CELLULAR MANUFACTURING SYSTEM FORMATION WITH FLEXIBLE PRODUCTION ROUTING USING GENETIC ALGORITHMS

Thesis

Submitted to International Program

Department of Industrial Engineering

The Requirements for the Degree of

Sarjana Teknik Industri

Universitas Islam Indonesia

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INTERNATIONAL PROGRAM

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UNIVERSITAS ISLAM INDONESIA

YOGYAKARTA

2023

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CELLULAR MANUFACTURING SYSTEM FORMATION WITH FLEXIBLE PRODUCTION ROUTING USING GENETIC ALGORITHMS

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PREFACE

Assalamualaikum Wr.Wb.

Alhamdulillahisyukur, all of the gratitude is praised to the presence of Allah ﷻ who has bestowed His grace and hidayah to all of us, especially the author so that the undergraduate thesis entitled "Cellular Manufacturing System Formation With Flexible Production Routing Using Genetic Algorithms" can be completed properly. We also give greetings to our Prophet Muhammad ﷺ, who has brought us from the darkness to the bright light of Islam.

In completing the undergraduate thesis, the author dealt with a lot of difficulties. However, the help of prayers, ideas, and references to thinking endlessly are given by the supervisor, lecturers, and friends to solve problems that arise. Therefore, the author would like to thank the parties who helped in the completion of this report, namely:

1. Both of my parents, who have been working hard and supporting me so that I can finish my thesis.
2. Ir. Muhammad Ridwan Andi Purnomo, S.T., M.Sc., Ph.D., IPM, as the supervisor who teach me how solve the problem in the thesis.
3. Mrs. Diana and Mrs. Devy who always provides me guides in administration regard the institution
4. Elsie Saniyyah Azzahro who always supporting me and giving me spirit to finish my thesis.

May God repay all the good they did with grace and additional guidance so that they can receive goodness for all of us.

The author realizes that in doing this undergraduate thesis, there are many shortcomings and weaknesses in terms of material and technical aspects. Therefore, the author apologizes and expects criticism and suggestions for the perfection of this undergraduate thesis. The author hopes that this undergraduate thesis report can be useful for many parties. May goodness always be with you, and may sadness pass from you. Finally, the author says thank you.

Wassalamu'alaikum Warohmatullahi Wabarakatuh

Yogyakarta, 27 March 2023

Afian Cavin Widyatama

MOTTO

I'll give it one more go and then many more and I won't stop until Allah put me to rest or the flame within me is running out.

ABSTRACT

Cellular Manufacturing System (CMS) formation with flexible production routing using Genetic Algorithms (GA) is an emerging approach that combines the benefits of both CMS and GA to achieve optimal production planning and scheduling. This approach involves grouping similar parts into families and forming cells based on part family production requirements. The GA algorithm is then applied to determine the optimal routing of parts within the cells to minimize setup times and production costs. This approach also allows for flexibility in production routing, where parts can be produced in multiple cells, reducing the risk of machine breakdowns and improving overall production efficiency. Additionally, the approach offers the potential for continuous improvement by allowing for the incorporation of new parts and updates to the production routing plan. The CMS formation with flexible production routing using GA approach has shown promising results in terms of reducing lead times, improving productivity, and lowering costs in various manufacturing environments, making it a viable solution for companies looking to optimize their production processes. The GA generates the best production routing of the parts that have been explained in the form of chromosomes. The GA generate 4 cell manufacturing system that is the best route of the product throughout the layout of machine which of the layout is grouped into the similar function of the machine to ease the handling of materials.

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CHAPTER I
INTRODUCTION

1.1 Background

Lately, the trend of customer demand is change very fast accompanied by a variety of diverse requests but in increasingly smaller quantities. With a state of change, there will be lots of interruptions in the production process, where it has to be re-set up based on the changing products. Or another risk is to continue with the current production system by keeping a very large inventory to deal with very fast changes. Since 1970, an increase in competitiveness among American industries has begun, and the adoption of new ideas such as just-in-time (JIT). The JIT philosophy is about the division of a large system into smaller subsystems. This makes it simple to manage because managing a subsystem is considerably easier than the entire large system (Asri et al., 2016). Cellular manufacturing (CM) is one of the most important applications of JIT, which takes advantage of the link between the flow-shop system (high rate of production) and job-shop systems (manufacturing flexibility and diversity of products).

An example of increased demand for goods is the increased demand for toilet paper during the early stages of the COVID-19 pandemic in Europe due to panic buying. In some countries, people even bought emergency supplies such as flour and canned food due to panic buying.

The increase in demand does not only occur in the finished goods production sector, ExxonMobil in its publication entitled Outlook for Energy: A View to 2030, states that rapid economic growth in developing countries that are not part of the Organization for Economic Cooperation and Development (OECD) will see energy demand surge by around 65% from 2005. The study expects an expansion of the natural gas supply, particularly in the US where unconventional gas supplies are expected to satisfy more than 50% of gas demands by 2030.

As a form of anticipation of changes in demand for finished goods, companies must determine a strategy to optimize the production of these goods.

One of the strategies that can be applied by the company is to identify the Production Routing Problem. The production routing problem is an integrated supply chain planning problem where the decisions concerning production, inventory, and routing are simultaneously determined (Y. Li et al., 2017).

An example of a Production Routing system Problem implementation in fish feed due to the increasing number of fish consumption in the world which reached 122% calculated from 1990 to 2018. It is estimated that the supply of wild fish has limited potential to meet the growing demand. Meanwhile, the aquaculture industry has been growing rapidly since 2012 with production reaching 114.5 million tons in 2018. With that in mind, in order for the aquaculture industry to meet the amount of demand for seafood products, fish feed providers must also be able to adjust production levels to meet this demand. Ivar Brekkå conducted research on Production Routing Problem on fish feed by proposing a heuristic, combining decomposition and the adaptive large neighborhood search (ALNS) heuristic, to solve the FFPRP. The decomposition-based ALNS heuristic is tested on a number of test instances which are generated based on vessel, factory, and order data from two of Norway's largest fish feed producers. For small problem instances, for which the commercial MIP solver is often able to prove optimality, the average optimality gaps of the proposed heuristic are relatively small, while for the larger problem instances, the heuristic significantly outperforms the commercial MIP solver both in terms of solution quality and run time (Brekkå et al., 2022).

Cellular Manufacturing System (CMS) is a manufacturing process system in which equipment and workstations are arranged in a more efficient order where flow, inventory, and materials are used to make products from start to finish in a single process flow, as well as minimizing transportation cost and waiting time. Cellular manufacturing is a subsection of just-in-time manufacturing and lean manufacturing that includes group technologies. The goal of cellular manufacturing is to move as quickly as possible, making a wide variety of similar products, while creating as little waste as possible. The benefit of this Cellular system is that it speeds up the response to changes in customer demand quickly because this cell is designed with a fast process, in other words the lead time is very short, inventory costs will drop drastically because the cell system demands are a one-piece flow.

Designing a CMS consists of four steps. The first and foremost is solving a cell formation problem (CFP). At this stage, parts that have similarities in shape and configuration, and are produced by the same or similarly required machines, are considered as the same family to process by a group of machines located in one cell. In the second step, facility layout is determined which involves cell layout at the level of the workshop and also machines within each cell. The third step is about scheduling the operation on each machine in the cells. Finally, the fourth step is the allocation of resources in which resources such as tools, manpower, and materials are assigned to machines and cells. Family formation for the parts and grouping of the machines have some advantages such as reducing the setup times, material handling cost, work-in-process (WIP) inventories, throughput times, and production cost(Singh & Rajamani, 1996).

