Eksplorium *p*-ISSN 0854-1418
Volume 46 No. 2, June 2025: 933–954 *e*-ISSN 2503-426X

Optimization of Process Design Time in a Distributed Multi-Factory Environment Using Genetic Algorithms to Organize the Process and Support the Development of Technical Designs for Part Production Based on Information Available in the Production Database and Process Mining

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Article Received: 18 May 2025, Revised: 15 June 2025, Accepted: 25 June 2025

Abstract: Today, with the increase in the power of computers in storing and processing data, as well as the advances made in the field of information technologies, especially artificial intelligence, the facilities and capabilities of CAD systems have increased significantly. In the fundamental approach, the process design is created based on the information available in the production database and process mining. In this approach, the process design system operates in the form of knowledge-based systems and artificial intelligence, and in some cases as a DSS system, in order to automate the design, and by receiving information about the details of the desired part, the types of production operations available and their capabilities in terms of accuracy and tolerance, experience related to previous parts, etc., it designs the appropriate process for the part. These systems have been created for the production process of parts that were previously carried out by specialists in manufacturing methods. These systems are very important in terms of integration. The outputs of a process design system include: selecting the appropriate operations and determining the sequence of these operations on the part, selecting the necessary machines to perform the operations, determining the tools and fixtures, as well as the operating instructions for adjusting the machine, the path of the tools, the operation parameters such as speed, duration, load, etc. Of course, it should be noted that since the planning and design of the parts manufacturing process is very dependent on the experience and judgment of the planners, automating all of the aforementioned activities is a very difficult task and most of the existing process design systems are not capable of performing all of the above activities, but in most cases they can only provide decision support services. In a distributed industrial environment, different factories with different machines and tools in different geographical locations are often combined to achieve the highest production efficiency. Process designs may differ due to different resource constraints. Therefore, obtaining an optimal or near-optimal process design seems important. In other words, it is necessary and essential to determine which factory and with which machines and tools each product should be produced. For this purpose, it is necessary to choose a design from different designs that minimizes the cost of producing products while being possible. In this research, a genetic algorithm is introduced that can quickly search for the optimal process design for a single manufacturing system as well as a distributed manufacturing system according to predetermined criteria such as minimizing the process time. This research presents an emerging genetic algorithm for process design with the help of data obtained from process mining that has a successful application in a traditional and distributed multi-factory environment. The application of genetic algorithm for a distributed multi-factory environment in distributed manufacturing systems was developed based on the geographical distribution of manufacturing machines and tools. It can produce an optimal or near-optimal process design compared to other main approaches for single-product manufacturing. The most suitable manufacturing plant can be established when the distributed manufacturing problems are considered. Furthermore, this approach is able to perform multiple optimization objectives based on the lowest production cost or the shortest production time. Based on the selected objectives, near-optimal solutions can be obtained by using genetic algorithm. Through experiments, it has been shown that the developed techniques are better or comparable to other systems in a distributed multi-factory environment.

Keywords: Computer-aided process organization, genetic algorithm, distributed industrial environment, computer-integrated manufacturing.

1-INTRODUCTION

Today, the use of information technology can be clearly seen in education, management and organization, medicine, business, military affairs, manufacturing and industry, research, transportation, traffic control and the publishing industry. The search for a better way to produce parts has always been the driving and fundamental factor in automation (1). Computer-integrated manufacturing is a type of technology that can be associated with and guided by any industry, meaning that each industry provides special conditions for computer-integrated manufacturing according to its own set of experiences, needs and situations. Hence, there are different definitions and descriptions for it. Below are some examples of the descriptions made (2). An integrated computer system involves the comprehensive and systematic computerization of the manufacturing process. Such systems integrate activities such as computer-aided design, computer-aided manufacturing, computer-aided engineering, testing, repair, and assembly using a common database (3,4,5,6). With a little more attention to the descriptions and perspectives mentioned above about integrated computer manufacturing, one can understand the role and importance of information and information technologies in realizing an integrated computer manufacturing system. In other words, it can be said that this system has emerged and expanded as an important activity alongside information technology during the development of information technology (7). To examine the role of information technology in this system, it is best to first clarify the aforementioned perspective. As Harn, Brown and Shionan point out in their book, the understanding of this system depends on the empirical background and the perspective of the individuals towards it. Hence, there are different attitudes and perspectives regarding it, some of which they have mentioned in their work. What is taken as the criterion here is the view that Harn and his colleagues themselves have presented about this system. This view, shown in Figure 1, seems to be the most appropriate view among the existing views in terms of comprehensiveness and systems perspective(8). Communication indicates the integrity of the set of operations and also indicates the closed loop of information feedback. In summary, it can be said that computer integrated production means the integration of automation islands related to administrative-financial operations, engineering support, production management and operations related to the executive level. This process is carried out by means of computer communications and data storage facilities (9).

In the past, the design of parts and products was done manually using large tables and drawing tools, and the drawings were often drawn on paper. For this reason, the designs were generally time-consuming and troublesome. Also, in the event of a mistake in drawing or a change in the design, correcting and redrawing the drawings took up a lot of time. This problem was more evident in cases where the product had numerous and complex parts. Maintaining and caring for the drawings was another issue that required a lot of space and also took a significant amount of time for coding, archiving and retrieving. However, these drawings only represented the geometric shape and position of the parts relative to each other, and that too in two dimensions (10).

