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WORKSTATION PLANNING AND SCHEDULING REQUIREMENTS TO SAVE ENERGY

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Master's Thesis

Supervisor

Asst. Prof. Dr. Engin SANSARCI

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The thesis/dissertation titled WORKSTATION PLANNING AND SCHEDULING REQUIREMENTS TO SAVE ENERGY prepared by SARMAD NOORI ALDEEN ALANI and submitted on 12/4/2024 has **been accepted unanimously/by majority of votes** for the degree of Master of Master of Science Industrial Engineering.

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Sarmad NOORI ALDEEN ALANI

Signature

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ABSTRACT

WORKSTATION PLANNING AND SCHEDULING REQUIREMENTS TO SAVE ENERGY

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Reducing energy consumption is a major challenge in many industries and it is not easy and has a direct and positive impact on preserving our lives first and the environment second by reducing emissions, as energy in the industrial section has increased in the past fifty years, as energy consumption is estimated to be output from industry. Minimizing energy consumption is an important aspect of planning and scheduling manufacturing processes. This leads to a multiple objective environment for the scheduling problems. In this thesis we considered a multi-objective scheduling problem in which the objectives are minimizing the makespan and energy consumption. We offered a new multi-objective Genetic Algorithm in which there are separate populations for different objectives and there is a mixing mechanism in the parent selection and crossover phases to improve both objectives simultaneously. We then presented an algorithmic implementation to tackle the problem. Simulation results for different parameter settings is given. We believe that this kind of genetic algorithm design can be beneficial in scheduling problems which aims to minimize energy consumption beside the other time-related objective like makespan.

Keywords: Parallel Machine Scheduling, Energy Saving, Multi-Objective Optimization, Multi-Objective Genetic Algorithm, Algorithmic Implementation.

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ABBREVIATIONS

$t_{P_{m,j,n}}$	:	Processing Time Of $O_{m,j,n}$ In Machine M_{M}.
$E_{P_{m,j,n}}$	:	Processing Energy Of $O_{m,j,n}$ In Machine M_{M}.
$E_{sP_{m,j' j,n' n}}$	:	Setup Energy Of Operation $O_{m,j,n}$ In Machine M.
$t_{sP_{m,j' j,n' n}}$	:	Setup Time Of $O_{m,j,n}$ In Machine M.
$O_{m,j,n}$	:	Operation N Of Job J In Machine M.
$rTWt_l$	:	Reduction Percentage Of Total Workload In L Iteration.
$rTTE_l$	:	Reduction Percentage Of Total Energy In L Iteration.
rC_{max_l}	:	Reduction Percentage Of Makespan In L Iteration.
$rTE_{id\ l}$	:	Reduction Percentage Of Non-Productive Energy Inrl Iteration.

LIST OF SYMBOLS

C	:	Represent the Makespan.
m	:	Represent the number of Machines.
PRS	:	Process Route Selection
AvR_l	:	Average Of Total Reduction
$FJSP$	:	Flexible Job Shop Problem
l_i	:	Is The Idle Time Of Machine

1. INTRODUCTION

Economic development is essential in our society as it is considered encouraging because of its economic and environmental benefit. Working on this subject is crucial due to the growing significance of energy efficiency in manufacturing and operational activities the study issue focuses on optimizing machine scheduling in manufacturing and computer settings to minimize energy consumption, as well as other performance measures including makespan, tardiness, and power costs. Beginning in Great Britain in the middle of the 18th and early 19th centuries, the Industrial Revolution was a time of significant invention and automation that eventually extended over much of the globe. The use of iron and coal for industrial purposes dominated the British Industrial Revolution. The American Industrial Revolution, sometimes known as the Second Industrial Revolution, started in the 1870s during the Gilded Age and lasted until World War II. The Industrial Revolution resulted in the creation of several technologies, such as the assembly line, telegraph, steam engine, sewing machine, and internal combustion engine.

Employment in the industrial sector during the Industrial Revolution offered more lucrative remuneration compared to those in the agricultural sector. The proliferation of manufacturing and urban migration resulted in environmental degradation, abysmal working and living conditions, and the exploitation of child labor. Scientists believed that nature does not run out of energy sources and raw materials extracted from nature, and they believed that manufacturing processes do not have a negative impact on nature, but with the growth of population and the development of science, the needs for energy became strong and thus the need for material extraction has become urgent and abundant.

Which led these manufacturing processes to the production of natural pollutants and a lot off emissions from manufacturing processes and power plants. Which led to the urgent need to hold a conference to solve this problem and give the subject importance Indeed, the Stockholm Conference was held, where it was held in 1972 [1], and the Supervised by of the United Nations, in which the bad effects on the environment happened because industry and the impact of industry on nature and on raw materials were discussed.

After the Portland meeting was held in 1987 [2] entitled "Our Common Future", and its aim was to decrease energy consumption and reduce the use of resources, the conference was The Environment Nature Conservation Resources and Development (UNCED), in (Brazil) in 1992 [3].

United Nations [4-5] tried to develop a program of common global, broad-based, socio-economic awareness. This conference a broader the basics and rules of sustainable development have been improved and developed. Almost ten years after the Earth Summit in Rio, followed by the World Summit on Sustainable improve and Nature Conservation, the meeting was in Johannesburg in 2002 [6]. The conference was also intended to speak sustainable development and nature conservation by the United Nations and draw the attention of the world and direct action to meet the challenges of preserving the environment and preserving nature and the resources extracted from it for the largest number of years.

1.1 ENVIRONMENTAL IMPACT MANAGEMENT SYSTEM (EIMS)

Environmental Impact Management System (EIMS) is a component of the overall system of different sectors of activity have demonstrated that the use of a management system environmental management (EIMS), also it is an effective tool to improve performance environmental. Instructions have been developed, which helped in the development of many matters related to the market and consumers. As companies began to focus and adopt strategies for preserving the environment and addressing various issues, factories are able to meet environmental and technical requirements, and address several issues, including.

a. Green manufacturing.
b. Energy efficient / energy consumption management.
c. Use of renewable energies.
d. Developing the product so that it has a longer life.
e. Durable goods market services and cleaner production techniques.

1.2 REDUCE CONSUMPTION ENERGY IN WORK SHOP

Engineers define energy as the ability to do a job or perform a task through a manufactured device or machine, or it is anything that has "the potential to make changes." energy use and demand are constantly increasing, related with global climate change and population growth

(DOE / EIA 2009) [7]. In 2030, according to statistics, demand is expected to increase by more than 55% compared to current levels [8], as shown in Chart 1.1.

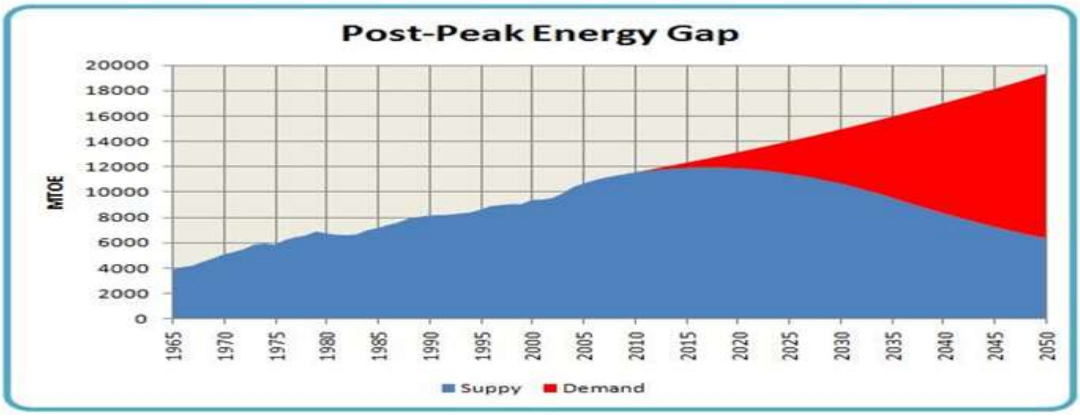

Chart 1.1: Increase Between Energy Supply and Demand.

Despite the development and spread of renewable energy technologies, it is expected that manufacturing activities will continue in the medium term to rely heavily on electricity generated from fossil fuels Chart 1.2, when we use energy correctly and more efficiently, it will be effective in terms of reducing costs, reducing carbon dioxide emissions, improving productivity, and contributing to energy savings to the greatest extent.

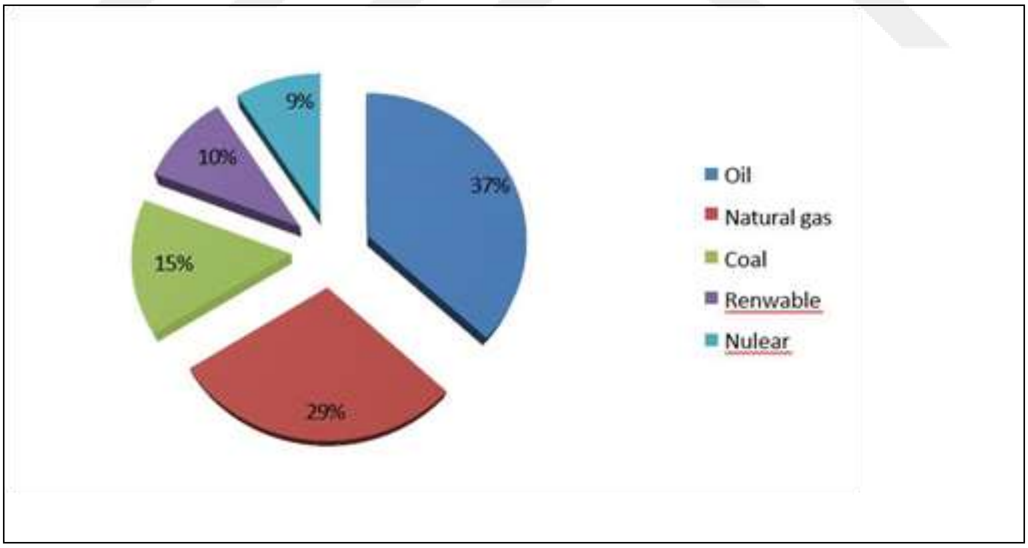

Chart 1.2: Total Energy Production (sources EC/PBL 2017).

Much research has been done on reducing energy consumption. It is possible to change energy from one form to another and then use it to do work, ride bicycles, move cars and boats, cook food, light, and make products with machines.

As mentioned earlier, industry is the major user of energy in recent times, as it is evaluated that it for near 40% of the all-energy use generated. This made the global focus on reducing fuel consumption in general. There are several ways and methods, and there are open and continuous areas in this direction. We will mention a group of discoveries by developers who have reduced energy consumption.

Energy consumption in production departments should be analyzed to reduce energy in the enterprise and in production planning, as it was improving, as the lines in the manufacturing line are balanced in order to reduce energy and that is a good way to decrease energy cost [9].

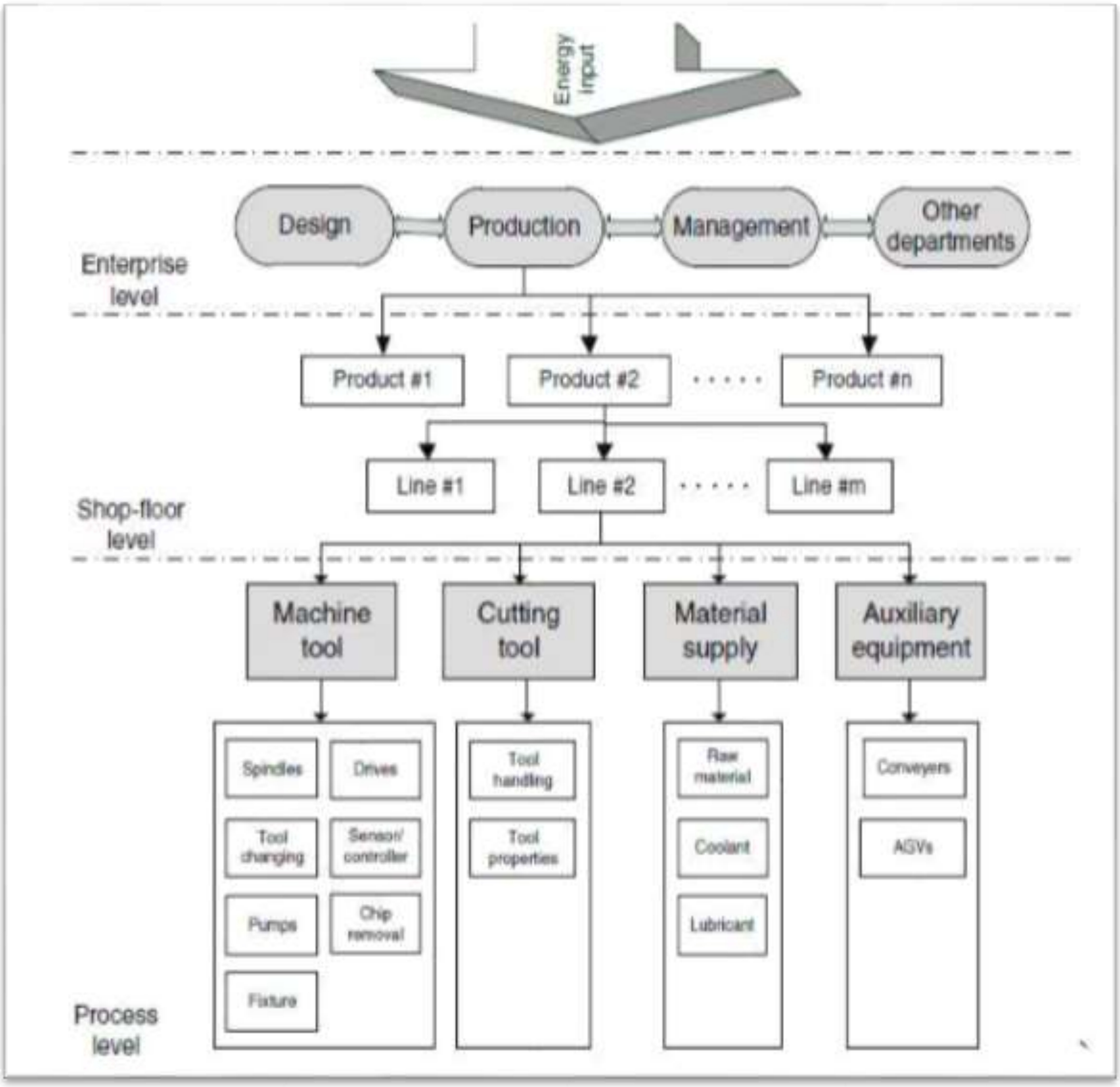

Figure 1.1: Energy Consumption in Enterprise [10].