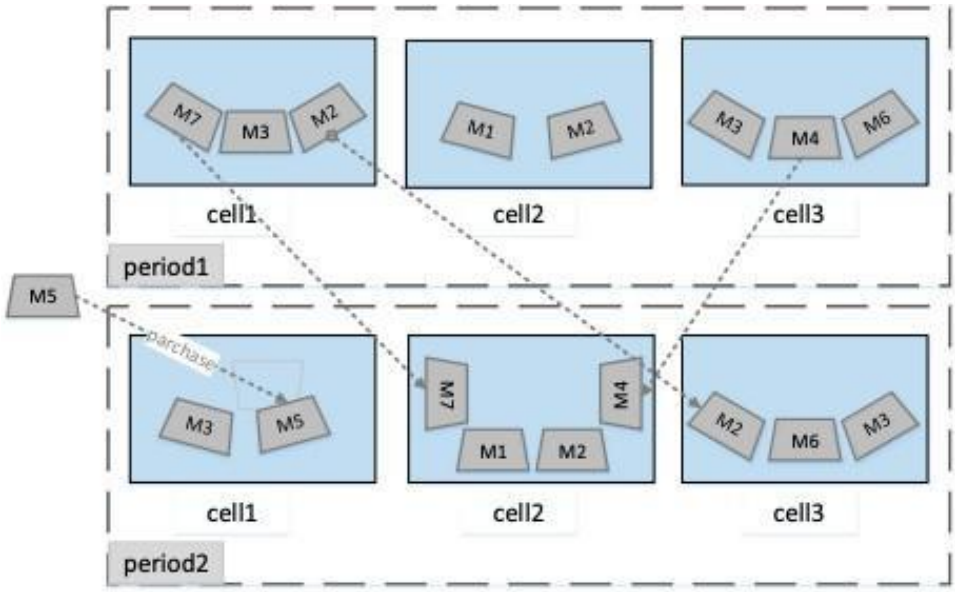


Figure 1. Changing of Cell Reconfiguration in CMS

In this case, Inc. X uses the CMS concept in its production. To produce, Inc. X requires several machines to manufacture several parts of the product and has several route options to complete the production. Inc. X has 17 machines that must produce 30 parts to make 1 product. With so many parts to be produced and the machines used, Inc. X has a system that will help effectiveness in production. There are several routes to choose each of the parts, and make sure to select the best routes of production based on CMS. Even though the entire production system becomes more accommodating, each individual cell is still optimized for a relatively narrow range of tasks in order to take advantage of the mass-production efficiencies of specialization and scale. To the extent that a large variety of products can be designed to be assembled from a small number of standardized parts, both high product variety and high productivity can be achieved. The conventional cellular manufacturing systems (CMS) do not respond to changes in part operation sequences while redesigning a part, variations in product mix, and demand size over time respond to changes in part operation sequences while redesigning a part, variations in product mix and demand size over time span.

In the conventional CMS, the product mix and part demand are considered to be stable for the entire planning span. Thus, the designed CMS configuration in one period may not be efficient for successive periods. In dynamic production conditions, a planning horizon breaks into multiple periods with different product mixes and part demand requirements (Rheault, Drolet & Abdulnour, 1995). Hence the manufacturing cells need to be reconfigured during successive periods to obtain optimal results. Reconfiguration involves machine relocation in the cells and modification in part process route in successive periods. The flexibility in the CMS is of paramount importance. The manufacturing industries have acknowledged the benefits of flexibility in part process routing (Kusiak, 1987; Mansuri, Husseini & Newman, 2000).

This paper suggests an integrated mathematical model for dynamic production in a cellular manufacturing environment. The dynamic part demand can be satisfied from internal production or through subcontracting part operations in successive period segments of the planning horizon. Multiple process plans for each

part and alternative process routes for each of them are considered. The proposed model for the design of CMS incorporates several production aspects simultaneously such as system reconfiguration, multiple part process routes, production capacity, machine duplication, material handling, in-house production, and subcontracting part operations. A Genetic Algorithm (GA) is applied to find which is the best route to use in this production. The basic idea is to use the genetic operators of genetic algorithms to quickly converge the search to near-global minima/maximal. In a nutshell, genetic algorithms (GA) are an optimization method that has many characteristics with Darwinian natural selection and biological reproductive changes. Genome-wide searches throughout concept space are encoded by genetic algorithms in their core, with each step striving to reach a coarse granularity of information (Goldberg 1988). Individuals of a species have the same characteristics as concept instances. It is determined which of these concepts will survive in the next generation by evaluating the changes and recombination of these ideas using an assessment function.

The benefit of this Cellular system is that it speeds up the response to changes in customer demand quickly because this cell is designed with a fast process, in other words the lead time is very short, and inventory costs will drop drastically because the cell system demands pieces flow. However, considering the complexity of this route, therefore, this research will discuss the solutions offered through genetic algorithms.

1.2 Problem Formulation

Based on the background above, the company needs to transform the facilities layout for the better setup of machines to form cellular manufacturing systems by using Genetic Algorithm to solve it. The problem formulations are :

1. What is the production routing of the parts?
2. What are the formed manufacturing cells using GA?

1.3 Objectives

The purpose of this research is as follows:

1. Identifying and analysing the steps for using the Genetic Algorithm (GA) in production machines
2. Identifying and analysing the formed of cells in production routing parts for the cellular manufacturing systems.

1.4 Limitation

In this research, there are several scope limitations of the discussion as follows:

1. The manufacturing cell formation doesn't consider machine scheduling in every formed manufacturing cell.
2. Optimisation of this study excludes the cost to re-layout the company
3. The solution of this study will not be implemented in real condition. Performance evaluation will be conducted based on a theoretical formula.

1.5 Significance

The research was conducted in order to meet several purposes as elaborated as follows:

1.5.1 For students

1. As a self-preparation to enter the field of work.
2. To extend the knowledge, concept of thought, and idea as well as to understand professionalism in real work.
3. To fulfill the requirements for obtaining a bachelor's degree.

1.5.2 For University

1. As a self-preparation to enter the field of work.
2. To extend the knowledge, concept of thought, and idea as well as to understand professionalism in real work.
3. To fulfill the requirements for obtaining a bachelor's degree.

CHAPTER II
LITERATURE REVIEW

2.1.1 Just in Time (JIT)

In the manufacturing industry, the speed with which products are delivered to market and the cost of production can make or break a company. Just-in-time (JIT) is a workflow methodology that aims to reduce flow time in the production system as well as response times from suppliers to customers.

Just-in-time is an inventory management method in which goods are received from suppliers only when they are needed. The main purpose of this method is to reduce inventory holding costs and increase inventory turnover. JIT helps companies control variability in their processes, enabling them to increase productivity while lowering costs.

JIT has a work event pol, namely the first, the customer places an order to the manufacturer. When manufacturers receive orders, they then order raw materials from suppliers. After the supplier receives the order, they send the required raw materials to the manufacturer. Raw materials that have been received by producers are then processed and sold to customers. Several advantages can be enjoyed in implementing the Just In Time production system, including the following:

1. Low Inventory Level or Stock Level so as to save storage space and related costs such as space rental costs and insurance costs.
2. Production materials are only obtained when needed, so they only require low working capital.
3. With a low inventory level, the possibility of waste due to products that are out of date, past expiration, and damaged or obsolete will be lower.
4. Avoiding the accumulation of unsold finished products due to sudden changes in demand.
5. Requires emphasis on the quality of production materials supplied by the Supplier so as to reduce inspection and rework time.

