik}^l on machine M_k is given by $P_{ik}^{lcutting}$. The overall processing time p_{ik}^l is defined as the time interval between the coolant switching on and off. The cutting time $t_{ik}^{lcutting}$ for an operation O_{ik}^l is often a slightly shorter time interval than the overall processing time. During the cutting time, the highest power level is required, that $P_k^{max} = P_k^{idle} + P_{ik}^{lruntime} + P_{ik}^{lcutting}$.

Assuming that the power levels remain constant during an operation, the basic energy consumption of a machine M_k during the whole processing time for operation O_{ik}^l can be defined as $E_{ik}^{lbasic} = P_k^{idle} \times p_{ik}^l$ and the additional energy required to put the machine into runtime mode is $E_{ik}^{lruntime} = P_k^{lruntime} \times p_{ik}^l$. The extra energy required for the cutting process during operation O_{ik}^l can be defined as $E_{ik}^{lcutting} = P_{ik}^{lcutting} \times t_{ik}^{lcutting}$. Hence, the job related processing electricity consumption (JPE) required to carry out an operation O_{ik}^l on machine M_k is $E_{ik}^l = E_{ik}^{idle} + E_{ik}^{lruntime} + E_{ik}^{lcutting}$.

According to the above definitions, E_{ik}^l can be treated as a constant for each operation O_{ik}^l, since the power levels (P_k^{idle}, $P_{ik}^{lruntime}$ and $P_{ik}^{lcutting}$), the process duration (p_{ik}^l) and cutting time ($t_{ik}^{lcutting}$) for each operation are fixed values. Therefore, it can be concluded that the processing electricity consumption (PE) required for all operations processed on a machine M_k, which is expressed as $\sum E_{ik}^l$, is also a constant. The value of $\sum E_{ik}^l$will not be affected by different scheduling plans. Thus, the objective to reduce the total electricity consumption of a job shop can be converted to reduce the total non-processing electricity consumption (NPE). Hence, the objective function can be set as the sum of all the NPE consumed by all the machines in a job shop to carry out a given job schedule:

$$minimise\left(\sum_{k=1}^{m} TEM_k^{np}(s)\right) \tag{3.6}$$

Where $TEM_k^{np}(s)$ is the NPE of machine M_k for schedule s. Unlike the PE, the NPE is a function of the scheduling plan. Hence, $TEM_k^{np}(s)$ needs to be expressed based on the specific order the different operations O_{ik}^{l} have been scheduled to run on a machine M_k. $M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^{l}}$ is the finite set of operations processed on M_k. γ_{ik}^{l} is a decision variable that $\gamma_{ik}^{l} = 1$ if the l-th operation of job J_i processed on M_k, 0 otherwise. With S_k^r and C_k^r respectively indicate the start and completion time of an operation m_k^r on M_k for a schedule s, this schedule can be graphically expressed as a Gantt chart as shown in **Figure 3.6**. Consequently, the calculation of the non-processing electricity consumption of machine M_k can be expressed based on the start and completion times defined for a schedule s:

If the Turn Off/Turn On is not allowed, then:

$$TEM_k^{np}(s) = P_k^{idle} \times [max\,(C_k^r) - min(S_k^r) - \sum_r (C_k^r - S_k^r)] \tag{3.7}$$

Equation (3.7) means that when the Turn Off/Turn On is not allowed, the NPE of M_k for schedule s is the difference between all the basic electricity consumption of M_k and the basic electricity consumption of M_k when it is processing jobs.

If the Turn Off/Turn On is allowed, then:

$$TEM_k^{np}(s) = P_k^{idle} \times \left[max\,(C_k^r) - min(S_k^r) - \sum\nolimits_r (C_k^r - S_k^r)\right]$$

$$-P_k^{idle} \times \sum_r \left(S_k^{r+1} - C_k^r\right) \times Z_k^r + E_k^{turn} \times \sum_r Z_k^r \tag{3.8}$$

To obtain the NPE of M_k for schedule s when the Turn Off/Turn On is allowed, Equation (3.8) firstly calculates the difference between all the basic electricity consumption of M_k and the basic electricity consumption of M_k when it is processing jobs. Then the basic electricity consumption during the original idle periods where the Turn Off/Turn On had been applied is subtracted. Finally the corresponding electricity consumed by all the Turn Off/Turn On operations (electricity required by all the start-up and shut down operations) is added.

According to Mouzon et al. (2007), E_k^{turn} is the electricity consumed by Turn Off/Turn On, that $E_k^{turn} = E_k^{turnoff} + E_k^{turnon}$.

$t_k^{OFF} = t_k^{turnoff} + t_k^{turnon}$, t_k^{OFF} is the time required to turn off M_k and turn it back on.

$E_k^{turnoff}$ and $t_k^{turnoff}$ are the electricity and time consumed to turn off the machine M_k and E_k^{turnon} and t_k^{turnon} are the electricity and time consumed to turn on the machine M_k.

For the purpose of simplification, the start-up and turn-off power spikes and their electricity consumption can be averagely allocated on t_k^{turnon} and $t_k^{turnoff}$.

Therefore, P_k^{turnon} is defined as the average power input for M_k during t_k^{turnon}, and $P_k^{turnoff}$ as the average power input of M_k during $t_k^{turnoff}$.

$E_k^{turnon} = P_k^{turnon} \times t_k^{turnon}$.

$E_k^{turnoff} = P_k^{turnoff} \times t_k^{turnoff}$.

B_k is the break-even duration of machine M_k for which Turn Off/Turn On is economically justifiable instead of running the machine idle, $B_k = E_k^{turn}/P_k^{idle}$. Z_k^r is a decision variable such that $Z_k^r = 1$ if $S_k^{r+1} - C_k^r \geq max(B_k, t_k^{OFF})$, 0 otherwise. **Figure 3.6** shows an example for the calculation of the NPE of M_k. $O_{i_1k}^{l_1}$, $O_{i_2k}^{l_2}$, $O_{i_3k}^{l_3}$, and $O_{i_4k}^{l_4}$ are processed by M_k. Based on Equation (3.7), to get the value of NPE which is represented by the blue grid area, firstly the total idle time of machine M_k in the above schedule needs to be calculated, which is $(C_k^4 - S_k^1) - \sum_{r=1}^{4}(C_k^r - S_k^r)$. Then, the aforementioned value is multiplied by the idle power level of machine M_k to obtain the NPE for a schedule.

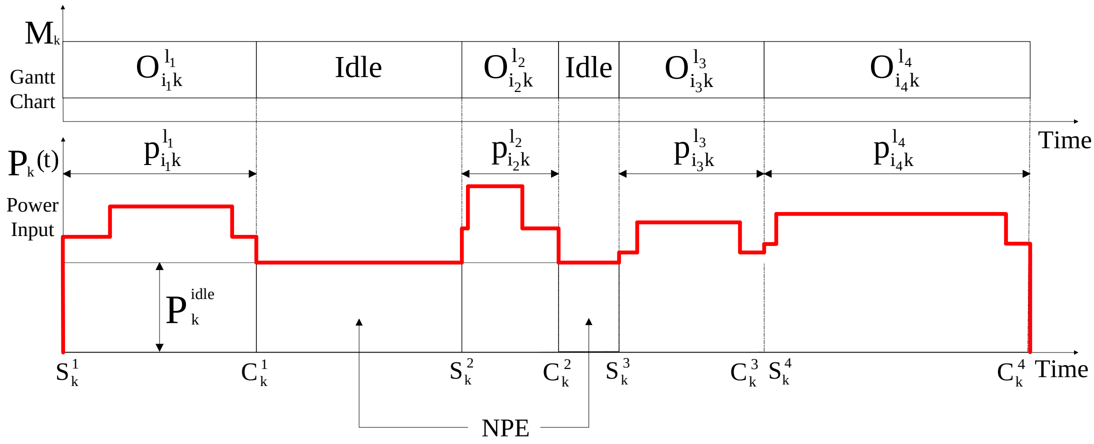


Figure 3.6: Gantt chart of M_k and its corresponding power profile

3.5 Electricity cost model

When the Rolling Blackout policy is applied, it will be difficult to estimate the loss for manufacturing companies during the period when no electricity is available from the public supplier (government electricity unavailable period, GUP). For the purpose of simplification, it could be supposed that manufacturing companies can start the private power supplementation with its associated higher cost. Thus, the loss during the electricity unavailable periods can be totally converted to increased electricity cost. This will simplify the calculation for cost. In reality, the Rolling Black policy would be executed as cutting off the government electricity supply for several days in every week. The policy needs to be generalised and abstracted as is seen in the mathematical model below. The objective function for electricity cost of a job shop based on the Rolling Blackout policy is:

$$minimise(TEC(s)) \tag{3.9}$$

$$TEC(s) = \sum_{k=1}^{m} TEC_k(s) \tag{3.10}$$

$$TEC_k(s) = p^e \times \int_0^{max(c_k^r)} P_k \quad p^e = \begin{cases} \beta_1, & t \in [(n-1)T,\ (n-1)T + t_s] \\ \beta_2, & t \in ((n-1)T + t_s, nT] \end{cases} \tag{3.11}$$

As seen in **Figure 3.7**, $TEC(s)$ and $TEC_k(s)$ refer to the total electricity cost of the job shop and M_k for a feasible schedule s, respectively.

p^e represents the electricity price such that $p^e = \beta_1\ Pounds/kWh$ if it is government electricity supply, and $p^e = \beta_2\ Pounds/kWh$ if it is private electricity supply such as diesel.

T denotes the cycle period of the Rolling Blackout policy.

t_s is the time point which separates T from Δt_s and Δt_o which respectively indicates the periods with (government electricity supply available period, GAP) and without the government electricity supply (GUP).

In this model, n is the natural number starting from 1; and t indicates the time.

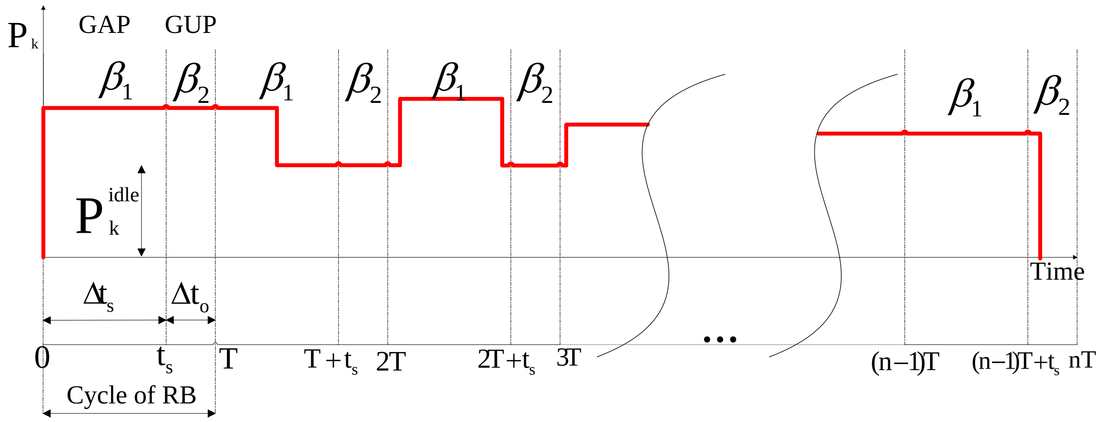


Figure 3.7: The timeline for the RB and the power input profile of M_k

3.6 Mathematical formalisation ECT and EC2T problem

The stated ECT and EC2T are multi-objective problems that have the following mathematical form:

$$minimise\ F(s) = \left(f_1(s), \dots, f_{nObj}(s)\right) \quad s \in S \tag{3.12}$$

where $f_k: S \mapsto \mathbb{R}$ is the k–th objective function and $nObj$ is the number of objectives. Vector F is a combination of objective functions, namely, $nObj = 2$ for the ECT problem and $nObj = 3$ for the EC2T problem. The quality of a schedule can be measured according to 2 or 3 criteria, including $f_1(s) = \sum_{i=1}^{n} w_i \times T_i(s)$ (Equation 3.5), $f_2(s) = \sum_{k=1}^{m} TEM_k^{np}(s)$ (Equation 3.7 and 3.8), $f_3(s) = TEC(s)$ (Equation 3.10).

Thus, the objective function of the ECT problem can be mathematically described as the following:

$$minimise\ F(s) = \left(f_1(s), f_2(s)\right)\ \ s \in S \tag{3.13}$$

The objective function of the EC2T problem can be mathematically described as follows:

$$minimise\ F(s) = \left(f_1(s), f_2(s), f_3(s)\right)\ \ s \in S \tag{3.14}$$

3.7 Generation of job shop and the Rolling Blackout policy instances

A modified job shop problem E-F&T 10×10 which incorporates electrical consumption profiles for the machine tools will be presented in the following section as an example to illustrate the required parameter definition approaches. For other modified job shop instances used in this research, see Appendix I Job shop instances for experiments.

3.7.1 Job shop and its related parameters

A modified job shop instance incorporates electrical consumption profiles for the machine tools: E-F&T 10×10 is developed based on the Fisher and Thompson 10×10 instance (F&T 10×10). To satisfy the requirements of this research, the due date and weight for each job and the time unit of the job shop problem need to be defined. According to the TWK due date assignment method (Sabuncuoglu & Bayiz 1999; Shi et al. 2007), $d_i = f \times \sum_{i=1}^{m} p_{ik}^{l}, i = 1,2,\cdots,n$ where f is the tardiness factor. The weight of each job J_i is randomly generated integer among 1, 2 and 3. The release time r_i for each job J_i is 0. The time unit is minutes. The parameters of the 10×10 job shop is given in **Table 3.2** and **Table 3.3**, where, for instance, $f = 1.5$, which represents a tight due date case (corresponds to 50% tardy jobs). In **Table 3.2**, for example, $M_1(29)$ means the first operation of job 1 (J_1) is processed on machine M_1 with a processing time of 29 minutes.

Table 3.2: The processing time p_{ik}^{l} of each operation O_{ik}^{l} and the technical route for each job $J_i$in the E-F&T 10×10 job shop instance (time unit: min)

$M_k(p_{ik}^{l})$	O_{ik}^{1}	O_{ik}^{2}	O_{ik}^{3}	O_{ik}^{4}	O_{ik}^{5}
J_1	$M_1(29)$	$M_2(78)$	$M_3(9)$	$M_4(36)$	$M_5(49)$
J_2	$M_1(43)$	$M_3(90)$	$M_5(75)$	$M_{10}(11)$	$M_4(69)$
J_3	$M_2(91)$	$M_1(85)$	$M_4(39)$	$M_3(74)$	$M_9(90)$
J_4	$M_2(81)$	$M_3(95)$	$M_1(71)$	$M_5(99)$	$M_7(9)$
J_5	$M_3(14)$	$M_1(6)$	$M_2(22)$	$M_6(61)$	$M_4(26)$
J_6	$M_3(84)$	$M_2(2)$	$M_6(52)$	$M_4(95)$	$M_9(48)$
J_7	$M_2(46)$	$M_1(37)$	$M_4(61)$	$M_3(13)$	$M_7(32)$
J_8	$M_3(31)$	$M_1(86)$	$M_2(46)$	$M_6(74)$	$M_5(32)$
J_9	$M_1(76)$	$M_2(69)$	$M_4(76)$	$M_6(51)$	$M_3(85)$
J_{10}	$M_2(85)$	$M_1(13)$	$M_3(61)$	$M_7(7)$	$M_9(64)$
$M_k(p_{ik}^{l})$	O_{ik}^{6}	O_{ik}^{7}	O_{ik}^{8}	O_{ik}^{9}	O_{ik}^{10}
J_1	$M_6(11)$	$M_7(62)$	$M_8(56)$	$M_9(44)$	$M_{10}(21)$
J_2	$M_2(28)$	$M_7(46)$	$M_6(46)$	$M_8(72)$	$M_9(30)$
J_3	$M_6(10)$	$M_8(12)$	$M_7(89)$	$M_{10}(45)$	$M_5(33)$
J_4	$M_9(52)$	$M_8(85)$	$M_4(98)$	$M_{10}(22)$	$M_6(43)$
J_5	$M_5(69)$	$M_9(21)$	$M_8(49)$	$M_{10}(72)$	$M_7(53)$
J_6	$M_{10}(72)$	$M_1(47)$	$M_7(65)$	$M_5(6)$	$M_8(25)$
J_7	$M_6(21)$	$M_{10}(32)$	$M_9(89)$	$M_8(30)$	$M_5(55)$
J_8	$M_7(88)$	$M_9(19)$	$M_{10}(48)$	$M_8(36)$	$M_4(79)$
J_9	$M_{10}(11)$	$M_7(40)$	$M_8(89)$	$M_5(26)$	$M_9(74)$
J_{10}	$M_{10}(76)$	$M_6(47)$	$M_4(52)$	$M_5(90)$	$M_8(45)$

Table 3.3: Parameters of each J_1 in the E-F&T 10×10 job shop, $r_i = 0$ (time unit: min)

J_i	d_i (due date)	w_i (weight)
J_1	592	1
J_2	769	2
J_3	852	3
J_4	982	1
J_5	589	3
J_6	744	2
J_7	624	3
J_8	808	2
J_9	895	1
J_{10}	810	1

3.7.2 Machine tools' electrical characteristics

The electricity characteristics for the E-F&T 10×10 job shop are generated and shown in **Table 3.4** based on the method described in **Section 3.2.1**.

Table 3.4: The electricity characteristics for the E-F&T 10×10 job shop

M_k	P_k^{idle}	$P_k^{turnoff}$	P_k^{turnon}	$t_k^{turnoff}$	t_k^{turnon}
M_1	2400W	1700W	1500W	1.2min	4.3min
M_2	3360W	1800W	2000W	1.6min	5.7min
M_3	2000W	1400W	1300W	0.8min	4.0min
M_4	1770W	1100W	1000W	0.8min	3.2min
M_5	2200W	1400W	1500W	1.3min	4.4min
M_6	7500W	2000W	2400W	1.5min	6.3min
M_7	2000W	1400W	1300W	0.8min	4.0min
M_8	1770W	1100W	1000W	0.8min	3.2min
M_9	2200W	1400W	1500W	1.3min	4.4min
M_{10}	7500W	2000W	2400W	1.5min	6.3min

3.7.3 Job-machine related electricity consumption:

The value of each P_{ik}^l , which is the average runtime operations and cutting power of O_{ik}^l on M_k, also need to be defined. Based on the references mentioned in **Section 3.2.1**, the interval of the average runtime operations and cutting power of each M_k is defined in **Table 3.5**. All of the P_{ik}^l values are uniformly distributed integers in these ranges. For instance, P_{11}^1 is the average runtime operations and cutting power of operation O_{11}^1, which is an integer within the interval of [2420W, 4000W]. Thus, for each P_{ik}^l, values are randomly generated within its reasonable interval for the E-F&T 10×10 job shop, as shown in **Table 3.6**. For example, $M_1(2450)$ means the first operation of job 1 (J_1) is processed on machine M_1 with an average runtime operations and cutting power of 2450 watts.

Table 3.5: The range of value for P_{ik}^l of each M_k

M_k	M_1(W)	M_2(W)	M_3(W)	M_4(W)	M_5(W)
P_{ik}^l	[2420, 4000]	[4200, 6100]	[3200, 5100]	[2200, 3600]	[3120, 5700]
M_k	M_6(W)	M_7(W)	M_8(W)	M_9(W)	M_{10}(W)
P_{ik}^l	[10000, 13000]	[3200, 5100]	[2200, 3600]	[3120, 5700]	[10000, 13000]

Table 3.6: The value of each P_{ik}^{l} in the E-F&T 10 × 10 job shop

$M_k(p_{ik}^l)$	P_{ik}^1(W)	P_{ik}^2(W)	P_{ik}^3(W)	P_{ik}^4(W)	P_{ik}^5(W)
J_1	M_1(2450)	M_2(5730)	M_3(5000)	M_4(2700)	M_5(4300)
J_2	M_1(3900)	M_3(3300)	M_5(5550)	M_{10}(11080)	M_4(3250)
J_3	M_2(5700)	M_1(2550)	M_4(3600)	M_3(4900)	M_9(5700)
J_4	M_2(4350)	M_3(4760)	M_1(3970)	M_5(3170)	M_7(3780)
J_5	M_3(4620)	M_1(3520)	M_2(5600)	M_6(12800)	M_4(2980)
J_6	M_3(5050)	M_2(4750)	M_6(11700)	M_4(3050)	M_9(4300)
J_7	M_2(6000)	M_1(2800)	M_4(3540)	M_3(5100)	M_7(3970)
J_8	M_3(4670)	M_1(3600)	M_2(4200)	M_6(13000)	M_5(4760)
J_9	M_1(3870)	M_2(5500)	M_4(2560)	M_6(10500)	M_3(3250)
J_{10}	M_2(5100)	M_1(2980)	M_3(3500)	M_7(4890)	M_9(3970)
$M_k(p_{ik}^l)$	P_{ik}^6(W)	P_{ik}^7(W)	P_{ik}^8(W)	P_{ik}^9(W)	P_{ik}^{10}(W)
J_1	M_6(11200)	M_7(4900)	M_8(2670)	M_9(5130)	M_{10}(10000)
J_2	M_2(5800)	M_7(4900)	M_6(12100)	M_8(3600)	M_9(5000)
J_3	M_6(10900)	M_8(2300)	M_7(4280)	M_{10}(12700)	M_5(3370)
J_4	M_9(5290)	M_8(2960)	M_4(2750)	M_{10}(13000)	M_6(12500)
J_5	M_5(5210)	M_9(4780)	M_8(3250)	M_{10}(11800)	M_7(5000)
J_6	M_{10}(12080)	M_1(2420)	M_7(4480)	M_5(3520)	M_8(2720)
J_7	M_6(13000)	M_{10}(12030)	M_9(3390)	M_8(3500)	M_5(5500)
J_8	M_7(5100)	M_9(5690)	M_{10}(10000)	M_8(2900)	M_4(3520)
J_9	M_{10}(10060)	M_7(3450)	M_8(2520)	M_5(4000)	M_9(4260)
J_{10}	M_{10}(12700)	M_6(10000)	M_4(3400)	M_5(5210)	M_8(3500)

3.7.4 The Rolling Blackout policy

This electricity supply pattern is developed based on the fact that in some areas in China the government electricity is available only from Monday to Thursday in one week, which means in $3/7$ of the production time private electricity has to be employed. In some other areas, the government electricity is available for several hours in a working day. The private electricity costs twice as much as the government supplied resource. Thus, it can be defined that the electricity price $p^e = 12.5\, pence/kWh$ if it is government electricity supply, while $p^e = 20.5\, pence/kWh$ if it is private electricity supply. The cycle period T of the Rolling Blackout policy is 10 hours. The government electricity supply available period $\Delta t_s = 480\, min$ and the government electricity supply unavailable period $\Delta t_o = 120\, min$

3.8 Summary

An experimental environment which includes six different scenarios is designed in this chapter. A scenarios comparison experiment is proposed to demonstrate that NSGA-II is effective in solving both ECT and EC2T problems, and the developed

Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) is effective in solving the ECT problem. The mathematical models for both of the ECT and EC2T are presented. Based on the models, a modified job shop instance has been developed and presented which incorporates electrical consumption profiles for machine tools and the Rolling Blackout policy constraints. The models proposed are one of the main contributions of this thesis, since the electricity consumption profile of machine tools has for the first time been formalised and integrated into the classical job shop model. On the other hand, the model for the Rolling Blackout policy has been formalised for the first time in this research.

CHAPTER 4 MINIMISING TOTAL ENERGY CONSUMPTION AND TOTAL WEIGHTED TARDINESS IN JOB SHOPS USING NSGA-II

4.1 Introduction

The goal in this chapter is to investigate the effectiveness of NSGA-II in reducing the total non-processing electricity consumption in a basic job shop by changing the processing sequence of jobs on each machine. This problem is modelled as a bi-objective optimisation problem (ECT) in Chapter 3. The multi-objective optimisation algorithm NSGA-II has been chosen to obtain a set of alternative solutions (a Pareto-front), which can be used by a manager to determine the most suitable solution that can be implemented. The performance of the algorithm has been tested on four extended version of job shop instances which incorporate electrical consumption profiles for the machine tools. The results are compared with the optimisation result of a well-established traditional scheduling approach of a manufacturing company without considering reducing the total electricity consumption as an objective. Employing Sequencing as the electricity and E-cost saving method, the NSGA-II is proved to be effective in solving the ECT and reducing the total non-processing electricity consumption.

4.2 The baseline scenario (Scenario 1)

Scenario 1 (S1) is created to represent the traditional circumstance when manufacturing companies develop their scheduling plans. The Shifting Bottleneck Heuristic (SBH) and Local Search Heuristic (LSH) approaches provided by the software LEKIN (Pinedo 2009) will be used as the optimisation techniques in this scenario. The parameters of Scenario 1 are defined in **Table 4.1**, where f is the tardiness factor, s^f is the optimised scheduling plan under different tardiness constraints; for instance, $s^{1.5}$ is the optimal scheduling plan obtained in the single optimisation circumstance when $f = 1.5$; twt_{s1}^{f} and npe_{s1}^{f} represent the total weighted tardiness and total non-processing electricity of the scheduling plan s^f, respectively. For the four job shop instances presented in Appendix I, both Shifting Bottleneck Heuristic and Local Search Heuristic are applied as the optimisation approach. The scheduling plans with minimum objective values are total weighted tardiness are adopted and the total non-processing electricity consumption is calculated, as shown in **Table 4.2**, **Table 4.3**, **Table 4.4** and **Table 4.5**. These results will be compared with the optimisation results delivered by NSGA-II in **Section 4.4**. The due date is decided by the tardiness factor f, where, for instance, $f = 1.5$, represents a tight due date case (corresponds to 50% tardy jobs). Thus, the value of f for each job shop instance is gradually increased until $f = 1.9$ in the experiments. When $f = 1.9$, in most of job shop instances the value of total weighted tardiness reaches 0, which means the due date is loose enough so that all jobs can be delivered before the deadline. For instance, the first row of **Table 4.2** shows that for the E-F&T 10×10 job shop, when the tardiness factor is 1.5, the optimal value of the total weighted tardiness ($twt_{s1}^{1.5}$) that can be achieved is 309 weighted minutes. This result is obtained by the Shifting Bottleneck Heuristic. Based on this optimal schedule, the value of the total non-processing electricity consumption ($npe_{s1}^{1.5}$) can be calculated, which is 181 kWh.

Table 4.1: Parameters of Scenario 1

Objective	• $minimise\ \sum_{i=1}^{n} w_i \times T_i(s^f)$
Indicators	• $twt_{s1}^{f} = \sum_{i=1}^{n} w_i \times T_i(s^f)$ • $npe_{s1}^{f} = \sum_{k=1}^{m} TEM_k^{np}(s^f)$
Optimisation Method	Shifting Bottleneck Heuristic (SBH) Local Search Heuristic (LSH)
ESMs implementation	No ESMs is applied

Table 4.2: The optimisation result of SBH and LSH of the E-F&T 10×10 job shop by LEKIN

Tardiness factor (f)	TWT (twt_{s1}^{f}) in weighted min	Total NPE (npe_{s1}^{f}) in kWh	Heuristic
1.5	309	181	SBH
1.6	127	181	SBH
1.7	25	169.7	LSH
1.8	0	169.7	LSH

Table 4.3: The optimisation result of SBH and LSH of the E-Lawrence 15×10 job shop by LEKIN

Tardiness factor (f)	TWT (twt_{s1}^{f}) in weighted min	Total NPE (npe_{s1}^{f}) in kWh	Heuristic
1.5	1321	212.8	LSH
1.6	694	207.7	LSH
1.7	293	230.7	LSH
1.8	53	169.3	LSH
1.9	0	200.0	LSH

Table 4.4: The optimisation result of SBH and LSH of the E-Lawrence 20×10 job shop by LEKIN

Tardiness factor (f)	TWT (twt_{s1}^{f}) in weighted min	Total NPE (npe_{s1}^{f}) in kWh	Heuristic
1.5	5099	153.5	LSH
1.6	4032	111.2	LSH
1.7	2805	122.1	LSH
1.8	2066	137.0	LSH
1.9	1352	126.7	LSH

Table 4.5: The optimisation result of SBH and LSH of the E-Lawrence 15×15 job shop by LEKIN

Tardiness factor (f)	TWT (twt_{s1}^{f}) in weighted min	Total NPE (npe_{s1}^{f}) in kWh	Heuristic
1.5	600	436.9	LSH
1.6	71	424.0	LSH
1.7	0	458.3	LSH

4.3 Solving the ECT with NSGA-II (Scenario 2)

In Scenario 2, minimising the total non-processing electricity consumption is considered as one of the objectives for proposing a job shop scheduling plan. The total non-processing electricity consumption in this scenario refers only to the idle electricity consumption when the machine is not in use. Only the Sequencing method is applied in this scenario, but not Turn Off/Turn On yet. NSGA-II is used as the optimisation approach. The Pareto-front formed by p non-dominated solutions (a group of scheduling plans) will be obtained after the optimisation process. Thus, indicators' values of Scenario 2 are:

$$twt_{s2}^{fq} = f_1(s^{fq}) = \sum_{i=1}^{n} w_i \times T_i(s^{fq}) \qquad (4.1)$$

$$npe_{s2}^{fq} = f_2(s^{fq}) = \sum_{k=1}^{m} TEM_k^{np}\,(s^{fq}) \qquad (4.2)$$

f is the tardiness factor, and s^{fq} is the q-th optimised scheduling plan in the total p solutions under different tardiness constraints. The parameters of Scenario 2 are shown in **Table 4.6**. twt_{s2}^{f} is the set of total weighted tardiness of solutions obtained by NSGA-II, where the subscript $s2$ represents Scenario 2. The superscript f represents the tardiness factor. twt_{s2}^{fq} is one of the elements in twt_{s2}^{f}, which represents the total weighted tardiness of the q-th optimised scheduling plan in p solutions under different tardiness constraints. Similarly, npe_{s2}^{f} is the set of total non-processing electricity consumption of solutions obtained by NSGA-II. npe_{s2}^{fq} is the total non-processing electricity consumption of the q-th optimised scheduling plan in p solutions.

Table 4.6: Parameters of Scenario 2

Objective	• $minimise\ \sum_{i=1}^{n} w_i \times T_i(s)$ • $minimise\ \sum_{k=1}^{m} TEM_k^{np}(s)$
Indicators	• $twt_{s2}^{f} = \{twt_{s2}^{fq}\}_{q=1}^{p}$ • $npe_{s2}^{f} = \{npe_{s2}^{fq}\}_{q=1}^{p}$
Optimisation Method	NSGA-II
ESMs implementation	Sequencing

Table 4.7: Expected results for scenarios comparison for the ECT problem

Scenarios comparison	**Expected result**
Compare Scenario 2 to Scenario 1	$twt_{s1}^{f} \leq minimum\ of\ twt_{s2}^{f}, \exists npe_{s2}^{fq} \leq npe_{s1}^{f}$

Table 4.7 presents the expected results of comparison between Scenario 2 and Scenario 1. It is used to justify the proposal NSGA-II in Scenario 2 can effectively reduce the total non-processing electricity consumption. However, decreasing in the total non-processing electricity consumption of a scheduling plan might degrade its performance on the objective of minimising the total weighted tardiness. It is the decision maker's responsibility to judge whether the loss in delivery is acceptable or not. Based on the aforementioned scenario comparison experiment, it can be ex-

pected that NSGA-II is effective in solving the ECT problem. This hypothesis will be proved by the following content of this chapter. The procedure of NSGA-II is introduced in the following section.

4.3.1 NSGA-II

The NSGA-II has two main operators: This algorithm has two main operators: the non-dominated sorting procedure and crowding distance sorting procedure. Non-dominated sorting procedure ranks the solutions in different Pareto fronts. The crowded distance sorting procedure calculates the dispersion of solutions in each front and preserves the diversification of the algorithm. In each generation of this algorithm, these two functions form the Pareto fronts (Rabiee et al., 2012). Vilcot and Billaut (2008) provide a summary for the working procedure of NSGA-II, as in following. For more information refer to Deb et al. (2002).

4.3.1.1 Non-dominated sorting procedure

All solutions of a certain population (denoted by P_t) are evaluated according to the non-dominated sorting method as shown in **Figure 4.1**. Level 1 contains all the dominant individuals within the population. If individuals in the first level are not considered, the second set of dominant individuals constitutes level 2. The process iterates until each individual belongs to one level. The level (rank) where an individual locates is the most important factor of its fitness. An individual with a lower rank is preferable. The fast non-dominated sorting procedure is described in **Figure 4.3**: $p \prec q$ means that solution p strictly dominates solution q.

For each solution we calculate two entities: 1) Domination count n_p, the number of solutions which dominate the solution p, and 2) S_p, a set of solutions that the solution p dominates. All solutions in the first non-dominated front will have their domination count as zero. p_{rank} is the order of front that the solution p belongs to. Then, for each solution p with $n_p = 0$, we visit each member (q) of its set S_p and reduce its domination count by one. In doing so, if for any member q the domination count becomes zero, we put it in a separate list Q. These members belong to the second non-dominated front. The above procedure is continued with each member of Q and the third front is identified. This process continues until all fronts are identified. For each solution p in the second or higher level of non-domination, the domination count n_p can be at most $N - 1$.

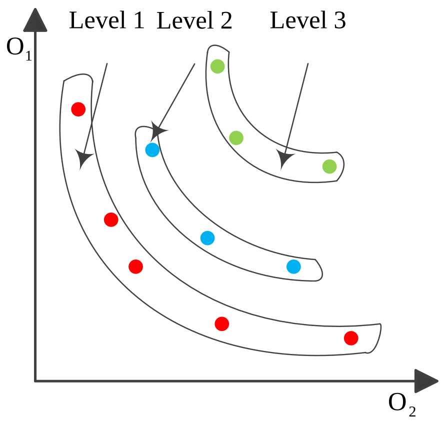


Figure 4.1: Non-dominated levels (Deb et al. 2002)

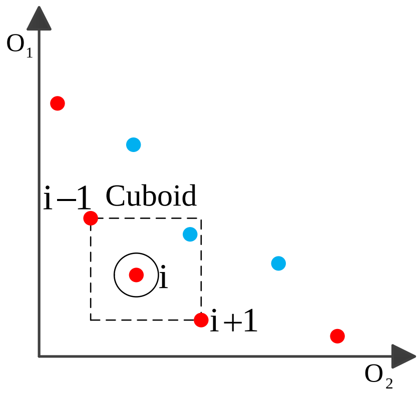


Figure 4.2: Computation of the crowding distance (Deb et al. 2002)

4.3.1.2 Crowding distance sorting procedure

The crowding distance of a solution is defined by Deb et al., (2002) as an estimate of the density of solutions in the perimeter of the cuboid formed by using the nearest neighbours as the vertices. The diversity of the population is guaranteed by using the crowding distance sorting procedure. For an individual, the crowding distance is the sum of the normalised distance between the right and left neighbours for each objective function. The extreme solutions have a crowding distance equal to infinity (see **Figure 4.2**). The algorithm in **Figure 4.4** outlines the crowding-distance computation procedure of all solutions in a non-dominated set I. Here, $I[i].m$ refers to the m-th objective function value of the i-th individual in the set I. f_m^{max} and f_m^{min} are the maximum and minimum values of the m-th objective function.

Fast-non-dominated-sort (P)	
for each $p \in P$	
$S_p = \emptyset$	
$n_p = 0$	
for each $q \in P$	
if ($p \prec q$) then	If p dominates q
$S_p = S_p \cup \{q\}$	Add q to the set of solutions dominated by p
else if ($q \prec p$) then	
$n_p = n_p + 1$	Increment the domination counter of p
if $n_p = 0$ then	p belongs to the first front
$p_{rank} = 1$	
$F_1 = F_1 \cup \{p\}$	
$i = 1$	Initialise the front counter
while $F_i \neq \emptyset$	
$Q = \emptyset$	Used to store the members of the next front
for each $p \in F_i$	
for each $q \in S_p$	
$n_q = n_q - 1$	
if $n_q = 0$ then	q belongs to the next front
$q_{rank} = i + 1$	
$Q = Q \cup \{q\}$	
$i = i + 1$	
$F_i = Q$	

Figure 4.3: The pseudo-code for the non-dominanted sorting procedure (Deb et al. 2002)

Crowding-distance-assignment (I)	
$l = \lvert I \rvert$	Number of solutions in I
for each i, set $I[i].distance = 0$	Initialise distance
for each objective m	
$I = sort(I, m)$	Sort using each objective value
$I[1].distance = I[l].distance = \infty$	So that boundary points are always selected
for $i = 2\ to\ (l - 1)$	For all other points
$I[i].distance = I[i].distance$	
$+ (I[i+1].m - I[i+1].m)/\left(f_m^{max} - f_m^{min}\right)$	

Figure 4.4: The pseudo-code for the crowding distance procedure (Deb et al. 2002)

4.3.1.3 Crowded-comparison operator

Based on **Section 4.3.1.1** and **Section 4.3.1.2**, every individual i in the population has two attributes:

1) Non-domination rank (i_{rank});
2) Crowding distance ($i_{distance}$);

The crowded-comparison operator (a partial order) $\prec_n$ can be defined as:

$$i \prec_n j \text{ if } (i_{rank} < j_{rank})$$

$$\text{or } (i_{rank} = j_{rank})$$

$$\text{and } (i_{distance} > j_{distance})$$

The selection operator is a binary tournament: between two randomly selected individuals, the selected individual is the one with the lower rank. If two individuals are on the same level, the winner is the one with the larger value of the crowding distance.

4.3.1.4 The procedure of NSGA-II

In the beginning of the algorithm, an initial population P_0 with the size of N is randomly generated. All the individuals of P_0 are sorted using the non-dominated sorting procedure and the crowding distance sorting procedure. Then, the algorithm employs selection, crossover and mutation operators to create the first offspring set Q_0 ($|Q_0| = N$). The selection process employs the crowded-comparison operator and binary tournament method described in **Section 4.3.1.3**. At a given generation t, R_t is defined as the union of the parents P_t and their offspring Q_t. Thus, $|R_t| = 2N$. Individuals of R_t are sorted following the aforementioned two procedures. Front F_f is defined as the set of non-dominated solutions of level f. The individuals in P_{t+1} are the solutions of front F_1 to F_λ with λ such that $\sum_{i=1}^{\lambda}|F_i| \leq N$ and $\sum_{i=1}^{\lambda+1}|F_i| > N$ plus the $N - \sum_{i=1}^{\lambda}|F_i|$ first solutions of $F_{\lambda+1}$ according to their descending value in crowding distance. The remaining solutions are rejected. Solutions from P_{t+1} are used to make the new offspring population Q_{t+1}. **Figure 4.5** illustrates the generation of population P_{t+1} and **Figure 4.6** shows the whole process of NSGA-II.

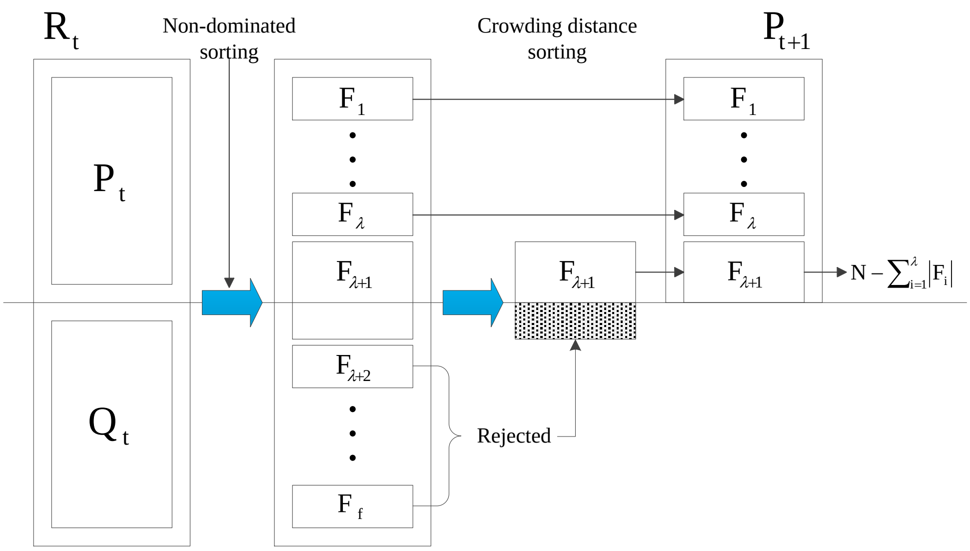


Figure 4.5: Construction of population P_{t+1}

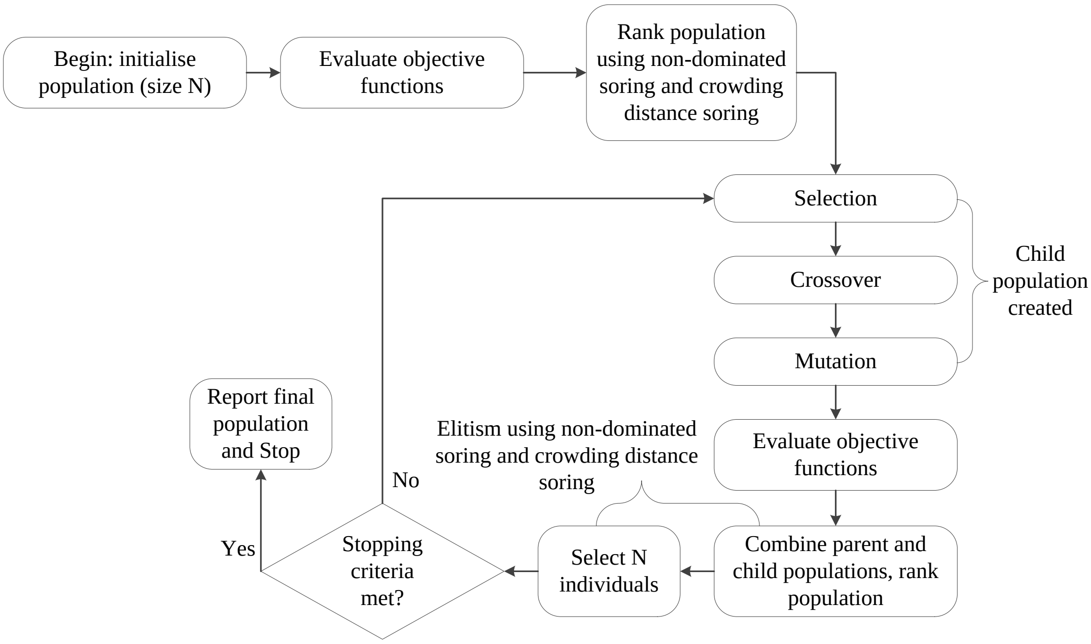


Figure 4.6: The flowchart of NSGA-II

The OBES and active schedule builder (see **Section 2.3.3**) are adopted in this Scenario. The binary tournament is adopted as the selection operator (See **Section 2.3.2**) Referring to Liu & Wu (2008), Cheng et al. (1999) and Ono et al. (1996), the crossover and mutation operators and stopping criteria are explained in the following section. These operators are selected since they have been widely used in solving job shop scheduling problems with genetic algorithms. The crossover operator described below is particularly suitable for job shop scheduling problems.