1.3 ENVIRONMENTAL AND ENERGY IMPACT MANAGEMENT SYSTEM

Considering that environmental challenges are important in processes productions and industry, the EIMS proves to be a tool to be promoted within the framework of sustainable development of industrial production.

EIMS is a tool that makes it possible to apply management principles general environmental issues associated with activities.

The main benefits that industrial production can obtain from the establishment of a EIMS are:

a. demonstrate their compliance with environmental standards;
b. improve management and overall environmental performance.
c. improve relationships with neighbors, regulators, customers and interested parties.
d. maintain or improve market access and competitiveness.

An EMS has four stages and a feedback loop (Figure 1.2), For each of stages, the standard establishes requirements that pig farms must meet to comply with the standard.

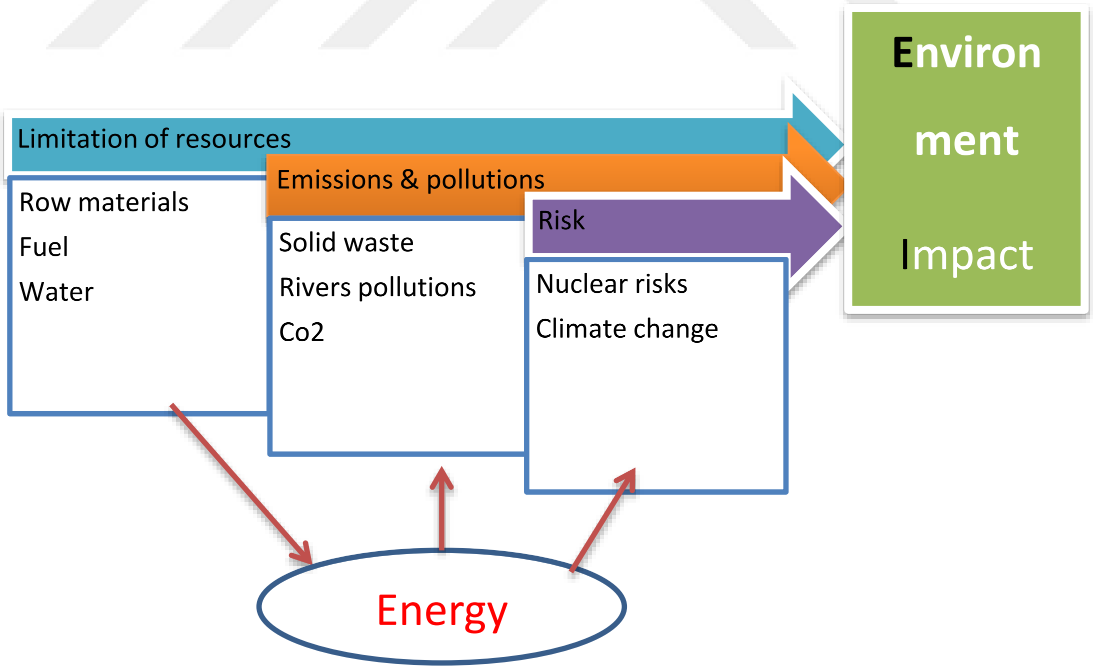

Figure 1.2: ERMS Steps and the Objectives.

Form the figur abuve we can find that energy palys a great and big role, becouse energy needs resoures, such as fuel and water, it also generates gas emissions and causes solid pollution as well as river pollution, we are also aware of the radio and nuclear risks, and the impact on climate change .

Fuels cost are exploding and the confrontations of decrease greenhouse gases have never so important, understanding your energy consumption is more Substantial than ever for any industrial group, service sector company or community. To do this, setting up an ERMS (Energy and Resources administration System) is the first station to improving energy administration. It is necessary to have both a clear vision at the global level and for each of its buildings (factories, premises, stores or even offices).

(ERMS) system helps establishments to constantly look their water, electricity and gas consumption, gain efficiency, smooth their processes, improve their profitability and decrease their environmental effect, count on the digital ripeness of the sites, energy management solutions are utilized to: Macro energy meters and billing tracking.

This study examines three key components related to energy management, data visualization, metering plan implementation, ISO 50001 certification [11], and the execution of one-off energy saving initiatives. The topic of reference modeling involves the application of advanced data analysis techniques to identify influential characteristics and detect real-time deviations by utilizing baselines. The utilization of Artificial Intelligence in simulation involves the creation of a digital replica of a physical location, sometimes referred to as a digital twin. This digital twin enables real-time simulations to be conducted, allowing for the evaluation and optimization of optimal circumstances and control-command strategies. The topic of discussion is to energy market intelligence, specifically focusing on the advanced management of energy flexibility and demand response. The integrated Energy and Environmental Management System encompasses all operations and services that fall under the realm of operational control.

However, in light of the constraints posed by limited raw materials and energy supplies, there is a growing need for the implementation of an Environment Impacts Management System.

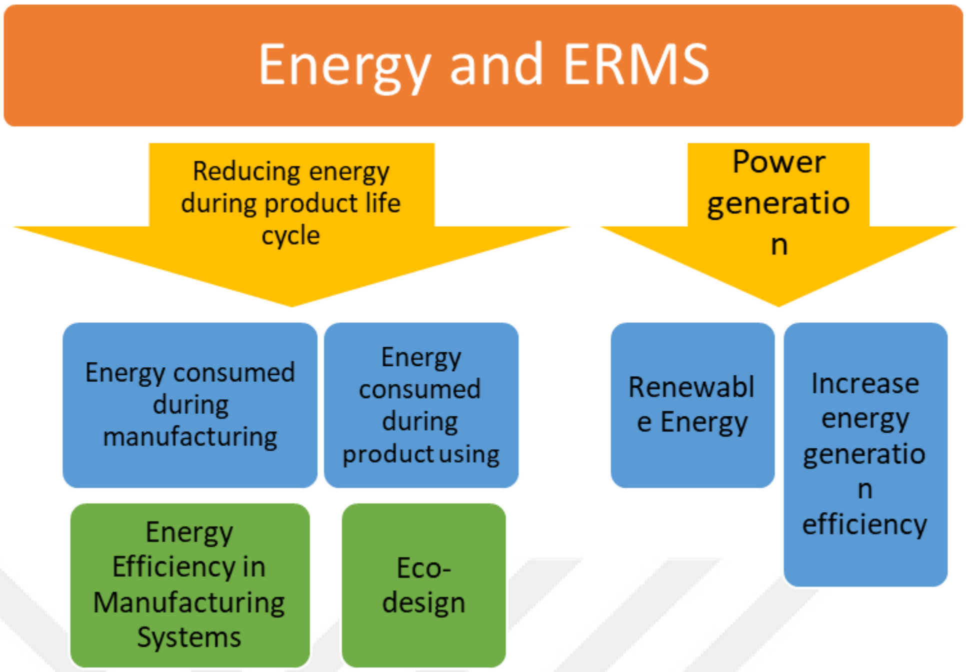

Figure 1.3: Energy and ERMS.

Companies have various motivations for incorporating environmental considerations into their policies. These motivations can be categorized as follows:

1. Compliance with regulations: Companies may include environmental policies to ensure they adhere to legal requirements and avoid penalties or legal consequences.

2. Cost savings: By reducing energy and resource consumption, companies can save money on operational expenses. Additionally, implementing environmentally friendly practices can help reduce environmental taxes imposed on businesses.

3. Improving community relations: Companies that are perceived as polluters or emit high levels of CO_2 may include environmental policies to enhance their relationships with local communities. This can help mitigate negative impacts and foster positive engagement.

4. Enhancing corporate image: Companies often adopt environmental standards to bolster their reputation and appeal to clients. Demonstrating a commitment to environmental sustainability can attract environmentally conscious customers and stakeholders. These motivations drive companies to prioritize environmental considerations and integrate them into their policies and practices.

1.4 ENERGY EFFECTIVENESS IN MANUFACTURING SYSTEMS

Energy efficiency can be succinctly defined as the quantifiable relationship between the outputs that are deemed "helpful" and the energy that is consumed by a given system, as eloquently stated by Herring in 2009 [12]. The user's text is concise and does not require any intellectual rewriting. The examination of energy efficiency can be classified into a hierarchical framework consisting of four distinct levels, as depicted in Figure 1.4.

a. The factory level: encompasses a diverse array of production lines and methods, which possess the potential for intricate interactions.

b. production line: At the production line level, one encounters a myriad of distinct machinery and various other equipment devices.

c. Machine level: A mechanized apparatus designed to ensure optimal conditions for the process of machining.

The process level encompasses the examination of the physical mechanisms underlying the process, as well as the identification of the process type and the determination of crucial process parameters such as feed rate and cutting speed.

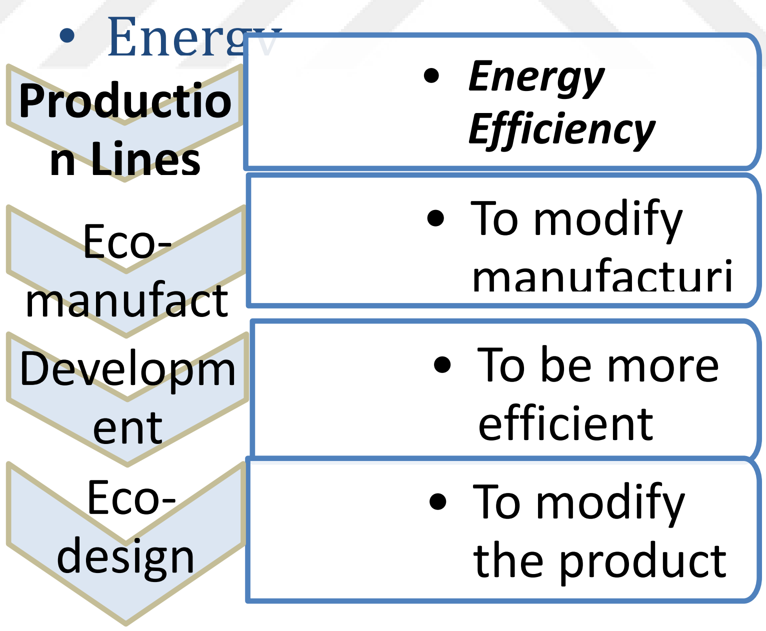

Figure 1.4: Energy Efficiency Methods.

In the world of manufacturing, the hot topic these days is all about reducing energy consumption. It's like a never-ending quest to become of resource efficiency. Companies are currently treating the idea of optimizing scheduling for power reduction like it's a distant relative they forgot to invite to the family reunion. It's high time corporate responsibility steps up and starts taking this issue seriously, because let's face it, their energy impact could use a serious makeover. In the realm of industry, there are four cunning methods employed to curb energy consumption:

a. The first entails concocting contraptions that are not only more efficient, but also less ravenous for energy.
b. The second involves the art of eco-design, where products and their life cycles are tinkered with to minimize their overall impact.
c. The third is the craft of eco-manufacturing, where manufacturing processes are skillfully altered.
d. The magical art of workshop scheduling! With a few tweaks here and there, production lines can achieve energy efficiency levels that would make even the most eco-conscious fairy proud (see Figure 1.5).