Although there are many advantages that can be obtained, this Just In Time Production System still has weaknesses, namely:

1. The Just In Time Production System has zero tolerance for mistakes or "Zero Tolerance for mistakes", so it will be very difficult to repair/rework production materials or finished products that are defective. This is because the level of inventory of production materials and finished products is very minimum.
2. Very high dependence on suppliers both in quality and delivery accuracy which is generally outside the scope of the manufacturing company concerned. A delay in delivery by one supplier will result in the delay of all planned production schedules.
3. Transaction fees will be relatively high due to the high frequency of Transactions.
4. The manufacturing company concerned will find it difficult to meet the sudden high demand because in reality there is no more finished product.

2.1.2 Cellular Manufacturing System (CMS)

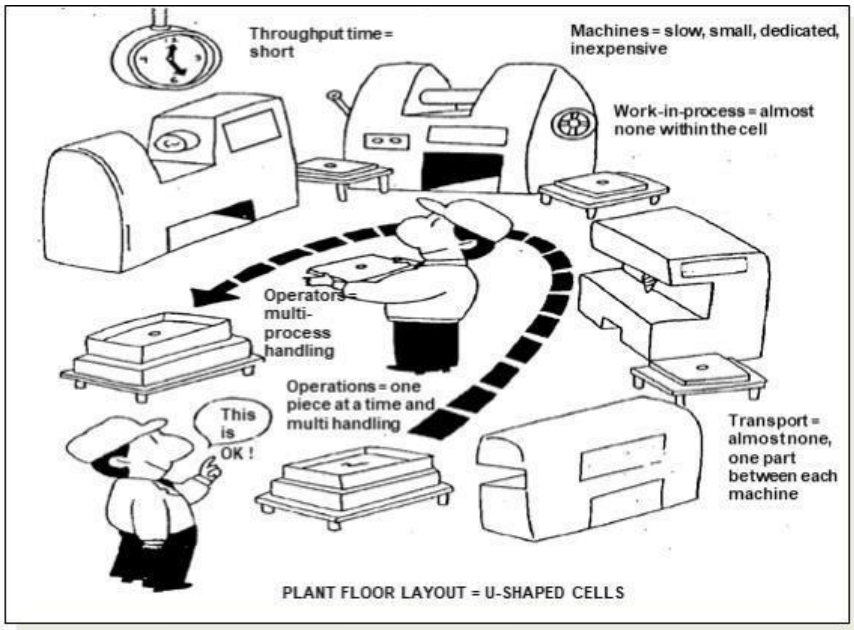


Figure 2. Layout Floor = U-Shaped Cell

Cellular Manufacturing System (CMS) is a manufacturing process system where equipment and workstations are arranged in a more efficient order where the flow, inventory, and materials to make products from start to finish are in a single process flow, and make transportation and waiting times shorter. minimal. There are 7 production flow demands including (1) Place the machine according to the process sequence, (2) Use compact (specialized and general purpose) machines, (3) One Piece Flow, (4) Take Time & Cycle time, (5) Multi-process operations, (6) Multi-skilled workers, (7) Production standing (without chairs), it is necessary to look at the type of work.

There are 4 phases of implementing the Cellular Manufacturing System (CMS) including (1) Understanding current conditions, (2) Anticipating future flow designs, (3) Changing and applying process flow to product layout orientation, (4) Continuous improvement of performance from cells. The benefit of implementing this Cellular system is to speed up the response to changes in customer demand quickly because this cell is designed with a fast process, in other words the lead time is very short, and inventory costs will drop drastically because

the cell system demands one piece of flow. Product results in terms of quality will increase because this cell system makes it easier for you to find problems easily and quickly in taking corrective actions. Improve worker skills because the cell system requires more than one job or is called multi-tasking, and productivity will increase significantly. And more than that, customer satisfaction will be fulfilled by using this cell system.

2.1.3 Genetic Algorithm

Genetic Algorithms (GAs), first introduced by John Holland in the early seventies, have become an important tool in machine learning and function optimization. To solve learning tasks, design tasks, or optimization tasks, a Genetic Algorithm organizes a population of "organisms" (bit strings) and modifies the population probabilistically, searching for the solution that is closest to the optimal point for a task. Providing favorable changes to parents that join their offspring, GA is a control structure that adapts to any problem solved by syntactic operations on bit strings (Rawlins, 1991).

Genetic Algorithm is a primary heuristic search method of classifier systems, a form of the stochastic production system; Genetic Algorithm has been tested on NP combinatorial optimization problems. Very difficult combinatorial optimization problems, such as network link optimization and traveling salesman problems; and Genetic Algorithm is very attractive as a primitive model for natural selection. (The classifier system is modeled on the economic system in a market economy.) Genetic Algorithms have been widely applied to problems such as semiconductor layout design and factory control, and have been used in AI systems and neuromorphic networks to model cognition processes such as language processing and induction. Genetic Algorithms may also provide a more favorable approach to machine learning problems than neuromorphic networks have provided. Like associative memory, neuromorphic networks, and simulated annealing ((Mcclelland, n.d.)), Genetic Algorithm and Genetic Algorithm-based

heuristic algorithms are one way to achieve sub-symbolic, graceful, and adaptive systems (Chen & Hu, 2022; Gao et al., 2022a)

Genetic Algorithms (GAs) are a subset of reproductive population algorithms. The followings are characteristics of many of the GAs found in many kinds of literature mentioning General Algorithms:

- All strings are of the same length
- Populations are of constant size
- A mutation is probabilistic and is usually independent of the string value.
- Reproductive sets are of size two, and members are chosen probabilistically, with probabilities weighted by string values.
- Mating is usually restricted to crossover. In the general crossover, the i^{th} symbol of an offspring is the i^{th} symbol of one of the members of the reproductive set.

  Most General Algorithms limit crossover such that symbols in positions 1...i of the new string come from one parent and those in positions i + 1... l come from the other parent, whereas i is chosen probabilistically.

2.1.4.1 Structure of Genetic Algorithm

GA is composed of distinct components. This is a particular strength because it means that standard components can be reused, with various adaptations to different GAs, making implementation easier. The main components of a GA are chromosome encoding, fitness function, selection, recombination, and evolutionary scheme.

i. Chromosome encoding

   GA manipulates a population of chromosomes, which are string representations of solutions to a particular problem. Chromosomes are abstractions of biological DNA chromosomes, which can be thought of as a series of letters from the alphabet {A,C,G,T}.

ii. Fitness

A fitness function is a computation that evaluates the quality of a chromosome as a solution to a particular problem. By analogy to biology, the chromosome is referred to as the genotype, while the solution it represents is known as the phenotype. The translation process can be very complicated. In GA time scheduling and manufacturing scheduling, for example, the chromosome is translated into a schedule or set of scheduled activities involving a large number of interacting resources. Fitness computation will then measure the success of this schedule in terms of various criteria and objectives such as completion time, resource utilization, cost minimization, and so on.

iii. Selection

GAs use fitness to distinguish the quality of solutions represented by chromosomes in the GA population. The selection component of GA is designed to use fitness to guide the evolution of chromosomes with selective pressure. Therefore, chromosomes are selected for recombination based on fitness. Chromosomes with higher fitness should have a greater chance of selection than chromosomes with lower fitness, thus creating selective pressure towards more fit solutions.

iv. Recombination

Recombination is the process by which chromosomes selected from the source population are recombined to form members of the successor population. The idea is to simulate the mixing of genetic material that can occur when organisms reproduce. Since selection for recombination is biased in favor of higher fitness, the balance of probability (hopefully) is that more fit chromosomes will evolve as a result.

v. Evolution

After recombination, the resulting chromosomes will be passed on to the successor population. The selection and recombination process are then iterated until a complete successor population is generated. At that point, the successor population becomes the new source population (next generation). The GA is iterated through a number of generations until an appropriate topping criterion is reached. This can include a fixed number of generations elapsed, the observed convergence to the best-fit solution, or the generation of a solution that fully satisfies a set of constraints.