4.3.2 Crossover operator

The operation-based order crossover (OOX) which is developed based on the job-based order crossover (JOX) is adopted as the crossover operator. The advantage of OOX is that it can avoid producing an illegal chromosome as offspring. Given parent 1-A_1 and parent 2-A_2, OOX generates child 1-A_1' and child 2-A_2' by the following procedure:

1. Randomly, choose the same operations from both parents. The loci of the selected operations are preserved.
2. Copy the operations chosen at step 1 from A_1 to A_1', A_2 to A_2', the loci of them are preserved in the offspring.
3. Copy the operations, which are not copied at step 2, from A_2 to A_1', A_1 to A_2', their order is preserved in the offspring.

For example, in a 3×3 job shop, $[321123321]$ and $[222333111]$ are feasible parent chromosomes. The loci of operations, which are O_{32}^1, O_{22}^2 and O_{13}^3 in the boxes are preserved.

$$A_1 = [\boxed{3}211\boxed{2}332\boxed{1}]$$

$$A_2 = [2\boxed{2}2\boxed{3}3311\boxed{1}]$$

A_1' and A_2' are feasible child chromosomes as shown below:

$$A_1' = [\boxed{3}223\boxed{2}311\boxed{1}]$$

$$A_2' = [2\boxed{2}1\boxed{3}1332\boxed{1}$$

The crossover rate will be added according to the experimental results.

4.3.3 Mutation operator

The swap mutation operator is employed which means that two different arbitrary genes of the chromosome in the mating pool after the crossover procedure are chosen and then the values are swapped. Following the above example, A_1'' is the final child chromosome of A_1 after applying mutation on A_1'.

$$A_1' = [32\boxed{2}3231\boxed{1}1]$$

$$A_1'' = [32\boxed{1}3231\boxed{2}1]$$

The mutation rate will be added according to the experimental results. After the mutation, all parents in the population will be replaced by offsprings.

4.3.4 Stopping criteria

The maximum number of generations is used as the stopping criteria. When the algorithm reaches this stage, the algorithm stops, and the approximate Pareto-front is contained in the current set of non-dominated solutions.

4.4 Comparison between Scenario 2 and Scenario 1

The optimal parameters settings of the NSGA-II for the operators and stopping criteria, which provide the best final solution, are obtained after the initial tuning process, as shown in **Table 4.8**, **Table 4.9**, **Table 4.10** and **Table 4.11**. The values of the tardiness factor f for each job shop are the same as those in Scenario 1, as described in **Section 4.2**. During the tuning process, the values used for the crossover rate are $[0.8, 0.9, 1.0]$, for the mutation rate are $[0.01, 0.02, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6]$, for the number of generations are $[25000, 30000, 35000, 40000, 45000, 50000]$, for the population size are $[500, 600, 700, 800, 900, 1000]$. Different combinations of the aforementioned values are tested in the experiments. Based on these tests, the optimal parameters setting of the NSGA-II for each case can be obtained. Take the first row in **Table 4.8** as an example, for the E-F&T 10×10 job shop, when the tardiness factor is 1.5, with the population size of 1000, crossover probability of 1.0, mutation probability of 0.6, the NSGA-II has been run for 40000 generations to achieve the optimal solution. Actually, during the test, the algorithm has been run for 50000 generations, but the solutions did not improve in the 40000's to 50000's generations. Thus, 40000 is the best value for the numbers of generations in this case. The same method has been applied to find the best value for the number of generations for other cases. It also can be found from **Table 4.8** that a comparatively high mutation probability is used in the algorithm for the E-F&T 10×10 job shop. The reason for this situation might be that the population size is not large enough. Since generally, a larger population size means a higher diversity of population. Thus, a lower mutation rate can be used if the diversity of the population is originally high. Therefore, in the future work, larger values in the population size will be tested.

Table 4.8: The parameters settings for the NSGA-II (E-F&T 10×10 job shop)

Tardiness Factor f	Population size N	Crossover probability p_c	Mutation probability p_m	Generation t
1.5	1000	1.0	0.6	40000
1.6	1000	1.0	0.6	40000
1.7	800	1.0	0.6	30000
1.8	800	1.0	0.6	25000

Table 4.9: The parameters settings for the NSGA-II (E-Lawrence 15×10 job shop)

Tardiness Factor f	Population size N	Crossover probability p_c	Mutation probability p_m	Generation t
1.5	500	0.9	0.1	30000
1.6	500	0.9	0.2	30000
1.7	800	0.9	0.2	30000
1.8	800	0.9	0.1	40000
1.9	800	0.9	0.2	40000

Table 4.10: The parameters settings for the NSGA-II (E-Lawrence 20×10 job shop)

Tardiness Factor f	Population size N	Crossover probability p_c	Mutation probability p_m	Generation t
1.5	500	0.9	0.1	20000
1.6	500	0.9	0.1	30000
1.7	500	0.9	0.1	30000
1.8	500	0.9	0.1	25000
1.9	500	0.9	0.1	30000

Table 4.11: The parameters settings for the NSGA-II (E-Lawrence 15×15 job shop)

Tardiness Factor f	Population size N	Crossover probability p_c	Mutation probability p_m	Generation t
1.5	1000	0.9	0.2	40000
1.6	1000	0.9	0.1	40000
1.7	800	0.9	0.2	30000

The algorithm has been developed based on the Jmetal framework (Nebro and Durillo, 2011). The comparisons between the solutions in S1 (a single objective job shop scheduling problem) and the solutions in Scenario 2 are shown in **Figure 4.7**, **Figure 4.8**, **Figure 4.9** and **Figure 4.10**.

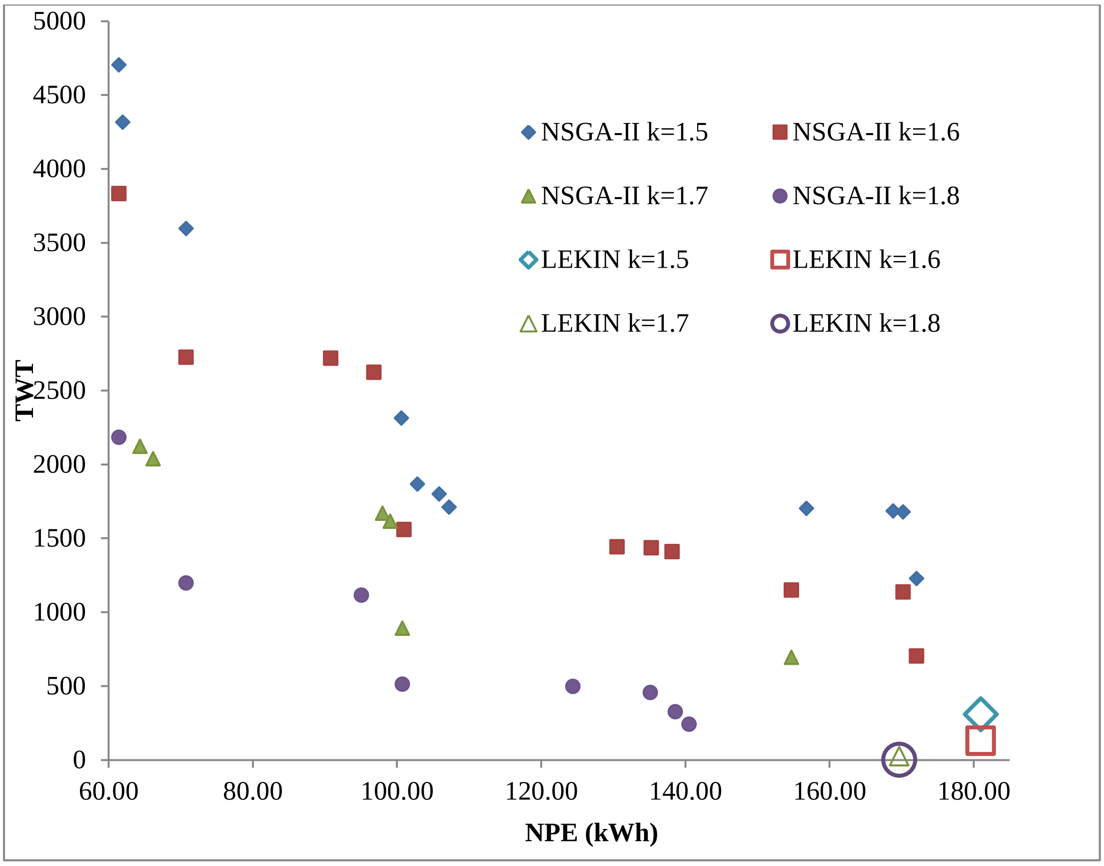


Figure 4.7:The solution comparison between NSGA-II and the baseline scenario (E-F&T 10 × 10 job shop)

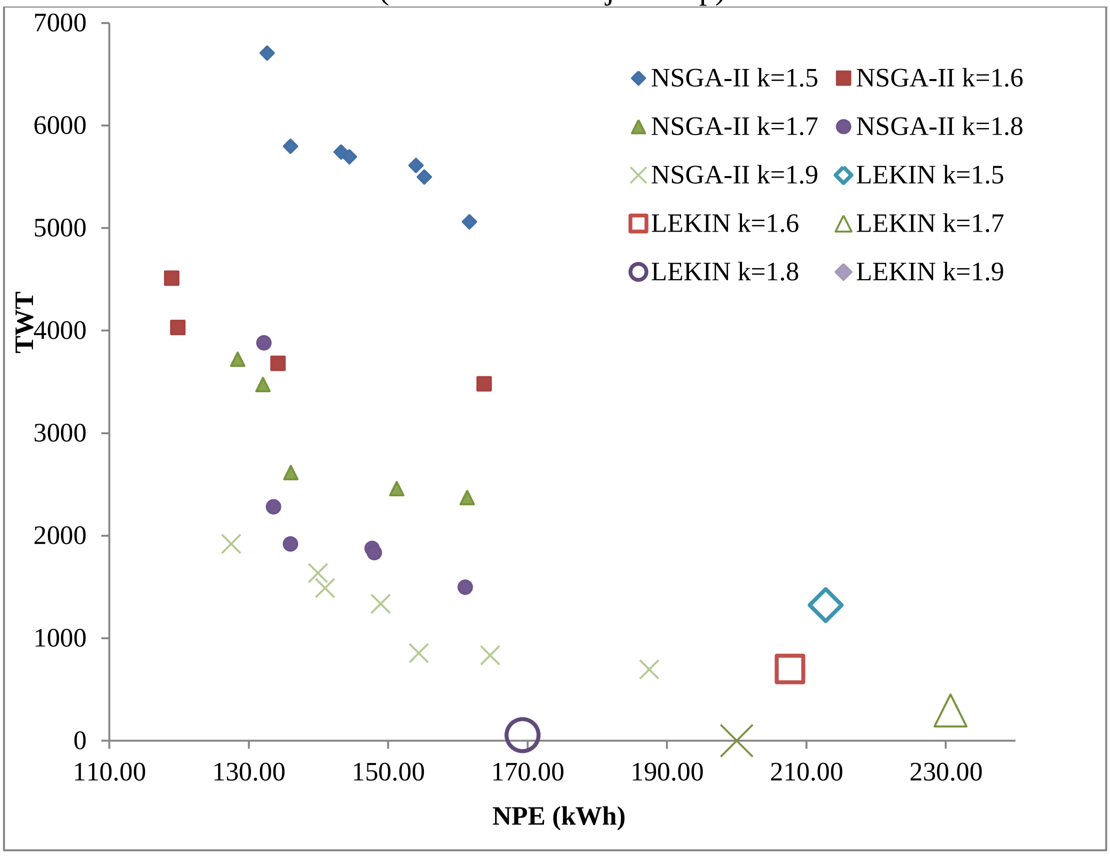


Figure 4.8: The solution comparison between NSGA-II and the baseline scenario (E-Lawrence 15 × 10 job shop)

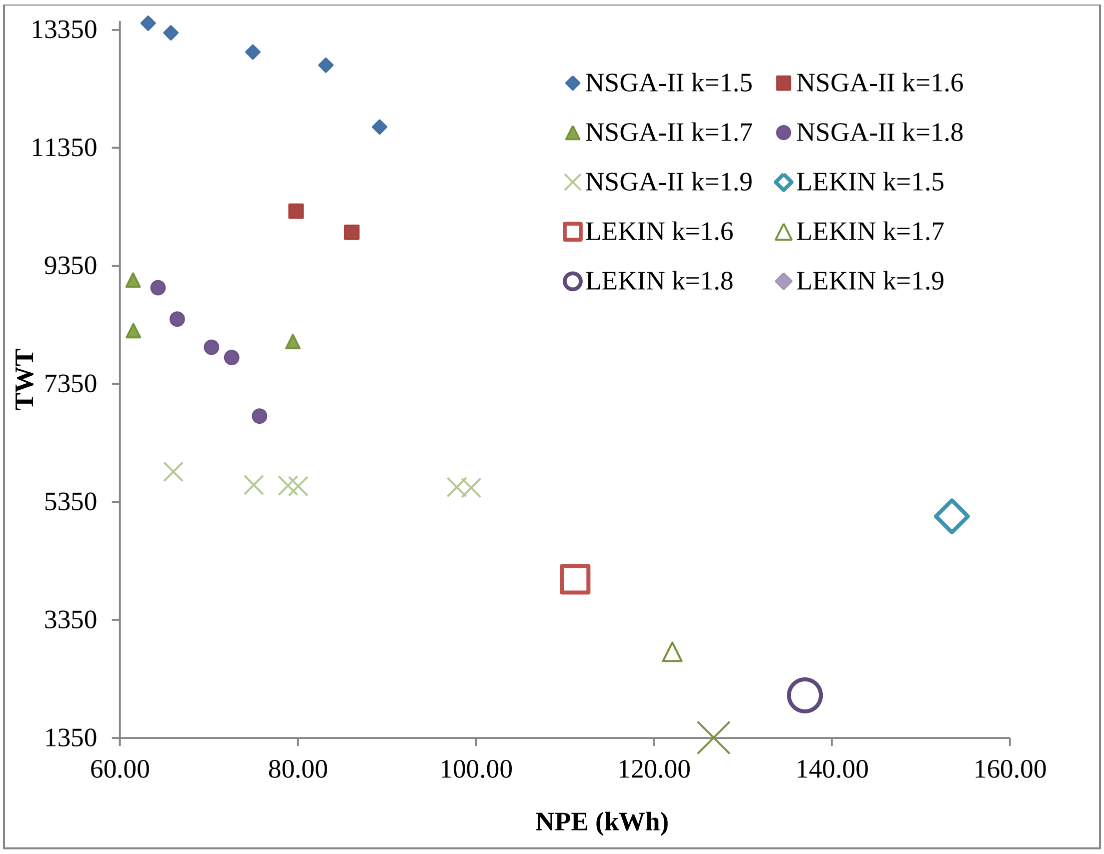


Figure 4.9: The solution comparison between NSGA-II and the baseline scenario (E-Lawrence 20 × 10 job shop)

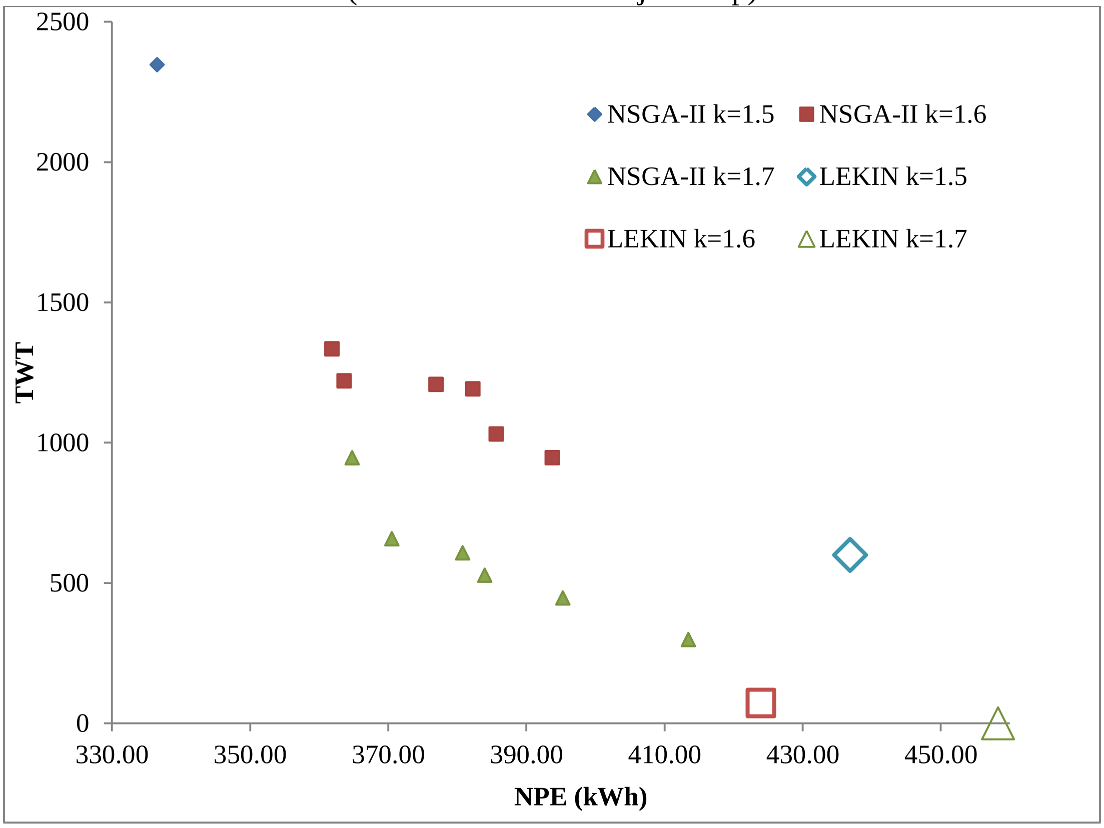


Figure 4.10: The solution comparison between NSGA-II and the baseline scenario (E-Lawrence 15 × 15 job shop)

In the above figures, the hollow points represent the optimisation results of LEKIN which had been shown in **Table 4.2-Table 4.5**. The solid points represent the optimisation results of NSGA-II. Analysing these figures, a considerable total non-processing electricity consumption reduction can be observed when employing NSGA-II as the bi-objective optimisation approach, compared to the single objective optimisation result of Shifting Bottleneck Heuristic and Local Search Heuristic. The non-processing electricity consumption reductions in percentage for each job shop are shown in **Table 4.12** and **Table 4.13**. Compared to the results of LEKIN, an increase in total weighted tardiness values of the NSGA-II results can also be observed from the above figures. The total weighted tardiness increases in weighted minutes for each job shop instance under different tardiness conditions are shown in **Table 4.14** and **Table 4.15**. These two tables demonstrate the range for the total weighted tardiness deterioration of the optimisation result of NSGA-II when compared to the LEKIN result. It can be observed that total weighted tardiness reduces when the due date become less tight, i.e. when the value of k increases. Take the E-F&T 10×10 job shop as an example, when $f = 1.5$, the minimum and maximum value of $npe_{s2}^{1.5}$ are 61 kWh and 172 kWh respectively, which means a 5.0% to 66.3% improvement in the total non-processing electricity consumption compared to the values obtained by LEKIN, which is 181Kwh. There is an increase in total weighted tardiness, the minimum value of $npe_{s2}^{1.5}$ is 1226 weighted min, while $twt_{s1}^{1.5} = 309$ weighted min. However, when the due date becomes less tight, the difference between twt_{s2}^{f} and twt_{s1}^{f} is much smaller. For instance, when $f = 1.8$, $\min\{twt_{s2}^{1.8}\} - twt_{s1}^{1.8} = 241$ weighted min, at the same time, the total non-processing electricity consumption reduction is 16.9% compared to the value obtained by LEKIN.

Table 4.12: The NPE improvement in percentage for E-F&T 10×10 and E-Lawrence 15×10

Compare NSGA-II to LEKIN		E-F&T 10×10				E-Lawrence 15×10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement	min	5.0%	5.0%	8.7%	16.9%	24.0%	21.1%	30.1%	4.9%	6.3%
	max	66.3%	66.3%	62.3%	64.1%	37.7%	42.7%	44.2%	21.9%	36.2%

Table 4.13: The NPE improvement in percentage for E-Lawrence 20×10 and E-Lawrence 15×15

Compare NSGA-II to LEKIN		E-Lawrence 20×10					E-Lawrence 15×15		
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9	f=1.5	f=1.6	f=1.7
NPE Improvement	min	41.9%	22.6%	34.9%	44.7%	21.5%	24.0%	21.1%	30.1%
	max	58.8%	48.1%	49.7%	53.1%	47.9%	37.7%	42.7%	44.2%

Table 4.14: The TWT increase in weighted minutes for E-F&T 10×10 and E-Lawrence 15×10

Compare NSGA-II to LEKIN		E-F&T 10×10				E-Lawrence 15×10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
TWT Increase	min	917	576	668	241	3736	2783	2076	1442	691
	max	4394	3706	2097	2182	5385	3816	3424	3824	1915

Table 4.15: The TWT increase in weighted minutes for E-Lawrence 20×10 and E-Lawrence 15×15

Compare NSGA-II to LEKIN		E-Lawrence 20×10					E-Lawrence 15×15		
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9	f=1.5	f=1.6	f=1.7
TWT Increase	min	6603	5881	5261	4734	4234	1747	875	298
	max	8359	6349	6299	6911	4506	1747	1263	946

4.5 Discussion

Based on the above, it can be observed that NSGA-II is effective in reducing the total non-processing electricity consumption in a scheduling plan while sacrificing its performance of total weighted tardiness to a certain extent, especially when a very tight due date is presented. However, it can be expected that this sacrifice can be neglected when there are more jobs to be processed in the work shop. For instance, when combining 100 such 10×10 job shop, the difference between twt_{s2}^{f} and twt_{s1}^{f} is very small compared to the total weighted production time. Nevertheless, the decrease in the total non-processing electricity consumption will become more and more considerable along with the increasing number of jobs. The upper (part A) and bottom (part B) parts of **Figure 4.11** represent the Gantt charts of optimised schedules of Shifting Bottleneck Heuristic and NSGA-II respectively. When $f = 1.5$ for the E-F&T 10×10 job shop. It can be observed that the schedule produced by NSGA-II has a higher ratio of Production Time compared to the Total Up-Time of the machines (PT/TUP) for most of the machines, as shown in **Figure 4.12**. In this case, the average values of PT/TUP for all machines in S1 and the NSGA-II optimisation scenario are 69.5% and 77.7% respectively. From above, the scheduling plans produced by NSGA-II are more preferable for managers when considering the real life job shop type manufacturing system. Since the varieties and amounts of components in the real manufacturing circumstance are largely increasing compared to the simple 10×10 job shop, and the PT/TUP is a very important indicator for shop floor management. As shown in **Figure 4.11**, the scheduling plan provided by NSGA-II is tighter than the scheduling plan provided in Scenario 1. This means that with the increase of the number of jobs, the NSGA-II scheduling plans can provide more space for new jobs to be scheduled in (as the comparison between the area circled by the red line between Part B and Part A). This further implies that when there are more jobs, the scheduling plan provided by the NSGA-II will keep its good performance on reducing the total NPE and increasing PT/TUP. In addition, it can be observed from **Figure 4.7** that the less tight the due date, the less deterioration there is in minimising the total weighted tardiness objective, i.e. the more non-bottleneck machines in the manufacturing system, the larger the opportunity to reduce the total NPE.

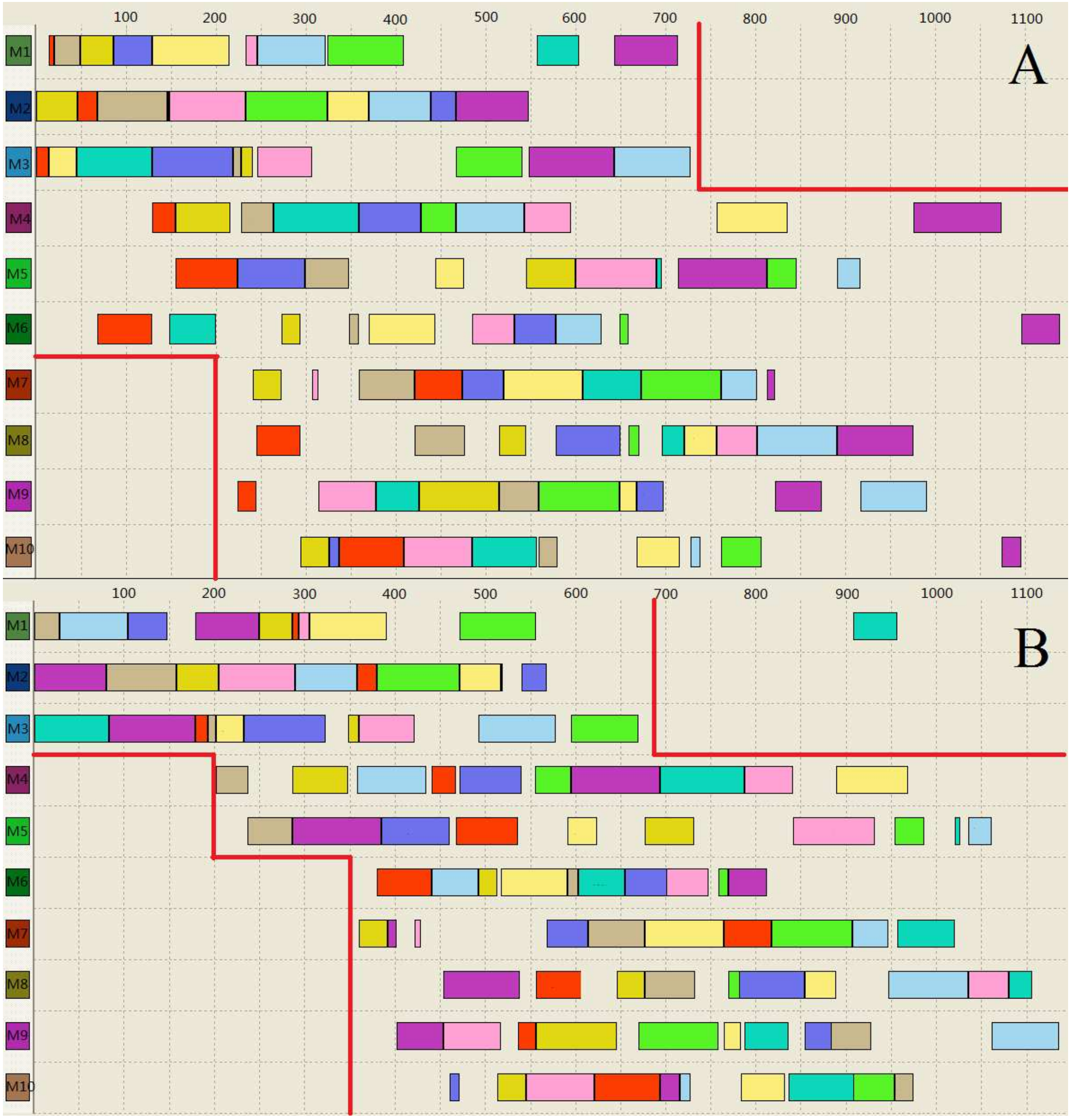


Figure 4.11: Gantt chart of optimised schedule of SBH while $f = 1.5$ (E-F&T 10×10 job shop)

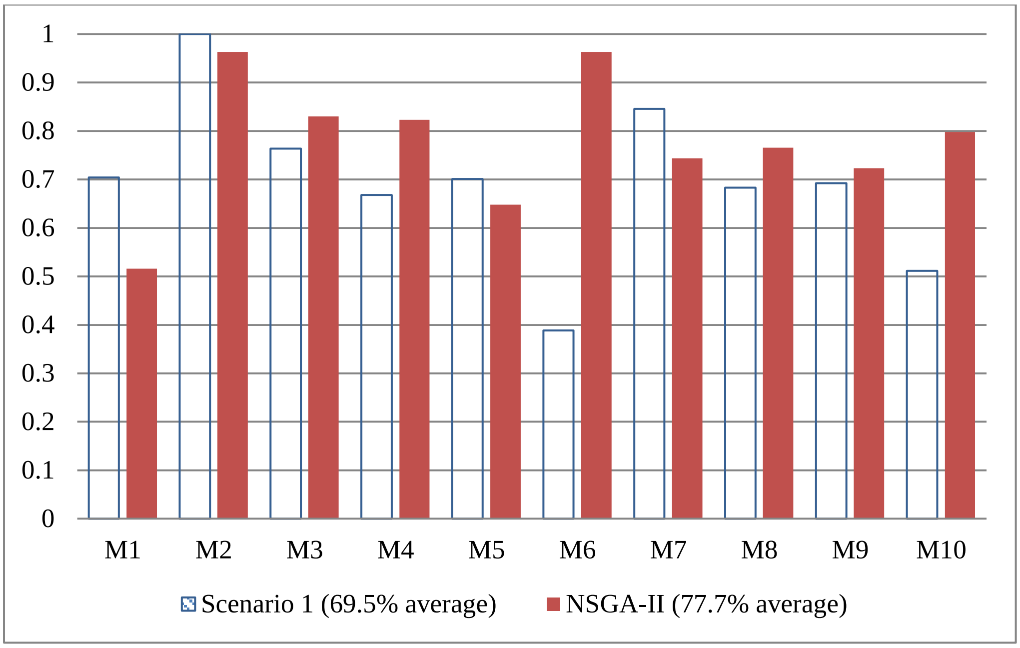


Figure 4.12: Comparison in machine utilisation
(E-F&T 10 × 10 job shop)

4.6 Summary

Reducing electricity consumption as well as keeping good performance on classical scheduling objectives for job shops is a difficult problem that can take a large amount of time to solve. For solving this problem, the multi-objective optimisation algorithm NSGA-II was applied. The performance of the algorithm has been tested on four extended versions of job shop instances which incorporate electrical consumption profiles for the machine tools. These instances include: Fisher and Thompson 10×10 job shop scenario, Lawrence 10×10, 20×10 and 15×15 job shop scenarios. In addition, comparison experiments have been applied where the Shifting Bottleneck Heuristic and the Local Search Heuristic had been adopted as the single objective optimisation techniques to deliver the baseline scenarios of the aforementioned job shops. The result of the comparison indicates that by applying NSGA-II, the total non-processing electricity consumptions in the job shop are decreased considerably, but at the sacrifice of their performance on the total weighted tardiness up to a certain extent. However, it can be expected that this sacrifice can be largely reduced if the number of jobs is increased. This chapter focused only on how to reduce the total non-processing electricity consumption in a basic job shop by changing the processing sequence of jobs on each machine. However, the Turn off/Turn on method developed by Mouzon et al. (2007) is another very effective approach in achieving this objective. Therefore, developing a new algorithm which enables both the Sequencing and Turn Off/Turn On approaches to be applied to solve the ECT problem is worth investigating. The developed new algorithm is presented in the next chapter.

CHAPTER 5 MINIMISING TOTAL ENERGY CONSUMPTION AND TOTAL WEIGHTED TARDINESS IN JOB SHOPS USING GAEJP

5.1 Introduction

The Turn off/Turn on method developed by Mouzon et al. (2007) is another very effective approach to reduce the total non-processing electricity consumption in a basic job shop. Thus, in this chapter, the goal is to develop a new algorithm which enables both of the Sequencing and the Turn Off/ Turn On approaches to be optimally utilised in solving the ECT problem. As a result, a multi-objective optimisation algorithm GAEJP is developed based on the NSGA-II (Scenario 3). Its corresponding scheduling techniques are developed as well. The performance of the algorithm has been tested on four extended version of several job shop instances which incorporate electrical consumption profiles for the machine tools. This is compared with the optimisation results of well-established traditional scheduling approaches of a manufacturing company where reducing the electricity consumption is not considered as an objective (Scenario 1). The GAEJP is proved to be effective in solving the ECT and reducing the total non-processing electricity consumption. In the comparison with the optimisation results of NSGA-II (Scenario 2), the GAEJP demonstrated superiority in solving the ECT problem.

5.2 Scenario 3 and expected results of the comparison experiment

The Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) will be developed in this scenario. The hypothesis is that the new solution is superior to the NSGA-II at solving the ECT problem. This is one of the main contributions of this PhD research. The parameters of Scenario 3 are shown in **Table 5.1**. twt_{s3}^{f} is the set for the objective function values of total weighted tardiness of solutions obtained by the GAEJP. The subscript $s3$ represents Scenario 3, the superscript f represents the tardiness factor. twt_{s3}^{fq} is one of the elements in twt_{s3}^{f}, which represents the total weighted tardiness of the q-th optimised scheduling plan in the total p solutions under different tardiness constraints. Similarly, npe_{s3}^{f} is the set for the objective function values of total non-processing electricity consumption of solutions obtained by the GAEJP. npe_{s3}^{fq} is the total non-processing electricity consumption of the q-th optimised scheduling plan in the total p solutions under different tardiness constraints.

Table 5.1: Parameters of Scenario 3

Objective	• $minimise\ \sum_{i=1}^{n} w_i \times T_i(s)$ • $minimise\ \sum_{k=1}^{m} TEM_k^{np}(s)$
Indicators	• $twt_{s3}^{f} = \{twt_{s3}^{fq}\}_{q=1}^{p}$ • $npe_{s3}^{f} = \{npe_{s3}^{fq}\}_{q=1}^{p}$
Optimisation Method	Modified NSGA-II (GAEJP)
ESMs implementation	Turn Off/Turn On; Sequencing

The optimisation objectives, performance indicators of Scenario 3 are the same as in Scenario 2. However, the Turn Off/Turn On method is applied in Scenario 3, which means the non-processing electricity consumption refers to idle and Turn Off/Turn On electricity consumption. An algorithm is proposed based on the NSGA-II as the new solution for the ECT. The Pareto-front formed by p non-dominated solutions (a group of scheduling plans) are obtained after the optimisation process. Thus, indicators' values of Scenario 3 are two sets where:

$$twt_{s3}^{fq} = f_1(s^{fq}) = \sum_{i=1}^{n} w_i \times T_i(s^{fq}) \tag{5.1}$$

$$npe_{s3}^{fq} = f_2(s^{fq}) = \sum_{k=1}^{m} TEM_k^{np}\,(s^{fq}) \tag{5.2}$$

f is the tardiness factor, and s^{fq} is the q-th optimised scheduling plan in the total p solutions under different tardiness constraints.

Table 5.2: Expected results for scenarios comparison for the ECT problem

Scenarios comparison	Expected result
Compare Scenario 3 to Scenario 1	$twt_{s1}^{f} \le minimum\ of\ twt_{s3}^{f}, \exists npe_{s3}^{fq} \le npe_{s1}^{f}$
Compare Scenario 3 to Scenario 2	$\exists npe_{s3}^{fq} \le \forall npe_{s2}^{fq}$

Table 5.2 presents the expected results of comparison between Scenarios 3 and 1, and the expected results of comparison between Scenarios 3 and 2. They are used to justify that the GAEJP in Scenario 3 will be effective in reducing the total non-

processing electricity consumption. However, decreasing the total non-processing electricity consumption of a scheduling plan might cause deterioration in its performance on the objective of minimising the total weighted tardiness. It is the decision maker's preference to judge whether the loss in delivery is acceptable or not. The comparison between Scenario 3 and Scenario 2 is to demonstrate that the optimisation approach developed in Scenario 3 is more effective than that in Scenario 2. Based on the aforementioned scenario comparison experiments, it can be expected that the approach delivered in Scenario 3 is currently the most effective one for solving the ECT problem. This hypothesis is proved by the following content of this chapter.

5.3 The reason for using the semi-active schedule builder in Scenario 3 and its decoding procedure

In Scenario 3, Turn Off/Turn On and Sequencing are selected and combined as the electricity and E-cost saving method. Thus, the way to reduce the total non-processing electricity consumption is to try to build longer idle periods during the operation sequence generating process on each machine M_k. Since it can create opportunities to execute the Turn Off/Turn On operation. This is also the reason for building the semi-active schedule at the initial stage instead of the active one, since in a semi-active schedule normally some operations can be shifted to the left without delaying other operations. This creates some longer idle periods which are opportunities for executing Turn Off/Turn On. In the next section, the decoding procedure of the semi-active schedule builder is explained. The semi-active schedule in **Figure 5.1** and **Figure 5.2** show how to develop a schedule which is a better solution for the ECT.

The definition of the semi-active schedule is introduced in **Section 2.2.3**. The procedures of using the active and the semi-active schedule builders to transform the example chromosome [222333111] into feasible schedules are depicted in **Figure 5.1**. In employing the semi-active schedule builder, the first step of the decoding procedure is the same as that of the active schedule builder as described in **Section 2.2.3**. The example chromosome can be firstly translated to a list of ordered operations as $[O_{23}^1 O_{22}^2 O_{21}^3 O_{32}^1 O_{31}^2 O_{33}^3 O_{11}^1 O_{12}^2 O_{13}^3]$. In the second step, the schedule generation still follows the one-pass heuristic. However, the allocation method for the current operation is different. To build the semi-active schedule, the current operation is not allowed to be put into an empty hole earlier in the schedule, which means the chromosome also describes the sequence of operations on M_k. The starting time of an operation is equal to the maximum between the completion time of its preceding operation (the same J_i, POJ) and the completion time of its preceding operation on the same machine M_k (POM). In **Figure 5.1**, the upper Gantt chart (part A) is the active schedule, while the lower Gantt chart (part B) is the semi-active schedule. Normally, the initial semi-active schedule has higher value in total weighted tardiness than the active one, but it provides more opportunity for improvement.

In Scenario 2, the active schedule builder is employed. In Scenario 3, a new algorithm GAEJP for the ECT is developed and the semi-active schedule builder is adopted as the initial decoding approach. The comparison between the results of these two scenarios is used to demonstrate that the proposed new optimisation technique, which includes the new algorithm and the semi-active schedule builder, outperforms the existing one which uses the NSGA-II and the active schedule builder for solving the ECT. A simple example is provided in **Figure 5.2** to show how the improved semi-active schedule outperforms the active one (part A) in terms of total weighted tardiness and total non-processing electricity consumption. In **Figure 5.2**, the bottom schedule (part C) is developed based on the middle schedule (part B) which is the semi-active schedule in **Figure 5.1**. O_{11}^{1} is shifted to the left of O_{21}^{3}, the description for the left shift can be referred to in **Section 2.2.3**.Then O_{12}^{2} is moved forward to follow O_{32}^{1}, finally O_{13}^{3} is shifted to the left of O_{33}^{3}. Assuming that the due date for every job is the 15th time unit, and it is justifiable to execute Turn Off/Turn On for each machine when the idle period is longer than 3 time units. Thus, it can be observed that the bottom schedule outperforms the other two schedules on both the objectives (minimisation the total non-processing electricity consumption and minimisation the total weighted tardiness). Therefore, in Scenario 3, the optimisation strategy is building a semi-active schedule in the first place, then trying to improve the schedule by performing left shift and left move operations.

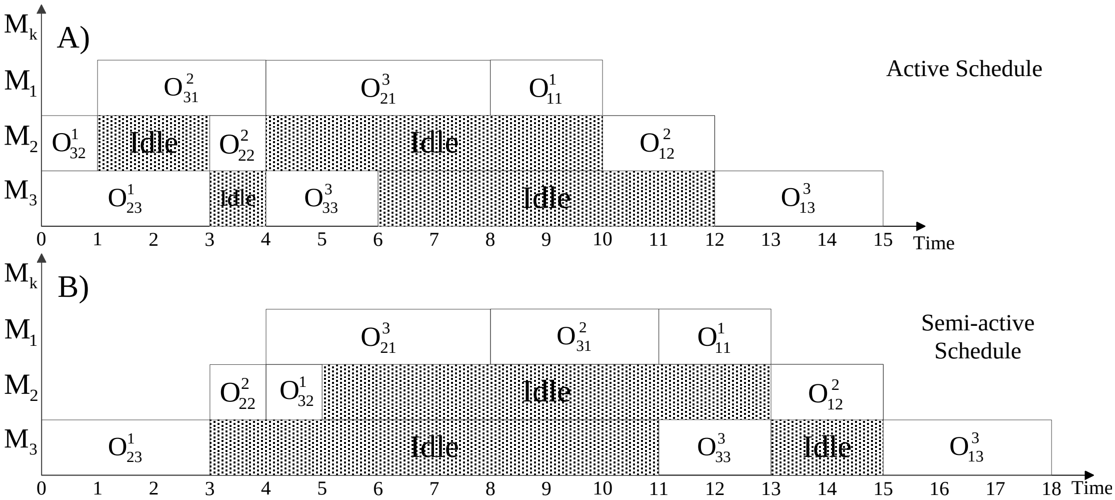


Figure 5.1: Transforming chromosome [**222333111**] to feasible active schedule and semi-active schedule, based on (Liu & Wu 2008)

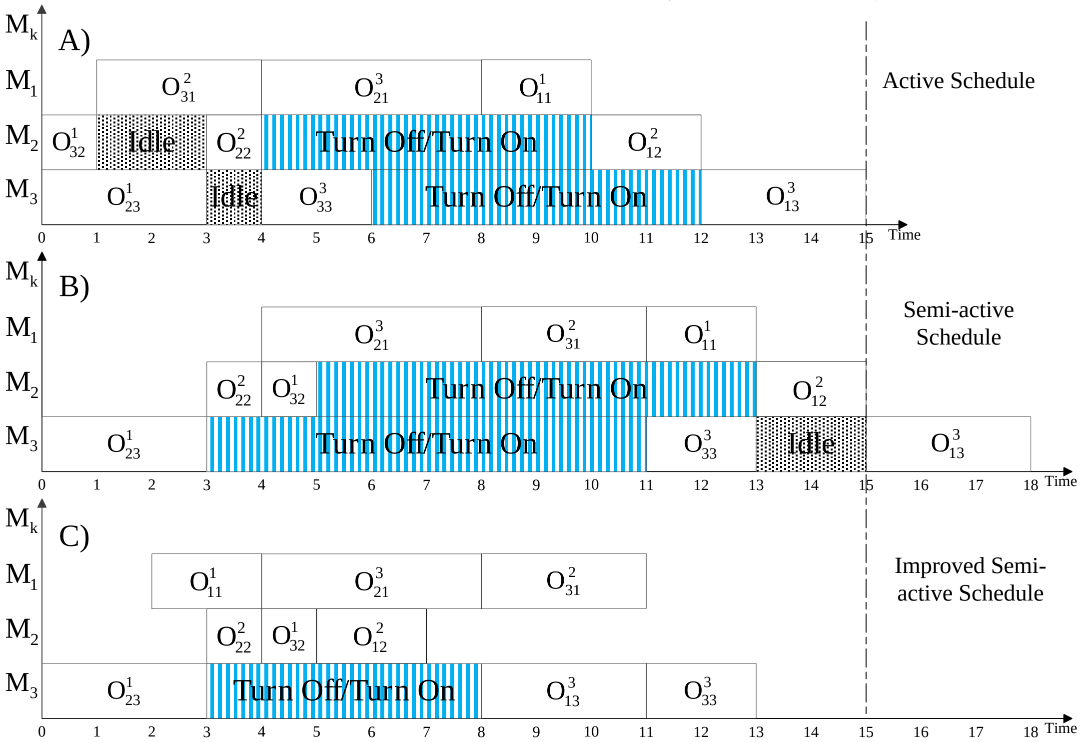


Figure 5.2: A better schedule for the ECT developed based on the semi-active schedule

5.4 A new algorithm GAEJP based on NSGA-II for solving the ECT problem (Scenario 3)

Apart from adopting the semi-active schedule builder, the encoding schema (OBES), crossover, mutation, selection operators, replacement strategy and stopping criteria used in Scenario 3 are the same as what has been used in the Scenario 2 (As described in **Section 4.3.2-4.3.4**). The flowchart of the new algorithm which is developed based on NSGA-II is shown in **Figure 5.3**. Two new steps are introduced. One is labelled "1 to n schedule building". The purpose of creating this new step is to use the advantage of the semi-active schedule builder to improve the schedules' performance on both the total weighted tardiness and the total non-processing electricity consumption objectives step by step. At the end of the 1 to n schedule building step, an individual chromosome can be decoded to several feasible scheduling plans (solutions). Some of these solutions can be defined as a family in the new "Family creation and individual rejection" step. The purpose of this step is to reserve the elitist solution within each family and abandon others, thereby guaranteeing the solution quality in each generation. These two steps will be explained in detail. The notation used is as follows: $P_t = \{I_{pt}\}_{p=1,t=1}^{N,G}$ where P_t is the population at generation t with N individuals, I_{pt} is the individual p in P_t.