Today, with the increase in the power of computers in storing and processing data, as well as the advances made in the field of information technologies, especially artificial intelligence, the facilities and capabilities of CAD systems have increased significantly. Today's advanced CAD software has provided the designer with the possibility of creating solid three-dimensional models. These software, by making extensive use of artificial intelligence techniques and thanks to the expert systems embedded in them, also have the ability to analyze designs. For example, they are able to calculate and determine the mass of the design, the volume of the design, and the center of gravity of the parts (11). They can examine the contact point or interface of assembled parts and analyze the mechanical properties of the parts such as stress or heat flow. Some of these software can also study the movement of parts, and others can determine the points and times of inspection of the part. They even create a database required for product production. The database includes all information related to the product from a design perspective, from geometric information, parts and materials lists, material specifications, etc. to additional information required for production. Current powerful CAD systems also have the ability to exchange information with database systems and transfer data to other manufacturing software, which has significantly increased their efficiency (12). Another of the process mining islands created in the field of manufacturing is the computer-aided process design system. These systems have been created to automate the design of the production process of parts that was previously done by manufacturing methods specialists. These systems are very important in terms of integration because they are one of the key points in creating a connection between CAD and CAM. (13) The outputs of a process design system include: selecting appropriate operations and determining the sequence of operations on the part, selecting the necessary machinery to perform the operations, determining the tools and fixtures, as well as the operating instructions for adjusting the machine, the path of the tools, the operation parameters such as speed, duration, load, etc. Of course, it should be noted that since the planning and design of the part manufacturing process is very dependent on the experience and judgment of the planners, automating all of the aforementioned activities is a very difficult task and most of the existing process design systems are not capable of performing all of the above activities, but in most cases they can only provide decision support services (14). The role of information technology in the process design system and process mining is also very evident. In general, there are two approaches in the development of these types of systems: 1 - the improvement or diversified approach; 2 - the generative or fundamental approach. In the improvement approach, which is based on the use of group technology and classification and coding tools, a master composite part is used to represent the range of manufacturing shapes in a family. Whenever the system identifies a new part as a member of a particular family, the process design of the composite part of that family is modified in such a way that it can create the process design of the new part. In this approach, the system uses part classification techniques to determine the shape of the parts and matches them with the corresponding shapes in the master parts (15). In the fundamental approach, the process mining design is created based on information available in the manufacturing and process mining database. In this approach, the process design system operates in the form of knowledge-based systems and artificial intelligence, and in some cases as a DSS system, and by receiving information about the details of the desired part, the types of manufacturing operations available and their capabilities in terms of accuracy and tolerance, experience with previous parts, etc., it designs the appropriate process for the part. In a distributed industrial environment, different factories with different machines and tools in different geographical locations are often combined to achieve the highest production efficiency. When producing different parts and products, process designs are produced by the existing factories. These designs include the type of machine, equipment, and tools for each operational process necessary to produce the part. Process designs may differ due to different resource constraints. Therefore, obtaining an optimal or near-optimal process design seems important. In other words, determining which factory and with which machines and tools each product is produced is necessary and essential. For this purpose, a design should be selected from among the various designs that minimizes the cost of producing products while still being possible (16). In this section of the research, a genetic algorithm is introduced that, according to predetermined criteria such as minimizing the process time, can quickly search for the optimal process design for a single manufacturing system as well as a distributed manufacturing system. Using the genetic algorithm, computer-aided process planning can create optimal or near-optimal process designs based on the considered criteria, and case studies clearly demonstrate the feasibility and robustness of the method. This work is carried out using the genetic algorithm in CAPP in both distributed and connected manufacturing systems. Case studies show that this method is similar to or better than conventional single-factory computer-aided process planning. After providing a summary of the work, we will describe the method in the following sections of the research (17). In the fundamental approach, the process mining design is created based on the information available in the production and process mining database. In this approach, the process design system operates in the form of knowledge-based systems and artificial intelligence, and in some cases as a DSS system, and by receiving information about the details of the desired part, the types of manufacturing operations available and their capabilities in terms of accuracy and tolerance, experience with previous parts, etc., it designs the appropriate process for the part. In a distributed industrial environment, different factories with different machines and tools in different geographical locations are often combined to achieve the highest production efficiency. When producing different parts and products, acceptable process designs are produced by the existing factories. These designs include the type of machine, equipment and tools for each operational process necessary to produce the part. Process designs may differ due to different resource constraints. Therefore, obtaining an optimal or near-optimal process design seems important. In other words, it is necessary and essential to determine in which factory and with which machines and tools each product should be produced. For this purpose, it is necessary to choose from among the different designs a design that minimizes the cost of producing the products while being possible (18). In this part of the research, a genetic algorithm is introduced that, according to predetermined criteria such as minimizing the process time, can quickly search for the optimal process design for a single manufacturing system as well as a distributed manufacturing system. Using the genetic algorithm, computer-aided process organization can create optimal or near-optimal process designs based on the considered criteria, and case studies clearly show the feasibility and robustness of the method. This work is carried out using the genetic algorithm in CAPP in both distributed and connected manufacturing systems. Case studies show that this method is similar to or better than the conventional computer-aided process organization of a single factory. After providing a summary of the work, we will describe the method in the following parts of the research (19). Increasing product variety, customer-oriented product and shortest lead times are the controversial points for a manufacturing plant. Existing manufacturing systems cannot adequately adapt to these needs. Due to their inflexible and fixed methods of decision making and the existence of these systems in a highly variable environment, it seems necessary to change the manufacturing system from the status quo to a new perspective in order to avoid facing various challenges. Several approaches have been developed such as compact factory, superhuman manufacturing systems, holonic manufacturing systems, distributed manufacturing systems, etc.(20,21) Further research and study have proven that distributed manufacturing enables marketers to achieve superior production quality, lower production cost and reduce management risk. This research aims to develop a genetic algorithm to solve the problem of computer-aided process organization based on the category of distributed manufacturing (22,23). A distributed industrial environment creates a high degree of complexity where there are different process design options. Obtaining an optimal or near-optimal process design is a difficult task for the manufacturing research group. Traditional CAPP systems aim to achieve optimal machine processes by limiting the machines and tools suitable for performing a specific manufacturing operation to the production resources available in a factory. However, in a distributed manufacturing environment, there are different factories to perform a specific production, and one of them may produce a better and more efficient process design. Therefore, the development of a CAPP system that can produce better process designs in a distributed manufacturing environment is the main objective of the present study. The complex nature of manufacturing systems and the difficulty of optimizing them necessitate the use of evolutionary algorithms that follow living systems in obtaining optimal solutions. In this study, the genetic algorithm is chosen to solve the optimization problem. The mechanized process design is based on the genetic algorithm. However, most of the reported works and case studies have dealt with the process design of a single factory that produces parts under certain conditions and a specific manufacturing environment.