2.2 Literature Review

According to previous research, the related concepts of the improved genetic algorithm were introduced, and a framework was designed for the agricultural greenhouse control system. In order to verify the feasibility of the developed software and hardware, a greenhouse experiment platform was designed and improved in the laboratory, and the system designed in this paper was debugged and tested. The experimental results show that through intelligent control of agricultural greenhouses, the deviation of air temperature is less than 0.5 C and the deviation of air humidity is less than 1% RH when stable. The value of carbon dioxide concentration after being basically stable has small fluctuations around the stable value, and the maximum relative fluctuation is less than 2.5% ((Chen & Hu, 2022)).

Other than that, previous research from (Hsu & Xie, 2019)) about genetic algorithms said that An automatic design process is proposed to generate an optimal prism based on the user's location. It uses Python to connect genetic algorithms, 3D computer-aided design, optical simulation software, and image-processed related technology for generating geometric parameter sets, modeling, optical simulation, and data evaluation. The optimal triangular sunlight-guiding prism calculated by the light-guiding fitness function for a 24 ◦ north latitude location has 100% light-guiding efficiency at 35◦–65◦ solar elevation angle and has more than 90% at 20◦ and 70◦. It shows that the proposed automatic design process could

provide the customized optimal design of the sunlight-guiding prism with a widely applicable solar elevation angle range based on the user's building condition.

Same as (Gao et al., 2022b), about Adaptive Genetic Algorithm, said that the classifier fuzzy rules and membership functions are stepwise optimized by AGA to improve the model output precision, and a novel nearby mutation operator is proposed in order to extract the rules more accurately. Finally, the fuzzy classifier is validated and also compared with the conventional fuzzy classifier. The results demonstrate that this proposed model optimized by AGA is not only effective for the dehumidifier fault diagnosis, but also has advantages over the conventional model.

(Wei & Chuan, 2022) also conducted research about Genetic Algorithm. In this study, a grey neural network prediction method coupled with a genetic algorithm is proposed. Firstly, a grey neural network model for forecasting product order demand is constructed based on the grey model and neural network theory. Secondly, the elevator product is taken as an example to demonstrate the prediction performance of the model. Lastly, the genetic algorithm is used to iteratively optimize the network weights and thresholds of the model in order to solve premature convergence and improve the global optimization capability in the prediction process. The results show that the accuracy and robustness of the optimized product prediction model are improved, which verifies the feasibility of the designed method.

Genetic algorithms research was performed by (Desai & Dingreville, 2022) They simulated the physical vapor deposition of a binary alloy thin film by employing a phase-field model, where deposition rates and diffusivities of the deposited species vary in time and are controlled via the genetic algorithm. Their genetic algorithm-guided protocols achieve targeted microstructures with lateral and vertical concentration modulations, as well as more complex, hierarchical microstructures previously not described in classical structure zone diagrams. By elucidating the process-structure mechanisms during physical vapor deposition and using this knowledge to achieve precise thin-film microstructures, our algorithm provides insights into the thin film, physical vapor deposition, and film

functionality communities looking for additional avenues to design novel thin-film microstructures.

(Gazioğlu & Etaner-Uyar, 2022) also, make some research about genetic algorithms. The research is about determining phenotype values, the well-known Bayesian Optimization Algorithm (BOA) has been injected into our algorithm to create a Bayes Network by using the previous population to exploit interactions between variables. With this algorithm, we have solved the well-known Dynamic Knapsack Problem (DKP) with 100, 250, and 500 items. Also, we have compared our algorithm with the most recent algorithm in the literature by using the DKP with 100 items. Experiments have shown that the proposed algorithm is efficient and faster than the peer algorithms in the manner of tracking moving optima without using an explicit memory scheme. In conclusion, using relationships between variables within the optimization algorithms is useful when concerning dynamic environments.

(Garcia & Lôndero, 2021) conducted some research to analyze the convergence profiles of the genetic algorithm, we present a sensitivity analysis that helps in choosing the input values for the genetic operators. Although the facies dispersion processes are different among the software mentioned, the use of genetic algorithms for parameter refinement is an idea that will contribute to future work.

(Agrawal et al., 2022) studied research about a Heuristic-based Genetic Algorithm that was proposed to find out the optimum set of routes in a computationally efficient manner. Efforts have also been made to determine the most suitable values of GA parameters. The output from the GAbased heuristic can be used as an upper bound on the objective function value to yield the optimal solution in a very computationally efficient manner. Statistical test performed shows that the proposed heuristic provides a solution computationally quite efficiently with statistically insignificant loss in the quality of the solution.

(Huang et al., 2022; Jafari & Yari, 2022) also, performed a research that its results showed =the best minimum adaptation value, which was determined as 0.03072. The thicknesses of the anode and cathode CLs are 0.0231 mm and 0.0315 mm, respectively. The performance improvement of the optimized model is

approximately 6.8%. The optimization method used in the study can effectively improve the performance of HTPEMFC and provide a reference for the design of HTPEMFC.

(Ghadami et al., 2022a) explained The stress distribution around the opening is calculated using Lekhnitskii's complex variable method and complex potential functions. The genetic algorithm is then implemented to find the optimal values for design parameters. The results show that by selecting the optimal parameters related to the anisotropic material and the opening's geometry, the stress intensity factor of the perforated anisotropic plates is remarkably reduced. Furthermore, this optimization algorithm can be extended to find the optimized parameters and achieve the optimal designs in anisotropic and isotropic perforated plates under thermal loadings.

(Ghadami et al., 2022b) in their study used a three-dimensional line-source model with direct search methods, including pattern search and genetic algorithms to optimize the well trajectories. This method was applied to several cases, with different forms of wells and reservoirs. In all cases, significant improvement was observed in the production rate. Furthermore, the production enhancement using the optimized well trajectories which have curved paths is compared to the case with linear well trajectories. It was shown that at least a 6% production increase is possible for the curved trajectory well with respect to the well with the constant slope lines. Besides, it was illustrated that oil production is boosted solely by altering the slope of the well or its laterals along the well path.

(J. C. F. Li et al., 2022) also, explained that a hybrid path-finding method combining genetic algorithm and A* / MAA* algorithm is proposed. The proposed method provides a family of near-optimal paths instead of a single optimal path for routing. A family of paths allows a project implementer to quickly adapt to unexpected situations as new information becomes available, and flexibly change network topology before or during implementation with minimal impact on project cost.

(Xu et al., 2022) conducted a research and the results demonstrated that: enhanced performance in predictive accuracy and generalization ability is achieved

through the presented GA-ELF technique; the ensembled predictive models, especially the Adaboost-enhanced models can be used as efficient and reliable alternatives to classical approaches for predicting wave forces on coastal bridges. It is envisioned that the GA-ELF could be extended to predict forces on other coastal engineering structures, thus facilitating the structural design and risk assessment during their service life.

(Daneshparvar & Beigzadeh, 2022) explained the effects of the two main geometrical parameters including baffle pitch and baffle angle on heat transfer coefficient and pressure drop were studied. The CFD modelling results were validated with experimental data. The validated data were employed to develop predictive correlations. Finally, the optimum geometries of the investigated helical baffles were suggested using multi-objective genetic algorithm (MOGA) optimization. The optimum results presented a trade-off between the heat transfer coefficient and pressure drop in the heat exchangers

(Yixuan, 2022) explored the implementation process of genetic algorithms in parametric design platforms and the characteristics of optimization calculation. The experimental model is established based on a genetic algorithm, combined with a computer-intelligent operation platform and modeling software. Combined with the EnergyPlus energy consumption simulation engine and daysim daylighting simulation engine, the optimization design process of genetic algorithm optimization is realized through Pareto intelligent solution programming. The optimization design method can quantitatively calculate and evaluate the spatial layout, and provide visual, more accurate, and intuitive output results.