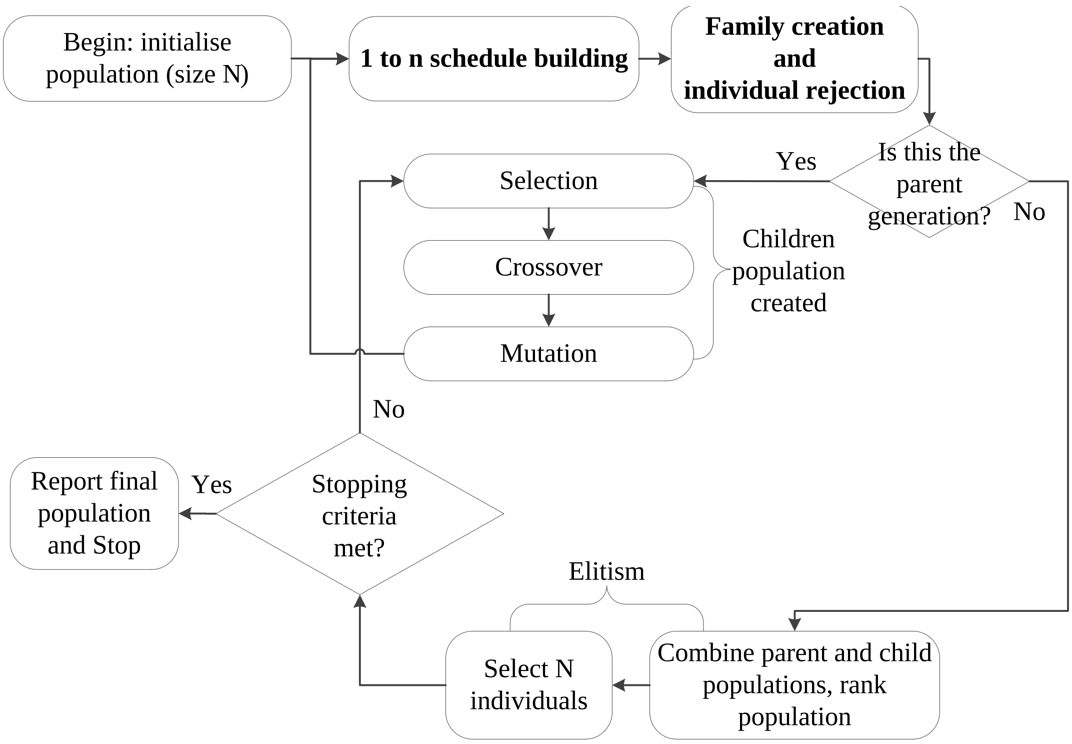


Figure 5.3: Flowchart for GAEJP

5.4.1 1 to n schedule building

As shown in **Figure 5.4**, the 1 to n schedule building process starts from the decoding procedure using the semi-active schedule builder. After obtaining the initial schedule, all the idle periods within it are evaluated to find those which are sufficiently long to allow a machine to be turned off and switched back on. Then the values of the objective functions are calculated based on the Turn Off/Turn On version of the scheduling plan. Thus, the first feasible solution corresponding to the chromosome is obtained. To improve the schedule's performance on the total weighted tardiness objective, some operations need to be shifted left. Thus, all the operations which are allowed to be shifted left within the aforementioned schedule need to be selected and ranked according to specific rules. The operation with the highest rank is shifted left to the earliest left-shifting-available idle period for it. After the left shifting, it might be found that some operations can be moved left to further improve the schedule's performance on the total weighted tardiness. Then all these permissible left move operations are selected and ranked. The operation with the highest rank is moved left to its earliest possible starting time. After completing all the aforementioned steps, the algorithm iterates the permissible left move operation selection, ranking, left moving steps until there are no further operations that can be moved left.

Then evaluating all the idle periods in the schedule without any permissible left move operations to find those for which it is justifiable to apply the Turn Off/Turn On method. The values of the objective functions can then be calculated based on the Turn Off/Turn On version of scheduling plan. Thus, the second feasible solution corresponding to the chromosome is obtained. Then, the algorithm goes back to the permissible left shift operations selection and executes the subsequent steps, and iterates until there is no permissible left shift operation within the schedule. The details of each step in the algorithm are described in the following.

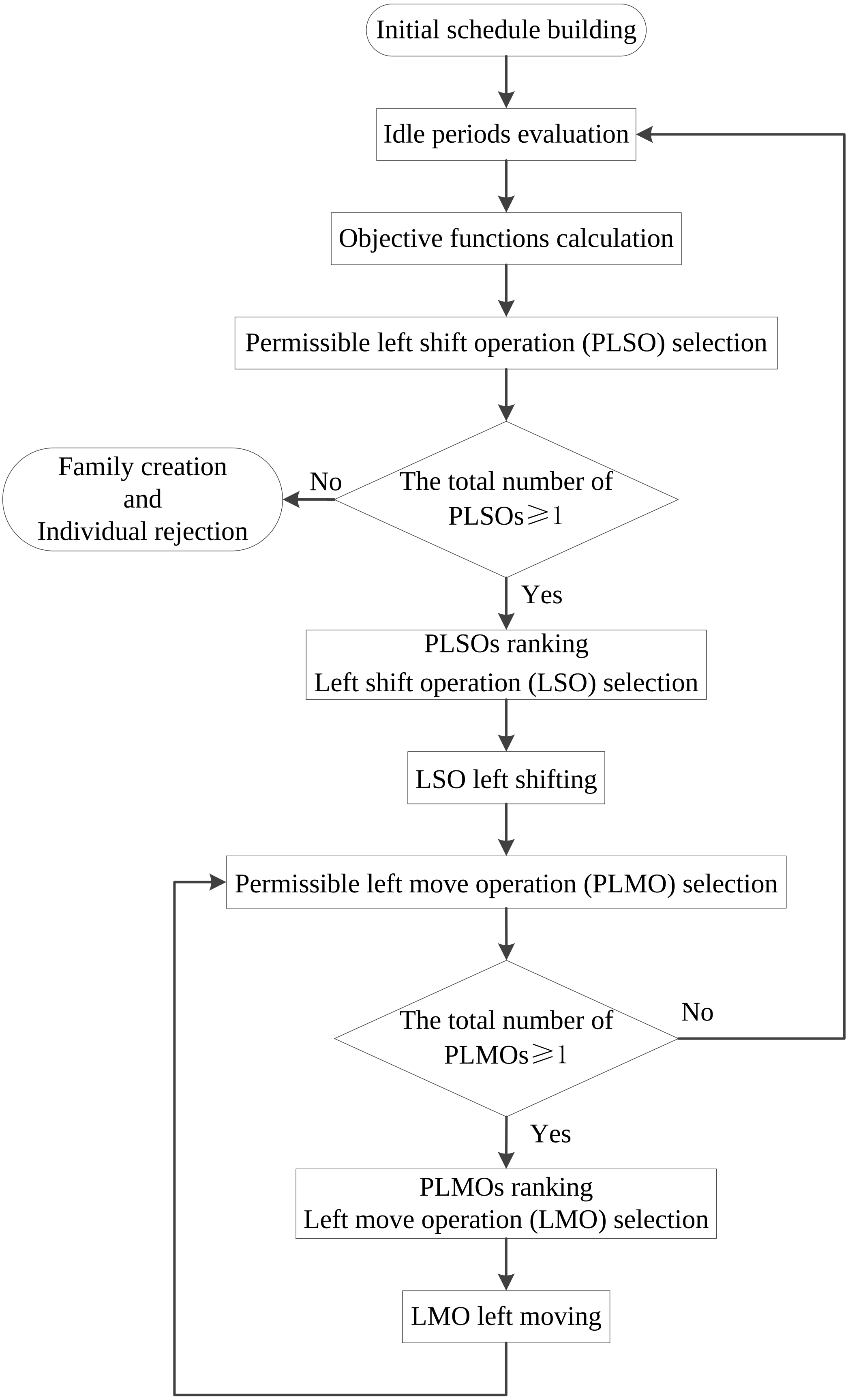


Figure 5.4: The flowchart of 1 to n schedule building step

Initial schedule building: Employ the semi-active schedule builder ($\xrightarrow{D_{semi}}$) to decode the chromosome I_{pt} to a semi-active schedule s_{pt}^{1}. The decoding process has been described in **Section 2.2.3**, and is denoted by $I_{pt} \xrightarrow{D_{semi}} s_{pt}^{1}$, G_{pt}^{1} is s_{pt}^{1}'s corresponding Gantt chart.

Idle periods evaluation: Evaluate all the idle periods (IPs) within schedule s_{pt}^{1} to find out those for which it is justifiable to apply the Turn Off/Turn On method. Then, apply the Turn Off/Turn On method to all eligible IPs. Thus, $s_{pt}^{1'}$-the Turn Off/Turn On version of s_{pt}^{1} is obtained. $s_{pt}^{1'}$ is the first feasible solution corresponds to individual I_{pt}.

Objective functions calculation: Calculate the values of the objective functions based on $s_{pt}^{1'}$, the calculation method can be referred to **Section 3.4**, where

$$twt_{s_{pt}^{1'}} = \sum_{i=1}^{n} w_i \times T_i\left(s_{pt}^{1'}\right) \tag{5.3}$$

$$npe_{s_{pt}^{1'}} = \sum_{k=1}^{m} TEM_k^{np}(s_{pt}^{1'}) \tag{5.4}$$

Thus, $O_{s_{pt}^{1'}} = \left(twt_{s_{pt}^{1'}}, npe_{s_{pt}^{1'}}\right)$, where $O_{s_{pt}^{1'}}$ denotes the objective function values of $s_{pt}^{1'}$.

Permissible left shift operations selection: Select all the operations which are allowed to be shifted left within s_{pt}^{1}. O_{ik}^{l} can be defined as a PLSO if there exists at least one idle period before it on machine M_k, and the length of the idle period is longer than the required processing time of O_{ik}^{l}. An example of a PLSO can be referred to part A of

Figure 2.8. The aforementioned condition can be mathematically expressed as following:

$$\exists ip_k^w \in ip_k \quad eip_k^w > S_{ik}^l \tag{5.5}$$

$$\exists ip_k^w \in ip_k \quad eip_k^w - sip_k^w \geq p_{ik}^l \tag{5.6}$$

$$\exists ip_k^w \in ip_k \quad eip_k^w - C_{ik'}^{l-1} \geq p_{ik}^l \tag{5.7}$$

Where

S_{ik}^{l} is the starting time of O_{ik}^{l}.

p_{ik}^{l} is the processing time of O_{ik}^{l} on M_k.

$ip_k = \{ip_k^w\}_{w=1}^{u_k}$ is a finite set of u_k ordered idle periods on M_k.

ip_k^w is the w-th idle period on M_k, has its own starting time and ending time, which are denoted by sip_k^w and eip_k^w. The eip_k^w is adopted to represent ip_k^w.

$C_{ik'}^{l-1}$ is the completion time of $O_{ik'}^{l-1}$ which is the preceding operation of O_{ik}^{l} in J_i.

The constraint (5.5) makes sure that ip_k^w ends before O_{ik}^{l} starts on M_k in a feasible schedule. The constraint (5.6) and (5.7) guarantee the time length of ip_k^w is long enough to accommodate the duration of operation O_{ik}^{l}.

Permissible left shift operations ranking: All of the PLSOs within schedule s_{pt}^{1} are found after the “Permissible left shift operations selection” step. Only one of them will be selected as the “Left shift operation” in this “Left shift adjusting loop”, thus they need to be ranked to find out the one with the highest priority for shifting left. The ranking rules are described below. $O_{ik}^{l} \prec_s O_{i'k}^{l'}$ means O_{ik}^{l} is prior to $O_{i'k}^{l'}$ in shifting left.

$$O_{ik}^{l} \prec_s O_{i'k}^{l'} \text{ if } \frac{w_i}{d_i} > \frac{w_{i'}}{d_{i'}} \tag{5.8}$$

else if

$$\frac{w_i}{d_i} = \frac{w_{i'}}{d_{i'}}, \text{ then } O_{ik}^{l} \prec_s O_{i'k}^{l'} \text{ if } w_i > w_{i'} \tag{5.9}$$

else if

$$w_i = w_{i'};\ d_i = d_{i'}, \text{ then randomly ranking } O_{ik}^{l} \text{ and } O_{i'k}^{l'} \tag{5.10}$$

else if

$$i = i', \text{ then } O_{ik}^{l} \prec_s O_{i'k}^{l'} \text{ if } l < l' \tag{5.11}$$

For operations from different job J_i, condition (5.8) means O_{ik}^l with a higher value of the ratio of its importance to its due date, $\frac{w_i}{d_i}$ gets the priority for shifting left. Condition (5.9**)** means when the values of $\frac{w_i}{d_i}$ are the same, the one with the higher value in w_i is prioritised. Condition (5.10) indicates that when weighted and due of the two operations are the same, randomly rank them. Finally, for operations from the same job, the one positioned earlier in the technology path is prioritised.

LSO left shifting: Based on the above step, it can be supposed that O_{ik}^l ranks the first in all permissible left shift operations, thus it is selected as the left shift operation and will be shifted to the earliest left-shifting-available idle period. Its new completion time is equal to the ending time of that idle period. In other words, idle periods on machine M_k that allow O_{ik}^l to be left shifted into can be denoted by a finite set $ip_{O_{ik}^l} = \left\{ip_{O_{ik}^l}^e\right\}_{e=1}^t$, then shift the O_{ik}^l to the idle period $ip_{O_{ik}^l}^e$ with the minimum value in ending time $eip_{O_{ik}^l}^e$. Defining the new completion time of O_{ik}^l as C_{ik}^{lnew}, where $C_{ik}^{lnew} = minimum \left\{eip_{O_{ik}^l}^e\right\}_{e=1}^t$. After the left shift, a new schedule for I_{pt} can be obtained, denoted by s_{pt}^2.

Permissible left move operations selection: After the left shifting step as above, there might emerge some operations which can be moved left. Select all the operations which are allowed to be moved left within schedule s_{pt}^2. O_{ik}^l can be defined as a permissible left move operation if there is an idle period just left attached to it and the completion time of its preceding operation (the same J_i, POJ) is smaller than the starting time of O_{ik}^l. An example of a permissible left move operation can be referred to part B of **Figure 2.8**. The aforementioned condition can be mathematically expressed as the following:

$$S_{ik}^l > maximum\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \quad X_{ik}^{lr} = 1 \tag{5.12}$$

Where

$M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^n \sum_{l=1}^{u_i} \gamma_{ik}^l}$ is a finite set of operations processed on M_k.

γ_{ik}^l is a decision variable that $\gamma_{ik}^l = 1$ if the l-th operation of J_i processed on

M_k, 0 otherwise.

m_k^r is the r-th operation processed on M_k within s_{pt}^2.

X_{ik}^{lr} is a decision variable, $X_{ik}^{lr} = 1$ if O_{ik}^l of J_i is scheduled in the r-th position for processing on M_k, 0 otherwise. Thus, in constraint (6.10), $m_k^r = O_{ik}^l$.

$O_{ik'}^{l-1}$ is the POJ of O_{ik}^l.

m_k^{r-1} is the POM of O_{ik}^l.

$C_{ik'}^{l-1}$ is the completion time of $O_{ik'}^{l-1}$.

C_k^{r-1} is the completion time of m_k^{r-1}.

This constraint (5.12) means if the starting time of O_{ik}^l is larger than the maximum between the completion time of its preceding operation (the same J_i, POJ) and the completion time of its preceding operation on the same machine M_k. It can then be defined as a permissible left move operation. However, the left shift operation which has just been shifted left in the LSO left shifting step does not participate the permissible left move operation selection.

Permissible LMO ranking: All of the permissible left move operations within schedule s_{pt}^2 are found after the permissible left move operation selection step. Only one of them will be selected as the left move operation in this "Left move adjusting loop", thus they need to be ranked to find out the one with the highest priority for moving left. The ranking rules are the same as the rules described in permissible left shift operations ranking step. $O_{ik}^l \prec_m O_{i'k}^{l'}$ means O_{ik}^l is prior to $O_{i'k}^{l'}$ in moving left.

LMO left moving: Moving O_{ik}^l left on M_k to its earliest possible starting time, which is the maximum between the completion time of its preceding operation (the same J_i, POJ) and the completion time of its preceding operation on the same machine M_k (POM). In other words, the new starting time of the left move operation O_{ik}^l is defined as S_{ik}^{lnew}, that $S_{ik}^{lnew} = maximum\left(C_k^{r-1}, C_{ik'}^{l-1}\right)$. After the left moving, a new schedule for I_{pt} can be obtained, denoted as s_{pt}^3.

After completing all the nine steps described above, the algorithm goes back to the permissible left move operations selection step, then executes permissible left moving operations ranking and left moving operation left moving, and iterates until there is no permissible left moving operation to be found. The schedule without any permissible left moving operation is denoted as $s_{pt}^{n_1}$. Once this schedule has been established, the idle periods within $s_{pt}^{n_1}$ need to be evaluated to find out those that justify applying the Turn Off/Turn On method. The Turn Off/Turn On method can then be applied to all eligible idle periods. Thus $s_{pt}^{n_1'}$, the Turn Off/Turn On version of $s_{pt}^{n_1}$ can be obtained. If there is no idle period available for applying the Turn Off/Turn On, then $s_{pt}^{n_1'} = s_{pt}^{n_1}$. Calculate the values of the objective functions based on $s_{pt}^{n_1'}$, the calculation method can be referred to **Section 3.4**, where

$$twt_{s_{pt}^{n_1'}} = \sum_{i=1}^{n} w_i \times T_i\left(s_{pt}^{n_1'}\right) \tag{5.13}$$

$$npe_{s_{pt}^{n_1'}} = \sum_{k=1}^{m} TEM_k^{np}(s_{pt}^{n_1'}) \tag{5.14}$$

Thus, $O_{s_{pt}^{n_1'}} = \left(twt_{s_{pt}^{n_1'}}, npe_{s_{pt}^{n_1'}}\right)$

$s_{pt}^{n_1'}$ is the second feasible solution corresponds to individual I_{pt}.Once the values for the objective functions have been obtained, the algorithm goes back to permissible left shift operations selection to select the permissible left shift operations within $s_{pt}^{n_1'}$, executes the subsequent steps, and iterates until there is no permissible left shift operation within the schedule. Finally, $h_{pt} + 1$ feasible solutions (schedules) can be obtained corresponding to I_{pt}, therefore, the solution set of I_{pt} can be denoted as $S_{pt} = \left\{s_{pt}^{1'}\right\} \cup \left\{s_{pt}^{n_v'}\right\}_{v=1}^{h_{pt}}$, and the objective function set of I_{pt} can be denoted as $O_{pt} = \left\{O_{s_{pt}^{1'}}\right\} \cup \left\{O_{s_{pt}^{n_v'}}\right\}_{v=1}^{h_{pt}}$, where $O_{s_{pt}^{n_v'}} = \left(twt_{s_{pt}^{n_v'}}, npe_{s_{pt}^{n_v'}}\right)$. An illustrative example is provided in the following section to further explain the the 1 to n schedule building process.

5.4.2 Illustrative example

A 3×3 job shop is employed as a case study to demonstrate the 1 to n schedule building process. The job shop information is shown in **Table 5.3**. Suppose the idle power of all machines is 1 power unit. It is justifiable to turn off then turn on a machine if the idle period is longer than 5 time units. To simplify the calculation, suppose $E_k^{turn} = 0$, E_k^{turn} is the electricity consumed by Turn Off/Turn On.

Table 5.3: 3×3 job shop parameters

O_{ik}^{l} \ J_i	O_{ik}^{1}	O_{ik}^{2}	O_{ik}^{3}	r_i	d_i (time unit)	w_i
J_1	$M_1(2)$	$M_2(2)$	$M_3(3)$	0	10	3
J_2	$M_3(3)$	$M_2(1)$	$M_1(4)$	0	10	2
J_3	$M_2(1)$	$M_1(3)$	$M_3(2)$	0	10	1

The sample chromosome is $I_{pt} = [222333111]$. Initially, I_{pt} is decoded by the semi-active schedule builder to the schedule s_{pt}^{1} $I_{pt} \xrightarrow{D_{semi}} s_{pt}^{1}$, the Gantt chart G_{pt}^{1} of schedule s_{pt}^{1} is shown in **Figure 5.5**. After the Turn Off/Turn On has been applied the resulting Gantt chart $G_{pt}^{1'}$ of $s_{pt}^{1'}$ is shown in **Figure 5.6**.

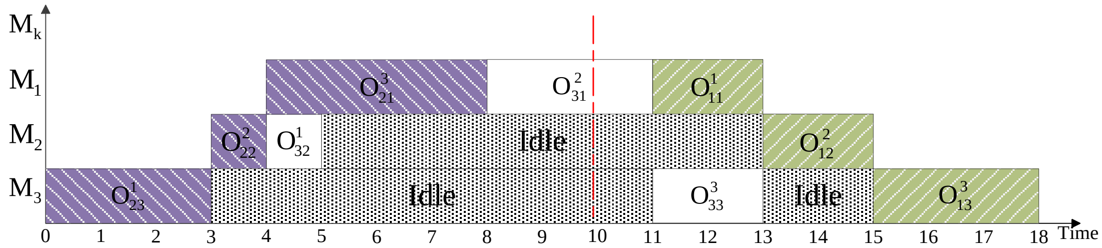


Figure 5.5: Gantt chart of s_{pt}^{1}

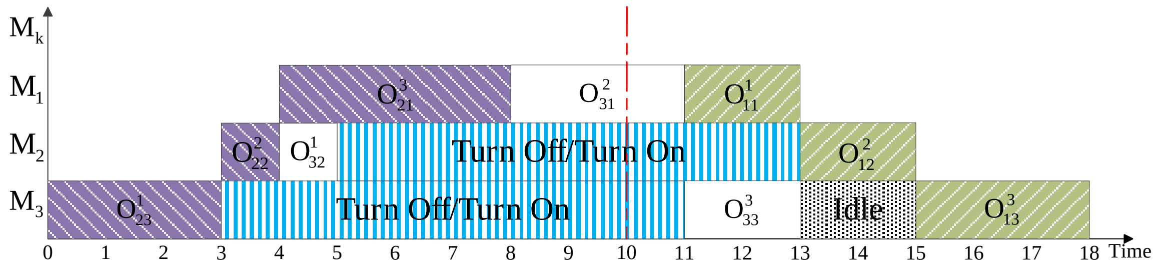


Figure 5.6: Gantt chart of $s_{pt}^{1'}$

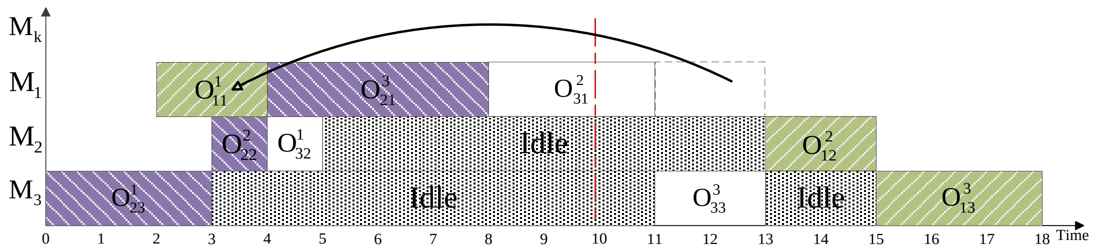


Figure 5.7: Gantt chart of s_{pt}^2

Based on **Figure 5.6**, it can be obtained that the values of objective functions of $s_{pt}^{1'}$ is $O_{s_{pt}^{1'}}$, that $O_{s_{pt}^{1'}} = \left(twt_{s_{pt}^{1'}}, npe_{s_{pt}^{1'}}\right) = (27{,}2)$. There are two permissible left shift operations in s_{pt}^1: O_{11}^1 and O_{32}^1. We select O_{11}^1 as the left shift operation since for J_1 the ratio w_1/d_1 equals to $3/10$ while for J_3 the ratio w_3/d_3 equals to $1/10$ (the job with the highest ratio is chosen). Then left shift O_{11}^1 according to the method described in the LSO left shifting step to get s_{pt}^2, the resulting Gantt chart, G_{pt}^2, is shown in **Figure 5.7**.

There is only one permissible left move operation in schedule s_{pt}^2: O_{12}^2. Thus, O_{12}^2 is selected as the left move operation. Left move O_{12}^2 to its earliest possible starting time results in s_{pt}^3. The corresponding Gantt chart G_{pt}^3 is shown in **Figure 5.8**.

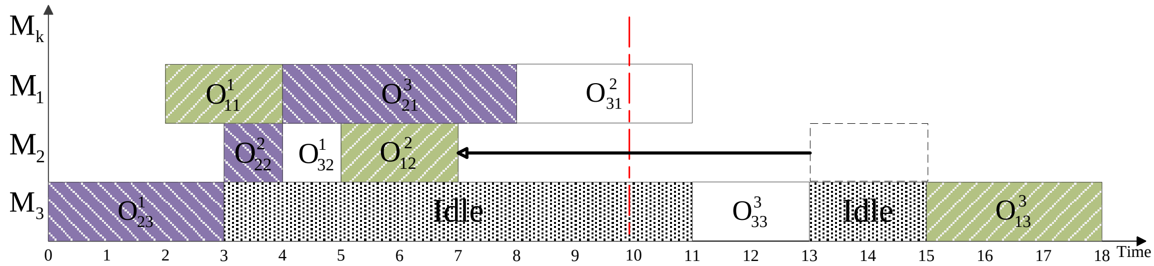


Figure 5.8: Gantt chart of s_{pt}^3

There is just one permissible left move operation in schedule s_{pt}^3, which is O_{13}^3. So it is selected as the left move operation. After move O_{13}^3 left to its earliest possible starting time, the schedule s_{pt}^4 is obtained. After this moving, there is no more available permissible left move operation in s_{pt}^4. The resulting Gantt chart G_{pt}^4 is shown in **Figure 5.9**. The Turn Off/Turn On can be applied to get $s_{pt}^{4'}$ since the idle time on machine M_3 between O_{13}^3 and O_{13}^3 is longer than 5 time units. $G_{pt}^{4'}$ is shown in **Figure 5.10**.

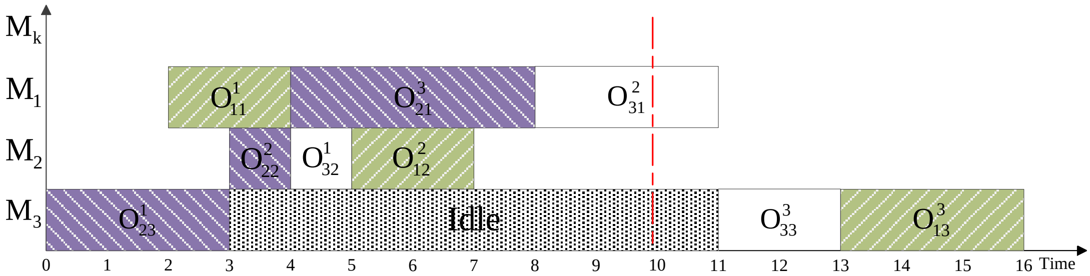


Figure 5.9: Gantt chart of s_{pt}^{4}

Next, the permissible left shift operations need to be searched for again. In s_{pt}^{4}, O_{13}^{3} and O_{32}^{1} are available permissible left shift operations. O_{13}^{3} is selected as the left shift operation since J_1 gets the highest value in w_i/d_i. Thus, s_{pt}^{5} can be obtained. However, there is no permissible left move operation within it, and it is not possible to apply the Turn Off/Turn On since the idle period on M_3 is just 5 time units. Thus $s_{pt}^{5'} = s_{pt}^{5}$, $G_{pt}^{5'}$ is shown in **Figure 5.11**. $O_{s_{pt}^{5'}} = \left(wt_{s_{pt}^{5'}}, npe_{s_{pt}^{5'}}\right) = (6{,}5)$. Based on **Figure 5.10**, it can be obtained that $O_{s_{pt}^{4'}} = \left(twt_{s_{pt}^{4'}}, npe_{s_{pt}^{4'}}\right) = (21{,}0)$.

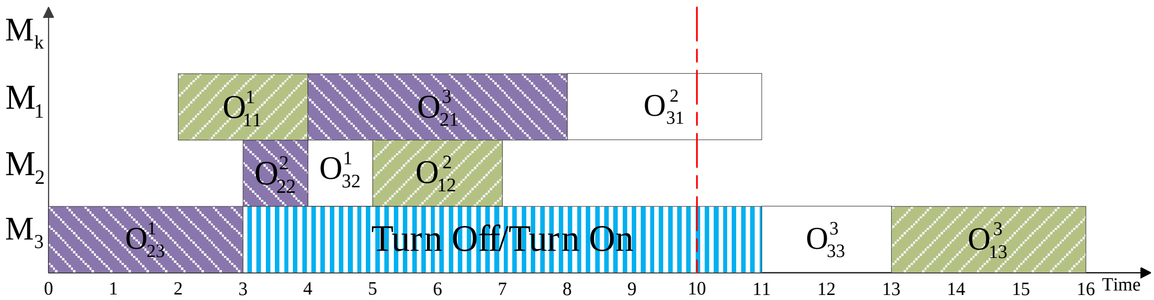


Figure 5.10: Gantt chart of $s_{pt}^{4'}$

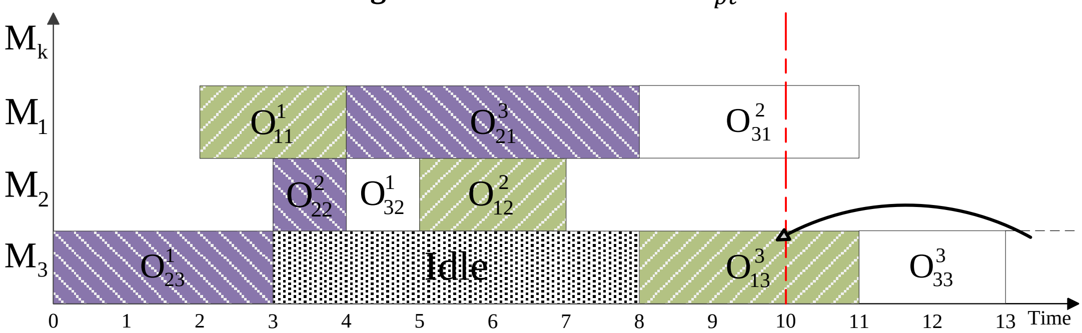


Figure 5.11: Gantt chart of s_{pt}^{5} and $s_{pt}^{5'}$

The third round of permissible left shift operation searching finds that there is only one permissible left shift operation: O_{32}^{1}, then left shift it to get s_{pt}^{6}, G_{pt}^{6} is shown in **Figure 5.12**.

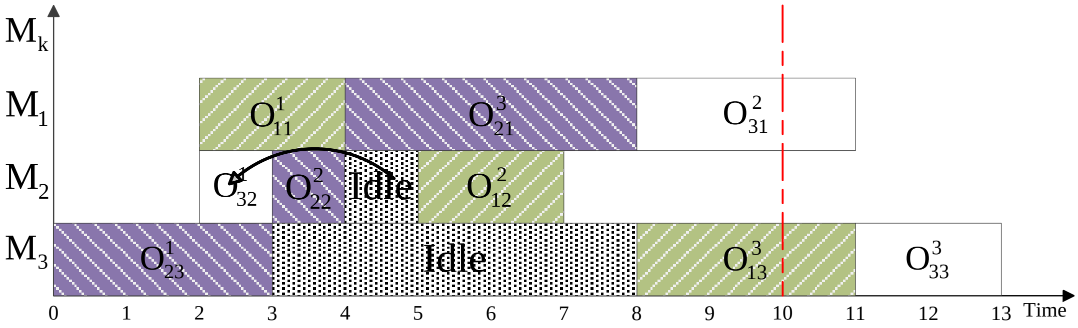


Figure 5.12: Gantt chart of s_{pt}^6

There is just one permissible left move operation in s_{pt}^6: O_{12}^2, so O_{12}^2 is selected as the left move operation. Left move O_{12}^2 to its earliest possible starting time. Then s_{pt}^7 is obtained.

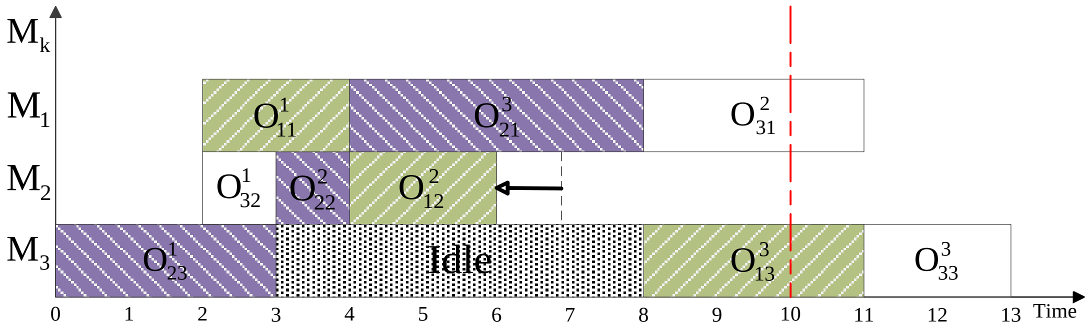


Figure 5.13: Gantt chart of s_{pt}^7 and $s_{pt}^{7'}$

In s_{pt}^7, there is no available permissible left shift operation, thus, the 1 to n schedule building process for the given 3×3 job shop is completed. $s_{pt}^{7'} = s_{pt}^7$, $G_{pt}^{7'}$ is shown in **Figure 5.13**. $O_{s_{pt}^{7'}} = \left(wt_{s_{pt}^{7'}}, npe_{s_{pt}^{7'}}\right) = (6,5)$.

According to the above process, $I_{pt} = [222333111]$ corresponds to four feasible solutions: $s_{pt}^{1'}$, $s_{pt}^{4'}$, $s_{pt}^{5'}$ and $s_{pt}^{7'}$, the values of their objective functions are $(27,2)$, $(21,0)$, $(6,5)$ and $(6,5)$. Although $s_{pt}^{5'}$ and $s_{pt}^{7'}$ have the same value in objective functions, they are different solutions for I_{pt} since the schedules are different.

5.4.3 Family creation and individual rejection

On Completion of the aforementioned schedule building process, the relationship between population individuals and solutions becomes 1 to n, where $n \geq 1$. To reserve the elitist solution in each family and abandon others, thereby guaranteeing the solution quality in each generation, an approach for converting 1 to n schedule building to 1 to 1 schedule building, and reducing population size has been developed, as shown in **Figure 5.3** as "Family creation and individual rejection". The individual steps of this algorithm will be described in detail in the following.

5.4.3.1 Step 1: Family creation

The non-dominated sorting algorithm is applied to all solutions in the set S_{pt} of each individual I_{pt}. The solutions is sorted into different levels. Only those located in the best level are preserved in S_{pt}, others will be abandoned. The non-dominated sorting method has been described in **Section 4.3.1.1**. With this approach, the number of elements of each I_{pt}'s solution set can be reduced from $h_{pt} + 1$ to u_{pt}, i.e. I_{pt} corresponds to u_{pt} feasible solutions, and S_{pt} becomes $S_{pt} = \{s_{pt}^{v}\}_{v=1}^{u_{pt}}$.

Copy each I_{pt} for $u_{pt} - 1$ times, a new set is created and denoted by $I_{pt} = \{I_{pt}^{v}\}_{v=1}^{u_{pt}}$. The procedure that I_{pt}^{v} is decoded to s_{pt}^{v} is defined as $I_{pt}^{v} \overset{D}{\rightarrow} s_{pt}^{v}$. Thus, the 1 to n decoding is converted to the 1 to 1 decoding. Thus, I_{pt} represents not only a single individual, but a set of individuals with the same genotype but a different phenotype. Therefore, instead of using the traditional name "individual", I_{pt} is referred to as "family", and all of the u_{pt} individuals in set I_{pt} can be called "family members". The solutions of individuals from the same family are different and non-dominate to each other. After the family creation, the population size of P_t increase from N to N', where $N' = \sum_{p=1}^{N} u_{pt}$. Aiming at reserving the elitist solutions and keeping the diversity of the population, the two steps individual rejection method is developed in the following to reduce the population size from N' back to N. In the first step, some of the individuals in each family are rejected based on the non-dominated sorting. At the end of this step, there is at least one individual survivor in each family. The second step is to reduce the number of members in each family to 1 based on the crowding distance value, i.e. finally only one member in each family is preserved.

5.4.3.2 Step 2: Individual rejection based on non-dominated front in the population

All solutions in population P_t with a size of N' are sorted according to non-domination. As a result, the solutions of individuals from the same family can be sorted into different levels. Thus, within a family I_{pt}, only individuals with solutions located in the lowest level are preserved, others are abandoned. For instance, it can be assumed that there are three individuals in I_{pt}: I_{pt}^1, I_{pt}^2 and I_{pt}^3, and their corresponding schedules are s_{pt}^1, s_{pt}^2 and s_{pt}^3. Based on the objective function value calculation and non-dominated sorting, assuming that s_{pt}^1 is located in level 2, s_{pt}^2 in level 3 and s_{pt}^3 in level 4. Thus, only I_{pt}^1 is preserved, while both I_{pt}^2 and I_{pt}^3 are abandoned. By completing this process, the solutions of all the individuals within a specific family are located in the same level, and the population size of P_t is decreased from N' to N'', $N'' \geq N$. Some members still need to be rejected from each family to reduce the population size back to N.

5.4.3.3 Step 3: Individual rejection based on the crowding distance value in each family

The solutions of P_t with a population size of N'' are sorted according to each objective function value in ascending order of magnitude. The crowding distance sorting procedure can be referred to in **Section 4.3.1.2**. The boundary solutions for each front F_i are definitely kept according to Deb et al., (2002) since they have an infinite value in the crowding distance. They need to be defined as in the following.

Defining boundary solutions

After the sorting, in each front F_i, two boundary solutions are found according to one of the optimisation objectives, respectively (here the bi-objective optimisation problem is used). The x-axis is selected to represent O_2 (see **Figure 5.14**) as the reference objective. Thus, the solution with a minimum value of O_2 is one of the boundary solutions which can be denoted by $BS_{F_i}^{min}$. The solution with a maximum value of O_2 is another boundary solution which can be denoted by $BS_{F_i}^{max}$. There are two possible relationships between the two boundary solutions:

Relationship type 1: the individuals which correspond to $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$ belong to different families. Then both the individuals are preserved.

Relationship type 2: the individuals which correspond to $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$ belong to the same family. Then randomly choose one of them and preserve it. Thus, another boundary solution needs to be found such that the individual corresponding to it belongs to a different family from the preserved one. The searching method is described as follows:

If $BS_{F_i}^{min}$ is preserved, then the new $BS_{F_i}^{max}$ needs to be found and vice versa. The searching starts with the original $BS_{F_i}^{max}$ in the list sorted by O_2 in descending order. The first solution with its corresponding individual belongs to a different family from that of $BS_{F_i}^{min}$'s belongs to is defined as the new $BS_{F_i}^{max}$. An example of the searching process is depicted in **Figure 5.14**. Analogue procedure applies if $BS_{F_i}^{max}$ is preserved and new $BS_{F_i}^{min}$ has to be found.