2-PROCESS MINING

Process mining is a relatively young, simple technology, and is essentially a data-driven process management approach. Despite its young age, its benefits and potential have been widely accepted in organizations and businesses of all sizes. Awareness of the technology has also been increasing worldwide since the publication of the Process Mining Manifesto by leading academic experts in the field in 2011 (16). Organizations that have used process mining tools and software have achieved an understanding of their processes that they have never experienced before. But how can such great results be achieved?

Today's organizations rely on a variety of information systems to support their business activities. Whether it is an ERP system to track manufacturing processes or a CRM system to coordinate sales and customer service processes, it is difficult to find a process today that is not supported by an IT system. These systems continuously collect large amounts of data (for example, data from every time a purchase order is placed or a service is delivered), or the digital footprint of a business process (25). In a typical organization, this results in thousands of events being recorded every day. Worthless information that is simply recorded every day. This is exactly where process mining comes in. Process mining uses data collected by IT systems (so-called event logs) to analyze the process in detail. Unlike traditional, intelligent business intelligence approaches, this not only reveals weaknesses, but also allows the user to find the cause of the problem. With the help of process mining tools, organizations can move away from the judgment-based approach to business process management (BPM) and move towards a data-driven approach, making fundamental changes based on real-time data. (26)

Process mining allows organizations to monitor, analyze, and improve their business processes with extraordinary accuracy. The true process model is easily revealed and monitoring process KPIs is easier than ever. The four functions of process mining are based on various analyses of event logs, which we will read together below. (27)

Figure 1 - Process mining

3- COMPUTER-AIDED PROCESS PLANNING

One of the applications of the computer is related to supporting the creation and development of technical designs required for the production of a part. In the terminology, this application is called Computer Aided Process Planning. This application is very important in terms of integration, because it is one of the key points in establishing the connection between CAD and CAM.

Automating all process planning activities is a difficult task that should not be underestimated. For this reason, computer-based systems are often unable to perform all of the above activities. In fact, existing CAPP systems can only provide decision support services in most of the above cases. In general, there are two approaches to developing CAPP systems (20):

The Diversified (or Improvement) Approach

The Generative (or Fundamental) Approach

3-1- Diversified Approach

In the diversified (or improved) approach, a standard or similar part design is used to prepare a process design. In the improved process design approach, a composite part is used to represent the range of production shapes in a family, and then a composite process design is developed for that composite part. In simpler terms, whenever a new part is identified as a member of a particular family, the composite process design of that family is modified in such a way that it can create the process design for that new part. The improved approach is widely used in practice, despite some important disadvantages. It is clear that only parts can be designed that are within the range of the existing part variety. Also, experienced designers in the field of process design are needed to carve out and modify the composite process design and to add the necessary details to it. Another approach tries to overcome some of these disadvantages, this approach is known as fundamental or generative process design.

3-2- Fundamental Approach

In the fundamental approach, the process design is created based on information available in the production and process mining databases. The requirements of this approach include a detailed description of the part, the types of manufacturing operations available, and the capabilities of the operations in terms of process accuracy, tolerances, etc. For example, in the field of machining, this system examines all the surfaces of interest and compares the tolerances of these surfaces with the tolerances achievable by the existing process. If the existing process is capable of achieving the desired tolerance, then that process may be used to create the surface. Otherwise, the process is eliminated from further consideration (22).

Assembly process planning support systems, which act as intelligent decision support systems (DSS), effectively leave the final decision on the selection of operations to the process designer. Developing a multi-stage design system is another way to plan the assembly process. The system is capable of detecting the contact points of parts, assessing the possibility of moving assembly parts, providing an analysis of the degree of accessibility of parts, selecting basic parts, and finally determining the sequence of assembly operations.