(Kaedi et al., 2022) make some papers and this paper proposes a novel approach to solve them simultaneously in order to increase the network lifetime. In the proposed scheme, the cluster head's role in transmitting the inter-cluster traffic is considered during the cluster head selection process. In other words, cluster heads are selected in a way, which reduces the energy consumption for transmitting data from a cluster head to the sink node. To achieve this goal, the genetic algorithm is used on two levels. The first-level genetic algorithm selects the cluster heads while the second-level one considers multi-hop routing among them. Simulation of the

proposed method and comparison of its results with three previously proposed schemes that solve the problems separately indicate the superiority of the proposed optimization scheme in improving the lifetime of the network.

(Arufe et al., 2022) explained the multi-level redundancy allocation problem is being addressed and solved comprehensively in this study using an advanced genetic algorithm (GA) and a penalty function approach in both crisp and intuitionistic fuzzy settings Finally, numerical examples are solved and sensitivity studies are carried out visually to evaluate the consequences of changing key parameters involved in GA. Also, the use of metaheuristic soft computing, GA is fruitful to tackle such complicated combinatorial problems.

(Arufe et al., 2022) in their research focused on QCCP for Quantum Approximation Optimization Algorithms (QAOA) applied to the MaxCut problem and consider Noisy Intermediate Scale Quantum (NISQ) hardware architectures. Based on the fact that these algorithms apply a set of basic quantum operations repeatedly over a number of rounds, they propose a genetic algorithm approach, termed Decomposition Based Genetic Algorithm (DBGA), that in each round extends the partial solutions obtained for the previous ones. DBGA is compared to the state of the art across a set of conventional instances. The results of the experimental study provided an interesting insight into the problem structure and showed that DBGA is quite competitive with the state of the art. In particular, DBGA outperformed the best current method on the largest instances and provided new best solutions to most of them.

CHAPTER III
RESEARCH METHODOLOGY

3.1 Research Object

The object of this research is the production activity in the cellular manufacturing system. This research was conducted by measuring the performance of the Genetic algorithm (GA) Algorithm in optimizing the cellular manufacturing system of production machines.

3.2 Data to Collect

The data to collect is production process alternatives of every part, number of parts, and number of machines.

3.3 Type of Data

The Data Collection method in this research is conducted as follows:

1. Observation

   Observations were made by direct observation of the Cellular manufacturing system of production machines to get the actual conditions. Direct observations to see the performance before and after the application of optimization using the ant colony algorithm, observations are made during the initial production process until the production process is complete.

2. Documentations

The documentation method in this study comes from the company's internal data which will be processed into calculations using the ant colony algorithm. The data obtained in this step is secondary data which includes:

1. Attendance data, as well as transfer in and transfer out data
2. Working hours of production machines
3. Output data (actual production result)
4. Defect data (Not Good product)

3.4 Data Analysis Method

The method of data analysis in this study is GA, Genetic algorithms use an evolutionary programming approach based on genetic biological processes, with the goal of finding the best solution to combinatorial problems. Genetic Algorithm is a primary heuristic search method of classifier systems, a form of the stochastic production system; Genetic Algorithm has been tested on NP combinatorial optimization problems. Very difficult combinatorial optimization problems, such as network link optimization and traveling salesman problems; and Genetic Algorithm is very attractive as a primitive model for natural selection. (The classifier system is modeled on the economic system in a market economy).

3.5 Research Flowchart

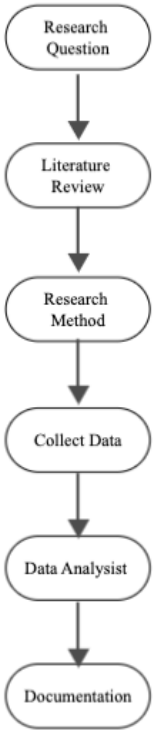


Figure 3.1 Flowchart Diagram

a. Research Question

The research question phase is the first phase in this observation. In the research question phase, the activities are below: Determine the problem formulation and the objectives of the research. In this phase the problem is included in the complexity of the CMS route, therefore, this research will discuss the solutions offered through genetic algorithms.

b. Literatur Review

Furthermore, the objectives of the literature review are to assist in conceiving the topic of the observation and to find out other information related to the observation. The information is available in books, journals, articles, the internet, and the other thesis.

c. Research Method

d. Data Collecting

Primary and secondary data are employed in this observation. Primary data is the data that is procured from the source directly without expediter.

e. Data Analysis

Suggests an integrated mathematical model for dynamic production in a cellular manufacturing environment. The dynamic part demand can be satisfied from internal production or through subcontracting part operations in successive period segments of the planning horizon. Multiple process plans for each part and alternative process routes for each of them are considered. The proposed model for the design of CMS incorporates several production aspects simultaneously such as system reconfiguration, multiple part process routes, production capacity, machine duplication, material handling, in-house production, and subcontracting part operations. A Genetic Algorithm (GA) is applied to find which is the best route to use in this production. The basic idea is to use the genetic operators of genetic algorithms to quickly converge the search to near-global minima/maximal.

f. Documentation

Documentation is any communicable material that is used to describe, explain or instruct regarding some attributes of an object, system, or procedure, such as its parts, assembly, installation, maintenance, and use, making paper and thesis.

CHAPTER IV
DATA COLLECTING AND PROCESSING

4.1 Data Collecting

The data was derived from company X which is mentioned in the form of a table that consists of 3 aspect points. The production routing of the parts, sequence of parts, and sequence of machines. The below table shows the raw data, in which the part number has only chosen 1 out of many production routes that the machine has already put in the process sequence column. The empty sequence table refers to the absence of machine activities on it. There are 30 parts and 17 machines with several numbers of production routing. the role of GA methods is to select the best way for each part of the product followed by one production routing.

Part No	Routing No	Process Sequence					
		1	2	3	4	5	6
1	1	11	6	13	15	4	
	2	6	13	1	8		
	3	14	7	3	15	2	
2	1	11	13	12	6	10	
	2	11	15	13	12		
3	1	4	15	12	6		
	2	17	1	9			
	3	6	13	1	8		
4	1	11	6	13	12		
5	1	11	6	13	12	10	
	2	8	1	5	6	11	
6	1	11	6	13	4	12	
	2	11	15	13	12		
	3	14	7	13	15	2	
	4	11	15	5	6	13	
7	1	8	1	5	6		
	2	11	15	5	6		
	3	8	5	4			
8	1	16	8	5	4		
9	1	14	7	3	15	2	
	2	8	1	5	6	9	
10	1	8	1	5	6	11	
	2	11	6	13	4	12	
	3	11	15	13	12		
	4	11	6	13	12	10	
...	...	...	...	...	...	...	...