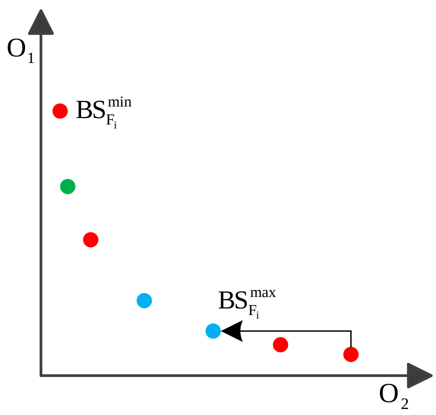


Figure 5.14: Defining boundary solutions

Neighbours searching

The aim of this step is to find and preserve the individual with the highest value in the crowding distance within each family. Other individuals are abandoned. The calculation method for the crowding distance is based on Deb et al. (2002). However, a new approach to define the neighbourhood is developed. Based on this approach, normally there are two groups of neighbours for each individual. To define the first group of neighbours of solution s_{pt}^{v}, firstly, the searching starts with s_{pt}^{v} according to O_2 in descending order. The first solution with its corresponding individual belongs to a different family from the one that individual I_{pt}^{v} belongs to can be defined as the first left neighbour of s_{pt}^{v} which is denoted by $N_{s_{pt}^{v}}^{l_1}$. Secondly, the searching starts with s_{pt}^{v} according to O_2 in ascending order. The first solution with its corresponding individual belongs to a different family from that I_{pt}^{v} belongs to and that $N_{s_{pt}^{v}}^{l_1}$'s corresponding individual belongs to, can be defined as the first right neighbour of s_{pt}^{v}, which is denoted by $N_{s_{pt}^{v}}^{r_1}$. Here, the first group of neighbours for s_{pt}^{v} is obtained, denoted by $N_{s_{pt}^{v}}^{n_1}$.

Then the second group of neighbours for s_{pt}^{v} needs to be found. The searching process is similar to the process presented above for the first group of neighbours. However this time the right neighbour is found first and then the left neighbour. Then, the second group of neighbours can be obtained, denoted by $N_{s_{pt}^{v}}^{n_2}$. Normally, two groups of neighbours can be found for a specific solution. However, a special case exists for some solutions that only have one group of neighbours that meets the above requirements. **Figure 5.15** depicts the neighbours searching process for $s_{pt}^{v_1}$ and $s_{pt}^{v_2}$. For solution $s_{pt}^{v_1}$, two groups of neighbours are found, but for solution $s_{pt}^{v_2}$, its first group of neighbours $N_{s_{pt}^{v_2}}^{n_1}$ is illegal since it is not possible to find the right neighbour with its corresponding individual that comes from a family different from the family that $N_{s_{pt}^{v_2}}^{l_1}$'s corresponding individual belongs to. So, its second group of neighbours $N_{s_{pt}^{v_2}}^{n_2}$ is the only feasible group of neighbours for solution $s_{pt}^{v_2}$.

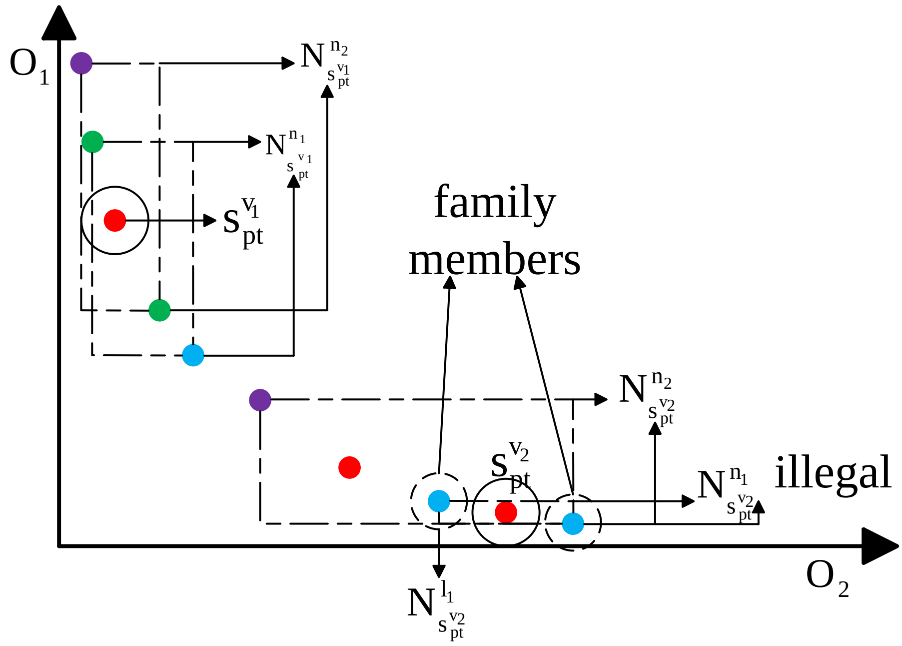


Figure 5.15: Neighbours searching process for $s_{pt}^{v_1}$ and $s_{pt}^{v_2}$

Crowding distance calculation

An infinite crowding distance value is assigned to boundary solutions $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$. Therefore, it is easy to conclude that the family members of individuals corresponding to $BS_{F_i}^{min}$ and $BS_{F_i}^{max}$ are abandoned. Hence, it is not necessary to search the neighbours of the solutions of the aforementioned members. The crowding distance values for them are defined as 0. For other solutions, the crowding distance calculation process is described as follows:

For the solutions with two groups of neighbours, like $s_{pt}^{v_1}$ in **Figure 5.15**, its crowding distance is denoted by $C_{s_{pt}^{v_1}}$, that $C_{s_{pt}^{v_1}} = maximum\left(C_{s_{pt}^{v_1}}^{n_1}, C_{s_{pt}^{v_1}}^{n_2}\right)$, where $C_{s_{pt}^{v_1}}^{n_1}$ and $C_{s_{pt}^{v_1}}^{n_2}$ are the alternative crowding distance values for $s_{pt}^{v_1}$, they are calculated respectively based on $N_{s_{pt}^{v_1}}^{n_1}$ and $N_{s_{pt}^{v_1}}^{n_2}$. The calculation method is based on Deb, et al. (2002).

For the solutions with just one legal group of neighbours, like $s_{pt}^{v_2}$ in **Figure 5.15**, $C_{s_{pt}^{v_2}} = maximum\left(C_{s_{pt}^{v_1}}^{n_x}, 0\right)$, where $C_{s_{pt}^{v_1}}^{n_x}$ denotes the crowding distance value for $s_{pt}^{v_2}$, which is calculated based on the only feasible group of neighbours $N_{s_{pt}^{v_1}}^{n_x}$, $x = 1$ or 2. 0 is assigned to the distance value of the illegal group of neighbours.

Crowding distance comparison and individual rejection

In a specific family, each individual's solution is compared in terms of crowding distance value. The individual whose solution has the highest crowding distance value is preserved and others are rejected. $I_{pt}^{v_2} \prec_c I_{pt}^{v_1}$ if $C_{s_{pt}^{v_2}} > C_{s_{pt}^{v_1}}$; randomly preserve one of $I_{pt}^{v_1}$ and $I_{pt}^{v_2}$ if $C_{s_{pt}^{v_1}} = C_{s_{pt}^{v_2}}$. Completing this step, the population size of P_t will be decreased to N. Only one individual in each family is preserved.

Crowding distance re-calculation

Some solutions that served as neighbours for other solutions might be rejected during the above process, which results in an unavailable crowding distance calculation for some of the preserved solutions. However, the crowding distance value of each solution is essential for producing the next generation Q_t. Thus, to redefine the neighbours and re-calculate the crowding distance value for all of the N solutions in P_t. At this stage, the solutions' corresponding individuals are different from each other, the typical approach for the crowding distance calculation can be followed as described in **Section 4.3.1.2**.

5.5 Comparison between Scenario 3, Scenario 2 and Scenario 1

In this section, the scenario comparison experiments are delivered to prove that the GAEJP is more superior in solving the ECT problem than the NSGA-II. The optimal parameters settings of the GAEJP for the operators and stopping criteria, which provide the best final solutions, are obtained after the initial tuning process. For all the job shop instances, the values are as follows: population size $N = 150$; crossover probability $p_c = 1.0$; mutation probability $p_m = 0.4$; generation $t = 8000$. During the tuning process, the values used for the crossover rate are $[0.8, 0.9, 1.0]$, for the mutation rate are $[0.1, 0.2, 0.3, 0.4, 0.5, 0.6]$, for the number of generations are $[5000, 6000, 7000, 8000, 9000, 10000]$, for the population size are $[80, 100, 150, 200, 300, 400, 500]$. Different combinations of the aforementioned values are tested in the experiments. Based on these tests, the optimal parameters setting of the GAEJP for each case can be obtained. During the tests, the value of the population size which is more than 500 has been tried, but the algorithm stopped due to a lack of RAM (4 GB RAM is used in this research). Thus, the maximum value of the population size which can be used in this research is 500. The optimal solutions were achieved with the population size of 150 and a comparatively high mutation rate of 0.4. It can be supposed that if the computational facility with a larger RAM had been used in the experiments, which would have allowed a bigger size of population, then a lower mutation rate could have been achieved. The algorithm has been run for more than 8000 generations, but the solutions have not been improved since that. Thus, 8000 is the best value for the generation. According to the experiments, it was quite time consuming to get the optimisation results of the GAEJP. Normally, it costs about half an hour to finish a single run. Thus, in the future work, optimising the algorithm and reducing the computational time of the GAEJP will be considered.

Considering the possibility of accelerating machine wear by frequent turn off and turn on operations, B_k, the break-even duration of a machine for which Turn Off/Turn On is economically justifiable instead of running the machine idle, is predefined to 30 min. This means the Turn Off/Turn On operation will only be applied when the idle time on the machine is longer than 30 min. The comparison among the solutions in S1 (a single objective job shop scheduling problem), the solutions in S2 (the bi-objective job shop scheduling problem solved by NSGA-II) and the solutions obtained by the GAEJP are shown in **Figure 5.16** to **Figure 5.19**.

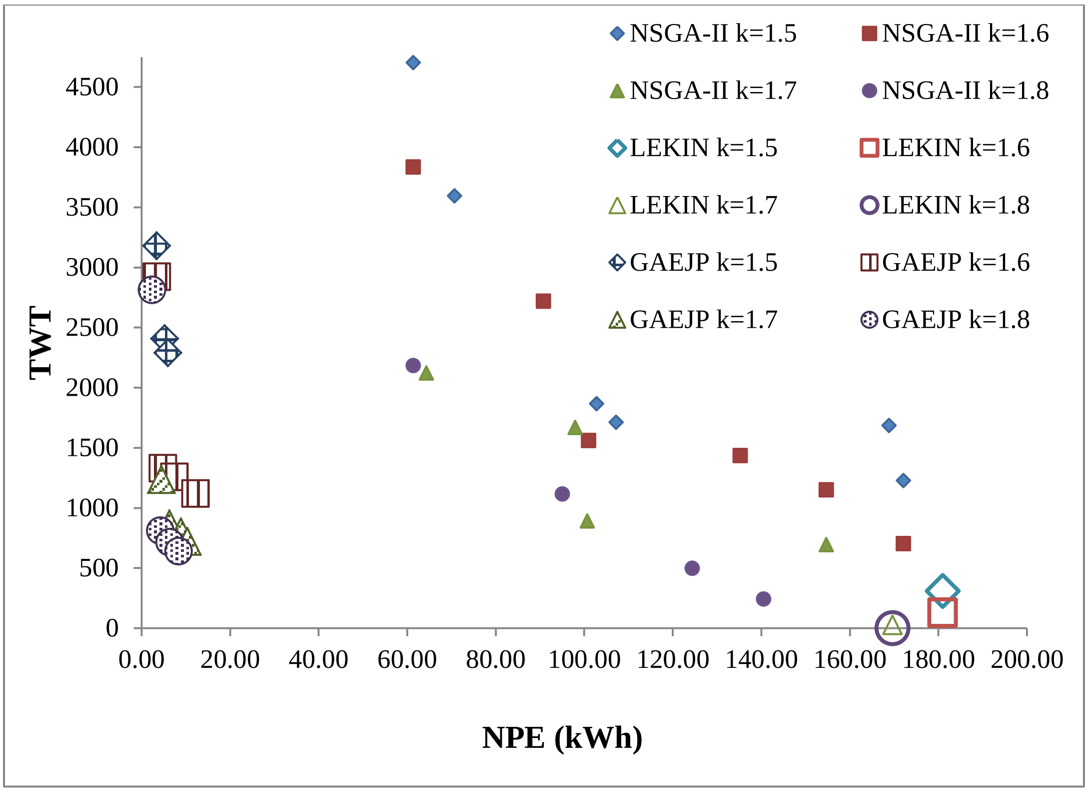


Figure 5.16: Solutions comparison among the GAEJP, the NSGA-II and the baseline scenario (E-F&T 10 × 10 job shop)

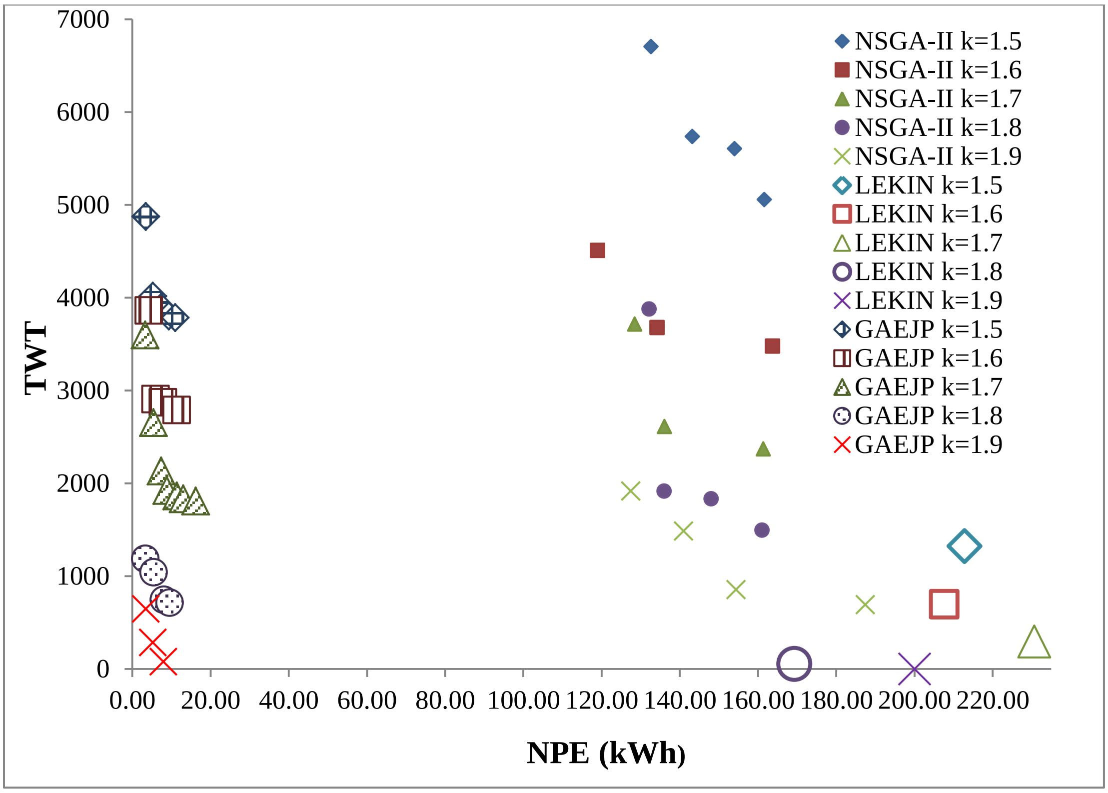


Figure 5.17: Solutions comparison among the GAEJP, the NSGA-II and the baseline scenario (E-Lawrence 15 × 10 job shop)

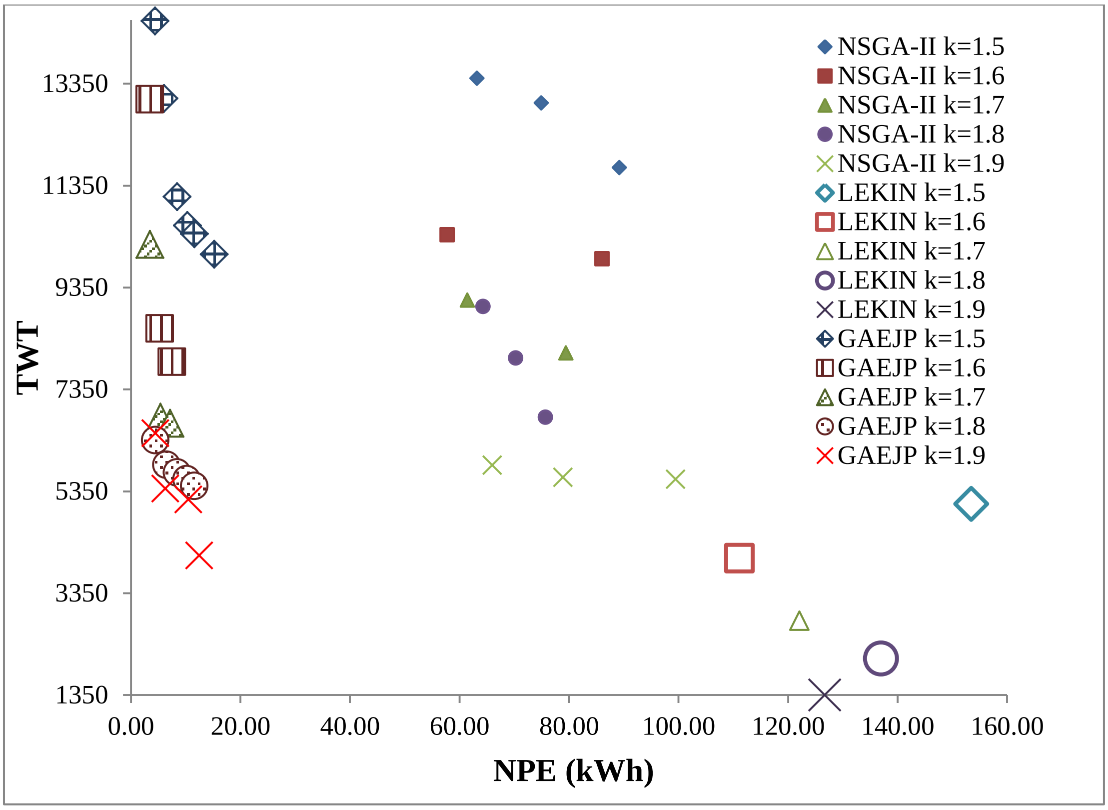


Figure 5.18: Solutions comparison among the GAEJP, the NSGA-II and the baseline scenario (E-Lawrence 20 × 10 job shop)

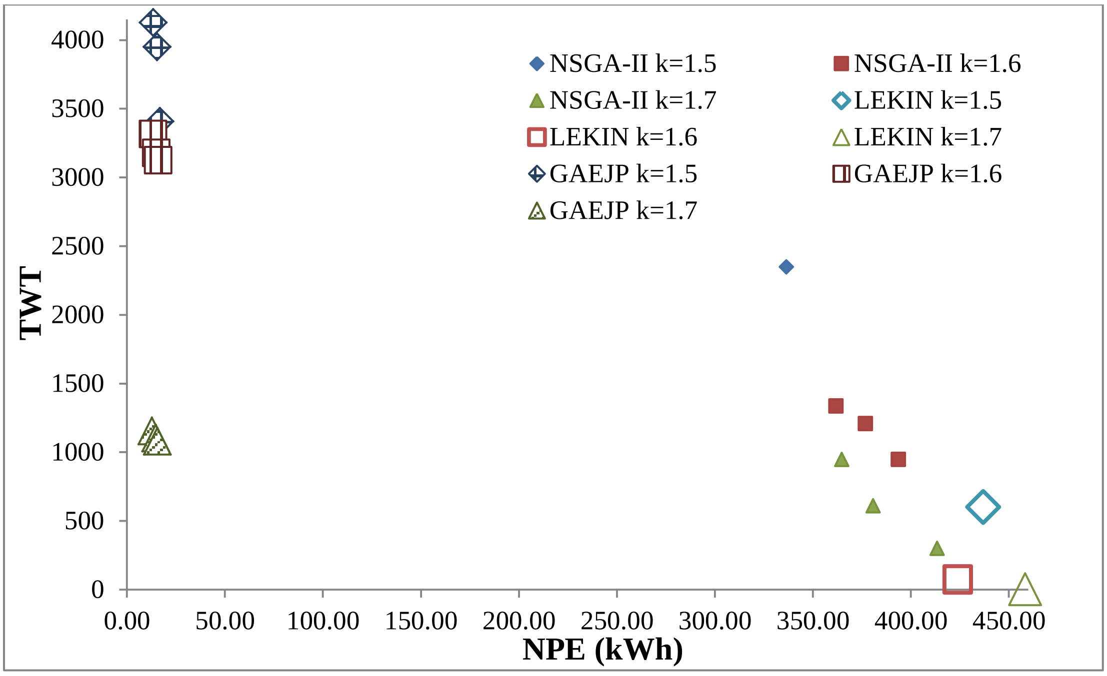


Figure 5.19: Solutions comparison among the GAEJP, the NSGA-II and the baseline scenario (E-Lawrence 15 × 15 job shop)

In the above figures, the LEKIN solutions and the NSGA-II solutions are the same as those shown in **Section 4.4**. The hollow points represent the optimisation results of the LEKIN which had been shown in **Table 4.2-Table 4.5**. The solid points represent the optimisation results of the NSGA-II. The points with different types of grid in them are the optimisation results of the GAEJP. Considering the demonstrated effect of the figures, not all the solutions on each Pareto-front are presented in **Figure 5.16** to **Figure 5.19**. The selection mechanism is as following: for each Pareto-front, all the solutions are ranked by the ascending sequence of non-processing electricity consumption value. Then both of the boundary solutions are shown, oddly ranking solutions like the 3rd, 5th and 7th are shown. Based on these figures, a considerable total NPE reduction can be observed when employing the GAEJP as the bi-objective optimisation approach. Compared to the bi-objective optimisation approach of the NSGA-II and the single objective optimisation result of the local search heuristic, the non-processing electricity consumption improvements are shown in **Table 5.4** and **Table 5.5**. Take the E-F&T 10×10 job shop as an example. When $f = 1.5$, the minimum and maximum value of $npe_{s3}^{1.5}$ are 3.5 kWh and 6.0 kWh respectively, which means a 96.7% to 98.1% improvement in the total non-processing electricity consumption compared to the values obtained by the LEKIN. When comparing with the optimisation result of NSGA-II, the improvement in total non-processing electricity consumption is 90.3% to 98.0%. The total weighted tardiness increases of the GAEJP (compared to the LEKIN result) in weighted minutes for each job shop instance under different tardiness conditions are shown in **Table 5.6** and **Table 5.7**. These two tables demonstrate the range for the total weighted tardiness deterioration of the optimisation result of the GAEJP when comparing to the LEKIN result. When considering the performance on both of the total non-processing electricity consumption and total weighted tardiness objectives, scheduling plans delivered by the GAEJP always have a much smaller non-processing electricity consumption than the scheduling plans delivered by the NSGA-II if they have similar value in total weighted tardiness. For instance, in the E-F&T 10×10 job shop, when $f = 1.6$, one of the boundary solutions delivered by the GAEJP is $(12.2\ (kWh), 1118)$, comparatively, the solution delivered by the NSGA-II with the closed value in the total weighted tardiness is $(170\ (kWh), 1136)$. This means the most of the solutions delivered by the NSGA-II are dominated by solutions delivered by the GAEJP. This can also be observed from the above figures. The comparison result between the GAEJP and the NSGA-II will be further discussed in the next section.

Table 5.4: The total NPE improvement in percentage for E-F&T 10 × 10 and E-Lawrence 15 × 10

Compare GAEJP to LEKIN		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement	min	96.7%	93.2%	93.9%	95.0%	94.8%	94.5%	93.0%	94.3%	96.0%
	max	98.1 %	98.1%	97.4%	98.6%	98.4%	98.0%	98.6%	98.0%	98.3%
Compare GAEJP to NSGA-II		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement	min	90.3%	80.1%	83.9%	86.3%	91.7%	90.4%	87.4%	92.8%	93.7%
	max	98.0%	98.0%	97.1%	98.3%	97.8%	97.4%	97.9%	97.9%	98.1%

Table 5.5: The total NPE improvement in percentage for E-Lawrence 20 × 10 and E-Lawrence 15 × 15

Compare GAEJP to LEKIN		E-Lawrence 20 × 10					E-Lawrence 15 × 15		
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9	f=1.5	f=1.6	f=1.7
NPE Improvement	min	90.1%	93.3%	94.1%	91.5%	90.1%	96.1%	96.2%	96.6%
	max	97.1%	96.9%	97.1%	96.7%	96.5%	96.9%	96.8%	97.2%
Compare GAEJP to NSGA-II		E-Lawrence 20 × 10					E-Lawrence 15 × 15		
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9	f=1.5	f=1.6	f=1.7
NPE Improvement	min	75.9%	87.0%	88.3%	81.9%	81.1%	95.0%	95.5%	95.7%
	max	95.0%	95.9%	95.6%	94.1%	95.5%	96.0%	96.6%	96.9%

Table 5.6: The TWT increase in weighted minute for E-F&T 10 × 10 and E-Lawrence 15 × 10

Compare GAEJP to LEKIN		E-F&T 10 × 10				E-Lawrence 15 × 10				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
TWT Increase	min	1979	991	695	638	2465	2094	1515	659	78
	max	2870	2794	1209	2811	3555	3165	3306	1131	647

Table 5.7: The TWT increase in weighted minute for E-Lawrence 20 × 10 and E-Lawrence 15 × 15

Compare GAEJP to LEKIN		E-Lawrence 20 × 10					E-Lawrence 15 × 15		
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9	f=1.5	f=1.6	f=1.7
TWT Increase	min	4898	3860	3880	3386	2738	2807	3052	1079
	max	9480	9008	7391	4281	5139	3526	3242	1152

5.6 Discussion

It can be observed that the GAEJP combined with the Turn Off/Turn On method is more effective in reducing the total non-processing electricity consumption in a scheduling plan than the NSGA-II without compromising the total weighted tardiness too much. For E-Lawrence 15 × 10 and 20 × 10 job shop, all solutions obtained by the NSGA-II are dominated by at least one solution obtained by the GAEJP, as shown in **Figure 5.20** and **Figure 5.21**. For the other two problems (E-F&T 10×10 and E-Lawrence 15×15), some of the NSGA-II solutions are not dominated by any of the GAEJP solutions. For these two problems, Pareto fronts generated by two algorithms are combined together to form new Pareto fronts, and only non-dominated solutions are preserved. It can be noticed that solutions obtained by the GAEJP take a larger proportion of the total number of solutions on the new Pareto fronts, as shown in **Figure 5.22** and **Figure 5.23**. Which means the GAEJP can provide more feasible options to the plant manager.

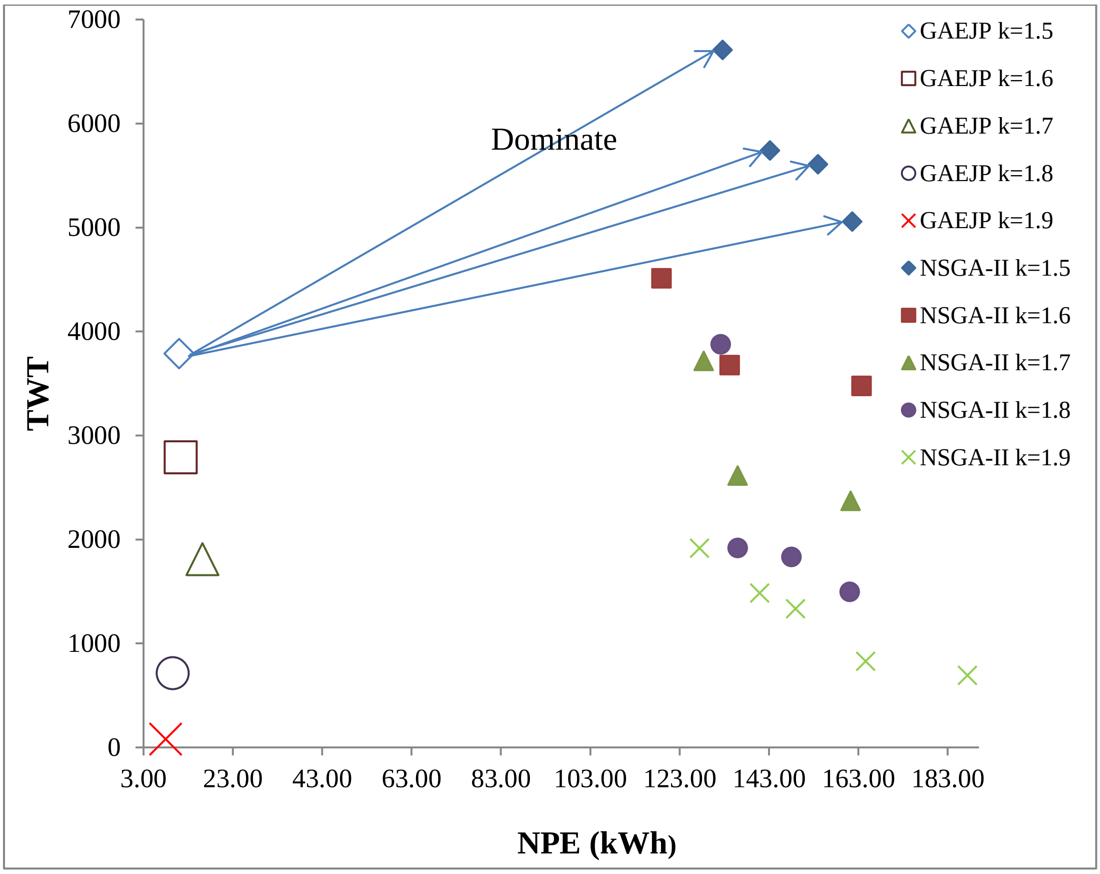


Figure 5.20: The solutions obtained by the GAEJP for E-Lawrence 15×10 job shop
(All of the solutions obtained by the NSGA-II had been dominated)

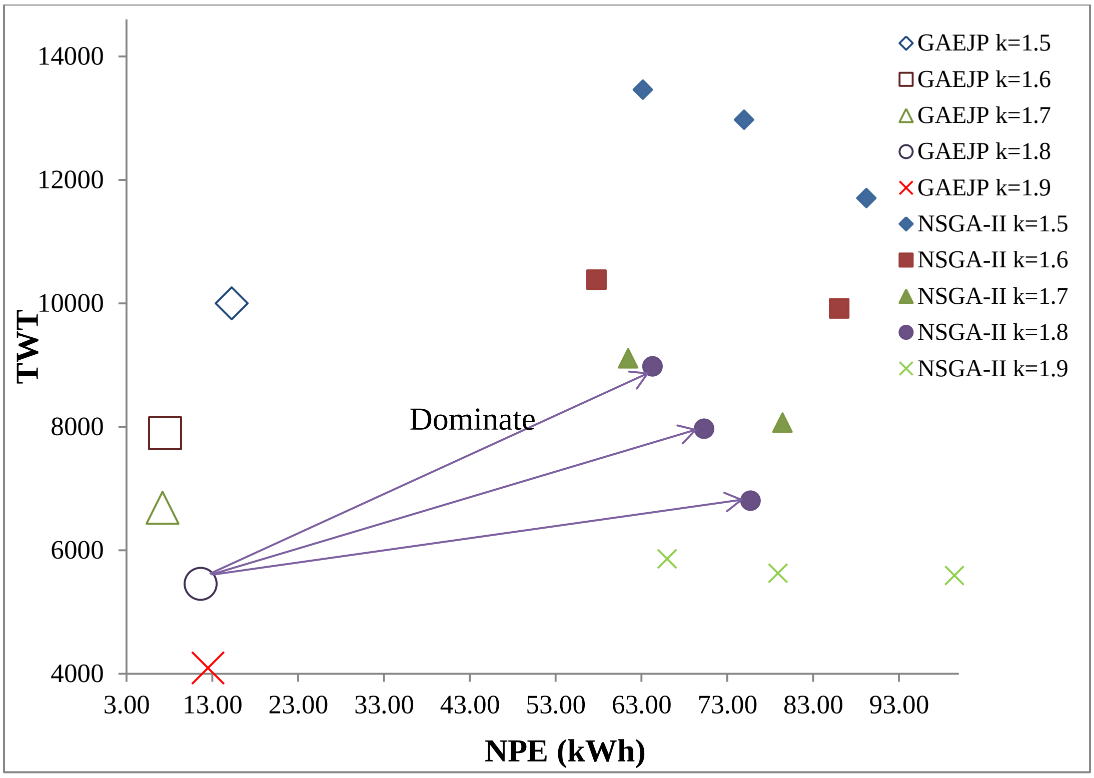


Figure 5.21: The solutions obtained by the GAEJP for E-Lawrence 20 × 10 job shop
(All of the solutions obtained by the NSGA-II had been dominated)

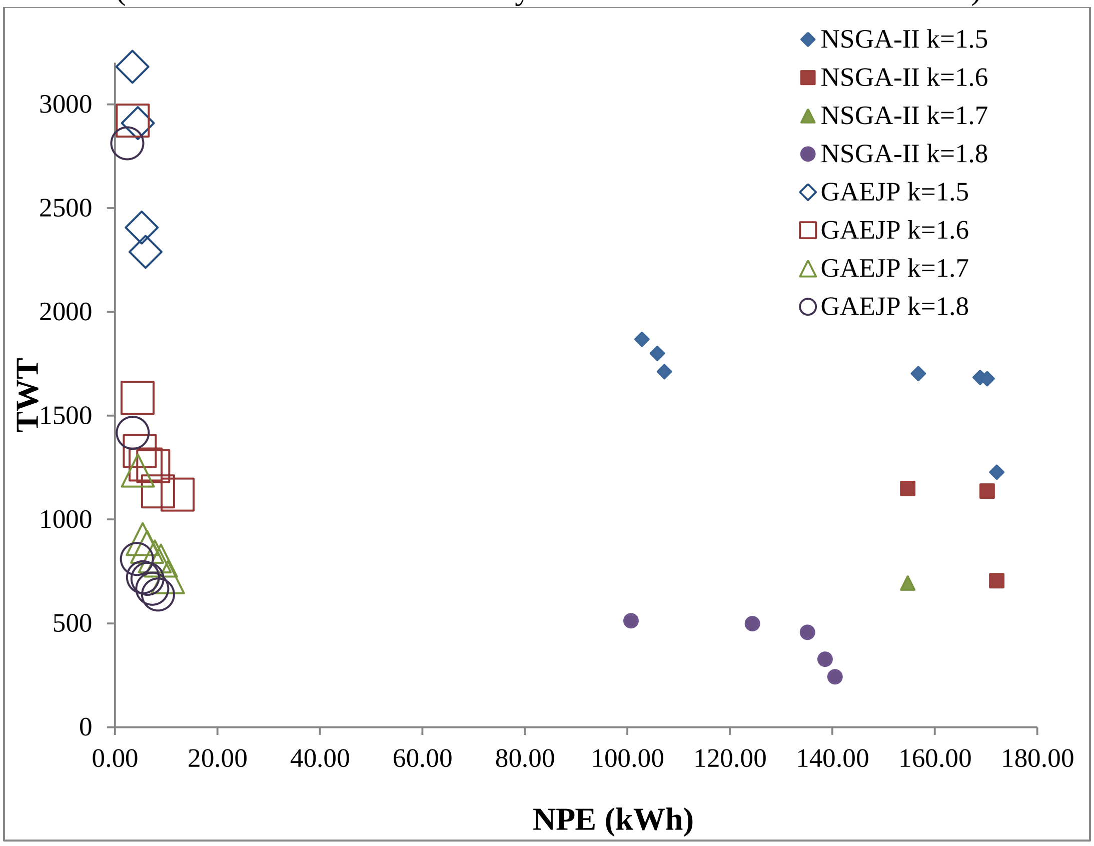


Figure 5.22: The new pareto fronts formed by solutions obtained by the GAEJP and the NSGA-II (E-F&T 10 × 10 job shop)

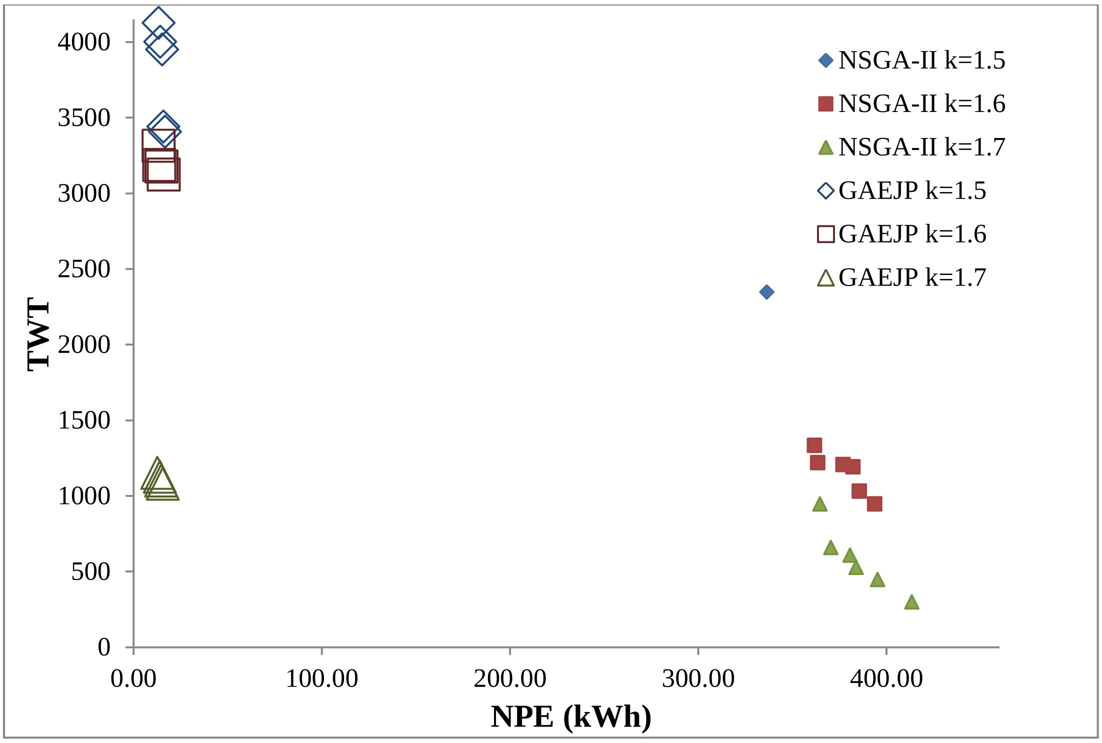


Figure 5.23: The new pareto fronts formed by solutions obtained the GAEJP and the NSGA-II (E-Lawrence 15 × 15 job shop)

The upper (part A) and bottom (part B) of **Figure 5.24** represent the Gantt charts of the optimal schedules produced by the GAEJP and the NSGA-II respectively for E-F&T 10 × 10 job shop when $f = 1.5$. It is possible to observe that the schedule produced by the GAEJP has a smaller total amount of idle periods on all machines (31 idles periods on schedule produced by the GAEJP and 37 idle periods produced by the NSGA-II), and normally the lengths of those idle periods are longer. This means when the varieties and amounts of components, increase, it is easier to place the new operations in the existing idle periods on scheduling plans produced by the GAEJP, thereby creating a more intense scheduling plan with a higher machine utilisation rate. From the above, the scheduling plans produced by the GAEJP might be more preferable for managers when considering the real life job shop manufacturing system. Someone may argue that when the Turn off/Turn on method is applied to the optimisation result of the NSGA-II, the GAEJP may lose its priority in solving the ECT problem. However, in the case presented in **Figure 5.24**, the original values for objective functions of scheduling plans conducted by the GAEJP and the NSGA-II are $(6.0\ (kWh), 2288)$ and $(170\ (kWh), 3595)$. When the Turn off/Turn method is applied to the bottom scheduling plan (part B) in **Figure 5.24**, the value of objective functions become $(14.5\ (kWh), 3595)$. Thus the solution delivered by the GAEJP is still preferable for the plant manager in this case. The effect of applying the Turn off/Turn on method to the optimisation results of the NSGA-II will be investigated in future research to further prove the GAEJP's priority in solving the ECT problem.