4- PROPOSED SYSTEM MODULES A METHOD FOR PROCESS ORGANIZATION USING GENETIC ALGORITHM

Computer-aided process organization is an important intersection between computer-aided design (CAD) and computer-aided manufacturing (CAM) in computer-integrated manufacturing (CIM). The development of the pre-programming module, as part of the CAPP system, is described. Pre-programming leads to a sequence at the form-form level (22).

In manufacturing systems, the process processing for a new part is automatically created and information is combined. For this purpose, the logical circuit is built inside the computer system in the form of a tree, table, system based on expert system, etc. (21).

These include process organization, operation selection, and sequence existence with two main tasks: selection of an operation based on the geometric form of the underlying process, which is the technological requirements, and mapping of these specifications to a specific operation or set of operations. The development of a graph theory for sequence operations was divided by Sundaram. In another work, the elimination of unsuitable sequences of operations and the use of three structures for counting all paths to separate the unsuitable sequences were reported. After analyzing the technological requirements and optimizing them, Rho based the sequence operations on the scale of tool cutting changes and tool travel time, and used the superiority matrix. The possibility of alternating sequences with available resources was not discussed in their paper. Irani used a Hamiltonian path analogy based on the preferred graph and the performance matrix for the process organization problem (20).

The most prominent of their research work is the use of heuristic or Arvind-like suggestions for the random generation of alternating sequences. Mr. Vaneza developed a genetic algorithm (GA) that had elements in each string corresponding to the shape states generated by the machine functions. It was reported that the use of mutation and merging operators resulted in about 10% of unsuitable sequences in the operators that had preferred elements. Messrs. Hip, Dutta and Dutta used a new coding strategy in GA for the sequence of machine-aligned functions, which used combinations of work-preserving and tool-preserving interactions.

In order to properly examine the problem of process organization, we can divide it into two parts: the primary and the secondary. The primary stage involves the sequence of form shapes, their geometry and their internal dependencies. The secondary and secondary levels of organization are related to the fabricated information such as operations, machine tools, cutting tools, operation sequences and fixed processing for the given part. This research also showed a trend towards CAPP-derived shapes. In a fully automatic process organization system, the shape interpretation is done from the CAP database. However, different interpretations may be created depending on the specific area such as design, machine, assembly, inspection, etc. Extensive research is being done to develop area-dependent schemas. An infallible method that can completely replace human intelligence is still being developed. For process organization, the existence of structural shapes is required. This plan should include a description of the composition of the shapes and their internal dependencies. In this work, active use is made of a purpose-adapted modeler.

In this work, the details of the preliminary organization method of rotating components with C-axis shapes were given. As the sequences can be obtained quickly, a proposal can be effectively used by a process organization with appropriate and alternating sequences to obtain a functional environment.

4.1- Modules of the proposed CAPP system

The modular structure of the proposed CAPP system is given in Figure 2-3, which is divided into preliminary planning and part planning (as shown by the broken lines). Preliminary planning includes the sequence at the form level that is not dependent on resources. Part planning includes the selection of operations, machine tools, cutting tools, the sequence of operations at the process level, and the optimization of machine parameters in production. The input base of any CAPP system is part information. In the absence of a CAD modeler that creates forms with geometric construction (shape, dimensions, etc.) and technological information (tolerance, surface smoothness, etc.), the user interface for form forms and their dependencies is expanded. The user activity causes the entry of details from the engineering drawing of the part. The system also creates a priority graph (FPG) using precedence and delay diagrams. There is an integrated research strategy in the system that includes 3 paths of research and generates suitable initial sequences. These sequences are optimally organized and include: shape proximity, shape preservation and shape reference. In the next phase, part planning has the ability to produce form forms based on geometric and technological requirements. Machine tools and cutting tools that can produce functions are implemented by a system from the machine tool database of the tool base information. After the selection of machines and cutting tools, the functions at the level The process is sequenced and the optimal cutting parameters are determined. Finally, the system produces a process that has a number of tabulated operations, operation descriptions, machine tools, cutting tools, and cutting parameters for each operation.