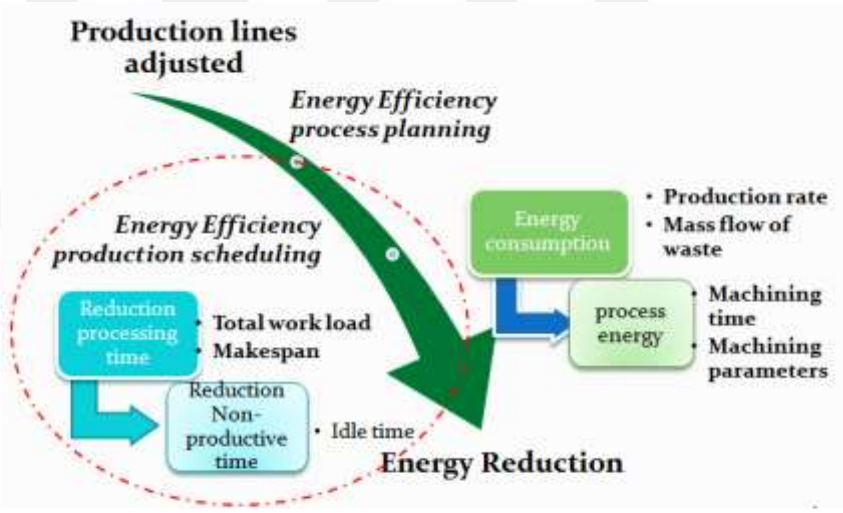

Figure 1.5: The Relationship Between Production Line and Energy Efficiency.

The first three methods, like elusive mirages in the desert of strategic intrigue. Alas, their allure is overshadowed by their exorbitant costs, leaving but a faint ripple of impact. Particularly for the humble small and medium-sized industries, whose budgets resemble a delicate butterfly's wings, the minimal impact renders these methods a mere trifle.

the grand finale here lies the golden opportunity to sprinkle some magic dust and transform mediocrity into magnificence, surpassing even the loftiest industry expectations.

the job shop problems, where criteria like total manufacturing time, cost, and other objective performance are given a subtle, yet undeniable, case of stage fright. So far, there have been a handful of researchers who have dabbled in the fascinating world of energy consumption during workshop planning. However, their efforts seem to be limited to simply tinkering with the overall workload and cutting down on those pesky moments of inactivity. It's like they're playing a game of energy-saving hide-and-seek, but only peeking behind the most obvious hiding spots.

Based on prior study and scholarly investigations, the decrease in energy use was attained by an indirect approach including the reduction of both task completion time and idle time. This thesis aims to reduce energy consumption by focusing on two key factors, the energy necessary for manufacture and the energy required for adjustment.

Previous research and studies have considered the impact of time on energy reduction, assuming a constant operating power of the machine throughout various tasks. Hence, it was postulated that just the duration of operation and the intervals of inactivity between operations were influential factors in determining the energy consumption.

We are completely aware of the magnitude of the energy drain caused by production and downtime. We also take into account the good direct effect that energy has on the chosen process. In practice, the capability of the process to execute tasks is not fixed, but rather dynamically adjusts to the process and the machine carrying out the job.

In our optimization methods, we utilize multiple populations to enhance efficiency and productivity. Each population represents a distinct set of values for processing energy, time, preparation energy, and duration associated with different operations. In our optimization methods, we can explore the possibility of incorporating multiple populations that represent different factors, such as processing energy, processing time, setup energy, and setup time. By considering the distinct energy values and setup energies of each operator, we are able to incorporate them into our analysis.

In this thesis, we develop multi-criteria optimization methods, using a multi-population genetic algorithm. We will finally discuss the introduction of fuzzy logic to deal with the imprecision of information without developing this point, we optimize total energy consumption for optimal workshop planning by minimizing the following criteria:

a. Developing a new fuzzy method to solve problems of uncertainty, taking into account the impact of energy on decision making,
b. Energy consumed and manufacturing time,
c. Energy consumed and preparation time,
d. Maximum manufacturing duration and total duration of non-productive operations.

Mathematical models for multi-criteria optimization of workshop scheduling with fuzzy multi decision making are proposed to model manufacturing times and energy consumption for resolution by genetic algorithms, for a bi-objective problem, we operation two populations, one to minimize the total energy consumption and the other to reduce the total weight.

2. ENERGY AND INDUSTRY

Products experience many stages during their lifecycle. The trio together participate in the production process, including the design and manufacturing aspects of the product. One of the primary goals of the Environment Impact Management System (MIES) is the reduction of consumption of energy in industrial operations. A significant quantity of energy is used in the conversion of raw materials into the end product via a series of technical processes. Stationary operating assembly systems, equipped with a driving system that is not reliant on direct human effort, may be defined as such [13]. Machine tools play a pivotal role in the use of energy within the production process. The machine tool undergoes many stages to achieve operational readiness.

The total energy consumption of the machine tool, including control systems, cooling and lubrication units, drive systems, spindle motor, and manufacturing process, is shown in Figure (2.1).

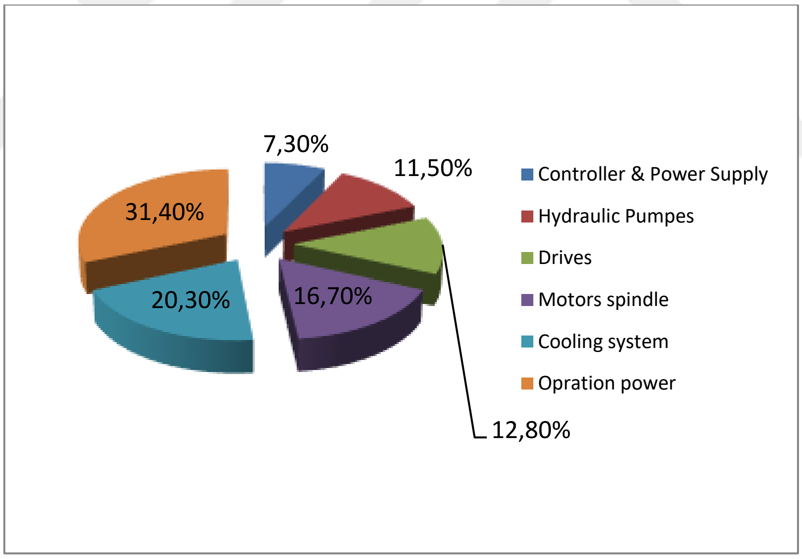

Chart 2.1: Consuming Energy at Machine Parts.

The energy consumption model is based on previous research work on environmental analysis of machining, so that energy data collecting in production may be standardized and presented in a globally comparable manner. Machine tool states are divided into two types, ‘‘Basic state” and “Cutting State”. The states are based on operational characteristics of the processes. In the ‘‘Basic state” for example electrical energy is needed to activate required machine components. In the ‘Cutting State’ the energy is demanded at the tool tip to remove work piece material as well as for modes of energy loss e.g., through machine noise or friction.

While sets the framework, it does not clarify the existence of a transitional state between the Start-up' and 'Cutting State'. We define a third and fourth and intermediate state called the 'Start up' and run time. These additional states are required to clarify the process that takes place after the machine is started. Theses stages of the process require more energy for the drives and spindle movement to bring the tool and work piece to the correct, about to cut position and to run time the necessary cutting velocity.

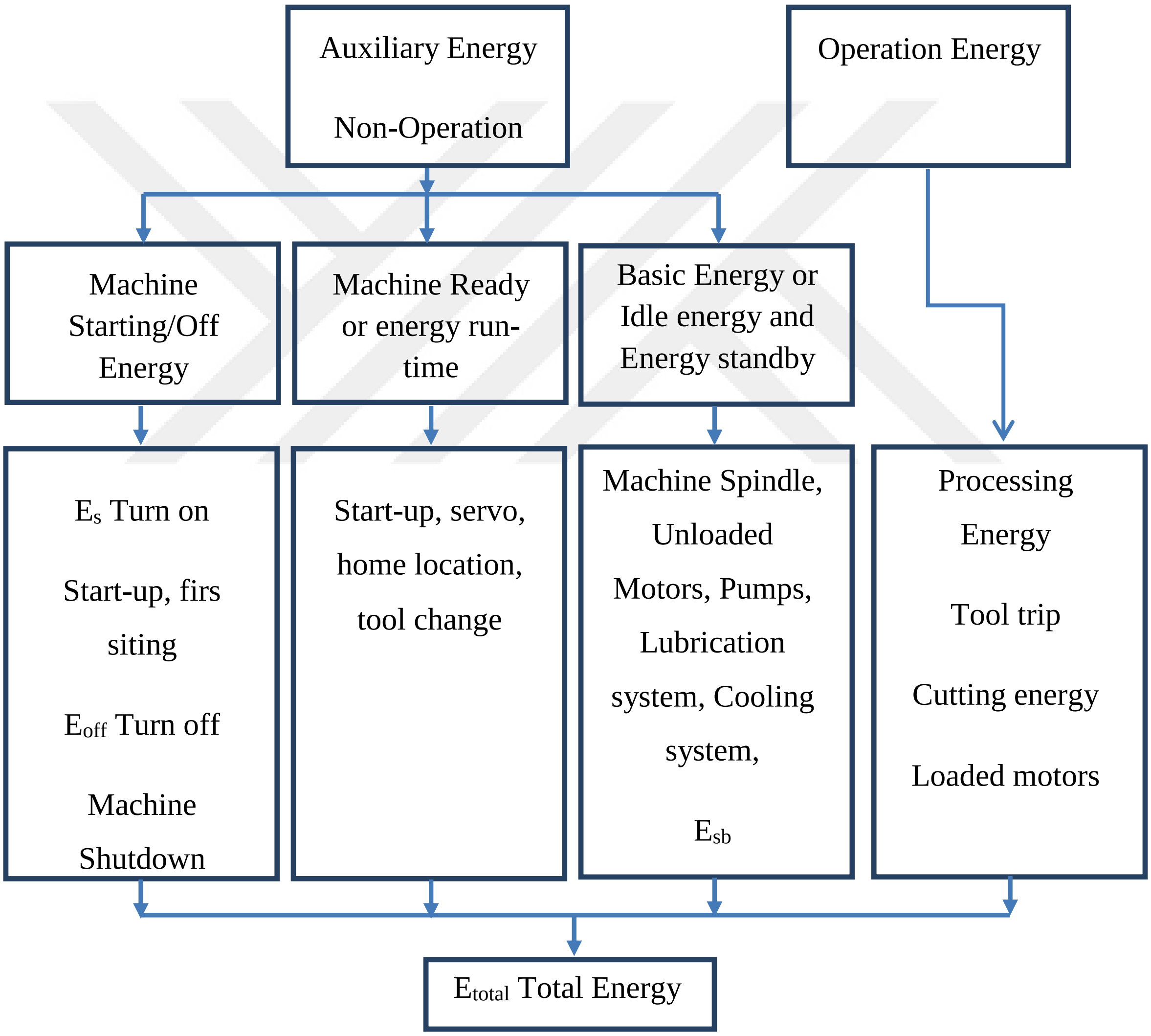

Figure 2.1: Classification Energy Types in Machine Tools.

Energy consumption model is based on existing research work on environmental analysis of machining. A simplified power input model at machine when it is working on operation has been developed.

Six levels of power to represent energy of machine: during standby, during idle time, when switched into set-up mode, to carrying out the actual operation; operations as cutting operation and at machine starting and shut down.

2.1. ENERGY EFFICIENCY AND MANUFACTURING PRECESSES

Energy efficiency is defined as the ratio of "useful" outputs to energy consumed by a system (Herring H, 2010) [12]. It can be measured by different ratios of physical or thermal indicators (tonne of steel per kWh (kilowatt hour) spent or the tonne of steel per tonne of coal consumed). The relevant data should be carefully chosen to measure, on a common scale, the energy equivalent on the one hand the useful outputs, on the other hand the elements consumed. At company level, energy efficiency can also be defined as the production compared to the energy use at the firm level for that production (thermal capacity of a cooling system, in BTU/h (British Thermal Unit per hour = 0,293W), per watt absorbed; output product amount per kWh spent).

For conventional processes [14], such as forming or material or removal processes, energy efficiency is measured as the volume of material removed per kWh consumed in the machine by the displacement of the axes and the losses in the machine structure and actuators [15]. For unconventional processes such as laser machining [16], it is necessary to add the energy consumed by the tool, such as the laser beam.

For this reason, the raw energy efficiency is not appropriate for the comparison of two production lines, since the energy is proportional to the size of the product, the number of parts in the product and the types of processes used for the production. A fortiori, the raw energy efficiency cannot be considered appropriate for the comparison of two factory configurations. Energy efficiency remains an important objective for industrial companies for ecological, political and economic reasons. The control of energy efficiency is essential for the implementation of energy efficient production strategies and therefore globally more efficient plants. Many studies aimed to optimize the energy efficiency of conventional manufacturing processes and, to a lesser extent, of unconventional processes such as laser machining [17].