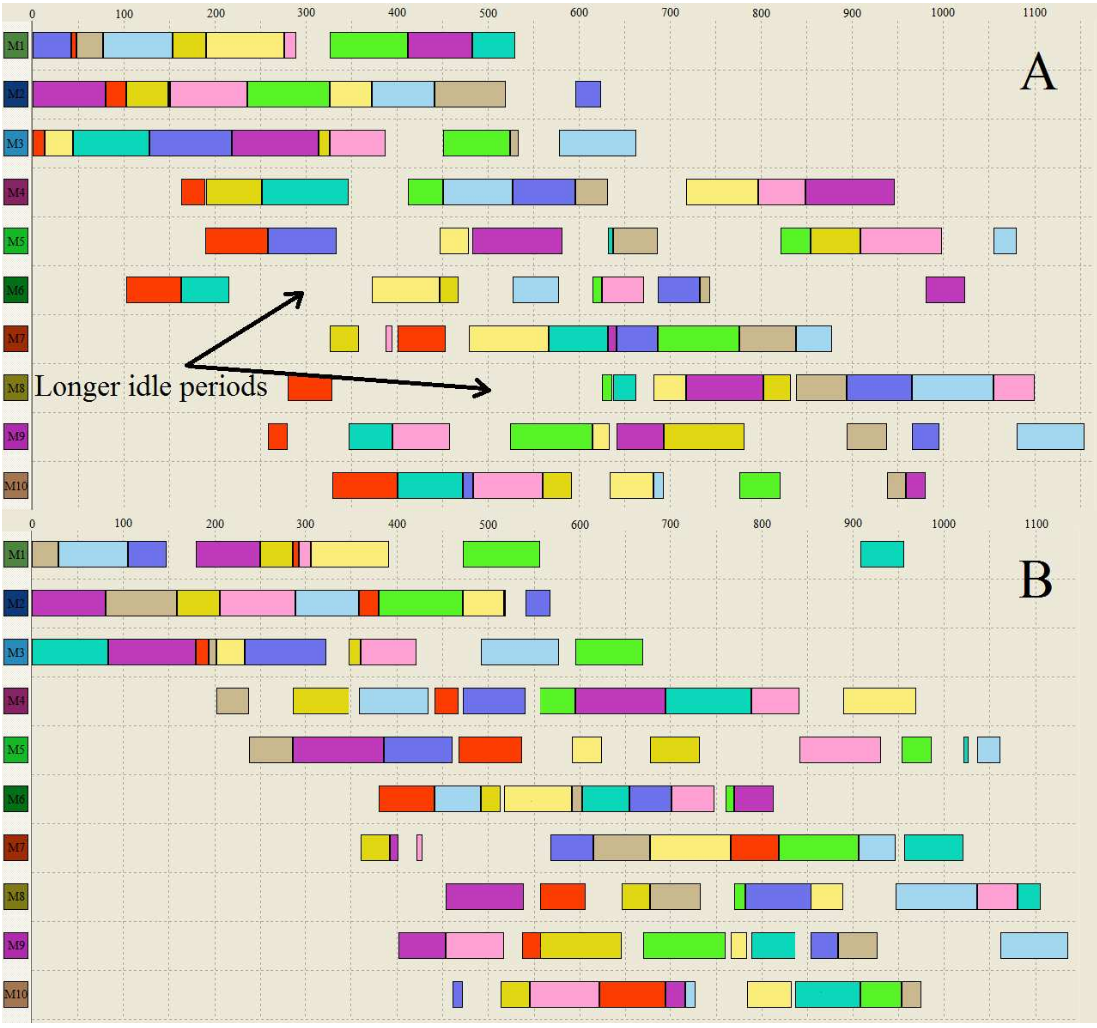


Figure 5.24: Gantt chart of optimal schedule by GAEJP (A) and Gantt chart of optimised schedule of NSGA-II (B) when $f = 1.5$
(E-F&T 10 × 10 job shop)

5.7 Summary

The Turn off/Turn on method developed by Mouzon et al. (2007) is a very effective approach in achieving the objective of reducing the total non-processing electricity consumption in a basic job shop. To optimally use this technique and the sequencing method to solve the ECT problem, the multi-objective optimisation algorithm GAEJP is developed based on the NSGA-II. The performance of the algorithm has been tested on four extended versions of job shop instances, which incorporate electrical consumption profiles for the machine tools. These job shop instances include Fisher and Thompson 10×10 job shop scenario, Lawrence 10×10, 20×10 and 15×15 job shop scenarios. In addition, comparison experiments have been applied to demonstrate the effectiveness of the GAEJP in solving the ECT problem. Firstly, the Shifting Bottleneck Heuristic and the Local Search Heuristic have been adopted as the single objective optimisation techniques to deliver the baseline scenarios of the aforementioned job shops. The result of the comparison indicates that by applying the GAEJP, the total non-processing electricity consumptions in the job shop decrease considerably, but at the sacrifice of the total weighted tardiness objective up to a certain level. Secondly, the Pareto fronts of the GAEJP have been compared with the ones obtained by the NSGA-II. It can be observed that the GAEJP combined with the Turn Off/Turn On and the Sequencing methods is more effective in reducing the total non-processing electricity consumption than the NSGA-II combined with the Sequencing method while not necessarily sacrificing its performance on total weighted tardiness. Thus, the superiority of the GAEJP in solving the ECT problem has been demonstrated.

CHAPTER 6 INVESTIGATION OF THE ROLLING BLACKOUT POLICY ON JOB SHOPS

6.1 Introduction

This chapter investigates how the Rolling Blackout policy affects the performance of the scheduling plans produced in Scenario 2 and Scenario 3 in terms of the total weighted tardiness, total non-processing electricity consumption and the total electricity cost. The performances of scheduling plans in two scenarios are compared in this chapter (Scenario 4 and Scenario 5). In Scenario 4, there is no private electricity supply during the government electricity unavailable periods. On the contrary, in Scenario 5, the private electricity is employed during all the government supply unavailable periods to maintain the production.

Scenario 4 is used to present how the Rolling Blackout policy deteriorates the manufacturing company's delivery. The job shop will stop working during the blackout periods since there is no private electricity supply. Thus, a scheduling plan adjustment scheme will be provided in this scenario (new heuristic). The scheduling plans produced in Scenario 2 and Scenario 3 will be performed in Scenario 4 for adjustment. The operations that initially execute during the blackout periods should be postponed to the next electricity supply available period, thus, leading to the construction of the new scheduling plan in Scenario 4. Based on the new scheduling plan, the values of indicators in Scenario 4 will be re-calculated.

Scenario 5 is used to present the influence of employing private electricity on the total electricity cost. Therefore, in this scenario, the private electricity is used to provide the power for the manufacturing companies during all the blackout periods. The scheduling plans produced in Scenario 2 and Scenario 3 will be performed in Scenario 5, i.e. the scheduling plans will stay the same, however the values of the total electricity cost should be re-calculated. In this investigation, the emphasis is on the cost element of using the private electricity supply rather than the environmental impact.

Based on the comparison experiments between the performance of the scheduling plans of Scenario 4 and 5, it has been found that it is necessary to develop compromised plans for using the private electricity to deliver the trade-off between the total weighted tardiness and the total electricity cost. This leads to the EC2T problem. In this chapter, NSGA-II will be adapted to solve the EC2T problem. The new encoding schema, crossover and mutation operators are provided. This method is used to decide whether to provide private electricity to a machine during each government electricity supply unavailable period. The performance of the algorithm will be tested on four extended versions of job shop instances which incorporate electrical consumption profiles for the machine tools. To compare the indicators' values in Scenario 6 to those in Scenario 4, a better performance on the total weighted tardiness should be observed; to compare the indicators' values in Scenario 6 to those in Scenario 5, a better performance on total electricity cost should be observed. Therefore, the NSGA-II and its related new encoding schema, crossover operator and mutation operator are proved to be effective in solving the EC2T problem.

6.2 Scenario 4, 5 and 6 and expected results of comparison experiment

In the EC2T problem, the Rolling Blackout policy is applied to the job shop. Obviously, the policy will exert a negative influence on the performance of the job shop, such as a deterioration in delivery and an increasing in the electricity cost if the private electricity is started for maintaining production. Thus, the total electricity cost the $TEC(s)$ is introduced as another indicator. The different responses of the manufacturing company to the Rolling Blackout policy are described respectively in Scenarios 4, 5 and 6.

Scenario 4 is used to investigate how the Rolling Blackout policy deteriorates the manufacturing company's delivery. Therefore, in this scenario, the private electricity supply such as the diesel generator is not used when the government supplied resource is unavailable. The job shop stops working during the blackout periods. The scheduling plans produced in Scenario 2 and Scenario 3 are performed in this scenario. The operations that initially execute during the blackout periods should be postponed until the next electricity supply available period, thus, constructing the new scheduling plan for Scenario 4. The adjustment is completed by the newly developed heuristic. Based on the new scheduling plan, the values of indicators in Scenario 4 can be defined as shown in **Table 6.1**. Since only the government supplied electricity is used in this Scenario, the electricity price $p^e = \beta_1\ Pounds/kWh$. s^{si} represents the scheduling plans after adjustment. For instance, s^{s2} represents the scheduling plans in Scenario 4 after adjusting the optimised scheduling plans in Scenario 2. The superscript S2 means Scenario 2. twt_{s4}^{si} is the value of the total weighted tardiness of the adjusted scheduling plan s^{si}, where the superscript si represents the original scenario. For instance, twt_{s4}^{s2} is the total weighted tardiness value of the Scenario 4 schedule s^{s2}. s^{s2} is the adjustment result of a schedule produced by the NSGA-II (Scenario 2). Similarly, npe_{s4}^{si} and ec_{s4}^{si} respectively represent the total non-processing electricity consumption value and the total electricity cost value of the adjusted scheduling plan s^{si}.

Table 6.1: Parameters of Scenario 4

Objective	The scheduling plans in Scenario 4 are developed from scheduling plans produced by the NSGA-II (Scenario 2) and the GAEJP (Scenario 3). This is not a multi-objective optimisation problem. Thus, there is no objective in Scenario 4.
Indicators	• $twt_{s4}^{si} = \sum_{i=1}^{n} w_i \times T_i(s^{si})\ \ i = 2, 3$ • $npe_{s4}^{si} = \sum_{k=1}^{m} TEM_k^{np}(s^{si})\ \ i = 2, 3$ • $ec_{s4}^{si} = TEC(s^{si})\ \ i = 2, 3$
Adjustment Method	Newly developed adjustment heuristic
ESMs implementation	Turn Off/Turn On (if the original scheduling plan is produced by the GAEJP) None (if the original scheduling plan is produced by the NSGA-II)

Scenario 5 is used to investigate the increase of employing private electricity on the total electricity cost. Therefore, in this scenario, the private electricity is started to provide power for the manufacturing company during all the blackout periods. The scheduling plans produced by the NSGA-II (Scenario 2) and the GAEJP (Scenario 3) are performed in Scenario 5. Here the electricity price $p^e = \beta_1\ Pounds/kWh$ when the electricity is supplied by the government, otherwise $p^e = \beta_2\ Pounds/kWh$. In **Table 6.2**, twt_{s5}^{si} is the total weighted tardiness value of the scheduling plan s^{si}, where the superscript si represents the original scenario. The value of the total weighted tardiness and total non-processing electricity consumption should equal the tardiness and consumption values in the original scenario, respectively, since the schedules have not been changed. The value of the total electricity cost ec_{s5}^{si} will be larger than the cost value in the original scenario (Scenario 2 or 3) because of the use of private electricity.

Table 6.2: Parameters of Scenario 5

Objective	The scheduling plans in Scenario 4 are developed from scheduling plans produced by the NSGA-II (Scenario 2) and the GAEJP (Scenario 3). This is not a multi-objective optimisation problem. Thus, there is no objective in Scenario 5.
Indicators	• $twt_{s5}^{si} = \sum_{i=1}^{n} w_i \times T_i(s^{si}) \;\; i = 2,3$ • $npe_{s5}^{si} = \sum_{k=1}^{m} TEM_k^{np}(s^{si}) \;\; i = 2,3$ • $ec_{s5}^{si} = TEC(s^{si}) \;\; i = 2,3$
Adjustment Method	None
ESMs implementation	Turn Off/Turn On (if the original scheduling plan is produced by the GAEJP) None (if the original scheduling plan is produced by the NSGA-II)

Table 6.3: Expected results for scenarios comparison and conclusion

Scenarios comparison	Expected result
Compare Scenario 4 to its original scenario, for instance, Scenario 3	$twt_{s3}^{f} < twt_{s4}^{s3}, npe_{s3}^{f} \neq npe_{s4}^{s3}$
Compare Scenario 5 to its original scenario, for instance, Scenario 3	$twt_{s3}^{f} = twt_{s5}^{s3}, npe_{s3}^{f} = npe_{s5}^{s3}$
Compare Scenario 5 to Scenario 4 (Take Scenario 3 as the original scenario)	$twt_{s5}^{s3} < twt_{s4}^{s3}$, $npe_{s4}^{s3} \neq npe_{s5}^{s3}$, $ec_{s4}^{s3} < ec_{s5}^{s3}$

Take Scenario 3 (GAEJP) as an example, as presented in **Table 6.3**, the comparison of indicators' values between Scenario 4 (the adjustment scenario) and Scenario 3 (GAEJP) can show how the Rolling Blackout policy affects the performance of the job shop on delivery when there is no remedial measure for the lack of electricity. It can be expected that firstly the total weighted tardiness will increase in Scenario 4. Secondly, the fluctuation of the total non-processing electricity consumption cannot be decided. Finally, the fluctuation of the total electricity cost related to the value of the total non-processing electricity consumption cannot be decided either. However the difference of the total non-processing electricity consumption between these two scenarios is not expected to be large.

The comparison of indicators' values between Scenario 5 (private electricity used) and Scenario 3 will show that the employment of private electricity would keep the job shop's performance on the total weighted tardiness from deteriorating. The electricity consumption amount in Scenario 5 is the same with that in Scenario 3, but the cost for electricity will definitely increase since the private electricity is much more expensive than the government supplied resource.

The aforementioned comparisons are expected to demonstrate that if insisting on the optimised scheduling plan for the ECT problem, at least the performance of one indicator is expected to be weakened when the Rolling Blackout policy is applied, despite whether the private electricity supply is started or not during the electricity unavailable periods. This hypothesis will be proved in the following sections in this chapter.

Therefore, to solve the EC2T problem, a compromised private electricity supply plan between Scenario 4 and Scenario 5 needs to be developed. The proper private electricity allocation plan for each machine tool during the blackout periods needs to be developed, i.e. it is not necessary to provide electricity to every machine tool in every electricity unavailable period. A decision should be made to use the private electricity as less as possible while guaranteeing the in time delivery. Based on the private electricity supply plan, new scheduling plans should be delivered. The new solution is proposed in Scenario 6. This is another contribution of this PhD research. The parameters of Scenario 6 are shown in **Table 6.4**.

Table 6.4: Parameters of scenario 6

Objective	• $minimise\ \sum_{i=1}^{n} w_i \times T_i(s)$ • $minimise\ \sum_{k=1}^{m} TEM_k^{np}(s)$ • $minimise\ TEC(s)$
Indicators	• $twt_{s6}^{f} = \{twt_{s6}^{fq}\}_{q=1}^{p}$ • $npe_{s6}^{f} = \{npe_{s6}^{fq}\}_{q=1}^{p}$ • $ec_{s6}^{f} = \{ec_{s6}^{fq}\}_{q=1}^{p}$
Optimisation Method	NSGA-II
ESMs implementation	Turn Off/Turn On; Sequencing

In this scenario, the encoding schema for the algorithm should be expanded since the decision for the private electricity allocation is taken into consideration in the chromosome encoding. The new encoding schema is developed in the following content of this chapter. The Pareto-front formed by p non-dominated solutions (a group of scheduling plans) is obtained after the optimisation process. Thus, the indicators' values of Scenario 6 are the following three sets:

$$twt_{s6}^{fq} = f_1(s^{fq}) = \sum_{i=1}^{n} w_i \times T_i(s^{fq}) \tag{6.1}$$

$$npe_{s6}^{fq} = f_2(s^{fq}) = \sum_{k=1}^{m} TEM_k^{np}\,(s^{fq}) \tag{6.2}$$

$$ec_{s6}^{fq} = f_3(s^{fq}) = TEC(s^{fq}) \tag{6.3}$$

f is the tardiness factor, and s^{fq} is the q-th optimised scheduling plan in the total p solutions under different tardiness constraints. twt_{s6}^{f} is the set for the objective function values of total weighted tardiness of solutions obtained by NSGA-II for the EC2T problem. The subscript $s6$ represents Scenario 6, and the superscript f represents the tardiness factor. twt_{s6}^{fq} is one of the elements in twt_{s6}^{f}, which represents the total weighted tardiness of the q-th optimised scheduling plan in the total p solutions under different tardiness constraints. Similarly, npe_{s6}^{f} and ec_{s6}^{f} respectively represent the set for the objective function values of total non-processing electricity consumption and the set for the objective function values of total electricity cost of solutions obtained by NSGA-II for the EC2T problem.

Table 6.5: Expected results for scenarios comparison for the EC2T problem

Scenarios comparison	**Expected result**
Compare Scenario 6 to Scenario 4 (Based on Scenario 3)	$\forall twt_{s6}^{fq} \leq twt_{s4}^{s3}; \forall ec_{s6}^{fq} \geq ec_{s4}^{s3}$
Compare Scenario 6 to Scenario 5 (Based on Scenario 3)	$\forall twt_{s6}^{fq} \geq twt_{s5}^{s3}; \forall ec_{s6}^{fq} \leq ec_{s5}^{s3}$

The optimisation result obtained in Scenario 6 is compared with Scenario 4 and Scenario 5 which are developed based on Scenario 3. Since only in Scenario 6 and Scenario 3, the Turn Off/ Turn on method has been applied. To compare the indicators' values in Scenario 6 to that in Scenario 4 (see **Table 6.5**), it can be expected to observe a better performance on the total weighted tardiness; to compare the indicators' values in Scenario 6 to that in Scenario 5, it can be expected to observe a better performance on total electricity cost. However, the comparison results on the total non-processing electricity indicator is currently hard to decide.

6.3 The procedure of the adjustment heuristic in Scenario 4

The procedure of the adjustment algorithm S4 are described by using a 3×3 job shop provided by Liu & Wu (2008) as shown in **Table 6.6**. It can be supposed that $[222333111]$ is a feasible chromosome. Decoded by the active schedule builder, the chromosome can be transferred to a feasible schedule s, as shown in **Figure 6.1**.

Table 6.6: 3×3 job shop parameters

O_{ik}^{l} \ J_i	O_{ik}^{1}	O_{ik}^{2}	O_{ik}^{3}	r_i	d_i (time unit)	w_i
J_1	$M_1(2)$	$M_2(2)$	$M_3(3)$	0	10	3
J_2	$M_3(3)$	$M_2(1)$	$M_1(4)$	0	10	2
J_3	$M_2(1)$	$M_1(3)$	$M_3(2)$	0	10	1

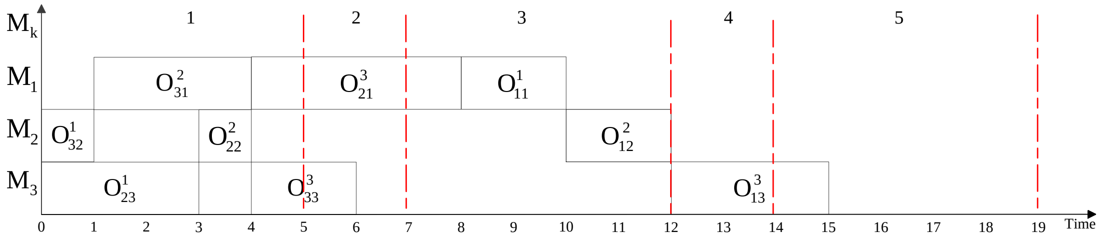


Figure 6.1: Transforming chromosome $[222333111]$ to a feasible active schedule and semi-active schedule, based on (Liu & Wu 2008)

In this case, the cycle period of the Rolling Blackout policy is 7 time units ($T = 7$) where $\Delta t_s = 5$ and $\Delta t_o = 2$, which indicates that the government electricity supply available period (GAP) is the first 5 time units of each cycle period and the government electricity supply unavailable period (GUP) is the next 2 time units. Based on the aforementioned information, all the GAPs and GUPs in s can be enumerated. The GAPs can be numbered as $2x - 1\ th$ period and GUPs can be numbered as $2x\ th$ period, where $x = 1, 2, 3 \ldots a$. As seen in **Figure 6.1**, the $1th$, $3th$ and $5th$ periods are the GAPs, while the $2th$ and $4th$ periods are the GUPs.

The idea for the heuristic developed in Scenario 4 is that when the Rolling Blackout policy is applied, the operations locate in the government electricity unavailable period and their subsequent operations on the same machine and in the same job are needed to be firstly postponed. As shown in **Figure 6.2**, 450 to 600 time unit is the first government electricity unavailable period. Thus, all operations after the red line which is the splitting line need to be moved right. The sequence and pattern of these operations are kept the same after the right move. Applying this kind of right move is based on the fact that the original scheduling plan is an optimal one, thus it is beneficial to keep the sequence and pattern during the right moving. Then, the operations locate in the second government electricity unavailable period, which is 1050 to 1200, and their subsequent operations on the same machine and in the same job are needed to be found out and postponed. After all the right move work is finished, it might be found that some of the operations can be moved left to improve the schedule's performance on the total weighted tardiness objective. The new scheduling plan can be obtained after finishing the left moving.

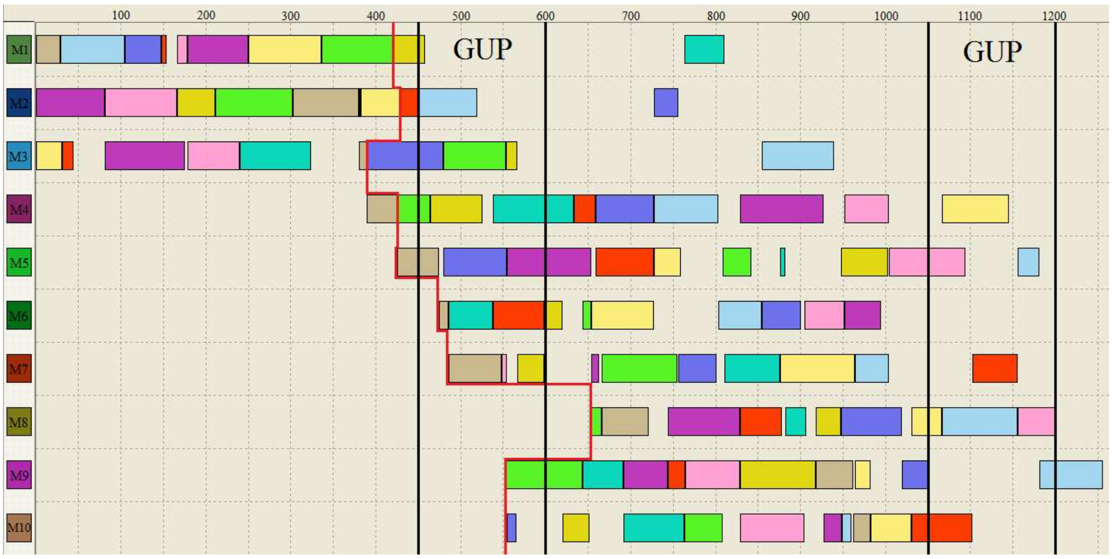


Figure 6.2: Example for right move

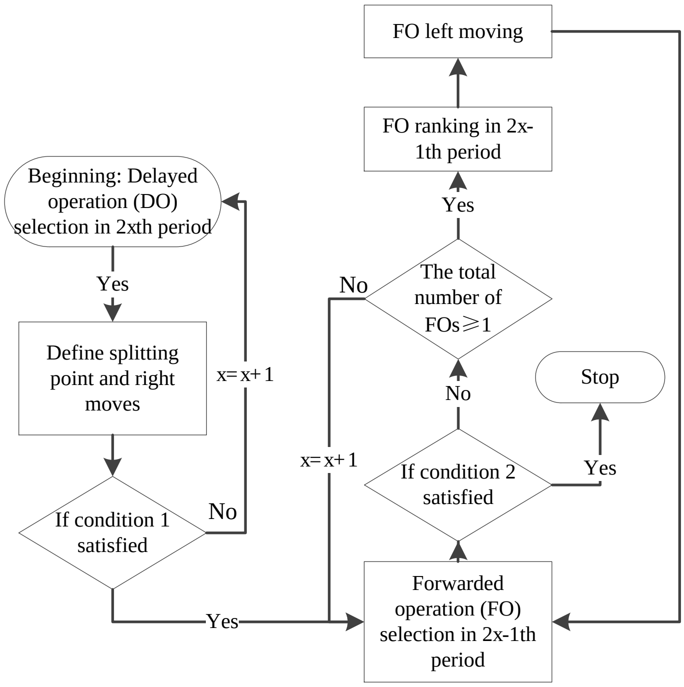


Figure 6.3: the flowchart of the adjustment heuristic in Scenario 4

Figure 6.3 presents the flowchart of the adjustment algorithm developed in Scenario 4. The process of the algorithm is detailed described in the following.

Delayed operation selection: The task in this step is to find out operations which need to be delayed for the unavailable electricity supply in $2x\ th$ period, where $x = 1, 2, 3 \ldots a$. The search starts from the period 2. O_{ik}^{l} can be defined as delayed operation related to the $2x\ th$ period if any part of its processing time locates in the $2x\ th$ period. The condition can be mathematically expressed as following:

$$\exists O_{ik}^{l} \in O_i \quad S_{2x} < C_{ik}^{l} \leq E_{2x} \tag{6.4}$$

$$\exists O_{ik}^{l} \in O_i \quad C_{ik}^{l} > E_{2x}, S_{ik}^{l} \leq E_{2x} \tag{6.5}$$

Where

S_{ik}^{l} is the starting time of O_{ik}^{l}.

C_{ik}^{l} is the completion time of O_{ik}^{l}.

S_{2x} is the starting time of the $2x\ th$ period.

E_{2x} is the ending time of the $2x\ th$ period.

Define splitting point and right moves after identifying all the delayed operations related to the $2x$ th period, the splitting line and splitting point on schedule s needs to be defined. The starting time of all the delayed operations form the splitting line, as the red line shown in **Figure 6.4**. The earliest starting time of all the delayed operations on the machine M_k are defined as the splitting point. In **Figure 6.4**, O_{21}^3 is the delayed operation on M_1 and O_{33}^3 is the delayed operation on M_3. Thus $S_{21}^3 = 4$ and $S_{33}^3 = 4$ form the splitting line. All of the operations after the splitting line will be postponed. Since $S_{21}^3 = S_{33}^3$, either of them can be defined as the splitting points. Here selecting S_{21}^3 as the splitting point. S_{min}^{DO} can be defined as the earliest starting time of all the delayed operations related to the $2x$ th period. Then the rule for the right moves is: $S_{min}^{DO} = S_{2x+1}$, which means the new value for the S_{min}^{DO} should equal the starting time of the government electricity supply available period (the period $2x + 1$) following the $2x$ th period. The result of the right moving based on **Figure 6.4** is shown in **Figure 6.5**.

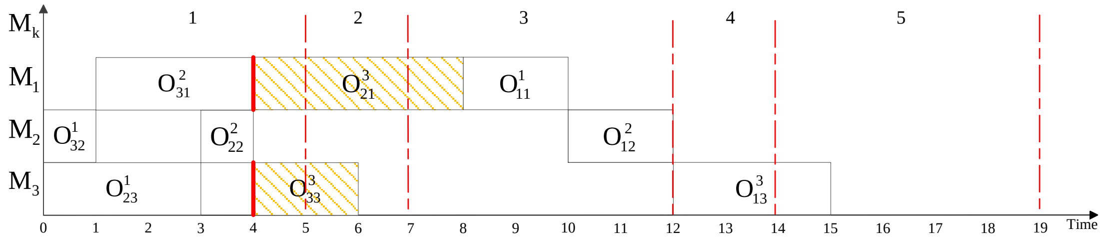


Figure 6.4: Splitting points on s

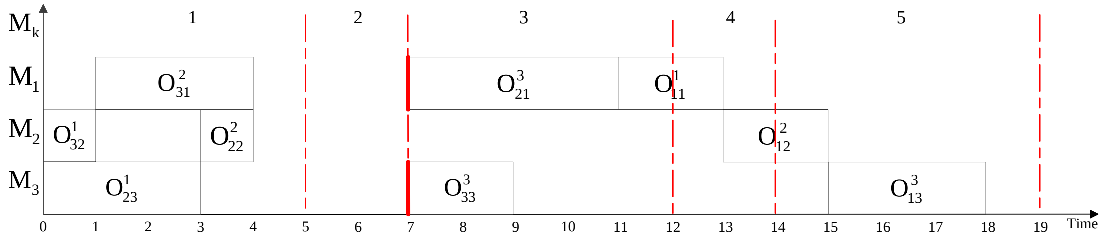


Figure 6.5: Postponed schedule based on s

Condition 1:

Condition 1 is used to judge whether all operations that need to be postponed have finished their right move. If yes, the algorithm goes to next step for forwarded operation selection. Otherwise, the algorithm goes back to the delayed operation selection. The condition can be mathematically expressed as follows:

$$\forall\, max(C_k^r) < S_{2x} \quad \forall m_k^r \in M_k' \tag{6.6}$$

Where

$M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^l}$ is a finite set of operations processed on M_k.

γ_{ik}^l is a decision variable such that $\gamma_{ik}^l = 1$ if the l-th operation of J_i is processed on M_k, 0 otherwise.

m_k^r is r-th operation processed on M_k within a feasible schedule s.

C_k^r is the starting time of m_k^r on M_k.

S_{2x} is the starting time of the $2x\ th$ period.

Condition (6.6) makes sure that all of the last operations on each M_k are finished before the starting time of the $2x\ th$ period. Thus, when it has been satisfied, all of the operations in schedule s have been moved to the government electricity supply available periods, and the algorithm goes to the forwarded operation selection step. If it is not satisfied, the delayed operation selection related to the $2(x+1)\ th$ period is executed. The result of finishing all the right moves within schedule s is shown in **Figure 6.6**. The new schedule can be denoted as s'.

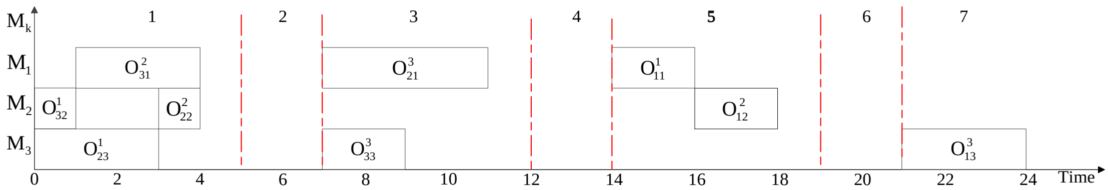


Figure 6.6: The result of finishing all the right moves within schedule s

Forwarded operations selection: After finishing all the right moves, normally it can be noticed that some of the operations can be moved forward (left), thus the schedule performance on the total weighted tardiness can be improved. Therefore, all of the forwarded operations in $2x - 1\ th$ periods within the schedule s' where $x = 1, 2, 3 \ldots a$, should be found out and moved forward. The search starts from the $1\ th$ period. If there is no forwarded operation related to the $2x - 1\ th$ period, then move to the $2(x+1) - 1\ th$ period to begin a new search procedure. An operation can be defined as a forwarded operation in the $2x - 1\ th$ period if its position on the scheduling plan looks like the target operation O_{ik}^{l} in **Figure 6.7-Figure 6.9**.

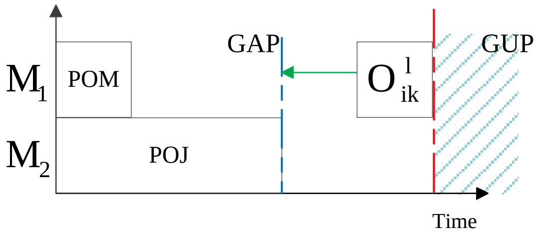


Figure 6.7: Feasible forwarded operation (in one GAP)

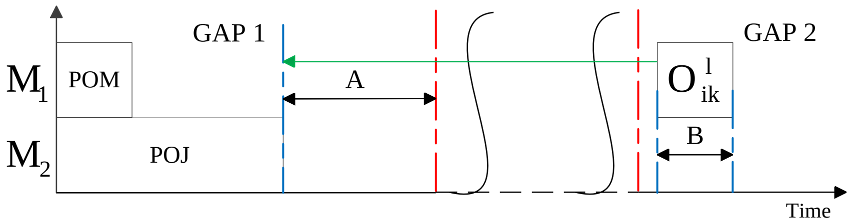


Figure 6.8: Feasible forwarded operation (in more than one GAP) situation 1

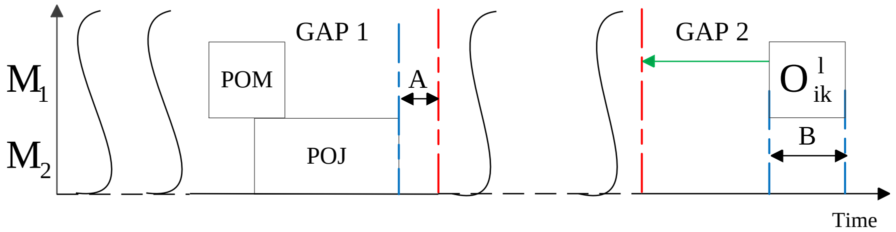


Figure 6.9: Feasible forwarded operation (in more than one GAP) situation 2

In **Figure 6.7**, O_{ik}^{l} and its preceding operation within the same job (POJ) and preceding operation on the same machine (POM) are in the same government electricity supply available period (GAP). There is a space for O_{ik}^{l} to move left to the blue line which is the maximum between the completion time of its POJ and the completion time of its POM. In **Figure 6.8**, O_{ik}^{l} and its POJ and POM are in different GAPs, but there is enough space for O_{ik}^{l} to move into GAP 1 where POJ locates (A > B, where B represents the processing time of O_{ik}^{l}). Then O_{ik}^{l} can be moved into GAP 1 to the blue line. In **Figure 6.9**, although O_{ik}^{l} and its POJ and POM are in different GAPs and A < B, O_{ik}^{l} can still be defined as a forwarded operation and it can be moved to the starting time of GAP 2. All the aforementioned conditions can be mathematically defined in the following:

$$S_{ik}^{l} > max\left(C_{k}^{r-1}, C_{ik'}^{l-1}\right) \quad X_{ik}^{lr} = 1 \tag{6.7}$$

If

$S_{2x-1} < max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) < E_{2x-1}$

$S_{2x-1} < S_{ik}^l < E_{2x-1}$

$$E_{2(x-y)-1} - max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \geq p_{ik}^l \quad X_{ik}^{lr} = 1 \tag{6.8}$$

$$S_{2(x-y)+1} < S_{ik}^l, \text{ if } E_{2(x-y)-1} - max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) < p_{ik}^l \quad X_{ik}^{lr} = 1 \tag{6.9}$$

If

$S_{2(x-y)-1} < max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \leq E_{2(x-y)-1}$

$S_{2x-1} < S_{ik}^l < E_{2x-1}$

Where

$\mathrm{x} = 2, 3, 4, \ldots, a.$

$\mathrm{y} = 1, 2, 3, \ldots, b.$

S_{ik}^l is the starting time of O_{ik}^l.

C_{ik}^l is the completion time of O_{ik}^l.

p_{ik}^l is the processing time of O_{ik}^l.

S_{2x-1} is the starting time of the $2x - 1$ th period.

E_{2x-1} is the ending time of the $2x - 1$ th period.

$S_{2(x-y)-1}$ is the starting time of the $2(x - y) - 1$ th period.

$E_{2(x-y)-1}$ is the ending time of the $2(x - y) - 1$ th period.

$M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^l}$ is a finite set of operations processed on M_k.

γ_{ik}^l is a decision variable that $\gamma_{ik}^l = 1$ if the l-th operation of J_i processed on M_k, 0 otherwise.

m_k^r is the r-th operation processed on M_k within s.

X_{ik}^{lr} is a decision variable, $X_{ik}^{lr} = 1$ if O_{ik}^l of J_i is scheduled in the r-th position for processing on M_k, 0 otherwise. Thus, in constraint (6.10), $m_k^r = O_{ik}^l$.

$O_{ik'}^{l-1}$ is the preceding operation within the same job of O_{ik}^l.

m_k^{r-1} is the preceding operation on the same machine as O_{ik}^l.

$C_{ik'}^{l-1}$ is the completion time of $O_{ik'}^{l-1}$.

C_k^{r-1} is the completion time of m_k^{r-1}.

The meaning of mathematical symbols in the above conditions can be seen in Nomenclature. This condition (6.7) means that when the starting time of $O_{ik}^l$and the maximum value in the completion time of O_{ik}^l's preceding operation within the same job (POJ) and the completion time of O_{ik}^l's preceding operation on the same machine (POM) are in the same government electricity supply available period, if the starting time of $O_{ik}^l$is larger than the maximum between the completion time of its POJ and the completion time of its POM, then it can be defined as a forwarded operation. When the aforementioned two time points belongs to different government electricity supply available periods, O_{ik}^l can be defined as forwarded operation if condition (6.8) or condition (6.9) can be satisfied. We can suppose that $C_{ik'}^{l-1} > C_k^{r-1}$, thus (6.8) means the processing time of O_{ik}^l is smaller than the gap between the ending time of the $2(x-y)-1\ th$ period where the completion time of O_{ik}^l's POJ locates and the completion time itself. When (6.8) is not satisfied, (6.9) means if the starting time of O_{ik}^l is larger than the starting time of the $2(x-y)+1\ th$ period which is the first government electricity supply available period following the $2(x-y)-1\ th$ period.

Condition 2:

Condition 2 is used to judge whether all operations that need to be moved forward have finished their left move. If yes, the algorithm is stopped. Otherwise, the algorithm checks if there is any forwarded operation in the $2x-1\ th$ period. If yes, the algorithm executes the forwarded operation ranking step. Otherwise, the algorithm will go back to the forwarded operation selection step.

$$\forall\ max(C_k^r) < S_{2x-1} \quad \forall m_k^r \in M_k' \tag{6.11}$$

Where

$M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^l}$ is a finite set of operations processed on M_k.

γ_{ik}^l is a decision variable that $\gamma_{ik}^l = 1$ if the l-th operation of J_i processed on M_k, 0 otherwise.

m_k^r is r-th operation processed on M_k within a feasible schedule s.

C_k^r is the starting time of m_k^r on M_k.

S_{2x-1} is the starting time of the $2x - 1\ th$ period.

Condition (6.11) makes sure that all of the last operations on each M_k are finished before the starting time of the $2x - 1\ th$ period. Thus, when it has been satisfied, all of the forward moving in schedule s have been finished, and the algorithm is stopped. Otherwise, the algorithm will check whether there is any forwarded operation in the $2x - 1\ th$ period. If there is none, the algorithm goes to $2(x + 1) - 1\ th$ period to do the forwarded operation selection. Otherwise, the algorithm executes the forwarded operation ranking step.

Forwarded operations ranking: After all forwarded operations in the $2x - 1\ th$ period have been found, they need to be ranked to find out the one with the highest priority for forward (left) moving. The ranking rules are described below. $O_{ik}^l \prec_f O_{i'k}^{l'}$ means O_{ik}^l is prior to $O_{i'k}^{l'}$ in forward moving.

$$O_{ik}^l \prec_f O_{i'k}^{l'} \text{ if } \frac{w_i}{d_i} > \frac{w_{i'}}{d_{i'}} \tag{6.12}$$

else if $\frac{w_i}{d_i} = \frac{w_{i'}}{d_{i'}}$,

$$\text{then } O_{ik}^l \prec_f O_{i'k}^{l'} \text{ if } w_i > w_{i'} \tag{6.13}$$

else if $w_i = w_{i'};\ d_i = d_{i'}$,

$$\text{then randomly ranking } O_{ik}^l \text{ and } O_{i'k}^{l'} \tag{6.14}$$

else if $i = i'$,

$$\text{then } O_{ik}^{l} \prec_f O_{i'k}^{l'} \text{ if } l < l' \quad (6.15)$$

For operations from different J_i, condition (6.12) means that operation O_{ik}^{l} with a higher value in $\frac{w_i}{d_i}$ gets the priority for forward moving. Condition (6.13**)** means that when the values of $\frac{w_i}{d_i}$ are the same, the one with higher a value in w_i gets the priority. Condition (6.14) indicates that when the w_i and d_i of the two operations are the same, either can be preferred. Finally, for operations from the same J_i, the one positioned forward in the technology path gets the priority.

Forwarded operation left moving: The different types of forwarded moving can be referred to as in **Figure 6.7-Figure 6.9**. Suppose O_{ik}^{l} gets the highest priority for forward moving in the $2x-1\ th$ period, defining the new starting time of O_{ik}^{l} as S_{ik}^{lnew}, the forward moving rules are presented below.

$$S_{ik}^{lnew} = maximum\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \quad X_{ik}^{lr} = 1 \quad (6.16)$$

If

$$S_{2x-1} < max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) < E_{2x-1}$$

$$S_{2x-1} < S_{ik}^{l} < E_{2x-1}$$

Else if

$$S_{2(x-y)-1} < max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \le E_{2(x-y)-1}$$

$$S_{2x-1} < S_{ik}^{l} < E_{2x-1}$$

$$E_{2(x-y)-1} - max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \ge p_{ik}^{l}$$

$$S_{ik}^{lnew} = S_{2(x-y)+1} \quad X_{ik}^{lr} = 1 \quad (6.17)$$

If

$$S_{2(x-y)-1} < max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) \le E_{2(x-y)-1}$$

$$S_{2x-1} < S_{ik}^{l} < E_{2x-1}$$

$$E_{2(x-y)-1} - max\left(C_k^{r-1}, C_{ik'}^{l-1}\right) < p_{ik}^{l}$$

$S_{2(x-y)+1} < S_{ik}^{l}$

Where

x $= 2, 3, 4, \dots, a$.

y $= 1, 2, 3, \dots, b$.

S_{ik}^{l} is the starting time of O_{ik}^{l}.

C_{ik}^{l} is the completion time of O_{ik}^{l}.

p_{ik}^{l} is the processing time of O_{ik}^{l}.

S_{2x-1} is the starting time of the $2x - 1\ th$ period.

E_{2x-1} is the ending time of the $2x - 1\ th$ period.

$S_{2(x-y)-1}$ is the starting time of the $2(x - y) - 1\ th$ period.

$E_{2(x-y)-1}$ is the ending time of the $2(x - y) - 1\ th$ period.

$M_k' = \{m_k^r\}_{r=1}^{\sum_{i=1}^{n}\sum_{l=1}^{u_i}\gamma_{ik}^{l}}$ is a finite set of operations processed on M_k.

γ_{ik}^{l} is a decision variable that $\gamma_{ik}^{l} = 1$ if the l-th operation of J_i processed on M_k, 0 otherwise.

m_k^r is the r-th operation processed on M_k within s.

X_{ik}^{lr} is a decision variable, $X_{ik}^{lr} = 1$ if O_{ik}^{l} of J_i is scheduled in the r-th position for processing on M_k, 0 otherwise. Thus, in constraint (6.18), $m_k^r = O_{ik}^{l}$.

$O_{ik'}^{l-1}$ is the POJ of O_{ik}^{l}.

m_k^{r-1} is the POM of O_{ik}^{l}.

$C_{ik'}^{l-1}$ is the completion time of $O_{ik'}^{l-1}$.

C_k^{r-1} is the completion time of m_k^{r-1}.

Based on **Figure 6.7-Figure 6.9**, rule (6.16) states that when the starting time of operation O_{ik}^{l} and the maximum value between the completion time of O_{ik}^{l}'s POJ and the completion time of O_{ik}^{l}'s POM are in the same GAP, moving O_{ik}^{l} left on M_k to its earliest possible starting time which is the completion time of the POJ, $C_{ik'}^{l-1}$ in this case (suppose $C_{ik'}^{l-1} > C_{k}^{r-1}$). Or when the aforementioned two time points belong to different GAPs, if the processing time of O_{ik}^{l} is smaller than the gap between the ending time of the $2(x-y)-1\ th$ period where the completion time of O_{ik}^{l}'s POJ locates and the completion time itself, moving O_{ik}^{l} left on M_k to its earliest possible starting time which is $C_{ik'}^{l-1}$ in this case. Rule (6.17) means that when the processing time of O_{ik}^{l} is larger than the gap between the ending time of the $2(x-y)-1\ th$ period where the completion time of O_{ik}^{l}'s POJ locates and the completion time of O_{ik}^{l} itself, and the starting time of O_{ik}^{l} is larger than the starting time of the $2(x-y)+1\ th$ period which is the first GAP following the $2(x-y)-1\ th$ period, then O_{ik}^{l} can be moved left on M_k to its earliest possible starting time which is $S_{2(x-y)+1}$. When finishing the left moving for the FO with the highest priority, the algorithm starts searching for FOs in the $2x-1\ th$ period again. Searching continues to the $2(x+1)-1\ th$ period if there is no FO in the $2x-1\ th$ period.