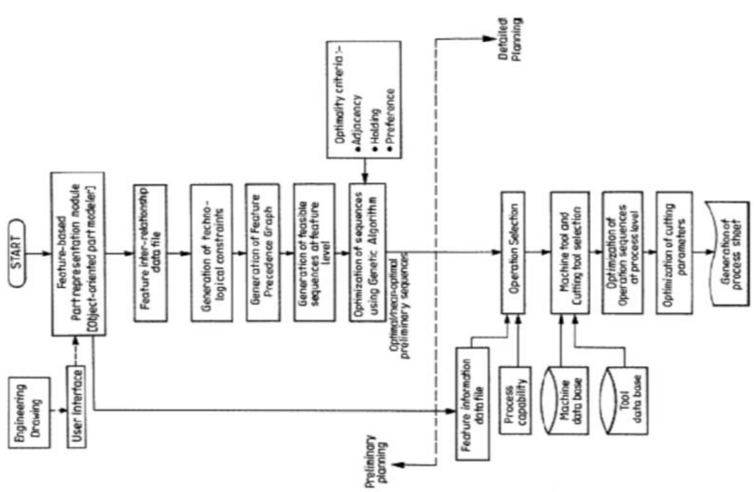


Figure 2- Proposed CAPP diagram

3.2- Visualization and storage of geometric and technological information

The system interacts with the user and technological information, geometric, related to each form. The classification of form classes (radial, axial hole, keyway, etc.) exists in the primary forms and details are added to this section. They are defined depending on the primary form. The term C-axis form is used in work that has a coordinated NC system and represents a set of forms that require additional control of the axis direction and the rotating tool that exists in the CNC center. The model of primary, secondary and C-axis forms was proposed in a parametric manner. Each form represented an example that existed as a form class among the part modelers (cylindrical, thread, radial hole). The number of data points across categories is shown in Figure 4. Figure 3 shows the classification of form shapes as primary, secondary, or C-axis shapes. Primary shapes (cylindrical, funnel-shaped, planar) give the section an overall shape. Both secondary shapes and C-axis shapes)cavity.

```
Class form_feature {
        protected:
                char name[15];                    // cylinder, cone, keyway,....
                char type[15];              // external or internal
                char subtype[15];                 // primary or secondary
                float ref_length;
                float pos_ref_tol;
                float neg_ref_tol;
                float surface_finish;
                geometric_tol  g_tol[ ];
        public:
                form_feature( );
                virtual void select_oprn( );
                virtual void print( );
                ........
};
class cylinder  :  public form_feature  {
        private:
                float length;
                float pos_len_tol;
                float neg_len_tol;
                float diameter;
                float pos_dia_tol;
                float neg_dia_tol;
                ......
        public:
                cylinder ( );
                void select_oprn( ) ;
                void print ( );
};
class cone  :  public form_feature  {
        private:
                float length;
                float pos_len_tol;
                float neg_len_tol;
                float major_dia;
                float minor_dia;
                ......
        public:
                cone ( );
                void select_oprn ( );
                void print ( );
};
```

Figure 3 - Structure within each form shown

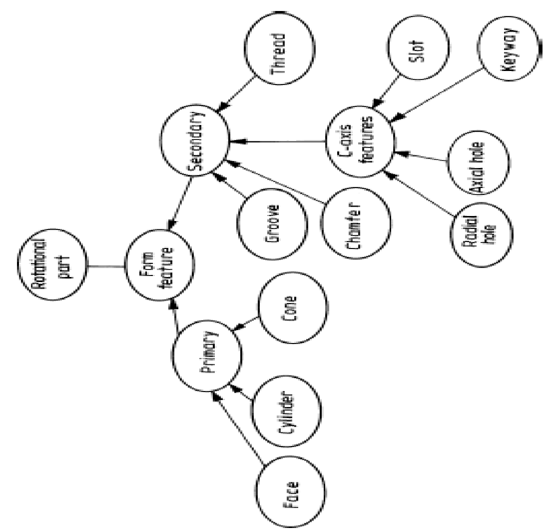


Figure 4 - Hierarchical structure of typical form features

It is quite obvious that the data is less general than the form class as a cylindrical, thread or radial hole class. For example, the form class contains data that is common to all forms of the form (shape feature, name, tolerance, surface finish, etc.). The cylindrical class contains data that is dependent on the form shape. (diameter, length, etc.) Each form class contains a guide that is considered as a reference for the form or forms. Each primary form contains a guide for secondary forms, and each secondary class will have a guide for its primary form. All this information is necessary to generate the appropriate requirements. Also shown in Figure 2-5 is the structure within each form that defines the procedure for selecting the function or sequence of operations. To produce a form with all technological features such as shape and dimensional tolerances (strategic, flat, rotational and cylindrical) and surface smoothness, the information is only needed at the part organization stage.

4.3-Generating Possible Sequences

In the preliminary organization, the emphasis is on the correct sequence of the shape process rather than the selection of the exact operation, machine, cutting tool, etc. To this end, a significant degree of abstraction is required for the shape process. The program abstraction basically generates a process shape, for example a hypothetical process for an external cylinder, the machines that operate may include: lathe motor, lathe head or wheel clamp, CNC lathes and CNC turning center. Also, a number of machine functions may be required to create the shape.

- Priority requirements

The priority requirements are shown in Figure 5. Before shape a is made, shape b cannot be machined. In other words, the machining of shape a must take precedence over the machining of shape b. Priority requirements can be classified based on location, accessibility and non-destructive requirements as previously reported.