Figure 4.1 Raw Data Table

...	...	...	...	...	...	...	...
11	1	16	8	5	4		
	2	8	1	5	6	11	
12	1	11	12	5	7		
	2	17	1	9			
13	1	14	7	3	15	2	
	2	13	12	10	5	9	
14	1	4	11	6	13	12	10
	2	10	5	9	4	12	6
15	1	12	10	5	9		
	2	8	1	5	6	11	
	3	4	12	6	13	10	
	4	10	5	9	4	3	
16	1	7	3	2	15		
17	1	14	7	3	15	2	11
18	1	1	5	6	11		
	2	14	7	3	15	2	
19	1	11	6	13	12	10	
	2	8	1	5	6	11	
20	1	11	12	5	7	8	
	2	17	1	9			
21	1	11	6	13	12		
	2	12	10	5	9		
22	1	8	4	16	5		
	2	12	10	5	9		
23	1	17	1	9			
	2	12	10	5	9		
24	1	14	7	3	15	2	
25	1	17	1	8	9		
	2	11	15	13	12		
	3	1	5	6	11		
26	1	10	5	9	13	12	
	2	14	7	3	15	2	
27	1	11	6	12	10		
	2	5	9	13	12		
28	1	11	6	13	12	10	
29	1	14	7	15	2		
	2	11	12	5	7	8	
30	1	5	16	8	4		

Figure 5.2 Raw Data Table

4.2 Genetic Algorithm

The GA calculates data with 4 steps of the process. The GA system will automatically search the best routes for each part of the product and choose the sequence of machines also in order to form a cell. The cell itself is called a cellular manufacturing system, where the machines are grouped into several categories. The category was determined from which the GA chooses the best solution in the form of several factors such as sequence of parts, number of parts, sequence of the machine, and production routing of parts. After the data are processed, , the table will directly form a square shape which is called the cell. The process of GA calculation including 4 steps of processes, as follows:

a. Chromosome Design

The solution to be found is the best production routing of parts, sequence of parts, and sequence of machines to form a cellular manufacturing system. The GA represents 20 kinds of chromosomes, in which each of chromosome contains 3 aspects which are production routing for parts, sequence of parts, and sequence of machines. There are 30 numbers for production routing for parts, 30 numbers for a sequence of parts, and 17 numbers for the sequence of machines. These 3 tables below show 1 of 20 GA chromosomes divided into 3 different colours.

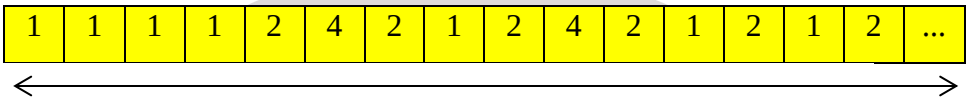


Table 1. Production Routing for Parts

The table above shows the GA chromosomes of the production routing of the parts. There are 30 parts in the layout, and how the GA assembles it to get the best routes for production. The first column show number 1 means that in part number 1, the GA chooses the first production routes. In the second column, the GA also chooses the first production routing. According to the data, each part contains 1 to 3 production routes.

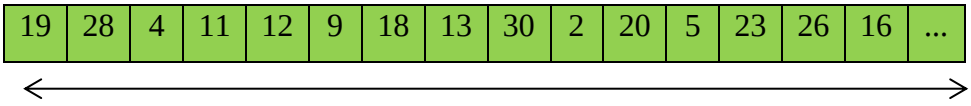


Table 2. Sequence of Parts

From the second table, the GA represents the sequence of parts. It creates 30 columns that choose which part of the product will go first. In the table, part number 19 will be processed first and will be followed by parts number 28, 4, 11, and so on.

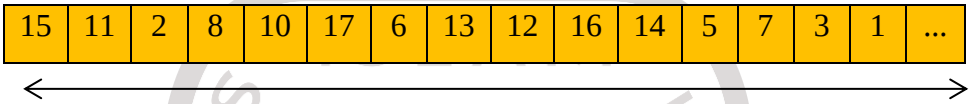


Table 3. Sequence of Machines

The last table, GA represents the sequence of machines by the following of chromosomes, the sequence of machine table in the last of a sequence of chromosomes. The GA sorts which machine will proceed with the first part of the product. Machine number 15 is the first machine that will proceed with the first part number. In the second column, machine number 11 will be proceeded with the second part of the product.

1 chromosome consists of 77 columns of three aspects. First column refers to part number 19 that will be processed in production routing number 1 by machine number 15. The second column means part number 28 will be processed in production routing number 1 by machine number 11. The chromosome will go down to 20 chromosomes. The best chromosome will be selected as the result of GA modeling.

b. Chromosome fitness

The machines of production are grouped in one cell based on the similarity of part of the production. In order to form a good cellular manufacturing system, the objective is to minimize the zero number inside a cell and the one number outside the cell, therefore the fitness of chromosomes is:

$$B - \sum_{i=1}^{17} |x_i - x_j| + \sum_{m=1}^{30} |x_n - x_m|$$

Where:

B = big number (relatively depends on researchers) is equal to 2000

i = production routing

j = production routing

m = number of machines

n = number of parts

The chromosome fitness evaluates the higher values of fitness that are assigned to reproduce another chromosome.

		MACHINES								
		14	**11**	**4**	**8**	**5**	**9**	**7**	**3**	**2**
PARTS	**11**	1	1	1						
	30	1	1	1			1			
	22	1	1	1						
	27				1	1	1			
	28				1	1	1			
	4		1		1	1	1			
	21							1	1	1
	10							1	1	1
	19							1	1	1

Table 4. Example of One Number Outside the Cell

From the table above, there are two numbers outside the cell, meaning that the route of part number 30 will be processed using machine number 9. Since machine number 9 is placed in the second cell, so part number 30 will be done in the second cell which will be more effective than in the first cell. Also, the part number 4 will be assigned in the first cell which it should be done in the second cell. The manufacturer has to add 1 more machine in the first and second cells if the budget is relatively low to add it.

MACHINES										
PARTS		15	11	4	6	5	7	17	5	2
	12	1	1	1						
	19	1	1	1						
	20		1	1						
	25				1	1	1			
	11					1	1			
	4				1	1	1			
	21							1	1	1
	12							1	1	1
	18							1	1	1

Table 5. Example of Zero Number Inside the Cell

From the table above, there are 2 zero numbers inside the cell, which means that there are two idle processing times in the machine number 15 and 6 that should be passed with part number 11 and 20.

c. Crossover operation

This is how the chromosomes produce the offspring throughout a one-cut point crossover naturally selected by the GA for parts production routing and the cutting point with repairing strategy for the machine and sequence of parts. GA uses 2 parents as the parents to produce two offspring.

Parent 1	3	2	2	1	2	3	3	1	2	4	2	1	2	…
Offspring 1	3	2	2	1	2	3	3	1	2	3	2	2	1	…
Offspring 2	2	1	1	1	1	4	2	1	2	4	2	1	2	…
Parent 2	2	1	1	1	1	4	2	1	2	3	2	2	1	…

Cutting point (one-cut point crossover)

Table 6. Production Routing in Chromosome

The table above is the table for production routing in chromosomes. The grey color indicates the parents' 1 chromosome that produces the first sequence grey column number to be offspring 1 and the second sequence of offspring 1 will be lowered by parent 2 which is in orange color. And also, the offspring 2 will be lowered by the first sequence of parent 2 and the second sequence will be lowered by parent number.

Parent 1	8	12	5	6	27	1	13	15	26	10	19
Offspring 1	8	12	5	6	27	1	13	15	21	17	9
Offspring 2	8	21	5	6	17	9	13	12	15	26	10
Parent 2	8	21	5	6	17	9	13	12	26	3	19

Table 7. Production Routing of Chromosome

From the table, offspring 1 is lowered by the first sequence of parent 1, the same strategy as the previous table. But in the second sequence the yellow color is lowered by parent 2 with a repairing strategy, which means that if in offspring 1 already had the same number in the first sequence, the GA will directly pass the number until it found the number that is not written before. it will be the same for the second offspring.

d. Mutation

The mutation is used to maintain the genetic diversity from one generation of a population of genetic algorithm chromosomes to the next.