Compared to S4, the procedure of S5 is less complex. Since the private electricity is provided during all the GUPs, thus the original schedule is not changed. Different values should be applied to the electricity price for GAPs and GUPs during the objective function calculation for the total electricity price.

6.4 Result comparison

The aim of this section is to demonstrate how the Rolling Blackout policy affects the performance of the scheduling plans produced in Scenario 2 (NSGA-II) and Scenario 3 (GAEJP) in terms of total weighted tardiness, total non-processing electricity consumption and total electricity cost. Based on the experimental results, all job shop instances behave the same. Thus, only the E-Lawrence 15×15 job shop with $f = 1.6$ is used as an example for the comparison, while other experimental results will be shown in Appendix II. The electricity supply pattern is developed based on the fact that in some areas in China, the government electricity is available only from Monday to Thursday in one week, which means in $3/7$ of the production time the private electricity has to be employed. The private electricity nearly doubles the price of the governmental one. Thus, it has been assumed that the electricity price $p^e = 12.5\, pence/kWh$ if it is government electricity supply, while $p^e = 20.5\, pence/kWh$ if it is private electricity supply. The cycle period T of the Rolling Blackout policy is 10 hours, $\Delta t_s = 480\, min$ and $\Delta t_o = 120\, min$

6.4.1 Comparison of results in Scenario 2 to its corresponding Scenario 4 and Scenario 5

The Turn Off/ Turn On method has not been applied to scheduling plans in Scenario 2 (NSGA-II has been used as the optimisation technique). This method was also not applied to scheduling plans in Scenario 4 which are developed based on plans in Scenario 2. Therefore the machines are only turned off during the government electricity supply unavailable periods, and stay idle during the electricity supply available period even if there is no operation being processed on it. In Scenario 2, 6 solutions form the Pareto-front of E-Lawrence 15×15 job shop when $f = 1.6$. These solutions are ranked by the ascending order of the non-processing electricity consumption objective function value. In **Figure 6.10-Figure 6.12**, the horizontal axis represents the number of solutions.

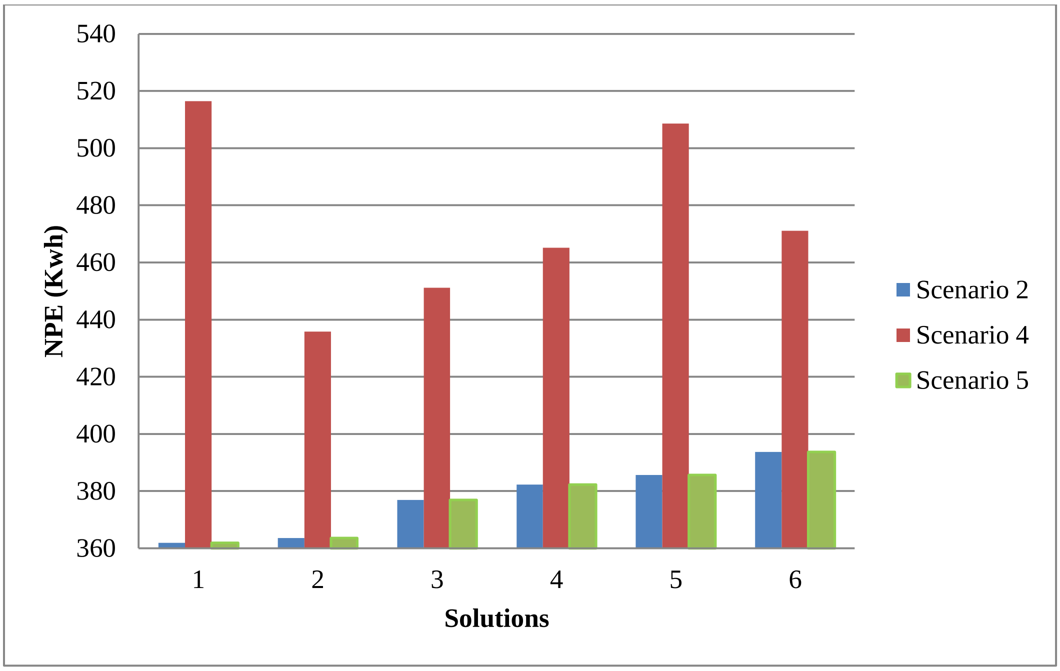


Figure 6.10: NPE comparison between Scenario 2 and its corresponding Scenario 4 and its corresponding Scenario 5

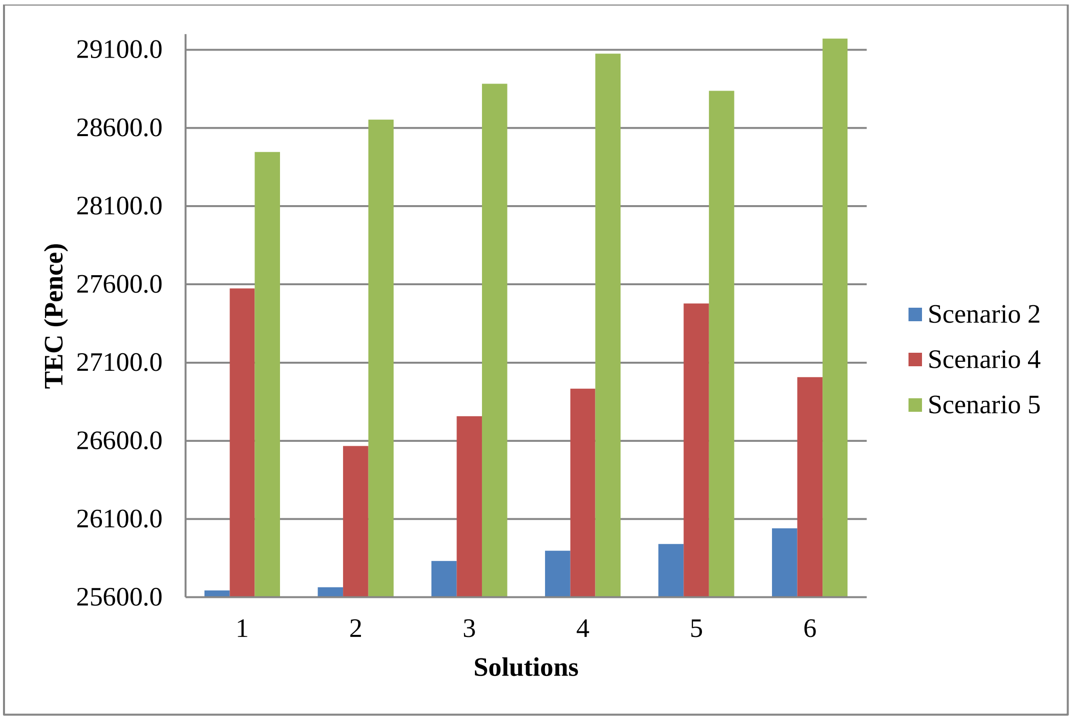


Figure 6.11: TWT comparison between Scenario 2 and its corresponding Scenario 4 and its corresponding Scenario 5

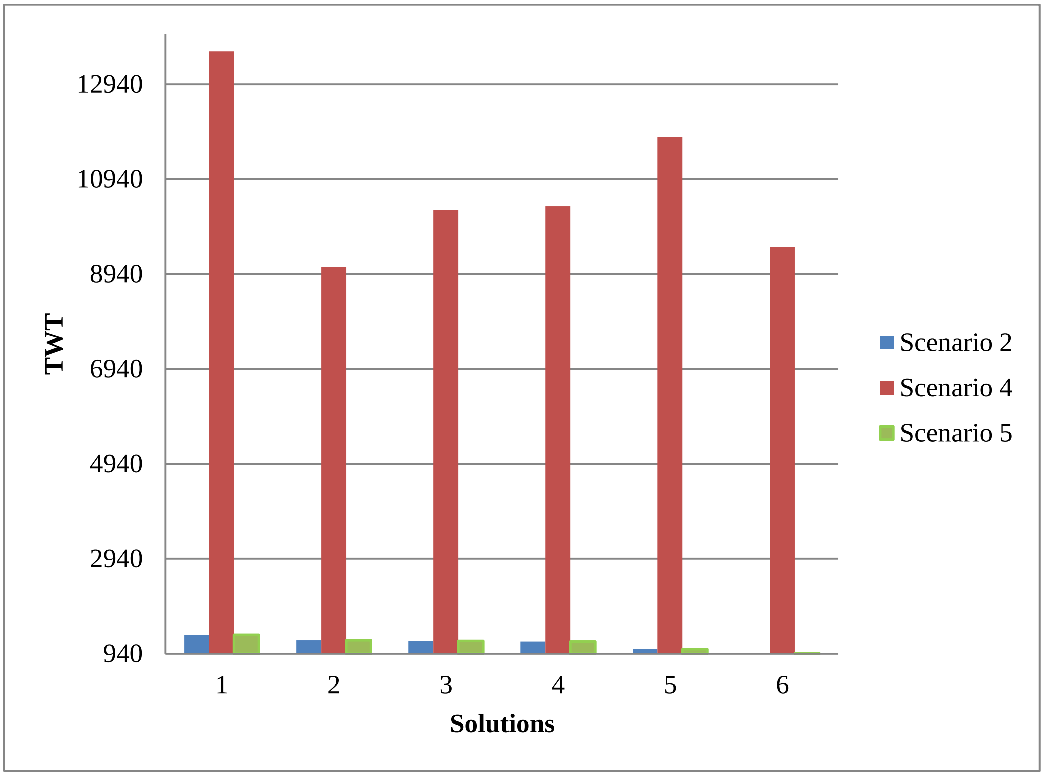


Figure 6.12: E-Cost comparison of Scenario 2, its corresponding Scenario 4 and its corresponding Scenario 5

6.4.2 Comparison of results in Scenario 3 to its corresponding Scenario 4 and Scenario 5

The Turn Off/ Turn On method has been applied to scheduling plans in Scenario 3 (GAEJP has been used as the optimisation technique). This method is also applied to scheduling plans in Scenario 4 which are developed based on plans in Scenario 3. Therefore the machines are turned off if the idle period is longer than 30 minutes. In Scenario 3, 4 solutions form the Pareto front of E-Lawrence 15×15 job shop when $f = 1.6$. Thus in **Figure 6.13-Figure 6.15**, the horizontal axis represents the number of solutions.

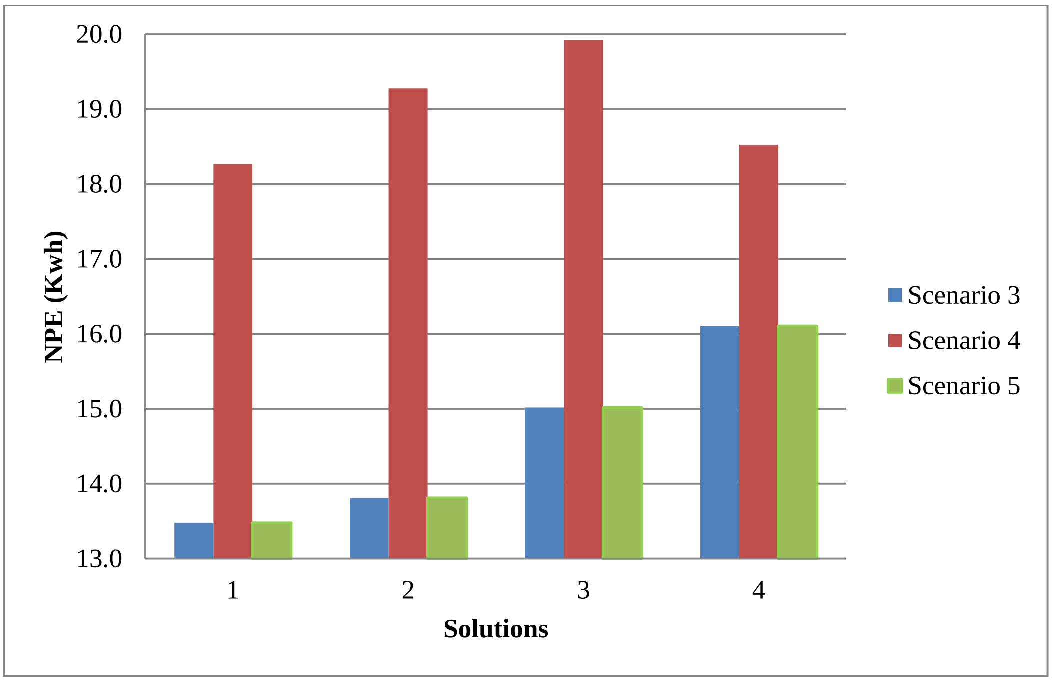


Figure 6.13: NPE comparison between Scenario 3 and its corresponding Scenario 4 and its corresponding Scenario 5

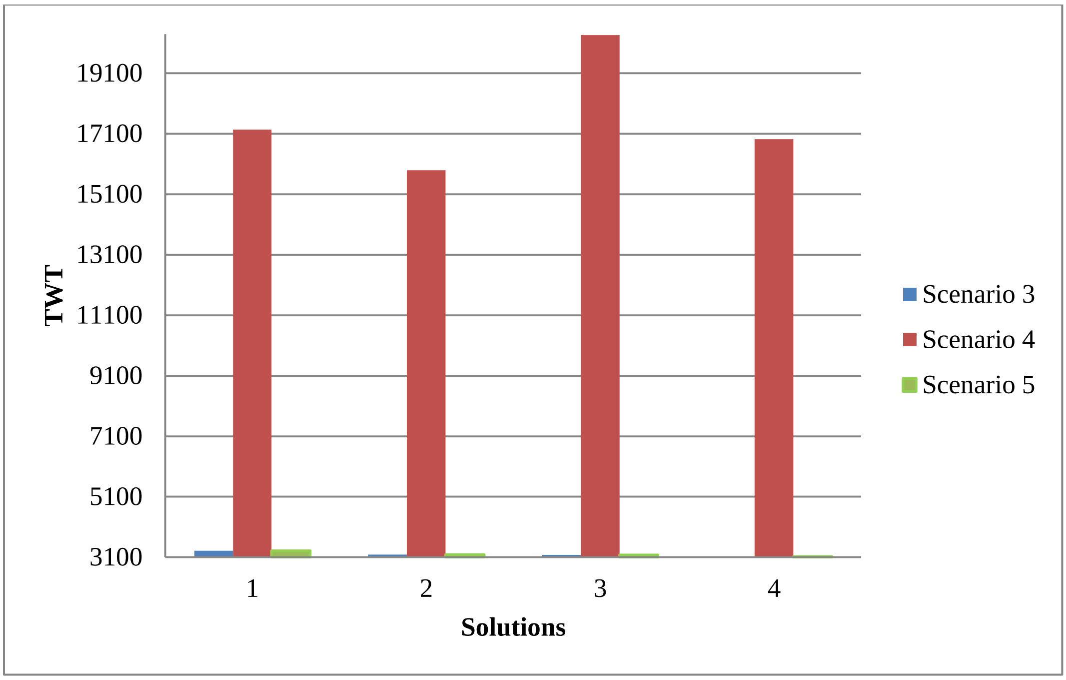


Figure 6.14: TWT comparison between Scenario 3 and its corresponding Scenario 4 and its corresponding Scenario 5

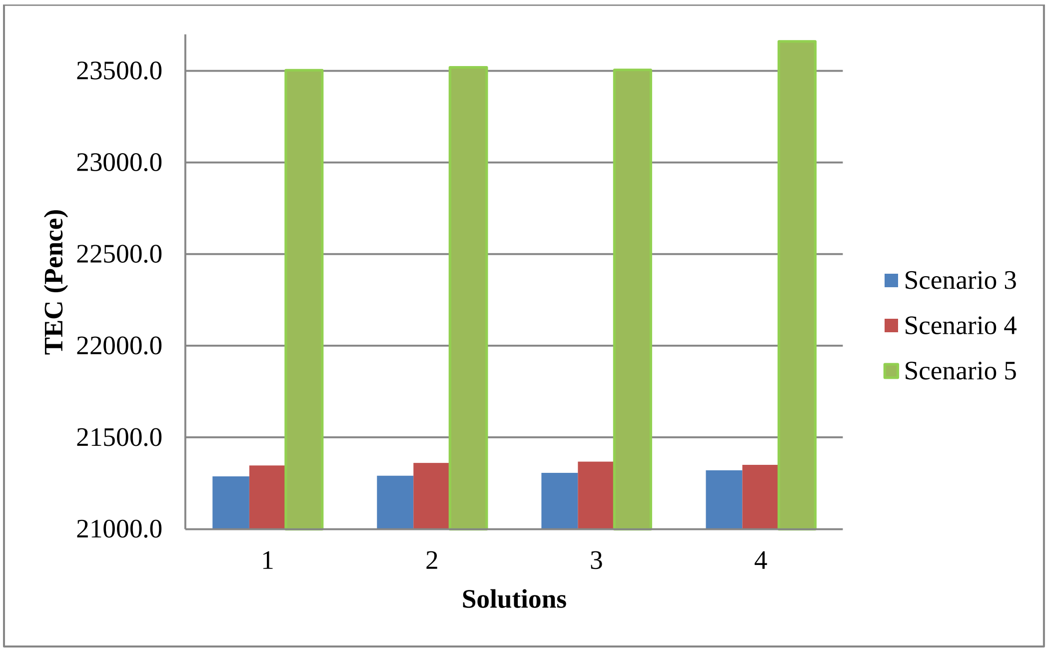


Figure 6.15: E-Cost comparison of Scenario 3, its corresponding Scenario 4 and its corresponding Scenario 5

Since the private electricity supply is unavailable in Scenario 4, it can be observed from **Figure 6.10**, **Figure 6.11**, **Figure 6.13** and **Figure 6.14** that both the total non-processing electricity consumption value and total weighted tardiness value increase in Scenario 4 after postponing some operations in Scenario 2 and Scenario 3 as anticipated in **Section 6.2**. Compared to the total electricity cost (TEC) value in Scenario 2 and Scenario 3, the total electricity cost values in Scenario 4 and Scenario 5 are increased, as anticipated in **Section 6.2**, the total electricity cost value in Scenario 5 is the highest since the private electricity supply is utilised in this scenario, as shown in **Figure 6.13** and **Figure 6.15**. Based on the above comparison experiments, it can be found that the total weighted tardiness is sacrificed if the private electricity is not used during the blackout periods, while the total electricity cost is sacrificed if the private electricity is used during all the blackout periods. To deliver the trade-off between total weighted tardiness and total electricity cost, compromised plans for using the private electricity need to be developed. This is the EC2T problem which is a tri-objective optimisation problem which is to reduce the total electricity cost, total electricity consumption and total weighted tardiness job shops. The solution for this problem will be detailed described below.

6.5 Solving the EC2T with NSGA-II (Scenario 6)

In the following section of this chapter, the goal is to generate compromised plans for using the private electricity where the NSGA-II is adapted to realise the trade-off between the total weighted tardiness and the total electricity cost. A new encoding schema, crossover and mutation operators are provided for solving the EC2T problem. The new method is used to decide whether to provide private electricity to each machine in the job shop during each government electricity supply unavailable period. The basic idea for the solution presented below is that when the Rolling Blackout policy is applied, and the private electricity supply is allowed to be used during the government electricity supply unavailable period, a plan for private electricity supply which is used to decide whether to provide the private resource to each machine in the job shop during each government electricity supply unavailable period needs to be produced. Then, the operations will be scheduled according to the final electricity supply situation. The optimisation method will be detailed described in the following sections.

6.5.1 Encoding schema

The chromosome used in Scenario 6 is composed of two parts. The first part is the OBES which had already been used in the aforementioned algorithm to represent the priority for operations to be assigned to the machines. The second part of the chromosome is created to represent the private electricity supply plan for each machine during each government electricity supply unavailable period which can be denoted by ESP (Electricity Supply Plan). A typical chromosome for the 3×3 job shop provided by Liu & Wu (2008) is shown below.

$$[222333111] + \begin{bmatrix} \boxed{1} & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

The electricity supply plan part of the chromosome is a matrix. The rows represent machines. For instance, the first row corresponds to machine M_1. The columns represent the government electricity supply unavailable periods. For instance, the first column corresponds to the first GUP in the scheduling plan. In ESP, “1” means the private electricity supply is available for a given machine M_k during a specific GUP, 0 otherwise. For a specific job shop, the size of the matrix for ESP is decided by the number of machines and the maximum number of GUPs in its schedules after the schedules have been adjusted in Scenario 4. Thus, the number of rows is equal to the number of machines and the number of columns is double the maximum number of GUPs. This chromosome design method is developed based on the fact that at the initial stage of the genetic algorithm, the operations allocation sequences are still not very good. It is highly possible that some solutions which are not very good in terms of their performance on the total weighted tardiness are in the population. In other words, these solutions need longer ESP (larger number in columns) to finish the scheduling plan. Otherwise, the algorithm is forced to stop. It can be found that normally scheduling plans provided in Scenario 4 (the none private electricity supply case) need to experience the maximum number of government electricity supply unavailable periods to complete. This means the number of columns that the ESPs need in the final stage of the algorithm is expected to be smaller than the maximum number of GUPs in Scenario 4. Based on this, some test experiments had been delivered and found that for a specific job shop, when the number of columns in the ESP doubles the maximum number of GUPs in its corresponding Scenario 4, the algorithm can execute successfully. For the above 3×3 job shop and the OBES part of the chromosome, based on the scheduling adjustment result in Scenario 4, **Figure 6.16** shows that 3 GUPs can be identified in the adjustment schedule. Thus, in the ESP part of the above chromosome, the number of rows is 3 and the number of columns is 6.

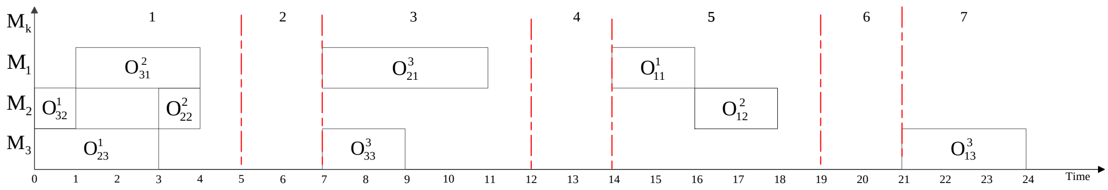


Figure 6.16: The result of finishing all right moves within schedule s

6.5.2 Crossover operator

The OOX crossover operator is employed for the OBES part of the chromosome. For the ESP part, the one point crossover operator is adopted. Given parent 1-A_1 and parent 2-A_2, the one point crossover operator generates child A_1' and child A_2' by the following procedure:

1. Randomly, choose the same crossover point from both of the parents.
2. Exchange all the genes before the crossover point in A_1 and A_2.

For example, in a 3×3 job shop, A_1 and A_2 are shown as below, $\vdots$ represents the crossover point.

$$A_1 = \begin{bmatrix} 1 & 0 \vdots & 0 & 1 & 1 & 1 \\ 0 & 1 \vdots & 0 & 0 & 1 & 0 \\ 1 & 1 \vdots & 1 & 0 & 1 & 0 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 0 & 0 \vdots & 0 & 1 & 0 & 1 \\ 1 & 1 \vdots & 0 & 0 & 1 & 0 \\ 1 & 0 \vdots & 0 & 0 & 1 & 0 \end{bmatrix}$$

A_1' and A_2' are feasible child chromosomes as shown below.

$$A_1' = \begin{bmatrix} 0 & 0 \vdots & 0 & 1 & 1 & 1 \\ 1 & 1 \vdots & 0 & 0 & 1 & 0 \\ 1 & 0 \vdots & 1 & 0 & 1 & 0 \end{bmatrix}$$

$$A_2' = \begin{bmatrix} 1 & 0 \vdots & 0 & 1 & 0 & 1 \\ 0 & 1 \vdots & 0 & 0 & 1 & 0 \\ 1 & 1 \vdots & 0 & 0 & 1 & 0 \end{bmatrix}$$

The latter half of all the columns in the ESP are just spare GUPs for schedule building, they rarely influence the scheduling result. So the crossover point is always located in the first half of the columns.

6.5.3 Mutation operator

The one point mutation operator is employed for solving the EC2T problem; namely an arbitrary gene in each row of the parent chromosome is chosen and its value is switched. Following the above example, A_1'' is the final child chromosome of A_1 after applying mutation on A_1'.

$$A_1' = \begin{bmatrix} \boxed{0} & 0 & 0 & 1 & 1 & 1 \\ 1 & \boxed{1} & 0 & 0 & 1 & 0 \\ 1 & 0 & \boxed{1} & 0 & 1 & 0 \end{bmatrix}$$

$$A_1'' = \begin{bmatrix} 1 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

6.5.4 Stopping criteria

The maximum number of generations is used as the stopping criterion. When the algorithm reaches this stage, the approximate pareto-front is obtained in the current set of non-dominated solutions.

6.5.5 Selection operator and decoding procedure

The selection operator is the binary tournament and the active schedule builder is employed. Each operation under treatment is allocated the best available processing time on the corresponding machine the operation requires. During the schedule building procedure, if any of the processing times of an operation overlaps with a GUP, then the operation is moved to the earliest available GAP, unless the private electricity supply is available for that GUP. This means the starting time of the specific operation is equal to the starting time of its earliest available GAP. For instance, the corresponding scheduling plan for the chromosome presented in **Section 6.5.1** is shown in **Figure 6.17**.

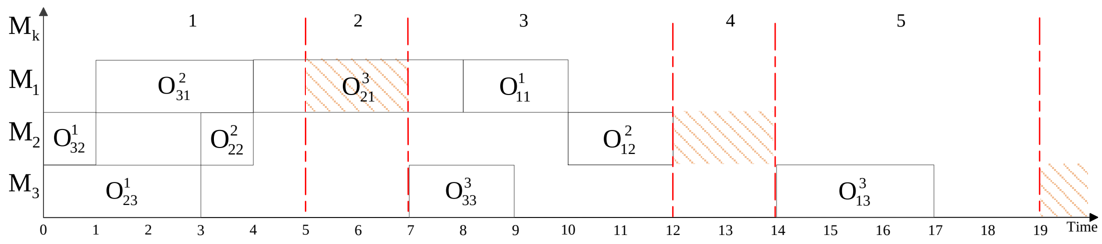


Figure 6.17: A typical scheduling result of Scenario 6

6.6 Comparison of Scenario 6 and Scenario 3 and its related Scenario 4 and Scenario 5

The optimal parameter settings of the NSGA-II for the operators and stopping criteria, which provide the best final solution, are obtained after the initial tuning process. For all the job shop instances, the values are as follows: population size $N = 500$; crossover probability $p_c = 0.9$; mutation probability $p_m = 0.2$; generation $t = 40,000$. During the tuning process, the values used for the crossover rate are $[0.8, 0.9, 1.0]$, for the mutation rate are $[0.01, 0.02, 0.05, 0.1, 0.2, 0.3, 0.4]$, for the number of generations are $[25000, 30000, 35000, 40000, 45000, 50000]$, for the population size are $[300, 400, 500, 600, 700, 800]$. Different combinations of the aforementioned values are tested in the experiment. Based on these tests, the optimal parameters setting of the NSGA-II for each case can be obtained. The NSGA-II has been run for 40000 generations to achieve the optimal solution. During the test, the algorithm has been run for 50000 generations, but the solutions have not been improved from the 40000thto the 50000th generation. Thus, the 40000 is the best value for the number of generation in this case. The same method has been applied to find the best value in the number of generation for other cases.

The aim of this section is to demonstrate that the compromised plans developed in Scenario 6 are effective in reducing the total electricity cost compared to Scenario 5 and reducing the total weighted tardiness compared to Scenario 4. Based on the data analysis, the changing trend of the two aforementioned objective function values are the same for all of the aforementioned job shop instances. Thus, only the E-Lawrence 15×10 job shop with $f = 1.6$ is used as the example for the comparison, other experiment results are shown in Appendix III. The electricity supply pattern is the same as the one which has been described in **Section 6.4**. The machines are turned off if the idle period is longer than 30 minutes. The comparison results are shown in **Fig-**

ure 6.18, **Figure 6.19** and **Figure 6.20**. There are 15 solutions on the Pareto-front obtained by the NSGA-II in Scenario 6, 7 solutions on the Pareto-front in Scenario 4 and 7 solutions on the Pareto-front in Scenario 5.

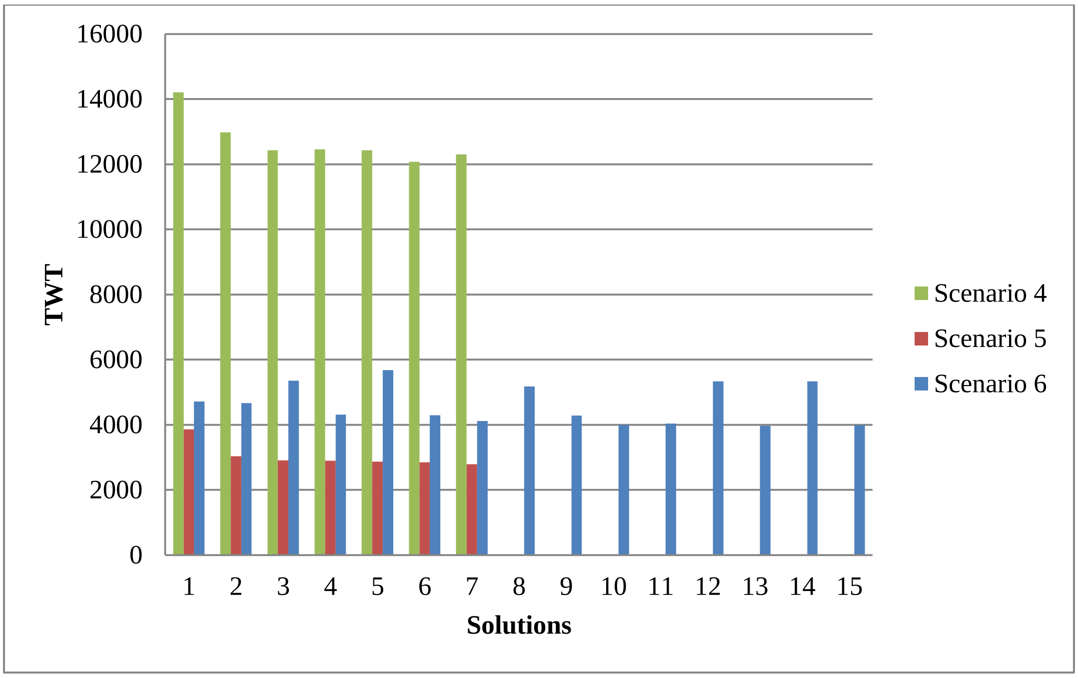


Figure 6.18: TWT comparison among Scenario 6, Scenario 4 and Scenario 5 (Scenario 4 and Scenario 5 are developed based on Scenario 3)

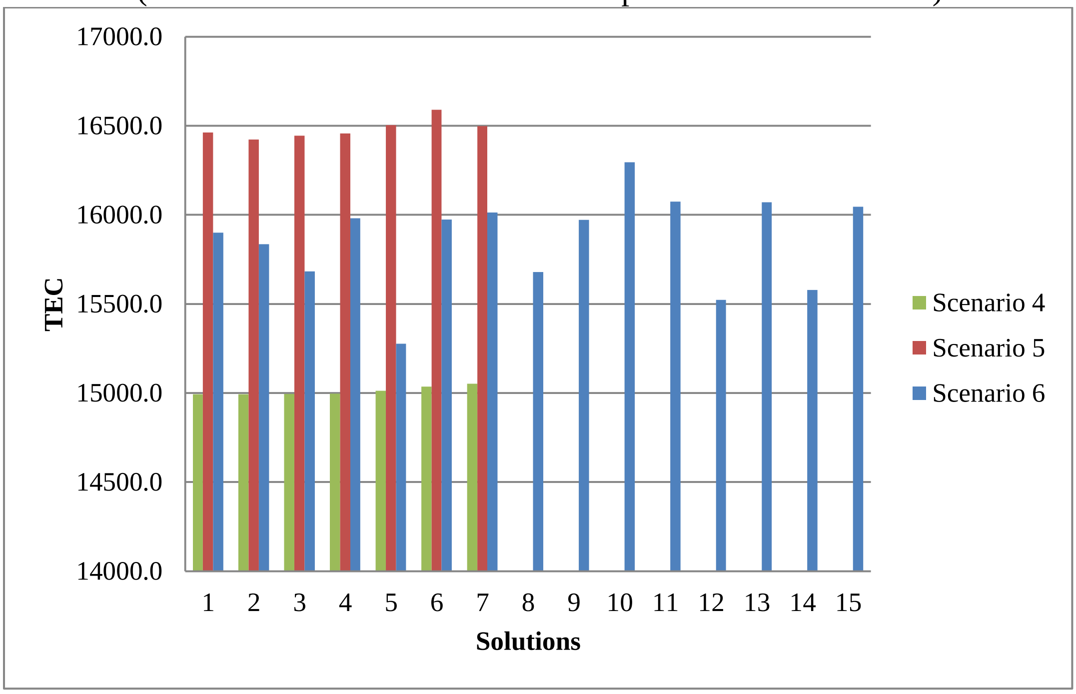


Figure 6.19: TEC comparison among Scenario 6, Scenario 4 and Scenario 5 (Scenario 4 and Scenario 5 are developed based on Scenario 3)

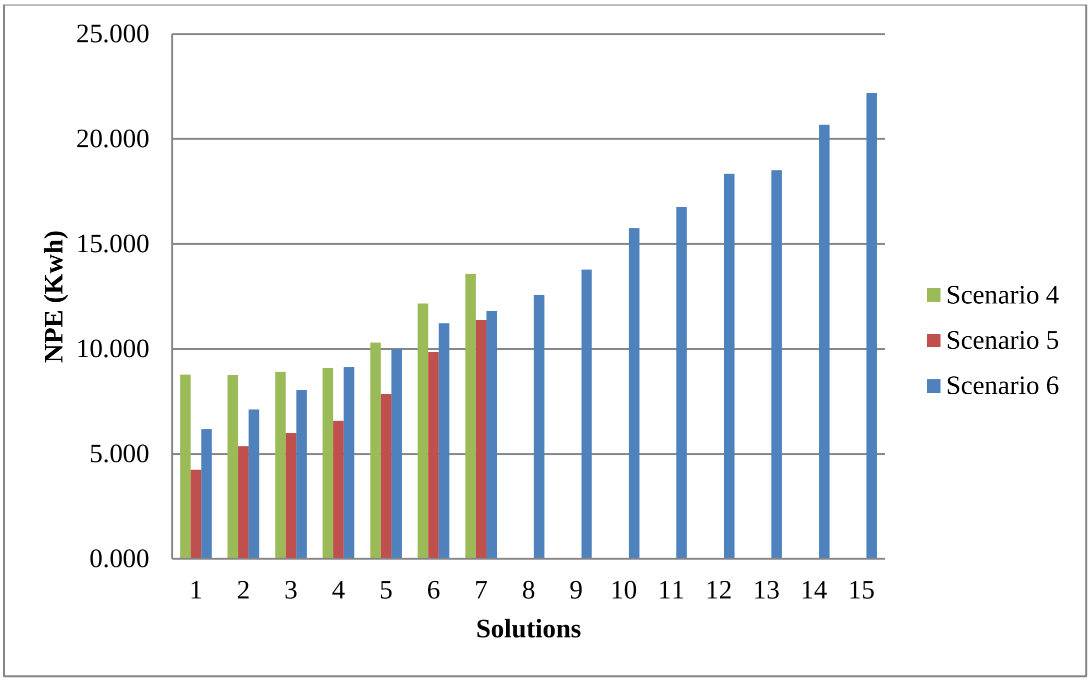


Figure 6.20: NPE comparison among Scenario 6, Scenario 4 and Scenario 5 (S4 and S5 are developed based on Scenario 3)

Table 6.7: The average TWT, TEC and NPE values for Scenario 4, 5 and 6

	Average TWT	Average TEC (pence)	Average NPE (kWh)
Scenario 4	12699.57	15018.2	10.228
Scenario 5	3028.571	16482.3	7.3
Scenario 6	4617.667	15860.0	13.0

According to **Figure 6.18** and **Table 6.7**, the scheduling plans obtained in Scenario 6 have a better performance on the total weighted tardiness compared to the plans delivered in Scenario 4 as expected. In Scenario 6, the average value in total weighted tardiness is 4617.7 weighted minutes while in Scenario 4 it is 12699.6 weighted minutes. The minimum improvement is 61.65%, the maximum improvement is 71.95% and the average improvement is 63.64%. According to **Figure 6.19**, the scheduling plans obtained in Scenario 6 have a better performance on total electricity cost compared to the plans delivered in Scenario 5 as anticipated. In Scenario 6, the average value in total weighted tardiness is 15860.0 pence while in Scenario 5 it is 16482.3 pence. The minimum improvement is 0.78%, the maximum improvement is 7.91% and the average improvement is 3.78%. According to **Table 6.7**, the average value of the total non-processing electricity is slightly increased in the NSGA-II solutions compared to the other two scenarios. However, it can be observed from **Figure 6.20** that some of the NSGA-II solutions outperform the adjusted schedules in terms of NPE. Thus, it can be concluded that the compromised plan for using private electricity developed in Scenario 6, produced by the NSGA-II, is effective to realise the trade-off between the total weighted tardiness and the total electricity cost. Therefore, the method developed based on the NSGA-II is effective in solving the EC2T problem.

6.7 Summary

The Rolling Blackout policy affects the performance of the scheduling plans produced in Scenario 2 and Scenario 3 in terms of total weighted tardiness, total non-processing electricity consumption and total electricity cost. The performances of scheduling plans in the two scenarios are compared in this chapter (Scenario 4 and Scenario 5). In Scenario 4, there is no private electricity supply during the government electricity unavailable periods. On the contrary, in Scenario 5, the private electricity is employed during all the government supply unavailable periods to maintain the production.

Scenario 4 provides a scheduling plan adjustment scheme. The scheduling plans produced in Scenario 2 and Scenario 3 have been adjusted in Scenario 4.The operations that initially execute during the blackout periods are postponed to the next electricity supply available period, thus, leading to the new scheduling plan for Scenario 4. In Scenario 5 the private electricity is started to provide power for the manufacturing company during all the blackout periods. The scheduling plans produced in Scenario 2 and Scenario 3 are performed in Scenario 5, i.e. the scheduling plans have been kept the same, however the values of the total electricity cost have been re-calculated.

A scenario comparison has been performed. As expected, both the total non-processing electricity consumption and total weighted tardiness are increased in Scenario 4 after postponing some operations in Scenario 2 and Scenario 3, and the total electricity cost is increased in Scenario 5 since the private electricity supply is utilised in this scenario.

A compromised plan for using private electricity is developed in this chapter for solving the EC2T problem (Scenario 6). The NSGA-II is applied to realise the trade-off between the total weighted tardiness and the total electricity cost. New encoding schema, crossover operator and mutation operator are provided. The new method is used to decide whether to provide private electricity to each machine in the job shop during each GUP. The performance of the algorithm has been tested on four extended versions of several job shop instances which incorporate electrical consumption profiles for the machine tools, including Fisher and Thompson 10×10 job shop scenario, Lawrence 10×10, 20×10 and 15×15 job shop scenarios. In addition, comparison experiments have been applied to demonstrate the effectiveness of the NSGA-II in solving the EC2T problem. To compare the scheduling plans in Scenario 4, the scheduling plans delivered in Scenario 6 have a better performance on total weighted tardiness. To compare the scheduling plans in Scenario 5, the scheduling plans delivered in Scenario 6 have a better performance on total electricity cost. Therefore, the NSGA-II and its related new encoding schema, crossover operator and mutation operator successfully realise the trade-off between the total weighted tardiness and the total electricity cost and proved to be effective in solving the EC2T problem.

CHAPTER 7 VALIDATION BASED ON A REAL-WORLD JOB SHOP SCHEDULING PROBLEM

7.1 Introduction

The aim of this chapter is to validate the effectiveness of the GAJEP in reducing the total non-processing electricity consumption in a real job shop case. The GAEJP is chosen in the validation process since it is the most innovative optimisation approach developed in this thesis. The test case (a real world ECT problem) is developed based on a Mechanical Engineering module at the University of Nottingham, Ningbo. This 7×5 job shop instance is an example used in education which resembles a real-world job shop. The performance of the algorithm has been tested on the aforementioned job shop instance. It is compared with the optimisation result of the well-established traditional scheduling approach which does not consider reducing the total electricity consumption as an objective (Scenario 1). The GAEJP is shown to be effective in solving the ECT and reducing the total non-processing electricity consumption for this real job shop instance. Additionally, it will be identified that the GAEJP merely deteriorates the total weighted tardiness objective for this test case.

7.2 The real-world job shop

The real-world job shop instance for validation is developed based on a workshop at the University of Nottingham, Ningbo, as shown in **Figure 7.1**. The test case is developed based on a Mechanical Engineering module where the students are divided into different groups and have to design and manufacture a simple cart using a spring as the source of power. The drawing for one of the spring carts is shown in **Figure 7.2**. Seven groups developed their own spring carts. All the parts of the seven carts were mainly machined on three turning machines and two milling machines; one of the turning machines is shown in **Figure 7.3**.