The main consideration of this approach is the division of energy efficiency analysis into four levels.

a. Factory level: At this level different production lines and production methods that may interact and include devices, required the mean objective at this level is line balance to reduce total energy in enterprise,
b. Production line level: At this different machines and any other equipment devices that may be required for manufacturing the products at production line. It is a fact that a very significant amount of energy is spent on the idle consumption of machines. The production schedule, which determines the idle times, one of the most objective of energy efficiency to reduce idle time between operations.
c. Machine level: This includes machine that ensure proper machining conditions. In some cases, the machine level can be identical with a machine tool; however, special care has to be taken when some peripheral devices are shared among different machines. At the machine level, any energy losses due to machine peripherals or machine inefficiencies have to be taken into account. For example, the processes are under study, are removing processes.

   The possible differences between the process-level "result" and the machine-level "result" have to be taken into account, at the same time.
d. Process level: That related to physical mechanisms of the process itself, select process type, processes parameters (feed rate cutting speed etc.) and technology. For example, in milling the energy in process level is the energy required to remove material, but in laser machining, it is the energy of laser beam (electricity currant).

2.2. ENERGY EFFICIENCY PROCESS PLANNING

Process planning is defined as the link between design processes and manufacturing processes to determine operations sequence that needed to produce a designed part. Process planning translates part and assembly design to physical products. Process planning is performed before actual manufacturing take place. Usually, it takes a significant amount of time and requires sufficient information to make the decision. In energy-efficient process planning, energy consumption is taken into consider, where it adds a newer dimension to traditional processes planning problem.

a. The first studies were deal with energy consumption, production rate, mass flow of waste streams and quality parameters need to be analysed at the planning state [18].

b. The second studies used to obtain process energy, machining time, mass of waste streams and quality parameters by using feature based two-phase planning scheme [19].

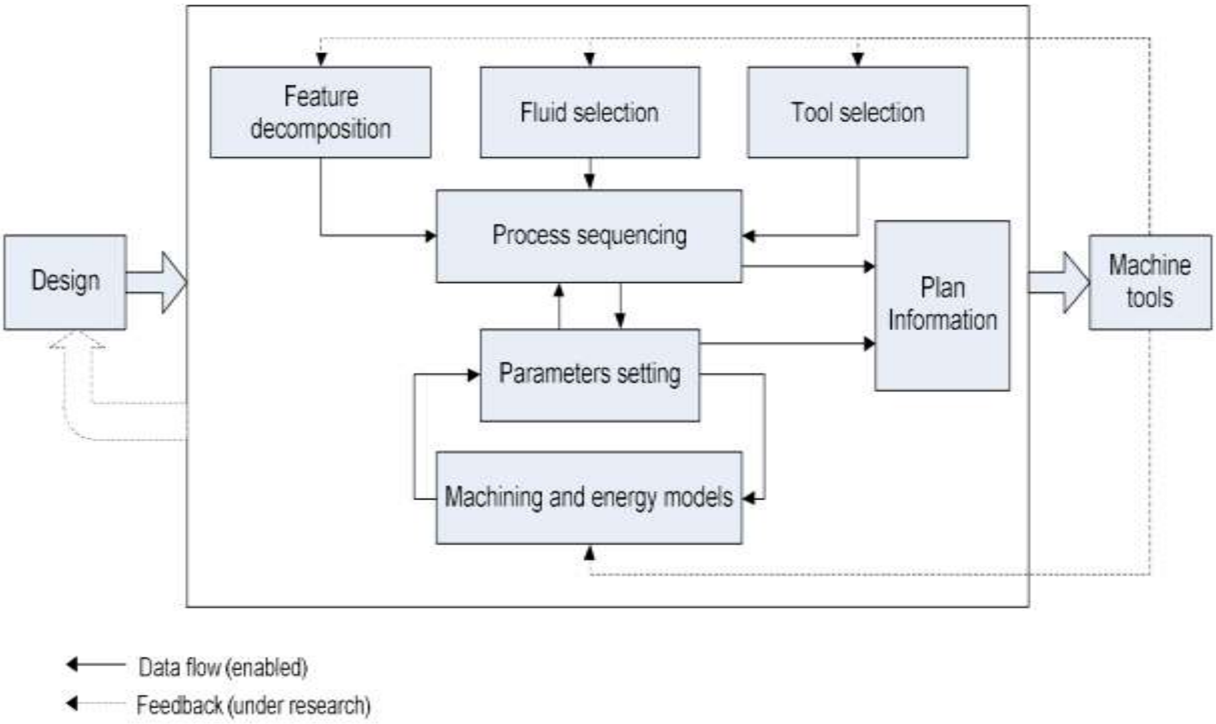

Figure 2.2: An Example of Process Planning Systems [10].

2.3. ENERGY EFFECTIVENESS PRODUCTION SCHEDULING

Energy consuming during processing of jobs represented a small amount of total energy that consumed in production lines. In another field, considers that rather than 40% of the total energy is consumed in system idle and losses. This dissertation is aimed to study an optimum energy consuming in job shop problem.

2.4. ENERGY EFFICIENCY IN FACTORY LEVEL

We present a comprehensive analysis of the state of the art in energy and resource efficiency in increasing technologies and techniques in the area of discrete component manufacturing, with emphasis given to the efficacy of the available alternatives. Diverse production rates result in varying degrees of energy consumption, according to studies on the use of energy in manufacturing. Employing corporate strategies to improve sustainability and energy efficiency, industrial corporations have identified this trend. As a consequence, individual operations might have a positive or negative impact on one another, and the overall energy efficiency of the production system does not immediately come from the sum of its components.

A comprehensive understanding of the intricate relationships between the many resources, processes, and structures inside a factory is necessary to fully use the energy optimization potential of the whole system or process. The optimization scheduling challenge for the system was made more difficult by the adoption of power control policies and tariffs, as an optimized plan that resulted in a decrease in electricity consumption did not always result in a decrease in total electricity costs. Notwithstanding the need to strike a balance between cost savings and decreased power use, very few research studies now address this issue. Operational approaches comprising dispatching rules, genetic algorithms, and adaptive search processes to minimize power usage and classical scheduling targets on a single machine and parallel machines should be investigated. These studies need to be predicated on the finding that, when non-bottleneck machines are idle in a production setting, they waste a significant amount of energy. Switching off this equipment while it is not in use might be one strategy. To be beneficial, this option must be able to be used over time periods greater than a critical threshold since it usually involves some starting energy consumption.

A standby mode that is intermediate in nature may be selected for shorter time periods. Every unnecessary peripheral device should be switched off when in this mode. Manufacturers of machine tools may assist in creating devices with these characteristics. Furthermore, if order estimates and lot sizes are made available sufficiently in advance, they may provide production managers with the knowledge they need to divide the load fairly, avoid delays, and keep resources from being idle.

2.5 ENERGY AND PRODUCTION SCHEDULING (JOB SHOP SCHEDULING)

Scheduling in the production process refers to the systematic arrangement and allocation of resources, tasks, and activities to optimize efficiency and meet production goals. The cost effectiveness of production scheduling is of paramount significance as it directly affects the profitability and competitiveness of an organization. Optimal use of resources, such as machinery, personnel, and materials, is achieved via efficient production scheduling, resulting in cost savings and enhanced financial performance. The four steps of production scheduling are initiation, planning, execution, and control. Within the realm of manufacturing, production planning and control may be categorized into four distinct stages: Routing, scheduling, dispatching, and follow-up are the key tasks involved in managing and coordinating the movement of resources or information.

Scheduling is the systematic organization, regulation, and enhancement of tasks and workloads within a production or manufacturing process. Scheduling is used to allocate plant and mechanical resources, strategize human resources, organize industrial processes, and procure commodities. The reference problem for applying the is the Flexible Job Shop Problem [19]. The FJSP consists of scheduling j job, denoted J, J = {J1, ..., Jj} on M machine.

M = {M1, ..., Mm}. Each Jj job is composed of an ordered sequence of Oi operations.

{Oi,1, ..., Oi}. Each Oij operation has a set of Mni qualified machines for realize, The FJSP is composed of two sub problems.

a. The first is the assignment of operations to a machine.
b. The second is to order the operations assigned to the machines, as in a Job Shop Problem (JSP).

The FJSP is NP-Hard with the objective of minimizing the maximum job completion dates the makespan (C_{max}). The FJSP is considered single-objective with the minimization of the makespan.

The following hypotheses are considered:

a. Batch operations are set in a predefined order.
b. Each batch has the same priority.
c. The batches are ready at time 0 and the machines start at time 0.
d. Setup and travel times are negligible compared to production time.
e. The machines are independent of each other.
f. The batches are independent of each other.
g. A machine only performs one operation at a time.
h. A batch can only have one solution in progress at a time.

i. Operations cannot be divided.

Each operation needs energy to processes at any machine as showing in table, where firstly machine M_m is starting, operation, and turning off after finished all operations.

Power consumption model machine M_m can be assuming by five levels:

(a) During starting time (black line) to switch on the machine, (b) basic mode (idle time) (blue lines), (c) Setup time (green lines) to prepare the machine

Generally, industrial job shop problems minimize such as the makespan or the cost but other objective and constraint can be addressed. Up to now, a few researchers studied the energy consumption as an important objective function in scheduling.

2.6 LITERATURE REVIEW AND MOTIVATION

In the literature, industrial problems such as minimizing the total cure time (makespan) have been studied, to reduce the consumption of electricity and thus reduce the cost, and other objective functions on a large scale. Research is still ongoing and great efforts have been made in this field, but the desired results have not been achieved. As for scheduling, the research is insufficient so far. However, many researches have spread on this topic in relation to “green and sustainable manufacturing” over the past years, which we will mention, in this part researches the topic of energy saving in several ways, not only in the scheduling method, but in several methods that have been researched and explored, and some of them have been applied to prove their efficiency.

a. Yan He, and Bo Liua., in (2011)[20] saved energy consumption in the production processes of the machining system, which is a large consumer of energy, by arranging the execution of tasks on machine tools that consume a huge amount of energy. They modelled task-oriented energy consumption by analysing the characteristics of energy consumption. In an automated driven manufacturing system, energy consumption in production processes depends dynamically on the variation of task flow and flexibility in handling.

   His proposed method was through modelling and solved through (Simulink simulation). The results show value in improving energy efficiency and he also used the graph in his thesis.

b. In 2013, author Jeffery K. Cochran., [21] proposed a multi-population genetic algorithm (MPGA) consisting of two stages. In stage one, multiple objectives are merged and solutions are arranged into several subsets, which become the initial populations for stage in stage two, the subset is then optimized separately from the other.

   To obtain two goals, the total delay and the temporary range, the elitist methodology for finding good solutions persists by continuing with each goal, and this approach has been applied in problems.

   He achieved better results for these goals to address the problems (parallel machine scheduling), as this MPGA genetic algorithm improves the scheduling problems 1. makespan, 2. TWT total weighted tardiness, and 3. total weighted completion times (TWC). After comparison, the researcher found that this algorithm works better. From MOGA to parallel machine scheduling problems with multiple objectives.

c. Researcher Susmita Bandyopadhyay., in (2013)[22] modified the NSGA-II algorithm for the parallel machine scheduling problem to reduce the total cost and delay and reduce processing.

   In his study, he relied on an improved version of the evolutionary algorithm NSGA-II and the original evolutionary algorithm NSGA-II, which is known as the non-dominated genetic sorting algorithm and the evolutionary algorithm Pareto Evolutionary Power II SPEA2. He proposed a new mutation and compared it with the previous three algorithms. And He achieved results with his proposed algorithm and it worked well

d. The author Ying Liu., published in (2015) [23]searched in multi-objective scheduling is optimized which reduces electricity consumption and weighted delay, where he worked on scheduling critical operations with less energy consumption during periods of powers outages, he adopted a multi-objective optimization problem where the importance of cost and production due date is important, a specific method was designed to investigate how Rolling Blackout policy affects the quality of existing scheduling plans. He devised a genetic sorting algorithm to solve this optimization problem. Thus, the total potential delay was developed.

e. The researcher Fadi Shrouf., study in (2015) [24]Using the internet of things (IOT) in discrete manufacturing to improve the efficiency of production processes and energy at the machine level by taking decision makers into account when they plan to improve energy efficiency in discrete industrial facilities. This goal was achieved through the use of the Internet, as these solutions achieved a high level and collected large amounts of data on energy and time. It focused on the pre-design of how to find energy monitoring solutions using the Internet of Things and energy management in companies.

f. The researcher Ying Liu., submitted his thesis in (2016) [25] to Employ sophisticated scheduling algorithms to merge fragmented times of device inactivity into longer intervals. Implementing a scheduling system will allow for the efficient use of resources by shutting down any idle ones, while yet ensuring continuous output. He introduced a model for a two-objective optimization issue that aimed to reduce both the overall power usage and the total delay in the business. To do this, he devised a novel multi-objective genetic algorithm that was built upon the NSGA-II framework. A novel multi-objective optimization technique, named GAEJP, was created, which is based on NSGA-II.

g. The author Xueqi Wu.[26], worked in (2018) on a dual-objective parallel machine scheduling task where the goal was to save energy in the shop or plant and reduce space. As the problem depends on a specific assignment of machines first and determining the appropriate speed level to suit each task and each individual piece of equipment, Xueqi Wu, (MDE) (Memetic Differential Evolution Algorithm) proposed three parameters (function, speed machine and speed equipment).