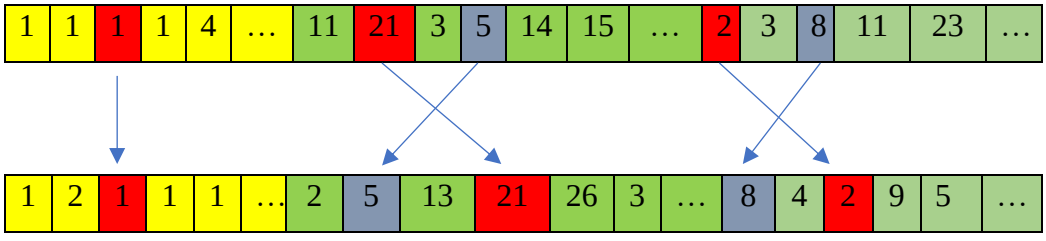
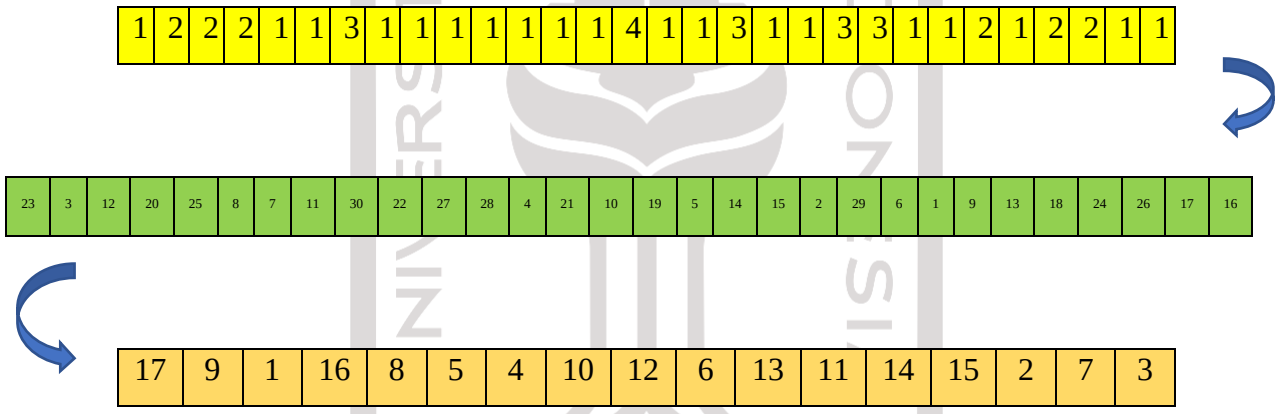


Table 8. Mutation of Chromosome

From the above is a chromosome that passes through mutation. The yellow color is part of routing production that mutated with the same number as the previous chromosome before it mutated called delta mutation. In the sequence of parts and the sequence of the machine, the swap mutation is conducted, in which two-locus will exchange with the next chromosomes.

After all the sequence of the GA programming with 20 populations of chromosomes repeated until 300 times. The GA found the best selection of chromosomes to create the cell of manufacture. The picture of the chromosome will be shown below:



4.3 Final Matrix

A sequence of parts and machines that have already been calculated that form a cellular manufacturing system will deliver the best routing system in which the machines has already grouped based on their similar function.

	17	9	1	16	8	5	4	10	12	6	13	11	14	15	2	7	3	
23	1	1	1															1
3	1	1	1															1
12	1	1	1															1
20	1	1	1															1
25	1	1	1		1													3
8				1	1	1	1											2
7					1	1	1											2
11				1	1	1	1											2
30				1	1	1	1											2
22				1	1	1	1											2
27								1	1	1	1	1						2
28								1	1	1	1	1						2
4									1	1	1	1						2
21									1	1	1	1						2
10								1	1	1	1	1						2
19								1	1	1	1	1						2
5								1	1	1	1	1						2
14							1	1	1	1	1	1						2
15							1	1	1	1	1							2
2								1	1	1	1	1	1					2
29													1	1	1	1		2
6											1		1	1	1	1		4
1													1	1	1	1	1	1
9													1	1	1	1	1	1
13													1	1	1	1	1	1
18													1	1	1	1	1	1
24													1	1	1	1	1	1
26													1	1	1	1	1	1
17												1	1	1	1	1	1	1
16														1	1	1	1	1
	1	1	1	4	2	2	4	4	2	2	4	6	2	1	1	1	1	90

Figure 6. Result of Cellular Matrix

The image above depicts the outcome of the matrix processed using GA. The green area represents the parts and machine arranged in a single cell layout, while the red area indicates that the machine must operate outside the cell to handle the parts. Alternatively, there are no parts processed by the machine within the cell.

CHAPTER V
DISCUSSIONS

5.1 Scheduling for the Formed Manufacturing Cells

In the previous chapter, the research method and the result have been explained. Two steps have been carried out simultaneously in the manufacturing cell formation, which are manufacturing process selection and based on the selected manufacturing process, the machines-cells grouping carried out. The machines-cells grouping considers only idle-machines and inter-cellular parts number, which is the main parameter in the manufacturing cells formation.

In the manufacturing cell formation, machines in every formed manufacturing cell will be arranged according to the flows of the layout in order to simplify the materials flow and could increase productivity. Therefore, job sequence is required to manage the job order to be processed in the machines with minimum *makespan*. In this study, job sequence is still not being considered in the manufacturing cell formation. It is commonly known that job sequence will affect the makespan, as illustrated in Figure 5.1.

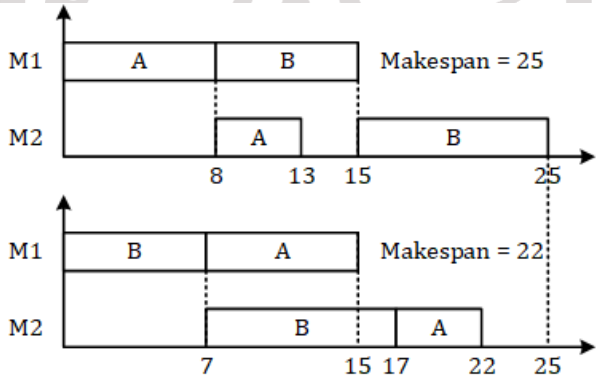


Figure 7. Illustration of Job Sequence that affects the Makespan

Figure 5.1 illustrates 2 jobs being processed in 2 serial machines (*flow shop*) with different processing times. There are 2 different job sequences with different

makespan. Therefore, it is recommended for further research to consider the job sequence to minimise the *makespan* when forming the manufacturing cells.

5.2 Reliability Analysis for the Formed Manufacturing Cells

In this study, the manufacturing cell formation did not consider the load of every machine. Sometimes, the load of the machines in a manufacturing cell is not balanced and it will generate work in the process in a bottleneck machine. The bottleneck phenomenon generates other problems such as increasing the probability of the work in process damage and required maintenance actions.

In a manufacturing system, reliability is required to ensure the production line is always ready for production. However, when a machine received a very high load due to the job assignment, the machine will be breakdown earlier and requires maintenance actions (corrective maintenance). Another maintenance action that can be taken is preventive maintenance, which also must be conducted earlier. Therefore, both maintenance actions require a longer time due to the machine load and it will lead to a longer makespan.

For further study, it is recommended to consider the machine's load to optimize maintenance activities that will be minimizing maintenance time as well as maintenance cost. These maintenance times and costs can be incorporated into the chromosome's fitness in the GA optimization. Therefore, the formed manufacturing cells will have higher performance.