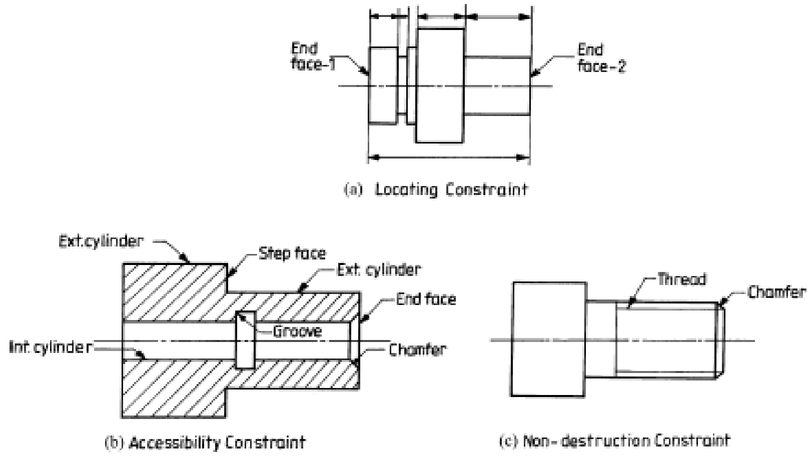


Figure 5 - Examples of Priority Requirements

4-4-Optimization using GA genetic algorithm

GA is an intelligent search method that requires a specific domain to solve the problem. The natural evolution of generations in GA is done by combining the most suitable generations randomly and changing information and producing children. In GA, the selected solution is the existence of members known as chromosomes or strings. In this case, each element (gene) in the string (chromosome) has a process form. The order of elements in the string indicates the sequence of different processes. The set of chromosomes is called the population and the population produces generations over time. The size of the population is maintained constant from generation to generation, which has a significant impact on the performance of GA. The judicious selection along with the appropriate sequences of genes using the relationship of activities and their precedence and backwardness creates the strings and causes the creation of the initial population, and the size of the initial population is determined by the user depending on the number of elements in the string and the complexity of the problem. This size is one to two times the elements in the strings. Table 3 shows the initial population.

Table 1 - Details for the sample fragment

	Features
Set 1	1, 2, 8, 9, 12, 14, 15, 19
Set 2	3, 4, 5, 6, 7, 10, 11, 13, 16, 17, 18

Table 2 - Priority and proximity patterns

djacency and preference templates	
djacency	
Template 1	1, 2, 19
Template 2	3, 4, 5, 6
Template 3	17,18
eference	
Template 1	1, 2, 19, 9, 8, 12, 15, 14
Template 2	6, 7, 3, 5, 4, 13, 10, 11, 16, 17, 18

Table 3 - Initial sequences

Initial population, fitness function and count

String no.	String	Total score (u)	Fitness value ($f = u_{\max} - u$)	Expected count ($E = f/f_{\text{ave}}$)	Actual count (C)
1	6 → 5 → 10 → 7 → 13 → 11 → 16 → 17 → 3 → 4 → 18 → 1 → 8 → 12 → 2 → 15 → 14 → 19 → 9	29	6	0.882	1
2	6 → 7 → 16 → 17 → 5 → 10 → 18 → 3 → 4 → 13 → 11 → 1 → 9 → 8 → 12 → 2 → 15 → 14 → 19	34	1	0.147	0
3	6 → 7 → 3 → 16 → 17 → 5 → 10 → 4 → 13 → 11 → 18 → 1 → 8 → 12 → 9 → 2 → 19 → 15 → 14	31	4	0.588	1
4	6 → 16 → 18 → 17 → 3 → 7 → 5 → 10 → 13 → 11 → 4 → 1 → 2 → 19 → 9 → 8 → 12 → 15 → 14	20	15	2.206	2
5	6 → 5 → 10 → 13 → 11 → 7 → 16 → 17 → 18 → 3 → 4 → 1 → 2 → 15 → 14 → 8 → 12 → 19 → 9	21	14	2.058	2
6	6 → 3 → 7 → 5 → 4 → 10 → 16 → 18 → 13 → 11 → 17 → 1 → 8 → 12 → 9 → 2 → 15 → 14 → 19	31	4	0.588	1
7	6 → 16 → 17 → 3 → 7 → 5 → 10 → 13 → 11 → 4 → 18 → 1 → 9 → 8 → 12 → 2 → 19 → 15 → 14	35 ($u_{\max}$)	0	0.000	0
8	6 → 3 → 16 → 18 → 17 → 7 → 5 → 13 → 4 → 10 → 11 → 1 → 8 → 12 → 9 → 2 → 19 → 15 → 14	27	8	1.176	1
9	6 → 7 → 3 → 5 → 10 → 13 → 11 → 4 → 16 → 17 → 18 → 1 → 9 → 8 → 12 → 2 → 15 → 14 → 19	28	7	1.029	1
10	6 → 5 → 10 → 13 → 11 → 16 → 17 → 18 → 7 → 3 → 4 → 1 → 9 → 2 → 19 → 8 → 12 → 15 → 14	26	9	1.323	1

In this study, a PMX operator is modified and used to generate a suitable child. The merging is done with a probability called the merging probability (PCROS). Only strings that fall within this probability range are merged. In generating a suitable child, two parents are randomly selected from the population, which is randomly generated based on the length of the string (number of elements in the string), the merging location (point). The child, child 1, is generated by ordering the elements of the selected part according to the other parent and then taken from the first parent while maintaining the order of the first part. The role of these parents is then changed to generate another child, child 2. The merge operator can be described as follows:

Choose 2 strings randomly from the population as parents 1 and 2:

Parent 1: [1,2,3,4,5,6,7]

Parent 2: [8,2,1,4,5,6,7,3]

The merge point is randomly set to X=3 and the part of parent 1 from the merge point to the end of the string is considered.[4,5,6,8,7]

Arrange the selected elements according to parent 2 and obtain [8,4,5,6,7]

Then the child, child 1, of parent 1 is produced as the opposite:[1,2,3,8,4,5,6,7]

The merge process for practical sequences is well illustrated in the example problem in Table 2-13.