   The goal is to speed up the algorithm, the vector develops a speed for each stage, and after applying a table to derive the function and machine stabilization vector, relying first on the need to determine its own speed, the MDE algorithm also achieved better results than SPEA-II and NSGA-II almost through his mathematical experiments.

h. The author Shijin Wang, Xiaodong Wang, worked in (2018)[27] on address this issue that is known to be NP-hard, a technique called enhanced ε -constraint approach is used to get an optimum Pareto front for examples that are of small-scale. A constructive heuristic technique with a local search strategy is suggested for medium- and large-scale examples, and the NSGA-II algorithm is used to create high-quality estimated Pareto fronts. A comprehensive series of computer experiments is undertaken using both randomly generated data and a real-world case study. The outcome demonstrates the efficacy and proficiency of the suggested approaches.

i. The author Zhang Z [28] work in 2018 based the approach on the Non-dominant Genetic Sorting Algorithm-II (NSGA-II), which does not rely on auxiliary and intrinsic factors to rationally choose the appropriate device for each process simultaneously. Moreover, experimental results were achieved Improved energy use. As is known, turning it off and restarting it for a long time is effective for saving energy. He combined it into one device and there was an improvement in energy consumption.

j. The author Alonso Campos, J.C.)[29] published in (2019) his work research into reducing energy costs in the irrigation system. It is known that proper operation of irrigation reduces the costs and quantity of water consumed. After obtaining the optimal operating parameters, a new scheduling methodology was studied and results were reached approximately 10 times faster. This methodology is also able to reduce energy when studying the increase in pressures at critical taps. Note that this study reduced the cost by about (6%-7%). The greatest computational efficiency was achieved through a multi-objective approach, obtained by parallelizing the number of computational time reductions and function evaluations (since the algorithm is parallel).

k. The researcher Zixiao Pan., [30]publish in 2020 his thesis that focused on energy saving by integrating machine mapping and plant mapping into an extended machine task to solve subproblems due to the complementarity of these two problems, he using behaviours NSGA-II and DE to minimize total time and consider an optimization algorithm (KTPO) A knowledge-based two-population optimization was proposed to reduce the overall delay and energy consumption.

   In this work, five characteristics are extracted by analysing the characteristics of (the distributed energy-efficient parallel machines scheduling problem) DEPMSP. The population relies on two heuristics, stochastic and knowledge previous-based on the problem. The genetic algorithm for sorting and differential evolution works collaboratively on the population in parallel, and he did a number of experiments to sure the effect of its and make compare KTPO with four algorithms

l. In (2017) Researcher Wenzhu Liao.[31] focused his thesis on machine reliability to solve the problem of parallel machine scheduling to reduce the maximum completion time with several deteriorating machines by determining the ideal machine maintenance time. He used water to distribute the jobs to obtain the best balance in the machine's capacity and proposed the algorithm (greedy with the water injection model). He achieved this through the results he obtained, the optimal solution for him to the problem of (scheduling parallel machine).

m. The researcher Oğuzhan Ahmet Arık., (2022) [32]in his work, he relied on (MA) the Memetic algorithm to solve the parallel machine scheduling problem using a simple dispatch rule that has no effect on the grayscale processing times of the parallel machine scheduling problem, where the goal is to reduce the expected completion times for tasks with unknown processing times.

   In a single machine with a specified processing time, tasks on the machine are arranged in a sequence that continues in increasing order with expected processing times. The author adopted this property and adapted it to some of his own local mechanisms to solve the resulting optimization. He proved the efficiency of the proposed algorithm by using the Memetic algorithm (MA) in his experiment.

   Uncertainty in processing times is shown in gray numbers. The study showed that the swap-based and short-time transmission rule was good and effective with the WSPT transmission rule.

In this study, we focused on two important issues: the multi-objective algorithm and its application to the problem of scheduling parallel machines and distributing jobs to each machine, as there is a set of N jobs that will be studied and processed on a set of (parallel devices) where each device can process Only one task or several tasks at different times. This thesis also contains several dimensions and features to determine energy characteristics and the effect of energy in serving the environment, we also provide the energy saving benefits of parallel machine scheduling.

3. ENERGY JOB SHOP SCHEDULING

The challenge is in allocating the work to the machines in a way that minimizes the duration of the schedule that is, the amount of time needed to do every activity. The job shop dilemma has many constraints: Before beginning a task for a work, the prior task must be completed, also the Job-Shop Scheduling Problem (JSSP) is a highly researched combinatorial optimization problem that is known to be NP-hard. The objective of the problem is to discover the most efficient schedule for distributing shared resources among competing activities, with the goal of minimizing the total time required to complete all tasks.

Energy efficiency has emerged as a significant concern for manufacturing companies, driven by environmental considerations, strict regulations, and the ever-increasing costs of energy. Implementing energy-efficient scheduling can yield significant benefits in terms of improved energy efficiency, resulting in reduced energy consumption, lower costs, and decreased pollutant emissions. Energy Uncertainty job shop scheduling, in traditional job shop problems processing time is known and fixed, but many jobs shop problems processing time uncertain or almost unavailable [16,17], because of this time has been affected by many parameters such as Due date, operation conditions, and also energy consuming during operation, And other influences on time.

The first time of any operation represent the early operation time and the second time is later operation time. But to build a solid solution to the scheduling problem, you must select a single time that represents the most likely time or the more possible time, through previous research, we find that there is more than one way to calculate this time.

In this study, we will introduce several methods to tackle the problem of optimizing both time and energy in scheduling also, we are going to demonstrate the implementation of Multi-Objective Genetic Algorithm on a parallel machine scheduling problem.

3.1. MULTI-OBJECTIVE GENETIC ALGORITHM

Genetic Algorithms (GAs) are a fascinating and powerful class of computational algorithms inspired by the principles of natural evolution and genetics. As a cornerstone in the field of evolutionary computation, GAs offer a unique approach to problem-solving, mimicking the process of natural selection to evolve solutions to complex problems.

The basic concept of GAs revolves around the idea of 'survival of the fittest'. It begins with a population of candidate solutions, each represented by a string, analogous to the chromosomes in biological organisms. These solutions are evaluated based on their 'fitness' – how well they address the specific problem.

Genetic Algorithms evolve solutions through a series of iterative processes, primarily:

Selection: This step involves choosing the fittest individuals from the population, similar to natural selection, where stronger individuals are more likely to reproduce.

Crossover: In this stage, segments of solutions are combined from two or more 'parent' solutions to create new 'offspring' solutions. This mimics biological reproduction.

Mutation: GAs introduce random changes in individual solutions to maintain diversity within the population, akin to natural mutations in species.

After establishing a foundational understanding of GAs, it is crucial to explore their significant role in multi-objective optimization. Multi-objective optimization involves solving problems that have multiple, often conflicting objectives. Here, the versatility of GAs becomes particularly valuable.

GAs are adept at exploring large and complex search spaces to find solutions that balance these competing objectives. They do this by evolving a diverse set of solutions, each representing a different trade-off among the objectives. This characteristic makes GAs an ideal tool for tasks like scheduling, where one must often balance multiple factors to find an optimal solution.

Genetic Algorithms provide a robust, adaptable, and highly effective methodology for tackling a range of complex problems, especially those involving multiple objectives. Their evolutionary approach allows for a dynamic exploration of solutions, making them an indispensable tool in fields requiring nuanced optimization strategies.

3.1.1 An Innovative Approach to Multi-Objective Genetic Algorithm in Scheduling

In this study, we address the challenge of optimizing both time and energy in production processes, identifying these as the two critical objectives to minimize. To effectively tackle this dual-objective optimization, we have innovatively adapted the classical genetic algorithm framework.

3.1.2 Dual-Objective Framework

Our approach is grounded in the selection of two specific objectives: The makespan (time taken to complete a set of jobs) and the energy consumed during production. Correspondingly, we introduce two distinct populations within our genetic algorithm: Population A and Population B. Population A is tailored to evolve with a focus on optimizing the makespan, while Population B is geared towards minimizing energy consumption.

3.1.3 Innovative Parent Selection Mechanism

A pivotal aspect of our modified genetic algorithm is the parent selection process. In a departure from traditional methods, parents are selected from each population using a criterion inverse to their primary objective. Specifically, a parent from Population A (primarily concerned with makespan) is chosen based on energy efficiency, and conversely, a parent from Population B (focused on energy) is selected for its makespan efficiency. This cross-objective selection strategy ensures that the chosen parents exhibit strengths in both dimensions - makespan and energy.

3.1.4 Crossover and Offspring Allocation

In genetic algorithms, crossover, which represents rearrangement or combination, is considered one of the genetic factors that helps in integrating genetic information taken from the parents to generate new offspring with combined specifications, which are taken from nature in the process of sexual reproduction. The condition can also be likened to the creation of solutions by cloning an existing solution (asexual reproduction), and newly born solutions can also be mutated before entering the population.

Algorithms have evolutionary behavior and have different data to store and retain genetic specifications, and each genetic representation can be recombined and arranged with different intersection operators. Typical data structures that can be recombined with intersection are trees vectors of real numbers, or bit arrays.

Upon selecting the parents, we employ a crossover mechanism to produce two offspring. Each offspring is then evaluated against the two objectives. The offspring exhibiting superior performance in makespan is integrated into Population A, replacing a less efficient solution. Similarly, the offspring excelling in energy efficiency is incorporated into Population B. Notably, in cases where an offspring outperforms in both objectives, duplicates of this superior solution are placed in both populations.

3.1.5 Expected Outcomes

This methodology aims to cultivate solutions in Population A that are not only optimal in terms of makespan but also exhibit commendable energy efficiency. Simultaneously, Population B is expected to evolve solutions that are energy-efficient while maintaining satisfactory makespan metrics. Through this dual-focused evolutionary strategy, we anticipate deriving solutions that achieve a balanced optimization of both time and energy in production processes, reflecting a significant advancement in the application of multi-objective genetic algorithms. The flowchart offered is given in the figure below.

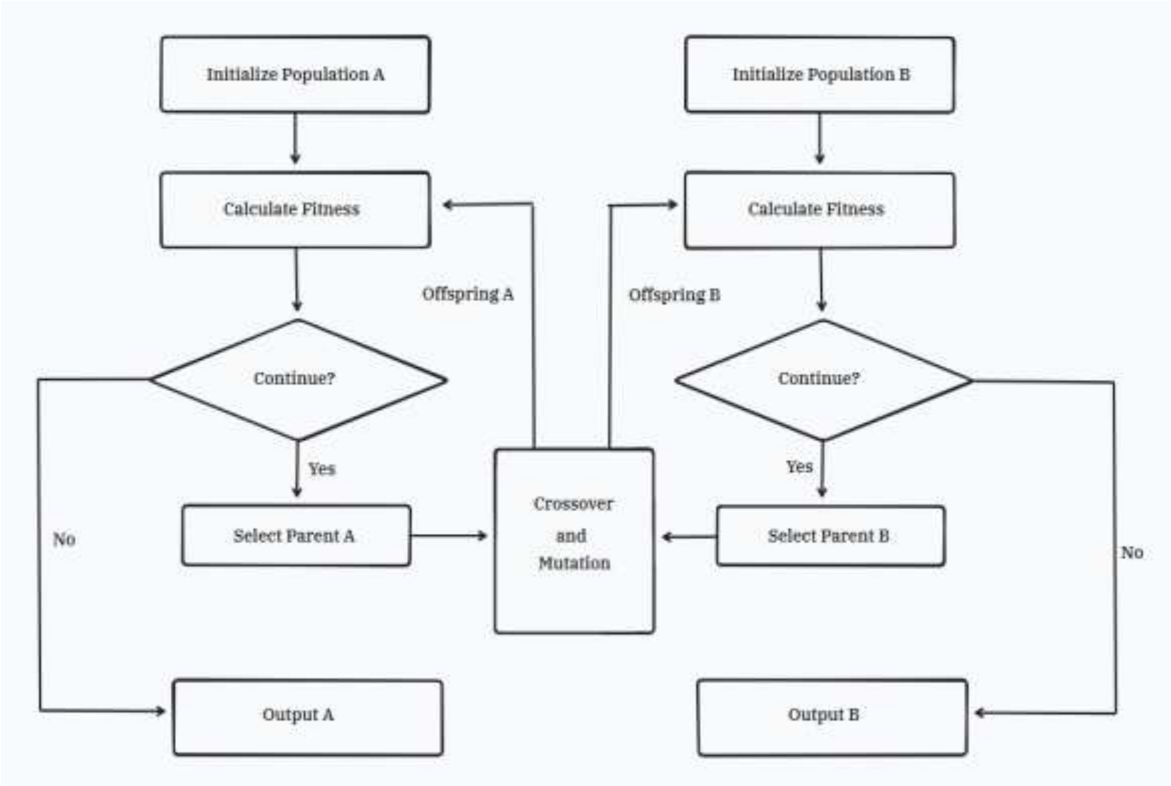

Chart 3.1: Application of Multi-Objective Genetic Algorithms.