Figure 7.1: The workshop used for validation

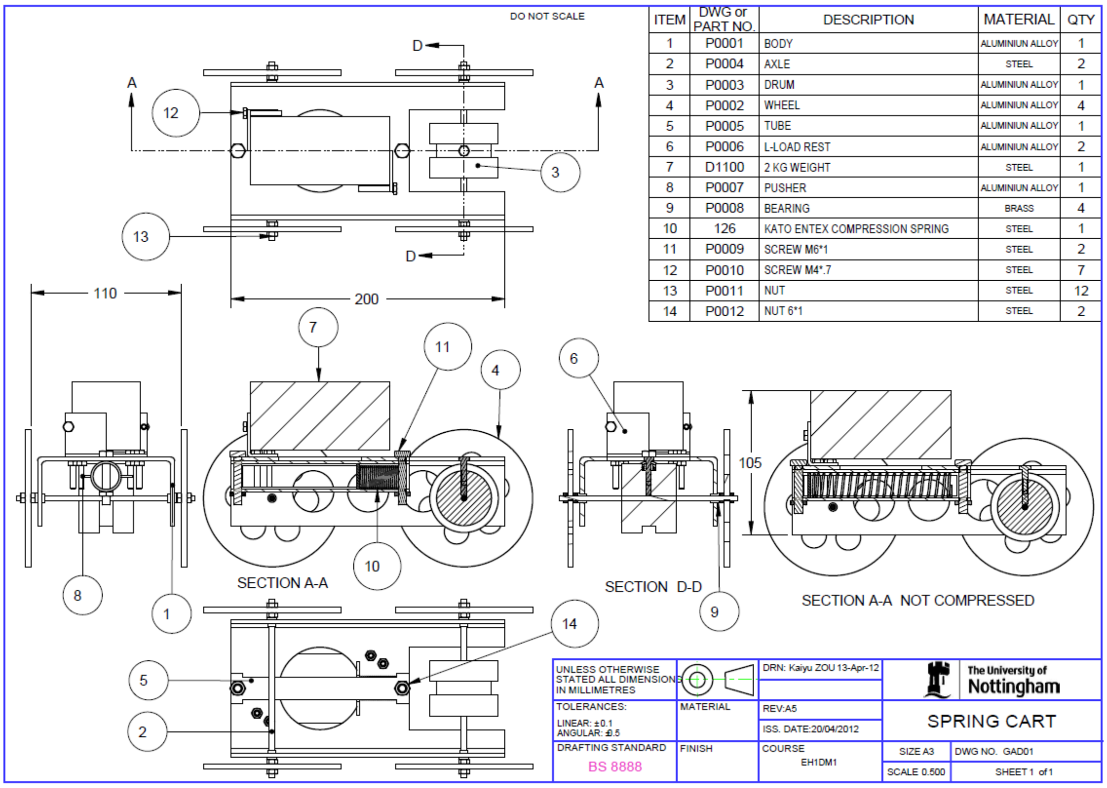


Figure 7.2: Drawing of the example spring cart

This situation can be generalised as a job shop. After grouping some parts which have the same process routines, a 7×5 job shop is developed for validation as shown in **Table 7.1**. The processing time for each operation is estimated by a very experienced technician. The different due dates are calculated based on the TWK due date assignment method which has been described in **Section 3.7.1** and the weights for each job are assigned randomly, as presented in **Table 7.2**. To validate the performance of the GAEJP in this real test case, the electricity characteristics that need to be known are the idle power level of each machine tool, the average power and the time consumed to turn off and turn on the machine tools. These electricity characteristics are measured by a VC3266B clamp-on multi-meter, the measurement method is following Kordonowy (2003). The values for the aforementioned characteristics are shown in **Table 7.3**. Based on the above information, the test experiments to verify the effectiveness of the GAEJP in reducing the total non-processing electricity consumption in a real job shop problem are presented in the next section.

Figure 7.3: One of the turning machines used in the test job shop case

Table 7.1: The p_{ik}^l of each O_{ik}^l in the 7×5 job shop instance

$M_k(p_{ik}^l)$	O_{ik}^1	O_{ik}^2	O_{ik}^3	O_{ik}^4	O_{ik}^5
J_1	$M_2(83)$	$M_1(49)$	$M_3(90)$	$M_5(77)$	$M_4(65)$
J_2	$M_3(27)$	$M_2(81)$	$M_1(35)$	$M_4(65)$	$M_5(42)$
J_3	$M_1(46)$	$M_2(55)$	$M_3(59)$	$M_4(69)$	$M_5(44)$
J_4	$M_2(65)$	$M_1(92)$	$M_3(87)$	$M_4(48)$	$M_5(59)$
J_5	$M_2(69)$	$M_4(32)$	$M_1(22)$	$M_5(78)$	$M_3(41)$
J_6	$M_1(80)$	$M_4(80)$	$M_3(65)$	$M_2(42)$	$M_5(24)$
J_7	$M_1(37)$	$M_3(39)$	$M_2(77)$	$M_4(89)$	$M_5(66)$

Table 7.2: Parameters of each J_1 in the 7 × 5 job shop, $r_i = 0$

J_i	$d_i(f = 1.5)$	$d_i(f = 1.6)$	$d_i(f = 1.7)$	$d_i(f = 1.8)$	w_i
J_1	546	582	618	655	3
J_2	375	400	425	450	1
J_3	409	436	464	491	2
J_4	526	561	596	631	2
J_5	363	387	411	435	3
J_6	436	465	494	523	1
J_7	462	492	523	554	2

Table 7.3: The electricity characteristics for the 7 × 5 job shop

M_k	P_k^{idle} (W)	P_k^{turnon} (W)	$P_k^{turnoff}$ (W)	t_k^{turnon} (min)	$t_k^{turnoff}$ (min)
M_1	510	200	140	0.9	0.7
M_2	600	220	150	1.1	1.0
M_3	220	150	100	0.8	0.7
M_4	460	170	160	1.0	0.8
M_5	280	140	120	0.8	0.7

7.3 Experiment and discussion

The Shifting Bottleneck Heuristic (SBH) and Local Search Heuristic (LSH) approaches provided by the software LEKIN (Pinedo 2009) are used as the optimisation techniques to provide the baseline scenario (Scenario 1) for the 7 × 5 job shop. Currently, no scheduling technique is currently applied to this work shop. The optimisation result of the LEKIN software can be seen as the first step of optimisation for this job shop. The scheduling plans with a minimum objective value in total weighted tardiness are adopted, while the total non-processing electricity consumption value are calculated based on each optimised scheduling plan under different due date conditions, as shown in **Table 7.4**, These results are compared with the optimisation results delivered by the GAEJP.

Table 7.4: The optimisation result of LSH of the 7 × 5 job shop by LEKIN

Tardiness factor (f)	TWT (twt_{s1}^f) in weighted min	Total NPE (npe_{s1}^f) in kWh
1.5	619	2.748
1.6	421	3.736
1.7	280	2.532
1.8	94	1.942
1.9	0	1.712

The parameter settings of the GAEJP are obtained after an initial tuning process; the values are as follows: population size $N = 150$; crossover probability $p_c = 1.0$; mutation probability $p_m = 0.4$; generation $t = 8000$. During the tuning process, the values used for the crossover rate are in the set $[0.8, 0.9, 1.0]$. The values used for the crossover rate are $[0.8, 0.9, 1.0]$, for the mutation rate are $[0.1, 0.2, 0.3, 0.4, 0.5, 0.6]$, for the number of generations are $[5000, 6000, 7000, 8000, 9000, 10000]$, for the population size are $[80, 100, 150, 200, 300, 400, 500]$. Different combinations of the aforementioned values are tested in the experiment. Based on these tests, the optimal parameter settings of the GAEJP for each case can be obtained. The Turn Off/Turn On operation are only applied when the idle time on the machine is longer than 15 min. Considering the effect of display in **Figure 7.4**, some of the representative solutions (solutions with maximum, minimum and medium value of total weighted tardiness in each front) on Pareto-fronts delivered by the GAEJP for the 7×5 job shop are shown in **Table 7.5**. The comparison between the results delivered by the aforementioned two optimisation techniques is shown in **Figure 7.4**.

Table 7.5: The representative solutions on Pareto-fronts delivered by GAEJP for the 7×5 job shop

Tardiness factor (f)	TWT (twt_{s3}^{f}) in weighted min	Total NPE (npe_{s3}^{f}) in kWh
1.5	1137	0.009
	759	0.024
	619	0.104
1.6	1021	0.009
	484	0.045
	421	0.177
1.7	599	0.009
	364	0.018
	280	0.189
1.8	396	0.010
	165	0.029
	103	0.170
1.9	201	0.010
	38	0.022
	0	0.035

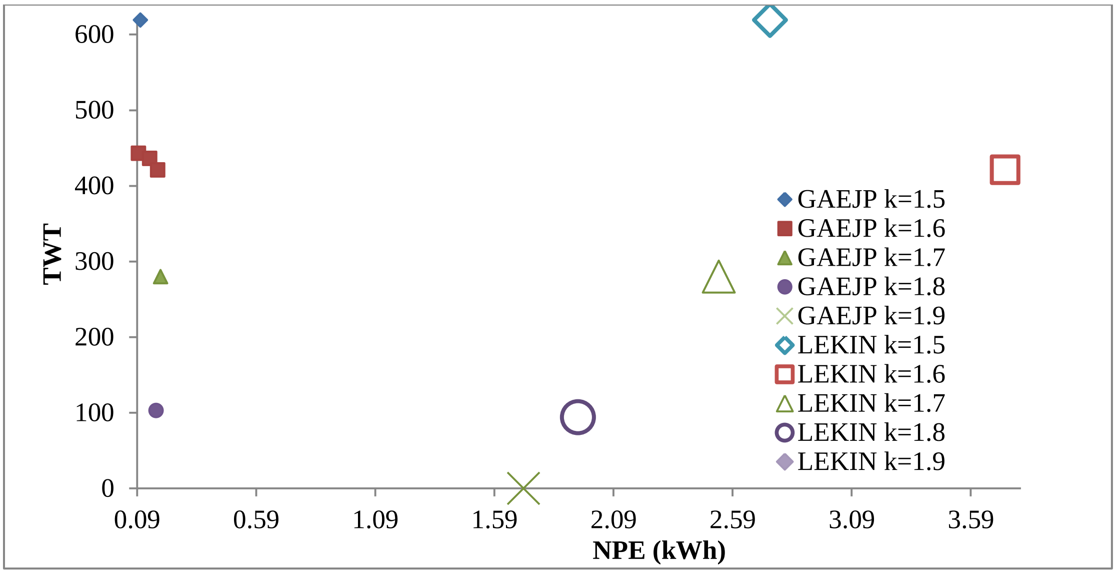


Figure 7.4: The solution comparison between GAEJP and the baseline scenario (7×5 job shop)

It can be observed that in this 7×5 job shop, the GAEJP combined with the Turn Off/Turn On method can reduce the total non-processing electricity consumption in a scheduling plan without deterioration of the total weighted tardiness in most cases (when $f = 1.5, 1.6, 1.7, 1.9$). When $f = 1.8$, the total weighted tardiness obtained by the LEKIN software is 94 weighted min, while the minimum total weighted tardiness obtained by the GAEJP is 103 weighted minutes, comparatively which is not a huge deterioration. The non-processing electricity consumption reductions in percentage are shown in **Table 7.6**. The total weighted tardiness increases in weighted minutes for each job shop are shown in **Table 7.7**.

Table 7.6: The NPE improvement in percentage for the 7×5 job shop

		7 × 5 job shop				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
NPE Improvement	min	96.2%	95.3%	92.5%	91.2%	98.0%
	max	99.7%	99.8%	99.6%	99.5%	99.4%

Table 7.7: The TWT increase in weighted minutes for the 7×5 job shop

		7 × 5 job shop				
		f=1.5	f=1.6	f=1.7	f=1.8	f=1.9
TWT Increase	min	0	0	0	6	0
	max	518	600	319	302	201

The performance of the GAEJP in this 7×5 job shop instance is better than in other job shop instances presented in Chapter 5 since there is nearly no deterioration in the total weighted tardiness objective. The difference in this 7×5 job shop instance from other instances is that it has a comparatively longer processing time for each operation. The minimum processing time of all operations is 22 minutes. Thus, it is possible to assume that the GAEJP might be more effective in reducing the total non-processing electricity consumption without a deterioration of total weighted tardiness for job shops which have a long processing time for every operation, and the differences in the processing time among all the operations are not large. This might be a new attribute for the algorithm. This result needs to be tested on a wider range of job shop instances in the future work to prove this trend.

7.4 Summary

The effectiveness of the GAEJP in solving the ECT problem has been tested in four classic job shop instances in Chapter 6. To further verify its effectiveness, a real job shop instance had been formalised to provide a test bed for this algorithm. The reason for only the GAEJP being tested is that it is the most innovative optimisation approach developed in this thesis. The test case (a real ECT problem) is developed based on a module of mechanical engineering in University of Nottingham, Ningbo where a 7×5 job shop instance has been formalised and the electricity characteristics of machine tools needed for the experiments have been measured. Based on the aforementioned real job shop instance, the performance of the algorithm has been tested. Compared with the optimisation results of the Local Search Heuristic, it has been found that, the GAEJP is very effective in reducing the total non-processing electricity consumption nearly without deteriorating the total weighted tardiness performance. Thus, the GAEJP has been proved to be effective in solving the ECT problem in a real job shop circumstance.

CHAPTER 8 CONCLUSIONS AND FUTURE WORK

The purpose of this chapter is to summarise and conclude this PhD research and propose the future research directions. Firstly, the research work is summarised and the conclusion is conducted that the optimisation techniques proposed in this research are effective for solving both ECT and EC2T problems. In addition, the contribution of this work is re-emphasised. Finally, future research directions based on the finding of this research are proposed.

8.1 Summary of the research work and conclusions

Reducing the electricity consumption and its related cost as well as maintaining a good performance in classical scheduling objectives in job shops is a difficult problem to optimally solve. In this thesis, the mathematical models for the electricity consumption pattern of machine tools and the Rolling Blackout policy has been formalised. Multi-objective models are proposed to solve different scheduling problems. For the first model, one of the objectives is to minimise the total non-processing electricity consumption (the ECT problem). For the other model, one of the objectives is to minimise the total non-processing electricity consumption and the other objective is to minimise the total electricity cost when the Rolling Blackout policy is applied (the EC2T problem).

Meta-heuristics are proposed to find solutions belonging to the near-optimal approximate Pareto front for each model. The NSGA-II is selected and applied to approximate the optimal Pareto front of both the ECT and EC2T problems and explore the opportunity for electricity saving in job shops. The algorithm is adapted for the problems described in an innovative way in terms of the encoding schema and the operators in the algorithm. Based on the optimisation results of the NSGA-II, it has been found that better optimisation techniques could be proposed to solve the ECT problem. Thus, the new Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) and its corresponding scheduling techniques have been developed based on the NSGA-II. To understand how the Rolling Blackout policy will influence the performance of existing scheduling plans, a new heuristic has been proposed to adjust scheduling plans when the policy is applied. This heuristic also provides a remedial measurement for manufacturing companies to reduce the deterioration of the total weighted tardiness objective when the Rolling Blackout is applied.

A research methodology including six scenarios and comparison experiments has been developed to prove the effectiveness of the aforementioned algorithms. Scenario 1 is the baseline scenario which represents the traditional single objective scheduling method to achieve a minimum total weighted tardiness. Scenario 2 and Scenario 6 have been used to present how optimisation solutions developed based on the NSGA-II can be applied to solve the ECT and EC2T problems respectively. Scenario 3 has been used to present how the proposed Multi-objective Genetic Algorithm for solving the ECT job shop scheduling problem (GAEJP) is effective in solving the ECT problem. Scenario 4 and Scenario 5 have been used to investigate the influence that the Rolling Black policy exerts on the performance of scheduling plans produced in Scenario 2 and Scenario 3 in terms of the objective values of the total weighted tardiness, total non-processing electricity consumption and the total electricity cost. The adjustment heuristic has been proposed in Scenario 4 to help the manufacturing plant manager to adjust the scheduling plans to reduce the total weighted tardiness as much as possible when the Rolling Blackout policy is applied. The scenario comparison between Scenario 2 and Scenario 1 has been used to prove that the NSGA-II is effective in solving the ECT problem. The scenario comparison among Scenario 3, Scenario 2 and Scenario 1 has been used to prove that the GAEJP is superior to the NSGA-II in solving the ECT. Finally, the scenario comparison of Scenario 6, Scenario 5 and Scenario 4 has been used to prove that the NSGA-II is effective in solving the EC2T problem.

The performance of all the aforementioned algorithms has been tested on an extended version of Fisher and Thompson 10×10, Lawrence 15×10, 20×10 and 15×15 job shop scenarios which incorporate electrical consumption profiles for the machine tools. Based on the tests and comparison experiments, it has been proved that by applying the NSGA-II, the total non-processing electricity consumption in the job shop decreases significantly with the sacrifice of the schedules' performance on the total weighted tardiness objective when there are tight due dates for jobs. When the due date becomes less tight, the sacrifice of the total weighted tardiness becomes much smaller. The Pareto fronts of the GAEJP have been compared with the ones obtained by the NSGA-II. It has been observed that the GAEJP combined with the Turn Off/Turn On and Sequencing methods is more effective in reducing the total non-processing electricity consumption than the NSGA-II combined with the Sequencing method while not necessarily sacrificing its performance on total weighted tardiness. Thus, the superiority of the GAEJP in solving the ECT problem has been demonstrated. The scheduling plan adjustment heuristic has been proved to be effective in reducing the total weighted tardiness as much as possible when the Rolling Blackout policy is applied. It also helps us to understand that both the value of the total non-processing electricity consumption and the value of the total weighted tardiness are increased if there is no private electricity available when the Rolling Blackout policy is applied. Comparatively, the value of the total electricity cost is increased if the private electricity is available during all periods when the government electricity is not supplied. This provides the basis for solving the EC2T problem, and the NSGA-II has been proved to be effective to generate compromised plans for using the private electricity to realise the trade-off between the total weighted tardiness and the total electricity cost.

To the author's best knowledge, the problems studied and models proposed in this thesis, examines for the first time in the literature, the minimisation of electricity consumption and electricity cost as part of the objectives for a job shop while minimising the total weighted tardiness. The contribution of this work can be summarised in the following points:

Filling the knowledge gap that a typical multi-objective job shop scheduling problem without parallel machines still has not been explored very well when considering reducing the total electricity consumption and electricity cost as part of the objectives.

- The mathematical model for the electricity consumption pattern of machine tools has been formalised.
- New multi-objective optimisation models considering reducing electricity consumption and its related cost as part of the objectives have been proposed for job shop scheduling problems.
- The model for the Rolling Blackout policy has been developed.

Filling the knowledge gap that the Turn Off/ Turn On method combined with the Sequencing method has not been applied in a job shop in previous research, and that there is no algorithm which enables both of the approaches to be optimally applied in solving the aforementioned multi-objective job shop scheduling problem.

- The NSGA-II has been applied for the first time to solve the bi-objective Total Electricity Consumption Total Weighted Tardiness Job Shop Scheduling problem and the tri-objective Total Electricity Cost, Total Electricity Consumption and Total Weighted Tardiness Job Shop Scheduling problem.
- A Multi-objective Genetic Algorithm based on the NSGA-II and its corresponding scheduling techniques have been developed to solve the bi-objective Total Electricity Consumption Total Weighted Tardiness Job Shop Scheduling problem.
- A new heuristic is proposed to adjust the existing scheduling plans when the Rolling Blackout policy is applied. This heuristic is a remedial measurement for manufacturing companies to reduce the deterioration of the total weighted tardiness objective when a Rolling Blackout policy is applied. It can also help us to understand how a Rolling Blackout policy will influence the performance of existing scheduling plans.

The optimisation techniques proposed in this thesis may be used to solve a large set of scheduling problems with different objectives. The developed techniques can be applied to companies which employ the job shop type manufacturing system to help them to achieve an electricity consumption reduction and an electricity cost reduction on the work shop level. However, there are some limitations and possible extensions that will define future research, which is presented in the next section.

8.2 Future Research

The optimisation methods developed in the previous chapters are useful to minimise electricity consumption and its related cost and the total weighted tardiness objective in a job shop model when the Rolling Blackout policy is applied. In future research, the proposed algorithms should be tested on a wider set of job shop instances to further validate their general applicability. The proposed mathematical models could be extended to more complex manufacturing environment, such as the flexible job shop environment where parallel machines with different working conditions such as processing times can be added in the job shop model. Also, a job shop including the lot sizing problem can be studied and the relevant optimisation techniques can be developed to extend the applicable range of the developed methodology. The trade-off between electricity saving and machine wear due to frequent turning on/off of machines is also worth investigating. The job shop scheduling problem which considers reducing the electricity consumption when all the jobs arrive at the work shop with a dynamic pattern also needs to be studied. Finally, Composite dispatching rules which include electricity consumption as an objective to minimise when jobs arrive over time can be developed, since they can approximate the Pareto front without complex calculations for job shop scheduling problems. A more detailed description of possible research directions is provided below.

8.2.1 Testing the algorithms in a wider set of job shop instances

The performances of the NSGA-II in solving both the ECT and EC2T problems and the GAEJP in solving the ECT problem has been tested on four job shop instances in this work. In future work, the algorithms should be tested on a wider set of job shop scenarios to validate their more general applicability. In addition, the effect of applying the Turn off/Turn on method to the optimisation results of the NSGA-II on ECT problem (Scenario 2) should be investigated. The new results should be compared with the optimisation results of the GAEJP to further prove the GAEJP's priority in solving the ECT problem. Finally, in the validation chapter, it has been identified that the GAEJP might be more effective in reducing the total non-processing electricity consumption without deterioration of the total weighted tardiness for job shops which have long processing times for every operation and the differences in processing times among all the operations are not large. Test experiments should be conducted on more job shop scenarios to verify this assumption.

8.2.2 Reducing the electricity consumption in flexible job shop

The flexible job shop is a generalisation of the job shop model where work centers have multiple machines in parallel (Pinedo, 2012). The flexible job shop is widely used in the manufacturing industry. For instance, the flexible job shop with recirculation is one of the most complex machine environments which is a very common setting in the semiconductor industry (Pinedo, 2012). When considering reducing the total electricity consumption, the new definition for different types of flexible job shop has been presented in **Section 2.2.3.2**. If the amounts of electricity consumed by any machine in a work centre i for processing job j are the same, the only chance for reducing the electricity consumption is to minimise the total non-processing electricity consumption. Otherwise, both the total non-processing electricity consumption and the processing electricity consumption can be reduced. To solve this problem, new model and optimisation techniques should be developed based on the existing research.

8.2.3 The lot sizing problem when considering reducing electricity consumption

From the model perspective, this research focuses on the typical job shop problem which is defined as: n jobs should be processed on m distinct machines in a predefined sequence. A job is completed only if it goes through all the machines. In the manufacturing industry, there are some more complex models. In some cases, the manufacturing system executes production according to the product orders. At least one type of product is required in each order and the quantity demanded for each type of product is more than one. For instance, assuming that a manufacturing company produces Product A and Product B, a typical order for this company would arrive at t (release time), requiring 100 units of Product A and 120 units of Product B, to be delivered at d (due date). So, the 100 units of Product A can be seen as the first job J_1, and 120 units of Product B can be seen as the other job J_2. Therefore, J_i can be defined as a batch of a certain type of product that is required by a product order, i.e. J_i is the non-single unit job. For the ease of presentation, a job is the same as a lot which contains a batch of identical items. Traditionally, it is assumed that a lot cannot be split. If this assumption is relaxed, lots can be split to possibly shorten the lead time. This leads to the problem of lot sizing which adds complexity to the basic model and makes it more close to some real manufacturing circumstances. The lot sizing deals with the decision of when and how to split a job into lots (S. Petrovic et al. , 2007). Thus, in the future research, a methodology should be defined for splitting J_i to proper sub-lots to reduce the total electricity consumption in the job shop.

8.2.4 Reliability study with machine setup

The turning off and on of a machine might deteriorate the reliability of a machine resulting from mechanical shocks. Further research should be conducted to determine the trade-off between electricity saving and machine wear due to the frequent turning on/off of machines. A model could be developed and included in the non-processing electricity minimisation method to capture the effect of turning on/off the machine on its reliability.

8.2.5 Reducing electricity consumption in a dynamic job shop

Reducing the electricity consumption in a dynamic job shop should be studied in the future. Existing dynamic scheduling algorithms should be extended to reduce the electricity consumption and improve productivity for job shops where the components arrive at the production system at randomly distributed times. This will extend the applicable range of the developed multi-objective optimisation methodology to include stochastic manufacturing systems which are widely used in the real manufacturing world.

8.2.6 Developing dispatching rules considering reduction in electricity consumption

A dispatching rule is a rule that prioritises all the jobs that are waiting for processing on a machine. The prioritisation scheme may take into account the job's attributes, the machines' attributes as well as the current time (Pinedo 2009b). Compared to exact algorithms and meta-heuristics, dispatching rules are easy to implement and fast to calculate, and can be used in real time to schedule jobs (Mouzon 2008). In other words, dispatching rules usually can deliver reasonably good solution in a relatively short time. Thus, in the future work, dispatching rules which include electricity consumption as an objective to minimise when jobs arrive at the production system at randomly distributed times should be developed. Techniques like genetic programming could be used to construct the composite dispatching rules.

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Appendix I Job shop instances for experiments

Appendix I-E-F&T 10 × 10 job shop

Appendix I-Table 1: The p_{ik}^{l} (min) of each O_{ik}^{l} the E-F&T 10×10 job shop

J_i	O_{ik}^{1}		O_{ik}^{2}		O_{ik}^{3}		O_{ik}^{4}		O_{ik}^{5}	
	M_k	p_{ik}^{1}	M_k	p_{ik}^{2}	M_k	p_{ik}^{3}	M_k	p_{ik}^{4}	M_k	p_{ik}^{5}
J_1	1	29	2	78	3	9	4	36	5	49
J_2	1	43	3	90	5	75	10	11	4	69
J_3	2	91	1	85	4	39	3	74	9	90
J_4	2	81	3	95	1	71	5	99	7	9
J_5	3	14	1	6	2	22	6	61	4	26
J_6	3	84	2	2	6	52	4	95	9	48
J_7	2	46	1	37	4	61	3	13	7	32
J_8	3	31	1	86	2	46	6	74	5	32
J_9	1	76	2	69	4	76	6	51	3	85
J_{10}	2	85	1	13	3	61	7	7	9	64
J_i	O_{ik}^{6}		O_{ik}^{7}		O_{ik}^{8}		O_{ik}^{9}		O_{ik}^{10}	
	M_k	p_{ik}^{6}	M_k	p_{ik}^{7}	M_k	p_{ik}^{8}	M_k	p_{ik}^{9}	M_k	p_{ik}^{10}
J_1	6	11	7	62	8	56	9	44	10	21
J_2	2	28	7	46	6	46	8	72	9	30
J_3	6	10	8	12	7	89	10	45	5	33
J_4	9	52	8	85	4	98	10	22	6	43
J_5	5	69	9	21	8	49	10	72	7	53
J_6	10	72	1	47	7	65	5	6	8	25
J_7	6	21	10	32	9	89	8	30	5	55
J_8	7	88	9	19	10	48	8	36	4	79
J_9	10	11	7	40	8	89	5	26	9	74
J_{10}	10	76	6	47	4	52	5	90	8	45

Appendix I-Table 2: The r_i, d_i and w_i of each J_1 in the E-F&T 10×10 job shop

J_i	$d_i(f = 1.5)$	$d_i(f = 1.6)$	$d_i(f = 1.7)$	$d_i(f = 1.8)$	w_i
J_1	592	632	671	711	1
J_2	769	816	867	918	2
J_3	852	908	965	1022	3
J_4	982	1048	1113	1179	1
J_5	589	628	668	707	3
J_6	744	793	843	892	2
J_7	624	665	707	748	3
J_8	808	862	916	970	2
J_9	895	955	1014	1074	1
J_{10}	810	864	918	972	1

Appendix I-Table 3: The idle electricity characteristics for the E-F&T 10×10 job shop

M_k	P_k^{idle} (W)	P_k^{turnon} (W)	$P_k^{turnoff}$ (W)	t_k^{turnon} (min)	$t_k^{turnoff}$ (min)
M_1	2400	1500	1700	4.3	1.2
M_2	3360	2000	1800	5.7	1.6
M_3	2000	1300	1400	4.0	0.8
M_4	1770	1000	1100	3.2	0.8
M_5	2200	2000	1800	4.4	1.3
M_6	7500	2400	2000	6.3	1.5
M_7	2000	1300	1400	4.0	0.8
M_8	1770	1000	1100	3.2	0.8
M_9	2200	2000	1800	4.4	1.3
M_{10}	7500	2400	2000	6.3	1.5

Appendix I-Table 4: The value of each P_{ik}^l (W) in the E-F&T 10×10 job shop

J_i	O_{ik}^1		O_{ik}^2		O_{ik}^3		O_{ik}^4		O_{ik}^5	
	M_k	P_{ik}^1	M_k	P_{ik}^2	M_k	P_{ik}^3	M_k	P_{ik}^4	M_k	P_{ik}^5
J_1	1	2450	2	5730	3	5000	4	2700	5	4300
J_2	1	3900	3	3300	5	5550	10	11080	4	3250
J_3	2	5700	1	2550	4	3600	3	4900	9	5700
J_4	2	4350	3	4760	1	3970	5	3170	7	3780
J_5	3	4620	1	3520	2	5600	6	12800	4	2980
J_6	3	5050	2	4750	6	11700	4	3050	9	4300
J_7	2	6000	1	2800	4	3540	3	5100	7	3970
J_8	3	4670	1	3600	2	4200	6	13000	5	4760
J_9	1	3870	2	5500	4	2560	6	10500	3	3250
J_{10}	2	5100	1	2980	3	3500	7	4890	9	3970

J_i	O_{ik}^6		O_{ik}^7		O_{ik}^8		O_{ik}^9		O_{ik}^{10}	
	M_k	P_{ik}^6	M_k	P_{ik}^7	M_k	P_{ik}^8	M_k	P_{ik}^9	M_k	P_{ik}^{10}
J_1	6	11200	7	4900	8	2670	9	5130	10	10000
J_2	2	5800	7	4900	6	12100	8	3600	9	5000
J_3	6	10900	8	2300	7	4280	10	12700	5	3370
J_4	9	5290	8	2960	4	2750	10	13000	6	12500
J_5	5	5210	9	4780	8	3250	10	11800	7	5000
J_6	10	12080	1	2420	7	4480	5	3520	8	2720
J_7	6	13000	10	12030	9	3390	8	3500	5	5500
J_8	7	5100	9	5690	10	10000	8	2900	4	3520
J_9	10	10060	7	3450	8	2520	5	4000	9	4260
J_{10}	10	12700	6	10000	4	3400	5	5130	8	3500

Appendix I-E-Lawrence 15×10 job shop

Appendix I-Table 5: The p_{ik}^l (min) of each O_{ik}^l the E-Lawrence 15×10 job shop

J_i	O_{ik}^1		O_{ik}^2		O_{ik}^3		O_{ik}^4		O_{ik}^5	
	M_k	p_{ik}^1	M_k	p_{ik}^2	M_k	p_{ik}^3	M_k	p_{ik}^4	M_k	p_{ik}^5
J_1	3	34	4	55	6	95	10	16	5	21
J_2	4	39	3	31	1	12	2	42	10	79
J_3	2	19	1	83	4	34	5	92	7	54
J_4	5	60	3	87	9	24	6	77	4	69
J_5	9	79	10	77	3	98	5	96	4	17
J_6	9	35	8	95	7	9	10	10	3	35

J_7	5	28	6	59	4	16	10	43	1	46
J_8	6	9	5	20	3	39	7	54	2	45
J_9	2	28	6	33	1	78	4	26	3	37
J_{10}	3	94	6	84	7	78	10	81	2	74
J_{11}	2	31	5	24	1	20	3	17	10	25
J_{12}	6	28	10	97	1	58	5	45	7	76
J_{13}	6	27	10	48	9	27	8	62	5	98
J_{14}	2	12	9	50	1	80	3	50	10	80
J_{15}	5	61	4	55	7	37	6	14	3	50

J_i	O_{ik}^{6}		O_{ik}^{7}		O_{ik}^{8}		O_{ik}^{9}		O_{ik}^{10}	
	M_k	p_{ik}^{6}	M_k	p_{ik}^{7}	M_k	p_{ik}^{8}	M_k	p_{ik}^{9}	M_k	p_{ik}^{10}
J_1	7	71	1	53	9	52	2	21	8	26
J_2	9	77	7	77	6	98	5	55	8	66
J_3	10	79	9	62	6	37	3	64	8	43
J_4	8	38	2	87	7	41	10	83	1	93
J_5	1	44	8	43	7	75	2	49	6	25
J_6	2	7	6	28	5	61	1	95	4	76
J_7	9	50	7	52	8	27	3	59	2	91
J_8	8	71	1	87	4	41	10	43	9	14
J_9	8	8	9	66	7	89	10	42	5	33
J_{10}	4	27	9	69	1	69	8	45	5	96
J_{11}	9	81	6	76	4	87	8	32	7	18
J_{12}	4	99	3	23	2	72	9	90	8	86
J_{13}	7	67	4	48	1	42	2	46	3	17
J_{14}	4	19	6	28	7	63	5	94	8	98
J_{15}	9	79	2	41	10	72	8	18	1	75

Appendix I-Table 6: The r_i, d_i and w_i of each J_1 in the E-Lawrence 15×10 job shop

J_i	d_i $(f = 1.5)$	d_i $(f = 1.6)$	d_i $(f = 1.7)$	d_i $(f = 1.8)$	d_i $(f = 1.9)$	w_i
J_1	666	710	754	799	843	3
J_2	864	921	979	1036	1094	1
J_3	850	907	963	1020	1077	3
J_4	988	1054	1120	1186	1252	2
J_5	904	964	1025	1085	1145	3
J_6	676	721	766	811	856	1
J_7	706	753	800	847	894	2
J_8	634	676	719	761	803	2
J_9	660	704	748	792	836	3
J_{10}	1075	1147	1218	1290	1362	1
J_{11}	616	657	698	739	780	2
J_{12}	1011	1078	1145	1213	1280	2
J_{13}	723	771	819	867	915	1
J_{14}	861	918	975	1033	1090	3
J_{15}	753	803	853	903	953	1

Appendix I-Table 7: The idle electricity characteristics for the E-Lawrence 15 × 10 job shop

M_k	P_k^{idle} (W)	P_k^{turnon} (W)	$P_k^{turnoff}$ (W)	t_k^{turnon} (min)	$t_k^{turnoff}$ (min)
M_1	2700	1500	1900	5.7	1.7
M_2	6500	2000	1700	4.3	1.6
M_3	3200	1300	1500	4.0	0.9
M_4	2770	1000	1100	6.3	0.7
M_5	2200	1500	1900	4.9	1.6
M_6	2500	2400	1400	3.2	1.4
M_7	3000	1300	1300	4.0	0.9
M_8	7500	1000	1100	3.2	0.8
M_9	3360	1500	2000	6.3	1.4
M_{10}	1770	2400	2200	4.4	1.5

Appendix I-Table 8: The average runtime operations and cutting power of each M_k

M_k	M_1(W)	M_2(W)	M_3(W)	M_4(W)	M_5(W)
P_{ik}^l	[2420, 4000]	[4200, 6100]	[3200, 5100]	[2200, 3600]	[3120, 5700]
M_k	M_6(W)	M_7(W)	M_8(W)	M_9(W)	M_{10}(W)
P_{ik}^l	[10000, 13000]	[3200, 5100]	[2200, 3600]	[3120, 5700]	[10000, 13000]

Appendix I-Table 9: The value of each P_{ik}^l (W) in the E-Lawrence 15 × 10 job shop

J_i	O_{ik}^1		O_{ik}^2		O_{ik}^3		O_{ik}^4		O_{ik}^5	
	M_k	P_{ik}^1	M_k	P_{ik}^2	M_k	P_{ik}^3	M_k	P_{ik}^4	M_k	P_{ik}^5
J_1	3	3450	4	2730	6	10500	10	2700	5	4300
J_2	4	3600	3	3300	1	3550	2	5080	10	12250
J_3	2	5700	1	2550	4	3600	5	4900	7	5100
J_4	5	4350	3	4760	9	3970	6	10170	4	2780
J_5	9	4620	10	12520	3	4600	5	3800	4	2980
J_6	9	5050	8	2750	7	3700	10	11050	3	4300
J_7	5	5000	6	12800	4	3540	10	10100	1	3970
J_8	6	10670	5	3600	3	4200	7	4000	2	4760
J_9	2	4870	6	10500	1	2560	4	2500	3	3250
J_{10}	3	5100	6	12980	7	4500	10	11890	2	5970
J_{11}	2	4700	5	5000	1	3100	3	5040	10	10250
J_{12}	6	10730	10	12480	1	2460	5	4540	7	3240
J_{13}	6	12820	10	12000	9	4830	8	3570	5	5440
J_{14}	2	4300	9	5060	1	3070	3	3660	10	12100
J_{15}	5	4170	4	2980	7	3990	6	10160	3	3600
J_i	O_{ik}^6		O_{ik}^7		O_{ik}^8		O_{ik}^9		O_{ik}^{10}	
	M_k	P_{ik}^6	M_k	P_{ik}^7	M_k	P_{ik}^8	M_k	P_{ik}^9	M_k	P_{ik}^{10}
J_1	7	4200	1	3900	9	4670	2	5130	8	3000
J_2	9	5700	7	4900	6	12100	5	3600	8	2200
J_3	10	10900	9	4300	6	10280	3	3700	8	3370
J_4	8	3290	2	4960	7	3750	10	13000	1	2500
J_5	1	4000	8	2780	7	4250	2	5800	6	13000
J_6	2	6080	6	12420	5	4480	1	3520	4	2720
J_7	9	4000	7	4030	8	3390	3	4500	2	5500
J_8	8	3100	1	3690	4	3000	10	12900	9	4520
J_9	8	2760	9	3450	7	4520	10	10000	5	4260
J_{10}	4	2700	9	5000	1	3400	8	5130	5	3500
J_{11}	9	5690	6	12300	4	2300	8	3160	7	4790
J_{12}	4	2360	3	4620	2	5070	9	3560	8	2440

J_{13}	7	4110	4	2750	1	3460	2	5320	3	3700
J_{14}	4	2550	6	10470	7	3900	5	5230	8	3180
J_{15}	9	4870	2	4800	10	10500	8	2900	1	2530

Appendix I-E-Lawrence 20×10 job shop

Appendix I-Table 10: The p_{ik}^{l} (min) of each O_{ik}^{l} the E-Lawrence 20×10 job shop

J_i	O_{ik}^{1}		O_{ik}^{2}		O_{ik}^{3}		O_{ik}^{4}		O_{ik}^{5}	
	M_k	p_{ik}^{1}	M_k	p_{ik}^{2}	M_k	p_{ik}^{3}	M_k	p_{ik}^{4}	M_k	p_{ik}^{5}
J_1	9	52	8	26	7	71	10	16	3	34
J_2	5	55	6	98	4	39	10	79	1	12
J_3	6	37	5	92	3	64	7	54	2	19
J_4	2	87	6	77	1	93	4	69	3	87
J_5	3	98	6	25	7	75	10	77	2	49
J_6	2	7	5	61	1	95	3	35	10	10
J_7	6	59	10	43	1	46	5	28	7	52
J_8	6	9	10	43	9	14	8	71	5	20
J_9	2	28	9	66	1	78	3	37	10	42
J_{10}	5	96	4	27	7	78	6	84	3	94
J_{11}	5	24	8	32	10	25	3	17	4	87
J_{12}	9	90	6	28	2	72	8	86	3	23
J_{13}	3	17	5	98	4	48	2	46	9	27
J_{14}	1	80	9	50	4	19	8	98	6	28
J_{15}	10	72	1	75	5	61	9	79	7	37
J_{16}	4	96	3	14	6	57	1	47	8	65
J_{17}	2	31	8	47	9	58	4	32	5	44
J_{18}	2	44	8	40	3	17	1	62	9	66
J_{19}	3	58	4	50	5	63	10	87	1	57
J_{20}	2	85	1	84	6	56	4	61	10	15
J_i	O_{ik}^{6}		O_{ik}^{7}		O_{ik}^{8}		O_{ik}^{9}		O_{ik}^{10}	
	M_k	p_{ik}^{6}	M_k	p_{ik}^{7}	M_k	p_{ik}^{8}	M_k	p_{ik}^{9}	M_k	p_{ik}^{10}
J_1	2	21	6	95	5	21	1	53	4	55
J_2	9	77	7	77	8	66	3	31	2	42
J_3	8	43	1	83	4	34	10	79	9	62
J_4	8	38	9	24	7	41	10	83	5	60
J_5	4	17	9	79	1	44	8	43	5	96
J_6	9	35	6	28	4	76	8	95	7	9
J_7	4	16	3	59	2	91	9	50	8	27
J_8	7	54	4	41	1	87	2	45	3	39
J_9	4	26	6	33	7	89	5	33	8	8
J_{10}	9	69	2	74	10	81	8	45	1	69
J_{11}	9	81	6	76	7	18	2	31	1	20
J_{12}	4	99	7	76	10	97	5	45	1	58
J_{13}	7	67	8	62	1	42	10	48	6	27
J_{14}	3	50	5	94	7	63	2	12	10	80
J_{15}	3	50	6	14	4	55	8	18	2	41
J_{16}	5	75	9	79	2	71	7	60	10	22
J_{17}	6	58	7	34	1	33	3	69	10	51
J_{18}	7	15	4	29	10	38	6	8	5	97
J_{19}	7	21	8	57	9	32	2	39	6	20
J_{20}	8	70	9	30	3	90	7	67	5	20

Appendix I-Table 11: The r_i, d_i and w_i of each J_1 in the E-Lawrence 20×10 job shop

J_i	d_i ($f = 1.5$)	d_i ($f = 1.6$)	d_i ($f = 1.7$)	d_i ($f = 1.8$)	d_i ($f = 1.9$)	w_i
J_1	666	710	754	799	843	1
J_2	864	921	979	1036	1094	3
J_3	850	907	963	1020	1077	2
J_4	988	1054	1120	1186	1252	2
J_5	904	964	1025	1085	1145	3
J_6	676	721	766	811	856	1
J_7	706	753	800	847	894	3
J_8	634	676	719	761	803	1
J_9	660	704	748	792	836	1
J_{10}	1075	1147	1218	1290	1362	3
J_{11}	616	657	698	739	780	2
J_{12}	1011	1078	1145	1213	1280	1
J_{13}	723	771	819	867	915	1
J_{14}	861	918	975	1033	1090	3
J_{15}	753	803	853	903	953	2
J_{16}	879	937	996	1054	1113	2
J_{17}	685	731	776	822	868	1
J_{18}	624	665	707	748	790	3
J_{19}	726	774	822	871	919	2
J_{20}	867	924	982	1040	1098	1

Appendix I-Table 12: The idle electricity characteristics for the E-Lawrence 20×10 job shop

M_k	P_k^{idle} (W)	P_k^{turnon} (W)	$P_k^{turnoff}$ (W)	t_k^{turnon} (min)	$t_k^{turnoff}$ (min)
M_1	2400	1500	1700	4.3	1.2
M_2	3360	2000	1800	5.7	1.6
M_3	2000	1300	1400	4.0	0.8
M_4	1770	1000	1100	3.2	0.8
M_5	2200	1500	1400	4.4	1.3
M_6	7500	2400	2000	6.3	1.5
M_7	2000	1300	1400	4.0	0.8
M_8	7500	1000	1100	3.2	0.8
M_9	2200	1500	1400	4.4	1.3
M_{10}	1770	2400	2000	6.3	1.5