The strings obtained after merging and mutation may deviate from the requirements in the previous section for generating suitable sequences checked. To prevent this, a new operator causes the elements of the resulting string to be properly checked. If any element of the string exceeds the constraints, the string is unsuitable and receives a high total score that cannot be passed to the next section.

The chromosomes resulting from these three operators, called transcription, crossover, and mutation, are often referred to as offspring, and these form the population of the next generation. This process is repeated for the required number of generations, usually until the system reaches a point where the execution sequences are significantly improved.

The GA variable parameters are: population size 25, merger probability 0.9, mutation probability 0.01, and number of generations 100.

The alternate optimal/near-optimal sequences are shown in Table 2-15 along with their scores.

Table 4-Optimal/Near-Optimal Sequences

Sequences	Score
6→7→3→5→4→13→10→11→16→17→18→1→2→19→9→8→12→15→14	11
6→3→5→4→10→13→7→16→18→17→11→1→2→19→9→8→12→15→14	12
6→5→3→4→13→16→17→18→7→10→11→1→2→19→9→8→12→15→14	12
6→3→5→13→16→17→18→7→10→4→11→1→2→19→9→8→12→15→14	14
6→5→7→13→3→4→16→17→18→10→11→1→2→19→9→8→12→15→14	15
6→7→3→5→4→13→16→18→17→10→11→1→2→19→15→14→9→8→12	16
6→3→16→18→17→7→5→13→4→10→11→1→2→19→9→8→12→15→14	16
6→5→3→7→13→10→11→4→16→17→18→1→2→19→9→8→12→15→14	16

Table 5 - Integration Process

String no. (parent 1)	Crossover?	Mate (i.e. parent 2) string no.	Site	Offspring (child)
1	Yes	4	8	6→5→10→7→13→11→16→17→18→3→4 →1→2→19→9→8→12→15→14
2	No	–	–	6→7→3→16→17→5→10→4→13→11→18 →1→8→12→9→2→19→15→14
3	Yes	8	14	6→16→18→17→3→7→5→10→13→11→4 →1→2→19→8→12→9→15→14
4	No	–	–	6→16→18→17→3→7→5→10→13→11→4 →1→2→19→9→8→12→15→14
5	Yes	6	9	6→5→10→13→11→7→16→17→18→3→4 →1→2→15→14→8→12→19→9
6	Yes	3	4	6→5→10→13→16→18→17→3→7→11→4 →1→2→19→9→8→12→15→14
7	No	–	–	6→3→7→5→4→10→16→18→13→11→17 →1→8→12→9→2→15→14→19
8	No	–	–	6→3→16→18→17→7→5→13→4→10→11 →1→8→12→9→2→19→15→14
9	Yes	2	11	6→7→3→5→10→13→11→4→16→17→18 →1→8→12→9→2→19→15→14
10	No	–	–	6→5→10→13→11→16→17→18→7→3→4 →1→9→2→19→8→12→15→14

5-PROPOSED ALGORITHM FOR APPLICATION OF GENETIC ALGORITHM IN DESIGN IN INDUSTRIAL ENVIRONMENT

5-1-Genetic Algorithm

- Distributed Manufacturing Systems

As shown in Figure 3-1, in a distributed manufacturing environment, various tools and machines of factory processes are in different geographical locations, and different production capabilities are selected to obtain the highest production efficiency. When the decision is made to produce different products and parts. Acceptable process designs are produced by existing factories according to the relationship between different operations of producing that part or product. The production operation can be performed by different machines and tools located in different locations. The final optimal or near-optimal process design will be obtained after comparing all the process designs of the part or product.

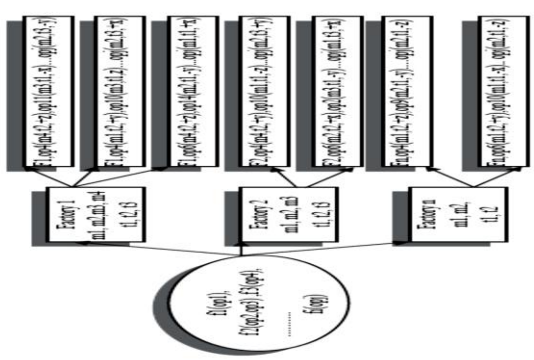


Figure 6. The proportion of a distributed production system

- Display process designs:

When dealing with a distributed production system, a chromosome does not only show the sequence of operations, but in addition to the factory where the process plan is out of place. Therefore, the factory identification number will be placed as the first gene of each chromosome and it does not matter that other genes are arranged irregularly. Other genes show the operation and machine identification number and tools and tools (TAD). As a result, a process layout will be displayed by a random set of genes. Figure 3-2 shows the process of the process of six operations. ID '001' the factory. OP4 shows Operation 4. M-02 and T-04 and +X in the second column, respectively, the tools and tools and tools of the tool

	Op4	Op1	Op5	Op6	Op3	Op2
001	m-02 t-04 +x	m-03 t-02 -y	m-02 t-03 +z	m-01 t-02 -x	m-03 t-01 +x	m-01 t-04 -y

Figure 7- An example of a process design

- the initial population:

Production of the primary population in the genetic algorithm is typically done by random, however, the initial population must include the stages of producing a piece along with the sequence of operations. Given that the number of chromosomes is given the initial community. The method of creating an early communion is as follows:

1- Randomating ID of a factory from the list of existing factories.

2- Randomly select an operation that has no suggestions.