3.2 ALGORITHMIC IMPLEMENTATION

In this study, we introduced several methods to tackle the problem of optimizing both time and energy in scheduling. In this chapter, we are going to demonstrate the implementation of Multi-Objective Genetic Algorithm on a parallel machine scheduling problem.

We consider a parallel machine scheduling problem with 4 machines and 30 jobs. Processing times and energy consumption of jobs depend on the machine they are assigned to and generated randomly as integers between 2 to 9. Setup times between jobs are also machine-dependent and generated randomly as integers between 1 to 5.

As the solution encoding, two arrays are used. The first one is the order of jobs, and the second one is the job-machine assignment. In our case, an array of 30 jobs and another array consisting of numbers between 1 to 4 (since there are 4 machines) together correspond to a true scheduling solution. Any true scheduling solution can be represented by at least one such encoded solution. A solution encoded in such a way for an 8-job case is as follows:

Table 3.1: .A Solution Encoded in Such A Way For An 8-Job Case.

Job Order:	4	3	8	7	1	6	5	2
Job-Machine:	1	2	3	4	2	3	4	1

Two populations are assumed in the Multi-Objective Genetic Algorithm, each of which consists of 50 solutions. The initial solutions are generated totally randomly. The details of the initial solutions can be seen in the MATLAB code given in APPENDIX.

The first population is designed to evolve to include solutions with lower makespan, while the second population is designed to include solutions with lower energy consumption. This is like two genetic algorithms are running in parallel. The novel property of our algorithm is that these genetic algorithms evolve together by mating parent solutions from two distinct populations.

For the parent selection phase, a parent is chosen from population A for the energy consumption values of the solutions. Another parent is chosen from population B for the makespan values of the solutions. After parent selection phase, job order and job-machine arrays are cross-linked between parents in order to generate two offspring. The offspring with better makespan value is replaced with a poor solution in population A, and the offspring with a better energy-consumption value is replaced with a poor solution in population B. At each iteration, only two offspring are injected to populations this way, instead of regenerating the entire population. As a result, we expect both objectives to evolve together in synchronization.

Two types of mutation are applied to each new solution randomly during the crossover phase. In the crossover phase, job order and job-machine arrays are cross-linked between parents in order to generate two offspring. However, the job-machine array source is switched to the other parent with a small probability as the first type of mutation. In the second type of mutation, two jobs are switched in position again with the same probability. The reference value of the probability in both mutations is set to be 1%.

The algorithm is simulated for 40.000 iterations and the results are plotted for every 10 iterations. At every 10 iterations, the best (minimum) makespan and energy consumption value in two populations are monitored. Also, for each solution, geometric average of makespan and energy consumption is also calculated and the minimum average value in two populations is also monitored. Figure 3.1, Figure 3.2 and Figure 3.3 below show the path of these values throughout 40.000 iterations.

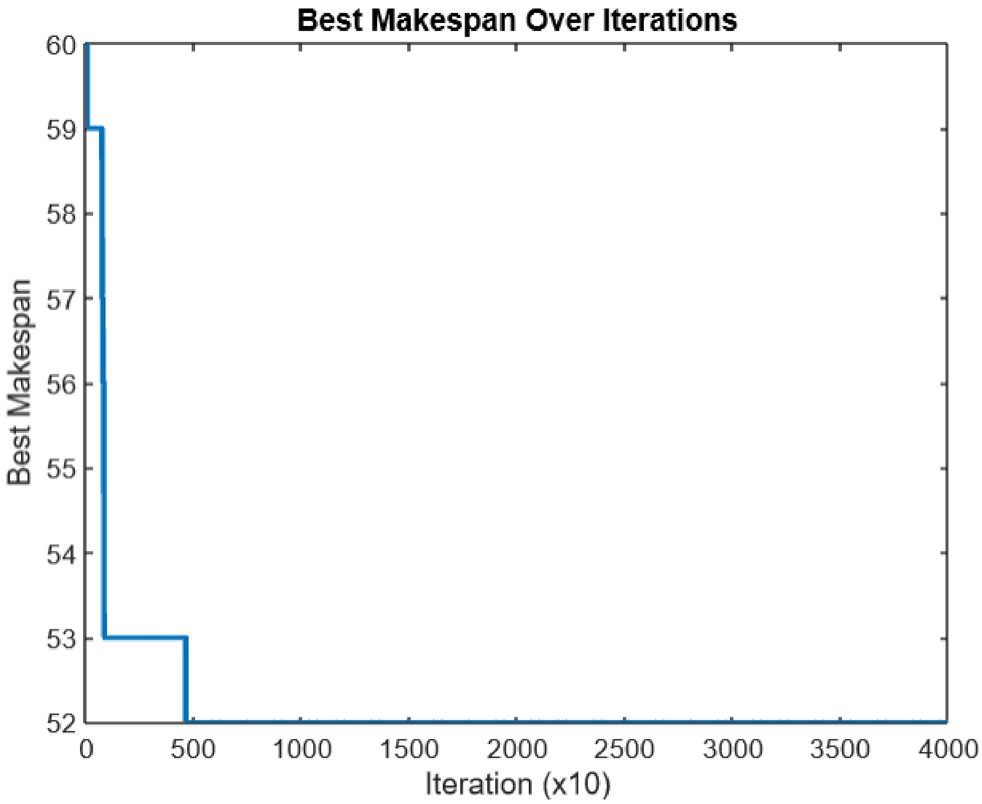

Figure 3.1: Best Makespan Value in Two Populations Over Iterations.

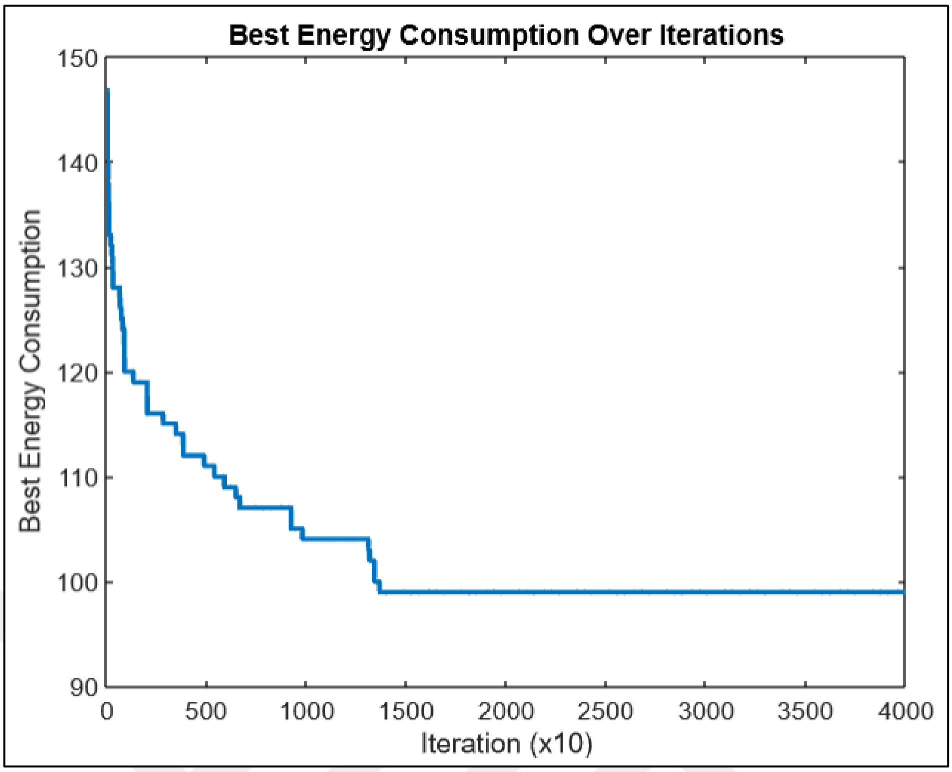

Figure 3.2: Best Energy Consumption Value in Two Populations Over Iterations.

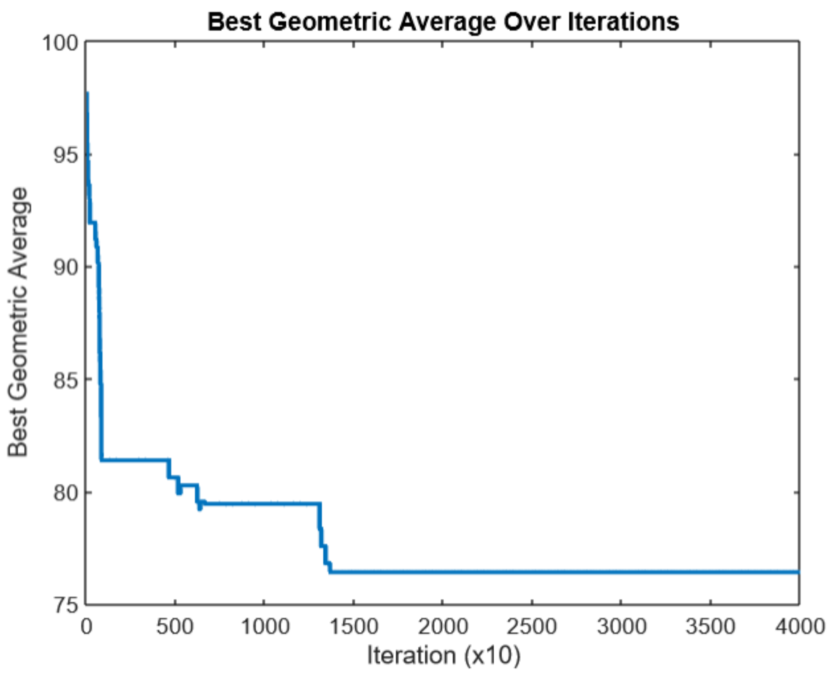

Figure 3.3: Best Geometric Average Value in Two Populations Over Iterations.

As seen in the figures above, both populations evolve such that best values decrease over time. Moreover, the geometric average is also decreasing. This means, the separate evolutions do not occur at the expanse of the other objective. Both objective values improve together in the system as expected.

As an experiment, a higher mutation probability is tested. In the original experiment, mutation probabilities are 1% for each. In order to search for better results, 10% mutation probability is applied for both mutation types. Figure 3.4, Figure 3.5 and Figure 3.6 show the simulation results for this new parameter setting.

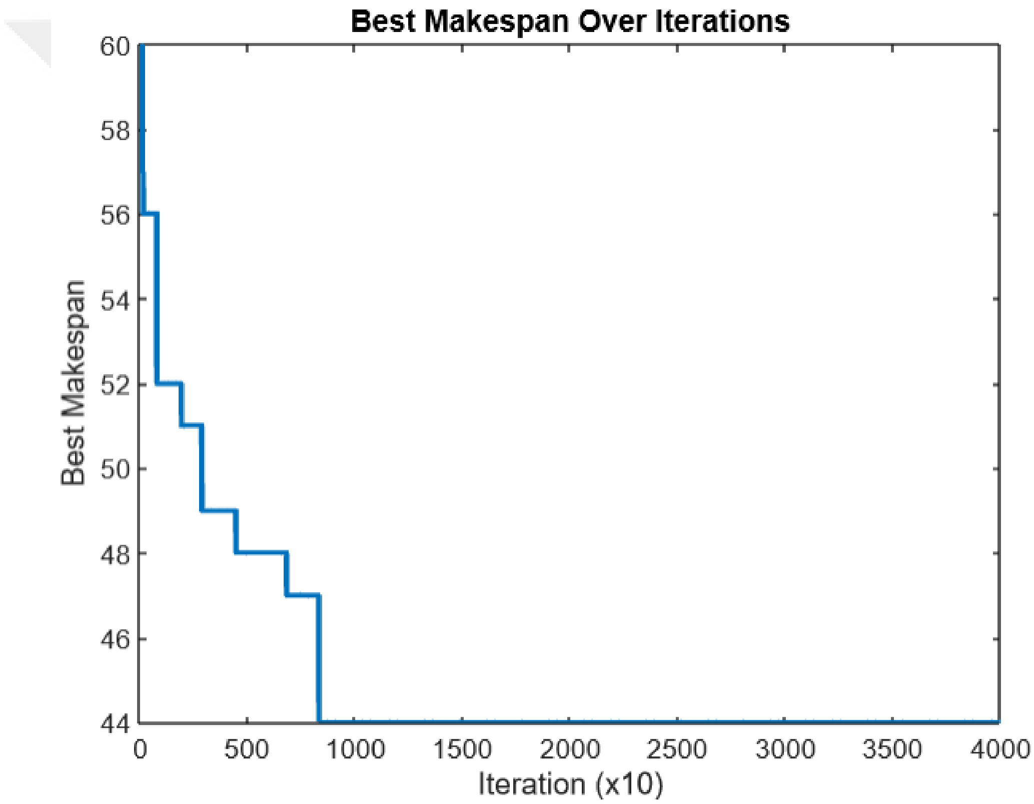

Figure 3.4: Best Makespan Value in Two Populations Over Iterations – 10% Mutation Probability.