Appendix I-Table 13: The average runtime operations and cutting power of each M_k

M_k	M_1(W)	M_2(W)	M_3(W)	M_4(W)	M_5(W)
P_{ik}^l	[2420, 4000]	[4200, 6100]	[3200, 5100]	[2200, 3600]	[3120, 5700]
M_k	M_6(W)	M_7(W)	M_8(W)	M_9(W)	M_{10}(W)
P_{ik}^l	[10000, 13000]	[3200, 5100]	[2200, 3600]	[3120, 5700]	[10000, 13000]

Appendix I-Table 14: The value of each P_{ik}^{l} (W) in the E-Lawrence 20×10 job shop

J_i	O_{ik}^{1}		O_{ik}^{2}		O_{ik}^{3}		O_{ik}^{4}		O_{ik}^{5}	
	M_k	P_{ik}^{1}	M_k	P_{ik}^{2}	M_k	P_{ik}^{3}	M_k	P_{ik}^{4}	M_k	P_{ik}^{5}
J_1	9	3450	8	2730	7	4000	10	12700	3	4300
J_2	5	3900	6	11300	4	3600	10	11080	1	3250
J_3	6	10000	5	4550	3	3600	7	4900	2	5700
J_4	2	4350	6	10760	1	3970	4	3170	3	3780
J_5	3	4620	6	11520	7	5100	10	12800	2	4980
J_6	2	5050	5	4750	1	3700	3	4050	10	10300
J_7	6	11000	10	12800	1	2540	5	5100	7	3970
J_8	6	12670	10	13000	9	4200	8	3000	5	4760
J_9	2	4870	9	5500	1	2560	3	4500	10	12250
J_{10}	5	5100	4	2980	7	3500	6	10890	3	3970
J_{11}	5	4700	8	3000	10	11100	3	5100	4	3250
J_{12}	9	4730	6	12480	2	4460	8	2540	3	3240
J_{13}	3	4820	5	5700	4	2830	2	5570	9	5440
J_{14}	1	4300	9	5060	4	3070	8	2260	6	12100
J_{15}	10	10170	1	2980	5	3990	9	4160	7	3600
J_{16}	4	2900	3	4630	6	10320	1	2440	8	2320
J_{17}	2	4300	8	3030	9	4730	4	2370	5	3510
J_{18}	2	5760	8	3500	3	4580	1	2920	9	4000
J_{19}	3	3860	4	2900	5	3470	10	10100	1	3950
J_{20}	2	4500	1	3100	6	10900	4	3470	10	11740
J_i	O_{ik}^{6}		O_{ik}^{7}		O_{ik}^{8}		O_{ik}^{9}		O_{ik}^{10}	
	M_k	P_{ik}^{6}	M_k	P_{ik}^{7}	M_k	P_{ik}^{8}	M_k	P_{ik}^{9}	M_k	P_{ik}^{10}
J_1	2	4200	6	11900	5	4670	1	3130	4	3100
J_2	9	5700	7	4900	8	3100	3	3600	2	5000
J_3	8	2900	1	3300	4	3280	10	12700	9	3370
J_4	8	2290	9	3960	7	3750	10	13000	5	5500
J_5	4	3210	9	4780	1	3250	8	2800	5	5000
J_6	9	5080	6	12420	4	3480	8	3520	7	4720
J_7	4	3500	3	5030	2	4390	9	3500	8	3500
J_8	7	5100	4	2690	1	4000	2	5900	3	3520
J_9	4	3060	6	10450	7	4520	5	4000	8	3260
J_{10}	9	5700	2	6100	10	3400	8	3130	1	3500
J_{11}	9	5690	6	12300	7	3300	2	5160	1	4790
J_{12}	4	2360	7	4620	10	10070	5	3560	1	2440
J_{13}	7	4110	8	2750	1	3460	10	11320	6	12700
J_{14}	3	4550	5	5470	7	3900	2	5230	10	13000
J_{15}	3	3870	6	12000	4	2500	8	2900	2	5530
J_{16}	5	4100	9	5650	2	4200	7	4980	10	10620
J_{17}	6	10740	7	3310	1	3500	3	4370	10	11420
J_{18}	7	4900	4	2820	10	11560	6	11330	5	3900
J_{19}	7	4800	8	3100	9	3800	2	4750	6	10380
J_{20}	8	2250	9	4300	3	4130	7	4700	5	3340

Appendix I-E-Lawrence 15×15 job shop

Appendix I-Table 15: The p_{ik}^{l} (min) of each O_{ik}^{l} the E-Lawrence 15×15 job shop

J_i	O_{ik}^{1}		O_{ik}^{2}		O_{ik}^{3}		O_{ik}^{4}		O_{ik}^{5}	
	M_k	p_{ik}^{1}	M_k	p_{ik}^{2}	M_k	p_{ik}^{3}	M_k	p_{ik}^{4}	M_k	p_{ik}^{5}
J_1	5	21	4	55	7	71	15	98	11	12
J_2	12	54	5	83	2	77	8	64	9	34
J_3	10	83	6	77	3	87	8	38	5	60
J_4	6	77	1	96	10	28	7	7	5	95
J_5	11	87	5	28	9	50	3	59	1	46

J_6	1	20	3	71	5	78	14	66	4	14
J_7	9	69	5	96	13	17	1	69	8	45
J_8	5	58	14	90	12	76	4	81	8	23
J_9	6	27	2	46	7	67	9	27	14	19
J_{10}	12	37	6	80	5	75	9	55	8	50
J_{11}	8	65	4	96	1	47	5	75	13	69
J_{12}	2	34	3	47	4	58	6	51	5	62
J_{13}	4	50	8	57	14	61	6	20	12	85
J_{14}	10	84	8	45	6	15	15	41	11	18
J_{15}	10	37	11	81	12	61	15	57	9	57

J_i	O_{ik}^{6}		O_{ik}^{7}		O_{ik}^{8}		O_{ik}^{9}		O_{ik}^{10}	
	M_k	p_{ik}^{6}	M_k	p_{ik}^{7}	M_k	p_{ik}^{8}	M_k	p_{ik}^{9}	M_k	p_{ik}^{10}
J_1	3	34	10	16	2	21	1	53	8	26
J_2	15	79	13	43	1	55	4	77	7	19
J_3	13	98	1	93	14	17	7	41	11	44
J_4	14	35	8	35	9	76	12	9	13	95
J_5	12	45	15	9	10	43	7	52	8	27
J_6	13	8	15	42	7	28	2	54	10	33
J_7	12	31	7	78	11	20	4	27	14	87
J_8	10	28	2	18	3	32	13	86	9	99
J_9	11	80	3	17	4	48	8	62	12	12
J_{10}	1	94	10	14	7	41	15	72	4	50
J_{11}	15	58	11	33	2	71	10	22	14	32
J_{12}	7	44	10	8	8	17	11	97	9	29
J_{13}	13	90	3	58	5	63	11	84	2	39
J_{14}	5	82	12	29	3	70	2	67	4	30
J_{15}	1	52	8	74	7	62	13	30	2	52

J_i	O_{ik}^{11}		O_{ik}^{12}		O_{ik}^{13}		O_{ik}^{14}		O_{ik}^{15}	
	M_k	p_{ik}^{11}	M_k	p_{ik}^{12}	M_k	p_{ik}^{13}	M_k	p_{ik}^{14}	M_k	p_{ik}^{15}
J_1	9	52	6	95	13	31	12	42	14	39
J_2	10	37	6	79	11	92	14	62	3	66
J_3	4	69	12	49	9	24	2	87	15	25
J_4	3	43	2	75	11	61	15	10	4	79
J_5	2	91	14	41	4	16	6	59	13	39
J_6	12	89	9	26	8	37	11	33	6	43
J_7	2	74	6	84	15	76	3	94	10	81
J_8	15	97	1	24	11	45	7	72	6	25
J_9	15	28	5	98	1	42	10	48	13	50
J_{10}	11	61	14	79	3	98	13	18	2	63
J_{11}	6	57	9	79	3	14	12	31	7	60
J_{12}	12	15	14	66	13	40	1	44	15	38
J_{13}	10	87	7	21	15	56	9	32	1	57
J_{14}	14	50	7	23	1	20	13	21	9	38
J_{15}	3	38	14	68	5	54	4	54	6	16

Appendix I-Table 16: The r_i, d_i and w_i of each J_1 in the E-Lawrence 15×15 job shop

J_i	$d_i(f = 1.5)$	$d_i(f = 1.6)$	$d_i(f = 1.7)$	w_i
J_1	999	1065	1132	1
J_2	1381	1473	1565	2
J_3	1338	1427	1516	3

J_4	1231	1313	1395	3
J_5	1038	1107	1176	3
J_6	963	1027	1091	2
J_7	1422	1516	1611	3
J_8	1281	1366	1451	2
J_9	1006	1073	1140	1
J_{10}	1330	1419	1507	1
J_{11}	1213	1294	1375	1
J_{12}	975	1040	1105	2
J_{13}	1290	1376	1462	2
J_{14}	949	1012	1076	2
J_{15}	1189	1268	1348	3

Appendix I-Table 17: The idle electricity characteristics for the E-Lawrence 15×15 job shop

M_k	P_k^{idle} (W)	P_k^{turnon} (W)	$P_k^{turnoff}$ (W)	t_k^{turnon} (min)	$t_k^{turnoff}$ (min)
M_1	2400	1500	1700	4.3	1.2
M_2	3360	2000	1800	5.7	1.6
M_3	2000	1300	1400	4.0	0.8
M_4	1770	1000	1100	3.2	0.8
M_5	2200	1500	1400	4.4	1.3
M_6	7500	2400	2000	6.3	1.5
M_7	2000	1300	1400	4.0	0.8
M_8	1770	1000	1100	3.2	0.8
M_9	2200	1500	1400	4.4	1.3
M_{10}	7500	2400	2000	6.3	1.5
M_{11}	2000	1300	1400	4.0	0.8
M_{12}	1770	1000	1100	3.2	0.8
M_{13}	2200	1500	1400	4.4	1.3
M_{14}	7500	2400	2000	6.3	1.5
M_{15}	2000	1300	1400	4.0	0.8

Appendix I-Table 18: The average runtime operations and cutting power of each M_k

M_k	M_1(W)	M_2(W)	M_3(W)	M_4(W)	M_5(W)
P_{ik}^l	[2420, 4000]	[4200, 6100]	[3200, 5100]	[2200, 3600]	[3120, 5700]
M_k	M_6(W)	M_7(W)	M_8(W)	M_9(W)	M_{10}(W)
P_{ik}^l	[10000, 13000]	[3200, 5100]	[2200, 3600]	[3120, 5700]	[10000, 13000]
M_k	M_{11}(W)	M_{12}(W)	M_{13}(W)	M_{14}(W)	M_{15}(W)
P_{ik}^l	[4200, 6100]	[3200, 5100]	[2200, 3600]	[10000, 13000]	[1800, 3600]

Appendix I-Table 19: The value of each P_{ik}^l in the E-F&T 15×15 job shop

J_i	O_{ik}^1		O_{ik}^2		O_{ik}^3		O_{ik}^4		O_{ik}^5	
	M_k	P_{ik}^1	M_k	P_{ik}^2	M_k	P_{ik}^3	M_k	P_{ik}^4	M_k	P_{ik}^5
J_1	5	3450	4	2730	7	5000	15	2700	11	5700
J_2	12	3900	5	3300	2	5550	8	3080	9	5080
J_3	10	12700	6	12550	3	3600	8	2900	5	4900
J_4	6	10350	1	3760	10	12970	7	3870	5	3170

J_5	11	4620	5	3520	9	5600	3	4800	1	2800
J_6	1	3050	3	4750	5	5700	14	13000	4	3050
J_7	9	5000	5	4800	13	3540	1	3100	8	3100
J_8	5	4670	14	13000	12	4200	4	3000	8	2700
J_9	6	13000	2	5500	7	3560	9	4500	14	10500
J_{10}	12	5100	6	12980	5	3500	9	4890	8	3090
J_{11}	8	2860	4	2240	1	2880	5	5550	13	2670
J_{12}	2	4600	3	3930	4	3180	6	10160	5	5450
J_{13}	4	2290	8	2670	14	11780	6	11800	12	3840
J_{14}	10	10090	8	2460	6	10650	15	1930	11	6100
J_{15}	10	11330	11	4400	12	3710	15	3570	9	5400
J_i	O_{ik}^6		O_{ik}^7		O_{ik}^8		O_{ik}^9		O_{ik}^{10}	
	M_k	P_{ik}^6	M_k	P_{ik}^7	M_k	P_{ik}^8	M_k	P_{ik}^9	M_k	P_{ik}^{10}
J_1	3	3200	10	11900	2	4670	1	3130	8	2200
J_2	15	2800	13	2900	1	4000	4	3600	7	5000
J_3	13	2900	1	3300	14	12280	7	4700	11	5370
J_4	14	11290	8	2860	9	4750	12	4700	13	2500
J_5	12	5100	15	2780	10	12250	7	3800	8	3000
J_6	13	3080	15	2420	7	4480	2	4520	10	12720
J_7	12	5000	7	5030	11	4390	4	3500	14	11500
J_8	10	10100	2	5690	3	4000	13	2900	9	3520
J_9	11	5060	3	3450	4	2520	8	3000	12	4260
J_{10}	1	2700	10	10000	7	3400	15	3130	4	3500
J_{11}	15	2070	11	5650	2	6070	10	12500	14	11720
J_{12}	7	4400	10	11340	8	3410	11	4340	9	4100
J_{13}	13	2300	3	4290	5	4130	11	6090	2	5760
J_{14}	5	3400	12	4870	3	3770	2	5110	4	3280
J_{15}	1	3460	8	2800	7	4700	13	3340	2	5580
J_i	O_{ik}^6		O_{ik}^7		O_{ik}^8		O_{ik}^9		O_{ik}^{10}	
	M_k	P_{ik}^6	M_k	P_{ik}^7	M_k	P_{ik}^8	M_k	P_{ik}^9	M_k	P_{ik}^{10}
J_1	9	5200	6	11900	13	2670	12	5100	14	10000
J_2	10	10800	6	10900	11	6100	14	13000	3	5000
J_3	4	2900	12	5300	9	4280	2	5700	15	3370
J_4	3	4290	2	3960	11	4750	15	3000	4	3500
J_5	2	5210	14	12780	4	3250	6	11800	13	3000
J_6	12	5080	9	5420	8	3480	11	5520	6	12720
J_7	2	6000	6	12030	15	3390	3	3500	10	10500
J_8	15	2100	1	3690	11	5000	7	3900	6	10520
J_9	15	3060	5	3450	1	2520	10	12000	13	2260
J_{10}	11	5700	14	10000	3	3400	13	3600	2	4500
J_{11}	6	12500	9	5560	3	5030	12	4030	7	4200
J_{12}	12	3690	14	10420	13	2990	1	3460	15	2300
J_{13}	10	11100	7	4160	15	3350	9	4230	1	2990
J_{14}	14	10740	7	4790	1	3170	13	2770	9	5450
J_{15}	3	3460	14	12760	5	5570	4	3020	6	11730

Appendix II Experiment result comparison among Scenario 2 (Scenario 3) and its related Scenario 4 and Scenario 5

Appendix II-Experiment result of E-F&T 10×10 job shop

Appendix II- Table 20: Experiment result of E-F&T 10×10 job shop (Based on Scenario 2)

$f = 1.5$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
58	5202	9676.7	10880.5	91	10962	10077.9
59	4942	9686.9	10827.8	84	10657	9998.1
61	5081	9715.1	10813.2	113	12076	10356.0
62	4893	9726.1	10909.1	101	10653	10211.7
63	4787	9736.6	10829.4	124	11964	10500.1
64	5308	9740.7	10864.4	97	11436	10164.4
65	4589	9759.7	10947.2	120	11203	10451.0
67	4131	9789.9	10855.8	119	9891	10437.4
68	3667	9797.8	10851.3	122	9388	10474.6
76	3414	9891.7	11040.0	136	9535	10647.9
83	3146	9987.5	11125.4	123	8267	10487.2
84	3036	10001.8	11187.4	124	7931	10501.5
87	2732	10032.4	11218.0	127	7321	10532.1
94	2646	10118.0	11303.6	142	6826	10723.1
110	2579	10322.1	11410.9	172	8027	11097.4
111	2564	10329.8	11390.9	154	6863	10875.4
112	2492	10348.2	11419.0	157	6887	10904.1
116	1853	10395.0	11540.8	158	6594	10916.9
142	1507	10724.2	11720.7	192	5812	11352.6

$f = 1.6$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
55	4207	9635.6	10724.4	112	11005	10343.3
58	4041	9668.6	10832.0	118	10899	10422.6
64	3785	9750.7	10871.4	130	10547	10577.5
66	3661	9766.0	10964.1	122	9849	10466.0
68	3046	9790.4	10883.2	123	8777	10486.1
70	2995	9824.1	10979.8	116	8797	10398.0
72	2891	9843.2	11018.2	109	7947	10312.0
76	2858	9902.2	11122.0	106	7657	10266.4
80	2756	9945.9	11186.2	108	7501	10296.6
81	2290	9955.9	11163.9	119	7168	10436.0
84	2214	9997.5	11147.7	124	6980	10499.3
89	2103	10060.4	11210.6	129	6559	10562.1
116	2013	10393.0	11503.7	183	8030	11233.2
120	1960	10444.7	11572.3	178	7121	11170.4

131	1841	10586.2	11657.4	174	6482	11122.6
136	1630	10650.8	11680.1	186	6188	11268.8
147	1517	10780.6	11859.1	199	6084	11436.2
154	1324	10866.7	12015.5	233	6543	11856.3

$f = 1.7$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
62	3092	9721.6	10922.8	95	8896	10133.1
65	2046	9757.6	10964.1	92	6667	10099.0
66	2038	9765.6	10917.5	106	6832	10276.3
82	1957	9973.3	11229.6	112	6642	10343.7
84	1793	10000.4	11141.0	154	7642	10865.8
87	1629	10033.3	11090.1	124	5912	10499.0
88	1529	10042.1	11195.8	115	5506	10389.4
97	1339	10164.8	11288.2	156	5819	10893.7
99	1184	10182.0	11364.8	145	5049	10761.8
105	818	10260.5	11338.5	141	4404	10705.4
122	808	10477.8	11669.6	184	5264	11246.7
130	572	10575.6	11733.2	195	5411	11381.7
160	461	10949.8	11993.8	196	3782	11394.9
171	377	11085.0	12268.5	218	3466	11666.7

$f = 1.8$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
60	3109	9701.8	10801.6	89	8827	10064.1
61	2165	9709.8	10893.3	118	8995	10423.9
62	1471	9715.6	10848.2	110	6596	10320.7
64	1460	9747.3	10887.5	107	6487	10283.5
73	1417	9864.3	10944.5	129	6786	10563.5
77	1282	9911.5	11014.4	129	7027	10564.4
78	1046	9919.7	11108.9	116	5391	10402.6
82	1026	9974.7	11156.5	121	5166	10457.6
85	1012	10009.0	11190.7	124	5300	10491.8
87	992	10033.7	11213.9	126	5368	10516.5
97	843	10154.1	11363.7	142	4635	10726.0
106	758	10268.5	11289.8	157	5152	10909.7
109	713	10304.9	11424.7	168	5799	11050.7
127	441	10529.7	11726.3	179	4717	11179.5
138	294	10672.0	11726.3	205	4617	11504.6
141	285	10713.7	11758.0	180	4292	11196.9
153	273	10857.2	12116.0	211	4224	11590.2

Appendix II- Table 21: Experiment result of E-F&T 10×10 job shop (Based on Scenario 3)

$f = 1.5$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	3179	8989.8	10148.5	5.7	7699	9018.2
4.5	2909	9002.6	9859.3	6.4	7922	9026.6
5.2	2406	9012.0	10002.7	10.8	6691	9082.0
6.0	2288	9021.1	10011.7	11.4	6699	9088.7

$f = 1.6$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	2921	8990.3	10140.0	11.7	8258	9093.1
4.5	1584	9002.3	9903.2	9.0	6508	9058.8
4.9	1329	9007.7	9956.3	9.6	6244	9066.5
6.0	1264	9021.2	9969.4	10.6	6313	9079.1
7.5	1242	9040.5	9981.6	12.2	6064	9098.6
8.4	1134	9051.9	9999.9	13.1	5393	9109.8
12.2	1118	9099.7	10057.8	9.6	4879	9067.0

$f = 1.7$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
4.5	1234	9002.8	10048.4	9.1	6228	9060.9
5.4	905	9014.2	9966.8	10.6	5842	9079.3
6.3	867	9025.7	9977.8	11.2	5877	9087.0
7.8	821	9044.5	10021.3	11.8	5442	9094.6
9.0	801	9058.6	10012.4	11.4	5448	9089.3
10.4	720	9076.4	10261.5	15.2	4973	9136.2

$f = 1.8$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
2.4	2811	8977.2	9753.3	4.7	8740	9005.0
3.5	1417	8990.0	9903.2	6.0	6163	9022.0
4.3	809	9000.6	9984.4	8.5	5212	9053.0
5.5	720	9015.2	10064.3	9.5	5277	9065.9
6.4	713	9026.5	10112.5	13.1	5608	9110.7
7.3	665	9037.6	10112.8	12.5	5600	9102.5
8.4	638	9052.1	10112.2	14.6	5509	9129.2

Appendix II-Experiment result of E-Lawrence 15 × 10 job shop

Appendix II- Table 22: Experiment result of E-Lawrence 15 × 10 job shop (Based on Scenario 2)

$f = 1.5$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
133	6706	16541.5	18167.9	241	18814	17891.3
136	6482	16586.1	18150.1	226	18062	17704.8
143	5738	16673.6	18187.0	234	15730	17807.5
144	5694	16688.5	18276.9	212	15013	17529.7
154	5607	16808.1	18397.0	238	15469	17854.5
155	5495	16823.1	18325.5	235	16157	17822.2
162	5057	16903.7	18558.1	258	15019	18112.5

$f = 1.6$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
119	4510	16370.3	17937.6	204	14475	17431.6
120	4028	16380.8	17860.6	203	12897	17417.8
134	3677	16560.8	18122.2	222	13610	17659.5
164	3477	16930.2	18554.7	261	12801	18146.0

$f = 1.7$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
128	3717	16488.6	17919.3	209	13806	17490.8
132	3471	16533.5	17966.7	236	15045	17833.4
136	2612	16583.6	18115.6	235	13706	17814.3
151	2456	16773.8	18366.7	233	12525	17801.3
161	2369	16899.8	18495.3	241	11498	17893.2

$f = 1.8$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
132	3877	16535.4	18149	193	12543	17298.7
134	2279	16552.8	18058	228	11433	17738.0
136	1916	16583.2	18137	216	10572	17587.3
148	1831	16733.3	18311	244	11963	17933.3
161	1495	16896.3	18571	232	10206	17785.7

$f = 1.9$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
128	1915	16477.1	18005.1	212	9918	17529.21
140	1633	16632.6	18241.2	215	9959	17569.98
141	1484	16645.3	18318.6	233	11195	17800.64
149	1333	16745.1	18211.6	209	9061	17496.23
154	852	16813.5	18463.9	230	8649	17754.21
165	828	16941.2	18637.2	253	9866	18050.83
187	691	17226.5	18896.0	272	8205	18277.03

Appendix II- Table 23: Experiment result of E-Lawrence 15×10 job shop (Based on Scenario 3)

			$f = 1.5$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	4762	14927.3	16152.5	12.6	13550	15040.0
4.5	4493	14939.0	16252.1	13.6	13095	15053.0
5.3	4016	14949.0	16150.5	9.8	12161	15005.6
6.5	3973	14964.0	16157.4	10.7	12118	15016.9
7.4	3895	14975.7	16145.1	12.0	12244	15033.0
7.9	3865	14981.4	16155.7	12.2	12214	15035.7
9.3	3802	14999.7	16196.8	12.7	11947	15041.2
9.9	3787	15006.5	16209.2	12.7	11932	15042.3
11.0	3786	15020.8	16248.5	14.2	11931	15060.3
			$f = 1.6$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
4.2	3859	14936.0	16462.4	8.8	14206	14992.7
5.4	3038	14949.9	16423.3	8.8	12983	14992.6
6.0	2906	14958.0	16443.7	8.9	12429	14994.5
6.6	2893	14965.3	16456.6	9.1	12461	14996.7
7.9	2869	14981.3	16502.8	10.3	12433	15011.8
9.9	2847	15006.3	16589.1	12.2	12080	15035.0
11.4	2788	15025.4	16498.6	13.6	12305	15052.8
			$f = 1.7$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.3	3599	14924.5	16345.5	6.0	12901	14957.8
4.3	3047	14936.3	16459.4	10.5	12913	15014.4
5.4	2655	14950.3	16473.2	13.0	12504	15045.2
6.5	2385	14964.7	16467.1	15.1	12773	15071.2
7.4	2131	14975.3	16374.9	11.2	11626	15023.2
8.3	1938	14987.2	16361.9	11.3	11431	15024.4
8.9	1923	14994.0	16364.7	11.7	11675	15028.8
10.3	1902	15012.1	16388.1	15.5	12047	15076.9
11.4	1865	15025.3	16397.1	13.7	11607	15053.8
12.5	1852	15039.2	16434.1	17.2	11654	15097.4
13.1	1832	15046.3	16422.2	17.5	11771	15101.6
15.4	1820	15076.1	16448.4	20.1	12109	15134.2
16.2	1808	15086.0	16469.1	24.0	11793	15183.5
			$f = 1.8$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.4	1184	14925.6	16306.2	7.6	9589	14977.8
4.5	1102	14938.8	16365.1	7.7	9039	14978.7
5.5	1038	14951.7	16221.9	10.1	8594	15008.8
6.5	893	14963.7	16232.4	9.8	8565	15005.7
8.1	744	14984.8	16266.7	11.6	8461	15028.4
8.1	744	14984.8	16266.7	11.6	8461	15028.4
9.6	712	15002.6	16226.4	13.1	8383	15046.2

$f = 1.9$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	647	14926.6	16362.2	7.2	8586	14972.7
4.5	526	14939.3	16338.7	8.7	9612	14992.3
5.3	284	14948.7	16408.4	8.1	7355	14984.2
6.3	202	14961.5	16435.7	9.8	6472	15005.6
6.9	81	14969.6	16370.1	8.9	5360	14994.0
8.0	78	14982.7	16374.4	9.4	5337	15000.7

Appendix II-Experiment result of E-Lawrence 20×10 job shop

Appendix II- Table 24: Experiment result of E-Lawrence 20×10 job shop (Based on Scenario 2)

$f = 1.5$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
63	13458	19527.2	21657.1	136	27912	20435.2
66	13295	19558.9	21731.6	135	27095	20419.8
75	12970	19674.4	21996.4	164	27766	20791.3
83	12749	19776.8	22040.7	178	27917	20968.0
89	11702	19852.6	21940.2	147	23266	20581.2

$f = 1.6$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
58	10381	19459.4	21713.1	131	24223	20380.8
80	10274	19735.1	21958.3	152	23596	20639.3
86	9913	19813.2	21942.6	147	23014	20578.8

$f = 1.7$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
61	9104	19506	21707.4	134	22385	20418.6
62	8247	19507	21721.7	140	22542	20482.6
79	8066	19731	21906.0	146	21225	20567.9

$f = 1.8$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
64	8977	19541.2	21766.8	150	24110	20617.4
66	8443	19568.1	21855.8	133	21079	20396.1
70	7965	19616.1	21815.5	139	21087	20471.3
73	7792	19644.4	21849.0	137	20853	20447.8
76	6800	19684.0	21918.0	165	20846	20803.3

$f = 1.9$

S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
66	5858	19562.8	21753.2	148	20446	20587.3
75	5636	19675.5	21928.6	135	17893	20422.7
79	5624	19723.9	21944.0	139	17881	20471.2
80	5612	19738.0	21996.8	158	18746	20718.1
98	5598	19961.0	22207.2	164	18085	20790.0
99	5586	19981.1	22282.8	181	18915	20996.3

Appendix II- Table 25: Experiment result of E-Lawrence 20×10 job shop (Based on Scenario 3)

$f = 1.5$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
4.4	14579	18792.9	21018.0	19.3	30367	18979.0
5.4	13419	18804.8	20996.2	9.9	26389	18861.4
6.1	13058	18813.3	21023.3	11.0	26103	18875.5
7.1	11666	18826.5	20916.2	12.5	26056	18893.4
8.5	11128	18843.4	21076.0	16.0	23721	18937.8
9.4	10718	18855.3	21021.2	17.0	23447	18949.8
10.3	10563	18866.4	21029.8	16.3	23449	18941.4
11.4	10483	18879.6	21043.0	17.4	23369	18954.6
11.6	10405	18882.8	21088.2	17.4	23797	18955.2
13.4	10291	18905.0	21036.6	17.7	23790	18959.0
14.3	10074	18916.6	21067.2	19.2	23723	18976.9
15.3	9997	18928.1	21096.2	18.6	23646	18970.6

$f = 1.6$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	13040	18781.2	21090.0	7.6	27463	18832.8
4.5	11347	18793.5	20995.8	10.6	25224	18870.4
5.3	8544	18803.7	20865.1	10.7	22427	18870.9
6.3	8147	18816.6	20935.7	11.6	22431	18882.1
7.5	7892	18831.1	20920.8	13.1	21872	18901.1

$f = 1.7$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
3.5	10196	18781.0	20972.8	6.3	25436	18816.0
4.4	7091	18792.0	20964.3	13.3	20617	18904.1
5.4	6804	18805.4	20937.6	12.6	19780	18895.3
6.4	6709	18818.0	20887.9	14.3	20349	18916.7
7.2	6685	18827.4	20955.5	14.7	20205	18921.4

$f = 1.8$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
4.5	6281	18793.9	20889.6	9.2	19880	18852.3
5.0	6073	18800.1	20839.5	10.5	19526	18869.1
6.5	5767	18818.4	21009.4	13.5	19121	18905.6
7.1	5767	18826.6	20895.6	10.4	18378	18867.5
8.4	5715	18843.1	20911.0	10.9	18324	18873.3
8.8	5634	18847.1	20792.1	11.3	18203	18878.1
10.2	5582	18864.8	20837.9	12.5	18151	18894.0
11.2	5460	18877.3	20955.8	13.5	18033	18906.6
11.6	5452	18882.9	20938.9	14.0	18025	18912.1

$f = 1.9$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
4.5	6491	18793.7	20743.2	15.6	21391	18932.6
5.5	5668	18806.2	20757.4	14.7	20934	18921.7
6.3	5400	18816.3	20733.1	14.9	20353	18923.5

7.5	5335	18830.9	20787.5	15.7	19278	18934.2
10.5	5186	18868.6	20812.8	15.4	17302	18930.2
10.5	5186	18868.6	20812.8	15.4	17302	18930.2
11.5	4785	18880.8	20880.3	23.2	18431	19027.7
12.4	4238	18892.4	20900.4	17.7	17383	18958.4
12.5	4090	18893.8	20964.0	18.0	16807	18962.0

Appendix II-Experiment result of E-Lawrence 15×15 job shop

Appendix II- Table 26: Experiment result of E-Lawrence 15×15 job shop (Based on Scenario 2)

			$f = 1.5$			
S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
337	2347	25326.2	28268.5	449	14055	26728.9
			$k = 1.6$			
S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
362	1334	25642.6	28446.1	516	13634	27574.2
364	1220	25664.3	28652.8	436	9086	26567.2
377	1207	25830.9	28881.2	451	10297	26758.2
382	1192	25897.7	29075.2	465	10370	26933.9
386	1031	25939.7	28836.1	509	11829	27477.1
394	946	26041.1	29171.5	471	9510	27007.8
			$f = 1.7$			
S2 NPE	S2 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
365	946	25678.8	28713.4	493	10017	27281.9
371	658	25751.0	28885.8	497	9642	27332.5
381	608	25878.9	28898.5	526	11148	27698.3
384	528	25918.7	28707.1	529	11034	27734.7
395	447	26060.7	29122.3	539	10972	27856.1
413	298	26287.8	29129.7	560	11952	28116.9

Appendix II- Table 27: Experiment result of E-Lawrence 15×15 job shop (Based on Scenario 3)

			$f = 1.5$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
13.4	4126	21286.5	23755.1	18.5	19510	21350.6
14.3	4002	21298.0	23770.2	18.6	19646	21351.5
15.3	3950	21310.6	23803.6	19.6	19594	21364.5
16.0	3440	21318.7	24000.9	19.5	17727	21363.1
16.9	3407	21330.1	23998.4	20.1	17700	21369.9
			$f = 1.6$			
S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
13.5	3313	21287.7	23503.4	18.3	17239	21347.5

13.8	3186	21291.9	23520.0	19.3	15892	21360.2
15.0	3177	21306.9	23506.2	19.9	20363	21368.2
16.1	3123	21320.5	23661.6	18.5	16923	21350.8

$f = 1.7$

S3 NPE	S3 TWT	S2 TEC	S5 TEC	S4 NPE	S4 TWT	S4 TEC
12.7	1152	21278.4	23596	23.6	16901	21414.0
14.1	1125	21295.8	23611.7	24.5	17345	21425.4
14.7	1101	21303.5	23638.6	24.6	16991	21427.2
15.6	1079	21314.1	23681.8	25.4	16786	21436.8

Appendix III Experiment result of Scenario 6

Appendix III- Experiment result of E-F&T 10×10 job shop

Appendix III-Table 28: Experiment result of E-F&T 10×10 job shop

$f = 1.5$			$f = 1.6$		
S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
4.2	9054	9540.8	3.9	9012	9478.3
4.4	9559	9539.1	4.1	7773	9668.5
4.6	8471	9568.1	4.3	7201	9660.3
4.7	7904	9579.8	4.8	7055	9692.1
5.6	5146	9648.0	4.9	6582	9347.8
5.9	4129	9355.9	5.2	5380	9358.8
6.0	3314	9511.2	5.3	5132	9354.7
6.3	3083	9520.9	5.5	4943	9708.0
6.5	3031	9493.8	5.8	4642	9609.9
6.5	2933	9554.8	5.9	4479	9566.4
7.2	2870	9538.1	6.1	4177	9714.0
8.0	2786	9609.2	6.7	3850	9215.7
8.3	2552	9659.5	6.8	3312	9305.9
9.0	2342	9560.8	7.0	2143	9760.5
9.6	2272	9651.0	7.1	1968	9612.8
10.2	2042	9947.6	7.5	1903	9650.8
10.3	1845	9782.1	7.7	1654	9747.9
11.0	1801	9692.2	8.0	1498	9745.3
11.4	1755	9795.8	8.2	1395	9727.5
11.6	1541	9916.9	8.4	1159	9881.4
12.6	1418	9695.1	8.5	1106	9845.4
12.8	1261	9712.4	9.0	1093	9930.3
13.1	910	9717.4	9.2	1019	9921.8
14.4	877	9759.3	9.4	974	9980.8
14.5	826	9779.5	10.1	946	9917.1
			10.7	898	9666.3
			11.8	689	9899.7

$f = 1.7$			$f = 1.8$		
S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
5.1	3859	9454.6	4.3	6945	9674.1
5.2	3921	9450.3	4.4	5485	9680.6
5.3	3374	9411.8	4.5	5164	9725.6
5.4	2564	9444.3	4.7	2065	9879.6
5.9	2452	9429.3	4.8	1859	9865.0
6.0	2425	9419.7	5.0	651	9794.9
6.1	2365	9430.9	5.8	432	9930.4
6.2	2325	9445.7	6.3	423	9799.9

6.3	2173	9807.9	6.5	155	9845.0
6.4	1985	9810.3	6.6	144	10004.1
6.8	1757	9628.0	6.7	105	10023.8
6.9	1625	9475.0	9.2	100	9957.5
7.2	1478	9670.1	10.3	61	9990.2
7.3	1367	9528.5			
7.4	1341	9681.1			
7.7	1273	10064.8			
7.9	1153	9919.3			
8.2	1054	9974.4			
9.1	970	9939.0			
9.2	942	9865.8			
9.7	928	9946.9			
10.0	847	9918.4			
11.1	561	9831.1			
11.2	500	9969.7			
12.3	443	9846.4			
13.0	416	9837.9			
13.6	347	9899.6			
14.8	335	9952.8			
17.1	208	9972.7			
22.2	202	9924.7			

Appendix III- Experiment result of E-Lawrence 15×10 job shop

Appendix III-Table 29: Experiment result of E-Lawrence 15×10 job shop

	$f = 1.5$			$f = 1.6$	
S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
5.4	5754	15798.8	6.2	4719	15899.1
5.7	5672	15946.2	7.1	4667	15835.1
5.9	5475	15913.9	8.0	5353	15681.8
6.1	5331	15955.2	9.1	4314	15980.1
6.8	5301	15963.2	10.0	5678	15277.1
7.4	4917	16130.3	11.2	4296	15974.2
8.1	4865	15970.1	11.8	4113	16013.6
8.6	4650	16128.5	12.6	5177	15678.6
9.5	4635	16246.8	13.8	4286	15971.4
10.1	4533	16345.7	15.7	4002	16295.1
11.3	4379	16335.6	16.8	4035	16074.7
12.3	4335	16352.3	18.3	5337	15522.7
13.0	4302	16335.7	18.5	3969	16070.1
			20.7	5334	15577.9
			22.2	3985	16044.6
	$f = 1.7$			$f = 1.8$	

S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
5.3	5554	15662.7	5.8	3931	16335.3
5.4	5174	15604.6	6.4	3794	16334.9
5.5	4572	15627.5	6.9	3774	16327.8
5.6	4360	15577.1	7.3	3750	16325.6
5.8	4288	15988.5	7.7	2256	16081.6
5.9	3710	15825.1	8.0	2218	16119.4
6.1	3536	15745.4	8.4	2163	16086.6
6.4	3506	15688.2	9.5	2147	16148.5
6.5	3327	15915.4	9.7	2008	16126.3
6.6	3125	16244.5	10.0	1867	16142.6
7.0	3122	16291.1	11.3	1860	16027.1
7.2	2908	16197.3	11.4	1756	16119.4
8.3	2865	16174.5	11.5	1738	16132.7
8.4	2823	16273.8	11.6	1735	16134.0
9.3	2666	16310.5	12.4	1708	16041.4
9.7	2619	16182.5	12.5	1652	16040.7
10.0	2552	16070.9	12.6	1559	16145.8
10.2	2464	16376.9	13.2	1543	16152.9
10.8	2360	16448.4	22.0	1497	16298.5
10.9	2353	16530.6		$f = 1.9$	
11.1	2266	16482.3	S6 NPE	S6 TWT	S6 TEC
11.6	1994	16460.3	5.2	2882	15868.8
13.0	1983	16491.5	5.4	1321	15938.5
13.1	1976	16526.0	7.0	1009	15880.9
13.9	1950	16475.6	7.6	896	16018.5
14.0	1943	16547.8	7.7	853	15985.7
14.9	1940	16496.7	8.4	797	16038.3
16.5	1912	16607.7	9.4	761	16026.5
			11.5	697	16052.1

Appendix III- Experiment result of E-Lawrence 20×10 job shop

Appendix III-Table 30: Experiment result of E-Lawrence 20×10 job shop

	$f = 1.5$			$f = 1.6$	
S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
7.7	12695	20545.9	12.0	16337	20406.5
7.8	12493	20377.7	15.6	16328	20431.6
8.0	11799	20413.2	15.8	16142	20285.7
9.0	11761	20457.8	16.0	13742	20522.9
11.1	11703	20499.1	19.8	12443	20746.1
11.2	11591	20548.7	23.6	11850	21147.9
	$f = 1.7$			$f = 1.8$	
S6 NPE	S6 TWT	S6 TEC	S6	S6	S6 TEC

			NPE	TWT	
8.3	8892	20661.4	12.4	15385	19990.48
8.8	8687	20696.7	12.5	13626	20145.62
8.9	8581	20688.0	13.8	12352	20670.66
9.3	8487	20541.2	14.3	12343	20519.71
10.5	8384	20547.4	14.5	10157	20536.32
10.8	7954	20713.3	15.5	9846	20768.39
11.4	7900	20697.9	17.6	8698	20801.6
12.4	7710	20645.6	33.4	8549	21214.06
12.5	7695	20667.1		$f = 1.9$	
13.8	7468	20677.8	S6 NPE	S6 TWT	S6 TEC
15.3	7465	20713.1	12.9	10441	20319.66
15.5	7448	20613.5	13.5	10371	20659.78
15.8	7416	20660.6	15.9	10042	20037.1
16.1	7373	20659.9	16.9	10007	20342.61
16.3	7330	20684.7	17.4	9282	20597.83
17.7	7235	20826.6	18.1	9253	20651.57
18.7	7220	20769.2	18.2	7908	20541.78
20.6	7185	20846.6	20.1	7832	20923.5
			25.1	7457	20990.47
			26.4	7077	20816.08

Appendix III- Experiment result of E-Lawrence 15×15 job shop

Appendix III-Table 31: Experiment result of E-Lawrence 15×15 job shop

	$f = 1.5$			$f = 1.6$			$f = 1.7$	
S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC	S6 NPE	S6 TWT	S6 TEC
19.8	11860	22060.3	18.2	6786	22238.06	20.3	6612	22398.5
20.3	10012	22754.01	19.3	5289	22674.6	20.9	5940	22581.31
20.5	9072	22749.41	20.0	3647	22518.58	21.2	5620	22807.71
21.8	8854	22839.5	22.0	2122	22948.79	21.7	4838	22323.2
22.1	8046	22845.08	23.3	1924	23071.75	22.2	3887	22794.79
22.8	6699	23199.11	24.8	1904	23179.85	24.0	3881	23056.36
27.4	6146	23049.65	25.3	1895	23185.59	25.2	3633	23006.18
28.7	5751	23362.29	26.9	1610	23247.18	25.4	2599	22780.51
29.7	5408	23612.47	27.2	1601	23297.61	26.5	2354	22890.53
30.3	5060	23616.61	28.1	1569	23265.79	28.2	2323	23324.95
			29.6	1514	23201.86	29.3	2288	22951.32
			30.0	1512	23278.7	32.2	2201	22650.28
			31.6	1458	23307.35	32.3	1932	22880.35
			32.3	1444	23316.49	32.4	1853	22924.09
						34.5	1714	23142.51
						38.1	1605	23098.56