5.3 Efficiency and efficacy test

5.3.1 Grouping efficiency

$\varphi = w\varphi_1 + 1 - w\ \varphi_2$

Where

φ = grouping efficiency

φ_1 = utilisation of the machines

φ_2 = inter-cell movement ratio

W = weight = 0.5 is recommended)

Answer

φ_1 = no of 1 in all cells / total no of 1 and 0 in all cells = 128 / 135 = 0.948

φ_2 = no of 0 in outside cells / total no of 0 and 1 in outside cells = 369 / 375 = 0.984

φ = 0.5 (0.948) + (1-0.5)0.984

φ = 0.474 + 0.492

φ = 0.966 = 96.6 %

5.3.2 Grouping efficacy

$\in = \frac{total\ no\ of\ 1\ in\ the\ matrix - no\ of\ 1\ outside\ cells}{total\ no\ of\ 1\ and\ 0\ in\ the\ matrix}$ x 100%

$\in$ = grouping efficacy

$\in = \frac{128}{510}$ x 100%

$\in$ = 0.251 x 100%

$\in$ = 25.1%

CHAPTER VI
CONCLUSION AND RECOMMENDATION

6.1 Conclusion

Based on the data processing and analysis conducted, the conclusion is:

1. There are several production routing of parts to choose. The GA generates the best production routing of the parts that have been explained in the form of chromosomes. The chromosomes produce 20 generations and picked just 1 the best chromosome to process the data.
2. The GA generates 4 cell manufacturing systems that are considered as the best routes of the product throughout the layout of the machine which of the layout is grouped into the similar function of the machine to ease the handling of materials.

6.2 Recommendation

For further study, it is recommended to consider the machine's load to optimize maintenance activities that will be minimizing maintenance time as well as maintenance cost. These maintenance times and costs can be incorporated into the chromosome’s fitness in the GA optimization. Therefore, the formed manufacturing cells will have higher performance.

REFERENCES

Agrawal, A. K., Yadav, S., Gupta, A. A., & Pandey, S. (2022). A genetic algorithm model for optimizing vehicle routing problems with perishable products under time-window and quality requirements. *Decision Analytics Journal*, *5*. https://doi.org/10.1016/j.dajour.2022.100139

Arufe, L., Rasconi, R., Oddi, A., Arias, R., & González, M. (2022). *Compiling Single Round QCCP-X Quantum Circuits by Genetic Algorithm* (pp. 88–97). https://doi.org/10.1007/978-3-031-06527-9_9

Asri, M. A. N. M., Nawi, M. N. M., Nadarajan, S., Osman, W. N., & Harun, A. N. (2016). Success factors of JIT integration with IBS construction projects- a literature review. *International Journal of Supply Chain Management*, *5*(2).

Brekkå, I., Randøy, S., Fagerholt, K., Thun, K., & Vadseth, S. T. (2022). The Fish Feed Production Routing Problem. *Computers & Operations Research*, *144*, 105806. https://doi.org/https://doi.org/10.1016/j.cor.2022.105806

Chen, Q., & Hu, X. (2022). Design of intelligent control system for agricultural greenhouses based on adaptive improved genetic algorithm for multi-energy supply system. In *Energy Reports* (Vol. 8, pp. 12126–12138). Elsevier Ltd. https://doi.org/10.1016/j.egyr.2022.09.018

Daneshparvar, M., & Beigzadeh, R. (2022). Multi-objective optimization of helical baffles in the shell-and-tube heat exchanger by computational fluid dynamics and genetic algorithm. *Energy Reports*, *8*, 11064–11077. https://doi.org/10.1016/j.egyr.2022.08.249

Desai, S., & Dingreville, R. (2022). Learning time-dependent deposition protocols to design thin films via genetic algorithms. *Materials and Design*, *219*. https://doi.org/10.1016/j.matdes.2022.110815

Gao, Y., Ma, C., & Wang, T. (2022a). Fault diagnosis for cooling dehumidifier based on fuzzy classifier optimized by adaptive genetic algorithm. *Heliyon*, *8*(12). https://doi.org/10.1016/j.heliyon.2022.e12057

Gao, Y., Ma, C., & Wang, T. (2022b). Fault diagnosis for cooling dehumidifier based on fuzzy classifier optimized by adaptive genetic algorithm. *Heliyon*, *8*(12). https://doi.org/10.1016/j.heliyon.2022.e12057

Garcia, L. G., & Lôndero, V. (2021). A parameter optimizer based on genetic algorithm for the simulation of carbonate facies. *Intelligent Systems with Applications*, *12*, 57. https://doi.org/10.1016/j.iswa.2021.20

Gazioğlu, E., & Etaner-Uyar, A. S. (2022). Experimental analysis of a statistical multiploid genetic algorithm for dynamic environments. *Engineering Science and Technology, an International Journal*, *35*. https://doi.org/10.1016/j.jestch.2022.101173

Ghadami, S., Biglarian, H., Beyrami, H., & Salimi, M. (2022a). Optimization of multilateral well trajectories using pattern search and genetic algorithms. *Results in Engineering*, *16*. https://doi.org/10.1016/j.rineng.2022.100722

Ghadami, S., Biglarian, H., Beyrami, H., & Salimi, M. (2022b). Optimization of multilateral well trajectories using pattern search and genetic algorithms. *Results in Engineering*, *16*. https://doi.org/10.1016/j.rineng.2022.100722

Hsu, W. H., & Xie, Y. Z. (2019). Design and manufacture of a novel sunlight guiding panel. *Coatings*, *9*(9). https://doi.org/10.3390/coatings9090562

Huang, T., Huang, J., Feng, M., Yi, D., Chen, X., Ou, C., Zhang, J., Zhang, Y., & Wan, Z. (2022). Optimization of the thickness of catalytic layer for HT-PEMFCs based on genetic algorithm. *Energy Reports*, *8*, 12905–12915. https://doi.org/10.1016/j.egyr.2022.09.111

Jafari, M., & Yari, S. (2022). Optimal thermal design of anisotropic plates with arbitrary cutouts using genetic algorithm. *Theoretical and Applied Mechanics Letters*, *12*(3). https://doi.org/10.1016/j.taml.2022.100343

Kaedi, M., Bohlooli, A., & Pakrooh, R. (2022). Simultaneous optimization of cluster head selection and inter-cluster routing in wireless sensor networks using a 2-level genetic algorithm. *Applied Soft Computing*, *128*, 109444. https://doi.org/https://doi.org/10.1016/j.asoc.2022.109444

Li, J. C. F., Zimmerle, D., & Young, P. M. (2022). Flexible networked rural electrification using levelized interpolative genetic algorithm. *Energy and AI*, *10*. https://doi.org/10.1016/j.egyai.2022.100186

Li, Y., Chu, F., & Chen, K. (2017). Coordinated Production Inventory Routing Planning for Perishable Food. *IFAC-PapersOnLine*, *50*(1), 4246–4251. https://doi.org/10.1016/j.ifacol.2017.08.829

Mcclelland, J. L. (n.d.). *A General Framework for Parallel Distributed Processing Simulating N400 amplitudes with neural network models View project Neural network modeling View project*. https://www.researchgate.net/publication/243672900

Rawlins, G. (1991). *Foundations of Genetic Algorithm* (Vol. 1).

Singh, N., & Rajamani, D. (1996). Introduction to design, planning and control of cellular manufacturing systems. In *Cellular Manufacturing Systems*. https://doi.org/10.1007/978-1-4613-1187-4_1

Wei, W., & Chuan, J. (2022). A combination forecasting method of grey neural network based on genetic algorithm. *Procedia CIRP*, *109*, 191–196. https://doi.org/10.1016/j.procir.2022.05.235

Xu, G., Wei, H., Xue, S., Wang, J., & Li, Y. (2022). Predicting wave forces on coastal bridges using genetic algorithm enhanced ensemble learning framework. *Ocean Engineering*, *266*, 112963. https://doi.org/https://doi.org/10.1016/j.oceaneng.2022.112963

Yixuan, W. (2022). Indoor Optimal Design of Building Renovation Environment Space Layout Based on Genetic Algorithm. *Procedia Computer Science*, *208*, 539–545. https://doi.org/10.1016/j.procs.2022.10.074

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