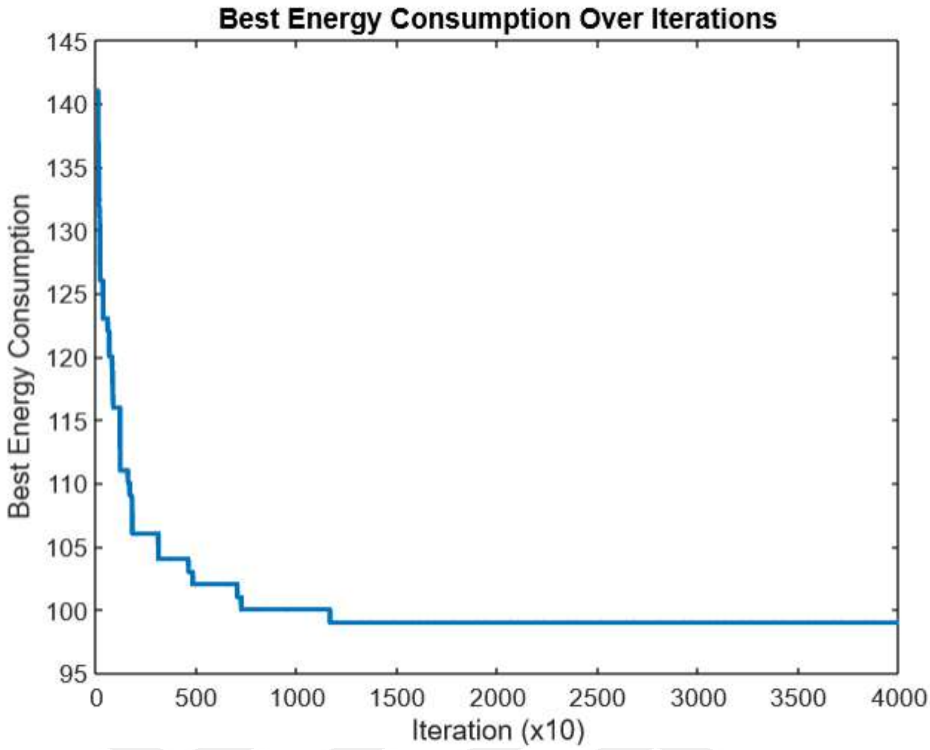

Figure 3.5: Best Energy Consumption Value in Two Populations Over Iterations – 10% Mutation Probability.

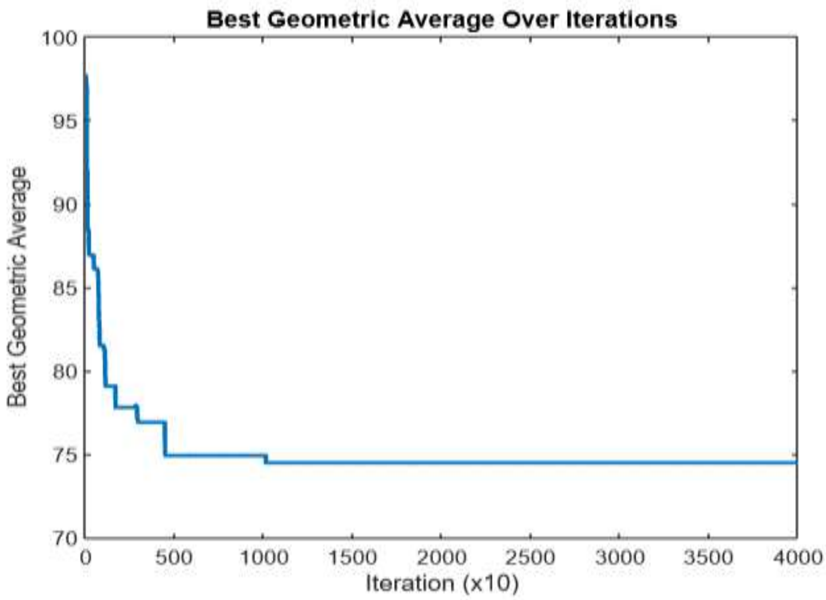

Figure 3.6: Best Geometric Average Value in Two Populations Over Iterations – 10% Mutation Probability.

According to experiments, 10% mutation probability gives better results in terms of best makespan and geometric average value. After this experiment, we decided to try 100 number of solutions for each distinct population (it was 50 in the reference simulation). Figure 3.7, Figure 3.8 and Figure 3.9 show the simulation results for this new parameter setting.

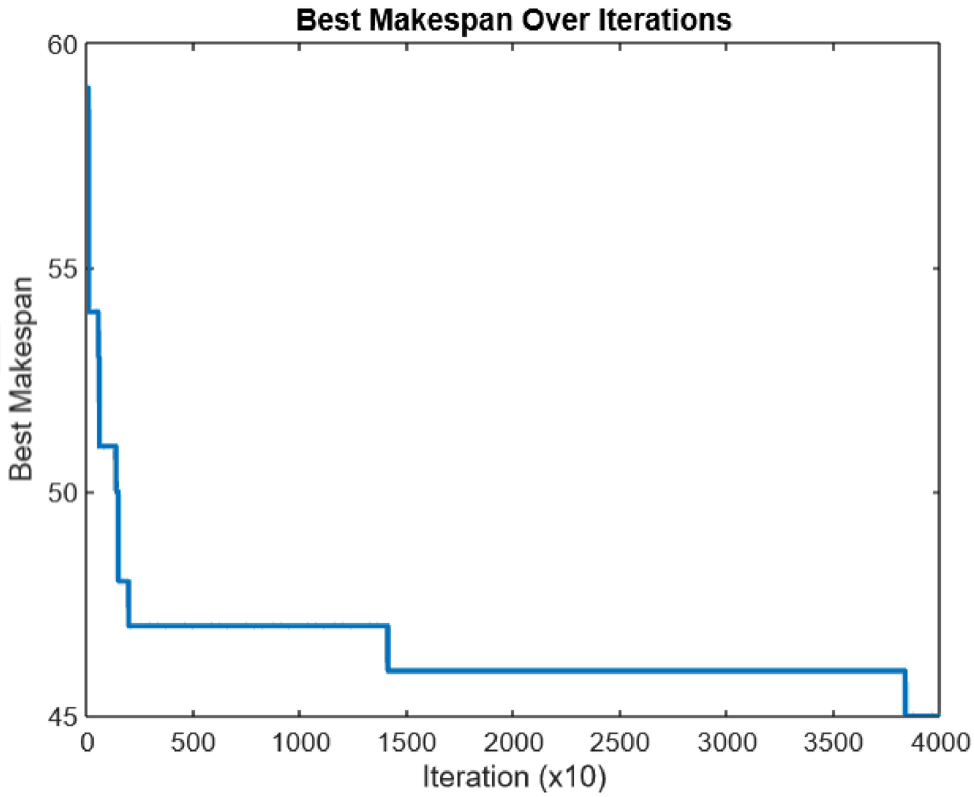

Figure 3.7: Best Makespan Value In Two Populations Over Iterations – Larger Population Size.

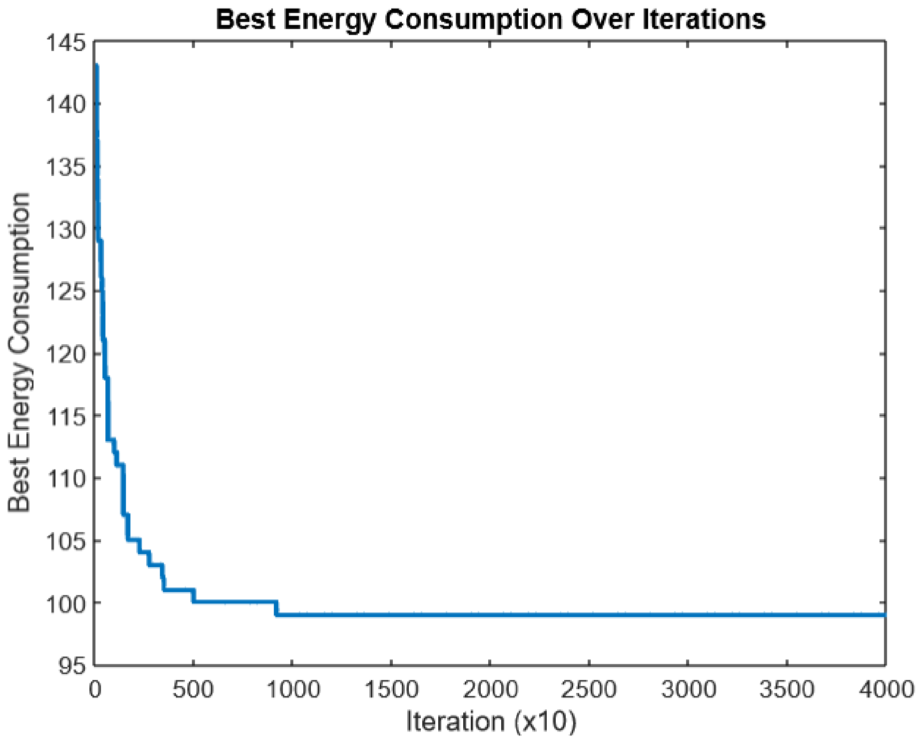

Figure 3.8: Best Energy Consumption Value in Two Populations Over Iterations – Larger Population Size.

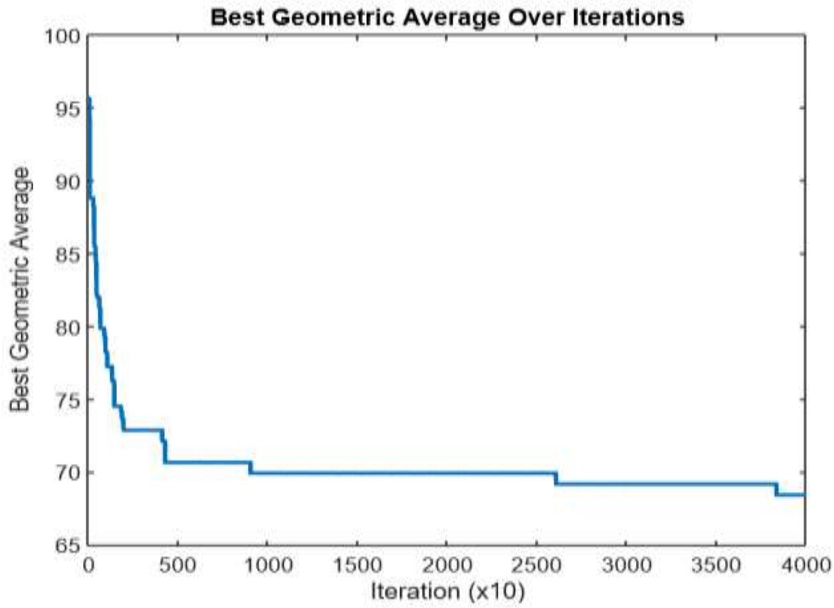

Figure 3.9: Best Geometric Average Value in Two Populations Over Iterations – Larger Population Size.

This new experiment gives worse makespan but better geometric average. We are not sure why larger population size lead to a worse makespan but we suspect it to be just a random effect. But a better geometric average can be interpreted as a larger population having more diverse results so it may be beneficial to get results that are good in both objectives.

In this section we presented an algorithmic application for a multi-objective genetic algorithm. We constrained the scope of this study and did not try parameter optimization with a larger parameter set. We believe that this multi-objective genetic algorithm is a useful tool for optimizing two objectives that are at odds with each other by nature.

4. CONCLUSION

This thesis has presented a comprehensive exploration of the critical need to optimize energy consumption in industrial manufacturing processes, a task that has become increasingly important in light of global energy scarcity. Through an in-depth analysis, it was established that energy efficiency is not only a matter of environmental concern but also a significant factor in enhancing the economic viability and sustainability of manufacturing operations. The proposed methodologies, rooted in the application of a multi-objective genetic algorithm, have demonstrated a robust approach towards minimizing both the energy consumption and production time, addressing two of the most pivotal aspects of modern manufacturing efficiency.

The implementation of these methods, as detailed in Chapter 4, reveals the practical applicability of the algorithmic approach in real-world manufacturing settings. By simultaneously reducing the makespan and total energy consumption, this research contributes to a more sustainable manufacturing future. It is important to note, however, that the scope of this research is limited by certain assumptions and specific conditions under which the algorithms were tested. Future studies may expand upon this work by exploring the application of these methods in a broader range of manufacturing environments, incorporating more dynamic variables that reflect the evolving nature of industrial processes.

In conclusion, this research underscores the urgency of addressing energy efficiency in manufacturing, offering practical solutions that could be pivotal in steering the industrial sector towards a more sustainable and economically feasible future. As industries worldwide continue to grapple with the challenges posed by energy scarcity, the findings of this thesis could serve as a valuable reference point for developing more energy-efficient manufacturing practices.

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APPENDIX A

```
%MULTI-OBJECTIVE GENETIC ALGORITHM MATLAB CODE

%FILE: main.m

%Problem Parameters
numJobs = 30;
numMachines = 4;

%Algorithm Parameters
parameters.mutation.jobOrderMutationRate = 0.01;
parameters.mutation.jobMachineMutationRate = 0.01;
parameters.ga.maxIteration = 40000;
parameters.ga.numSolutions = 50;

%Define problem
processingTime = [
    4, 2, 9, 3;
    9, 9, 4, 5;
    4, 3, 4, 9;
    8, 8, 9, 5;
    5, 6, 6, 2;
    4, 5, 5, 4;
    9, 3, 2, 8;
    9, 9, 8, 4;
    4, 9, 3, 3;
    2, 5, 6, 9;
    4, 9, 7, 2;
    8, 5, 2, 6;
    3, 4, 6, 2;
    3, 9, 6, 7;
    4, 6, 5, 8;
    6, 8, 3, 3;
    5, 9, 7, 8;
    6, 7, 4, 5;
    4, 9, 7, 9;
    5, 4, 7, 5;
    5, 5, 8, 2;
    4, 8, 4, 6;
    4, 3, 5, 5;
    2, 7, 2, 4;
    8, 9, 2, 8;
    5, 6, 6, 4;
    4, 9, 2, 7;
    2, 4, 5, 7;
    7, 6, 9, 2;
    6, 6, 6, 3
];


energyConsumption = [
    6, 7, 9, 4;
    9, 8, 9, 6;
    2, 8, 9, 9;
```

```
    8, 7, 2, 9;
    5, 7, 6, 5;
    9, 3, 8, 5;
    7, 5, 6, 6;
    5, 2, 6, 2;
    8, 3, 7, 6;
    9, 6, 8, 8;
    8, 8, 9, 6;
    6, 2, 8, 8;
    9, 4, 5, 9;
    2, 8, 3, 7;
    4, 5, 4, 5;
    6, 6, 9, 3;
    5, 6, 5, 5;
    7, 3, 3, 8;
    6, 3, 4, 3;
    9, 7, 5, 4;
    2, 6, 4, 4;
    2, 6, 7, 5;
    9, 4, 3, 6;
    4, 3, 7, 8;
    5, 2, 8, 9;
    8, 7, 5, 2;
    5, 6, 2, 9;
    3, 7, 6, 5;
    4, 7, 5, 6;
    2, 4, 6, 6
];

% Initialize the cell array
setupTime = cell(1, numMachines);

% Generate a setup time matrix for each machine randomly
rng(1);
for m = 1:numMachines
    setupTime{m} = randi([1, 5], numJobs, numJobs);
end


%Create problem object
problem  =  struct('numJobs',  30,  'numMachines',  4,  'processingTime',
processingTime, 'energyConsumption', energyConsumption);
problem.setupTime = setupTime;

GA(problem, parameters);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: GA.m


function [mySolutionsA, mySolutionsB] = GA(problem, parameters)


    %GA Parameters
```

```
    numSolutionsA = parameters.ga.numSolutions;
    numSolutionsB = parameters.ga.numSolutions;
    maxIteration = parameters.ga.maxIteration;


    %best solutions will be updated every 10 iteration
    bestMakespan = zeros(maxIteration / 10, 1);
    bestEnergy = zeros(maxIteration / 10, 1);
    bestGeoAvr = zeros(maxIteration / 10, 1);


    %Define solution array
    mySolutionsA(numSolutionsA) = struct('jobOrder', [], 'jobMachine', []);
    mySolutionsB(numSolutionsB) = struct('jobOrder', [], 'jobMachine', []);

    %Set random seed to a specific value, i.e. 1
    rng(1);
    makespanA = zeros(1, numSolutionsA);
    makespanB = zeros(1, numSolutionsB);
    totalEnergyA = zeros(1, numSolutionsA);
    totalEnergyB = zeros(1, numSolutionsB);

    %Create initial solutions
    for i=1:numSolutionsA
        mySolutionsA(i).jobOrder = randperm(problem.numJobs);
        mySolutionsA(i).jobMachine    =    randi([1,    problem.numMachines],    1,
problem.numJobs);
        schedule = generateSchedule(problem, mySolutionsA(i));
        makespanA(i) = calculateMakespan(problem, schedule);
        totalEnergyA(i) = calculateEnergy(problem, mySolutionsA(i));
    end

    for i=1:numSolutionsB
        mySolutionsB(i).jobOrder = randperm(problem.numJobs);
        mySolutionsB(i).jobMachine    =    randi([1,    problem.numMachines],    1,
problem.numJobs);
        schedule = generateSchedule(problem, mySolutionsB(i));
        makespanB(i) = calculateMakespan(problem, schedule);
        totalEnergyB(i) = calculateEnergy(problem, mySolutionsB(i));
    end

    %Calculate makespan and total energy
    for j=1:numSolutionsA
        schedule = generateSchedule(problem, mySolutionsA(j));
        makespanA(j) = calculateMakespan(problem, schedule);
        totalEnergyA(j) = calculateEnergy(problem, mySolutionsA(j));
    end

    for j=1:numSolutionsB
        schedule = generateSchedule(problem, mySolutionsB(j));
        makespanB(j) = calculateMakespan(problem, schedule);
        totalEnergyB(j) = calculateEnergy(problem, mySolutionsB(j));
    end


    for i=1:maxIteration
```

```
        %Select parents and generate offsprings
        parentAindex = selectParentIndex(totalEnergyA);
        parentBindex = selectParentIndex(makespanB);

        [offspring1,    offspring2]    =    crossover(mySolutionsA(parentAindex),
mySolutionsB(parentBindex), problem, parameters);

        schedule1 = generateSchedule(problem, offspring1);
        offspring1makespan = calculateMakespan(problem, schedule1);
        schedule2 = generateSchedule(problem, offspring2);
        offspring2makespan = calculateMakespan(problem, schedule2);
        offspring1energy = calculateEnergy(problem, offspring1);
        offspring2energy = calculateEnergy(problem, offspring2);

        if offspring1makespan < offspring2makespan
            [mySolutionsA,  makespanA,  totalEnergyA]  =  replace(mySolutionsA,
makespanA,    makespanA,    totalEnergyA,    offspring1,    offspring1makespan,
offspring1makespan, offspring1energy);
        else
            [mySolutionsA,  makespanA,  totalEnergyA]  =  replace(mySolutionsA,
makespanA,    makespanA,    totalEnergyA,    offspring2,    offspring2makespan,
offspring2makespan, offspring2energy);
        end

        if offspring1energy < offspring2energy
            [mySolutionsB,  makespanB,  totalEnergyB]  =  replace(mySolutionsB,
totalEnergyB,    makespanB,    totalEnergyB,    offspring1,    offspring1energy,
offspring1makespan, offspring1energy);
        else
            [mySolutionsB,  makespanB,  totalEnergyB]  =  replace(mySolutionsB,
totalEnergyB,    makespanB,    totalEnergyB,    offspring2,    offspring2energy,
offspring2makespan, offspring2energy);
        end

        %update the best values once in every 10 iterations
        if mod(i, 10) == 0  % Check if the iteration number is a multiple of 10
            geoAvrA = sqrt(makespanA .* totalEnergyA);
            geoAvrB = sqrt(makespanB .* totalEnergyB);

            bestMakespan(i/10)  =  min(min(makespanA),  min(makespanB));  %  Store
value at i/10 index
            bestEnergy(i/10) = min(min(totalEnergyA), min(totalEnergyB)); % Store
value at i/10 index
            bestGeoAvr(i/10) = min(min(geoAvrA), min(geoAvrB)); % Store value at
i/10 index

            disp(i);
        end

    end


    % Plotting the results
    figure; % Create a new figure
```

```
    plot(bestMakespan, 'LineWidth', 2); % Plots the graph in the full figure window
    title('Best Makespan Over Iterations'); % Adds a title to the graph
    xlabel('Iteration (x10)'); % Labels the x-axis
    ylabel('Best Makespan'); % Labels the y-axis

    minValue = min(bestMakespan);
    disp(['Minimum makespan so far is: ', num2str(minValue)]);

    figure;

    plot(bestEnergy, 'LineWidth', 2); % Plots the graph in the full figure window
    title('Best Energy Consumption Over Iterations'); % Adds a title to the graph
    xlabel('Iteration (x10)'); % Labels the x-axis
    ylabel('Best Energy Consumption'); % Labels the y-axis

    minValue = min(bestEnergy);
    disp(['Minimum energy consumption so far is: ', num2str(minValue)]);

    figure;

    plot(bestGeoAvr, 'LineWidth', 2); % Plots the graph in the full figure window
    title('Best Geometric Average Over Iterations'); % Adds a title to the graph
    xlabel('Iteration (x10)'); % Labels the x-axis
    ylabel('Best Geometric Average'); % Labels the y-axis

    minValue = min(bestGeoAvr);
    disp(['Minimum geometric average so far is: ', num2str(minValue)]);


end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: calculateEnergy.m



function totalEnergy = calculateEnergy(problem, solution)
    % Initialize total energy consumption
    totalEnergy = 0;

    % Calculate energy consumption for each job
    for job = 1:length(solution.jobMachine)
        machine = solution.jobMachine(job);
        totalEnergy = totalEnergy + problem.energyConsumption(job, machine);
    end
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: calculateMakespan.m
```

```
function makespan = calculateMakespan(problem, machineSchedules)
    numMachines = problem.numMachines;
    processingTime = problem.processingTime;
    setupTime = problem.setupTime;

    % Initialize an array to hold the completion time of each machine
    completionTimes = zeros(1, numMachines);

    % Calculate the completion time for each machine
    for m = 1:numMachines
        currentTime = 0;
        currentSchedule = machineSchedules{m};
        numJobsInSchedule = length(currentSchedule);

        for j = 1:numJobsInSchedule
            job = currentSchedule(j);
            if j > 1
                prevJob = currentSchedule(j - 1);
                currentTime = currentTime + setupTime{m}(prevJob, job);
            end
            currentTime = currentTime + processingTime(job, m);
        end

        completionTimes(m) = currentTime;
    end

    % The makespan is the maximum completion time across all machines
    makespan = max(completionTimes);
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: crossover.m



function [offspringA, offspringB] = crossover(parentA, parentB, problem,
parameters)
    % Offspring A inherits jobOrder from parentA and jobMachine from parentB
    offspringA.jobOrder = parentA.jobOrder;
    offspringA.jobMachine = parentB.jobMachine;
    offspringA = mutation(offspringA, problem, parameters);

    % Offspring B inherits jobOrder from parentB and jobMachine from parentA
    offspringB.jobOrder = parentB.jobOrder;
    offspringB.jobMachine = parentA.jobMachine;
offspringB = mutation(offspringB, problem, parameters);
end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: generateSchedule.m

function machineSchedules = generateSchedule(problem, solution)
    numMachines = problem.numMachines;
    jobOrder = solution.jobOrder;
    jobMachine = solution.jobMachine;

    % Initialize arrays for each machine
    machineSchedules = cell(1, numMachines);
    for m = 1:numMachines
        machineSchedules{m} = [];
    end

    % Distribute jobs to machines based on jobOrder and jobMachine
    for idx = 1:length(jobOrder)
        job = jobOrder(idx);
        machine = jobMachine(job);
        machineSchedules{machine} = [machineSchedules{machine}, job];
    end

    % machineSchedules is the output, a cell array of arrays
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: mutation.m


function result = mutation(solution, problem, parameters)

    result = solution;

    if rand() < parameters.mutation.jobOrderMutationRate
        swapIndices = randperm(problem.numJobs, 2);
        temp = result.jobOrder(swapIndices(1));
        result.jobOrder(swapIndices(1)) = result.jobOrder(swapIndices(2));
        result.jobOrder(swapIndices(2)) = temp;
    end

    for i=1:length(solution.jobMachine)
        if rand() < parameters.mutation.jobMachineMutationRate
            result.jobMachine(i) = randi([1, problem.numMachines]);
        end
    end

end



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: replace.m
```

```
function [finalSolutions, finalMakespan, finalEnergy] = replace(mySolutions, criteria, makespan, totalEnergy, solution, solutionCriteria, offspringMakespan, offspringEnergy)
    finalSolutions = mySolutions;
    finalMakespan = makespan;
    finalEnergy = totalEnergy;

    [worstSolutionValue, worstSolutionIndex] = max(criteria);
    if worstSolutionValue > solutionCriteria
        finalSolutions(worstSolutionIndex) = solution;
        finalMakespan(worstSolutionIndex) = offspringMakespan;
        finalEnergy(worstSolutionIndex) = offspringEnergy;
    end

end



%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%FILE: selectParentIndex.m




function minIndex = selectParentIndex(makespanArray)
    % Randomly select three indices
    randomIndices = randperm(length(makespanArray), 10);

    % Find the index of the minimum makespan value among the three
    [~, minPosition] = min(makespanArray(randomIndices));
    minIndex = randomIndices(minPosition);
end
```