3. Randomly selection of operations that do not require or previously selected from the remaining operation.

4- Repeat Step 3 until all operations are selected only for once (for the first time we are selected).

5. Re-inspect the first selected operations.

6. Randomly selected machines and tools from the selected plant that can be used for construction operations.

7. Randomly select a path from all possible routes to access tools.

8. Repeat Steps 6 and 7 until each operation of a machine is allocated to the tool and tool access (TAD).

9. Repeat steps 1 to 8 until the chromosome number is obtained.

-Production like:

A genetic search begins with randomized primary population. Subsequent generations are manufactured using genetic algorithm operations. This generation of generation eventually leads to a generation with people with excellent ability. Usually there are three operators in a regular genetic algorithm: the integration operator, the transformation and mutation operator, the inversion operator. In the genetic algorithm, transformation operators and integrations on chromosomes are used to create a new tissue called generation child.

The method of integrating the operation described as described (Fig. 8)

p-ISSN 0854-1418
e-ISSN 2503-426X

Parent 1		4	1	6	2	5	3
	003	m-06	m-06	m-07	m-08	m-08	m-07
		t-09	t-10	t-10	t-12	t-14	t-13
Patent 2		2	6	1	3	4	5
	005	m-16	m-15	m-17	m-17	m-16	m-18
		t-22	t-22	t-20	t-23	t-21	t-21
Child1		4	2	6	1	5	3
(after exchange)	003	m-06	m-16	m-15	m-17	m-08	m-07
		t-09	t-22	t-22	t-20	t-14	t-13
Child2		2	1	6	3	4	5
(after exchange)	005	m-16	m-06	m-07	m-07	m-16	m-18
		t-22	t-10	t-10	t-13	t-21	t-21
Child1		4	2	6	1	5	3
(after legalization)	003	m-06	m-08	m-08	m-07	m-08	m-07
		t-09	t-11	t-12	t-10	t-14	t-13
Child2		2	1	6	3	4	5
(after legalization)	005	m-16	m-16	m-16	m-17	m-16	m-18
		t-22	t-23	t-21	t-22	t-21	t-21

Figure 8. The integration operator

-Correction and mutation

. In the genetic algorithm, the mutation for the chromosomes twice, one for the selected factory (mutation 1) and the other for operations (mutation 2). The Method of Leap 1 is described as follows:

1- Randomating ID of a factory from the list of factories IDs that do not exist in the current generation.

2. In order to legalize the chromosomes, machines and tools, all operations will be allocated again in accordance with the new factory ID.

The method of mutation 2 is described as follows:

1- Randomly chromosome selection

2. Randomly select several pairs of genes and move their position.

Although the mutation may detect some different species of genes and prevent being caught in a local optimized place, it may be discredited due to the defects of new chromosomes. Therefore, a suitable algorithm for the chromosome mutation will be used by guaranteeing non -production of invalid chromosomes.

In practice, changing the machine is an important factor in calculating the process time and production cost. The high frequency of car change increases the time and cost to realize and perform an activity. Overall, the designer of an experience will try to allocate the same machines to a large number of operational operations. This study suggests a method by modifying the algorithm used by Racha and others to minimize the status change that will be used after the mutations.

- Chromosome evaluation

When all possible process plans are created in the population, in other words, the operation of abandonment is guaranteed and they can be evaluated on the basis of the purpose of the operation. The purpose of the CAPP issue is to obtain an optimized operation sequence, optimize resource optimization and minimize operation costs plus the process time. In this study, two criteria for optimization, in other words, minimize process times and production costs are used to calculate the capability of each process design and measure the efficiency of a manufacturing system.

A) Minimize process time:

The process time is often used as a criterion in practice and usually consists of machining time, machine change time, tool change time, and preparation time. Here are four time indicators to evaluate a process plan: machine change time index, tool change time index, preparation time index, and machining time index. The time index of the machining is estimated to reflect the importance of the machining time throughout the process, and this is estimated from the time of machining a specified volume that is assumed to be a fixed value for a specific compound of the type of operation and machine. Machinery time indicators are specified for any operation with specific machines with known parameters for each user. Therefore, depending on the volume and machine specified for the specific operation, the total production time will be determined. However, the features may sometimes require more than one type of operation to create in the real industrial environment. So it was difficult to determine the volume of generation for each operation. It is estimated here that the sum of the remaining volume will be divided by its operational number to create a feature and the result will be considered as the volume produced for each operation. In practice, this is not true. Since the volume depends on the type of operation and machine used, it is used to ease the calculation of the machining time for each feature.

B) Minimizing Production Costs:

One of the criteria that is often used to select the process plan is to produce the cost of production. General production costs include car change (MCC), overall change cost (TCC) and change cost. In addition, similar to the role of machining time in calculating the process time, it also includes combining the cost of machining with the cost of the machine and the overall costs.

6- CASE STUDIES

6-1- Traditional process

Although the genetic algorithm has been introduced to create an optimized or close -up process from several factories, the proposed genetic algorithm can also address the single factory issue. In this case, the first genes in each chromosome will be assigned to the factory ID and the factory mutation code (mutation 1) will be ignored.

Construction information, such as the TAD/T/M operation feature and the operation designed for each piece feature is shown in Table 6. As shown in Table 7, a workshop with four machines (a drill press, a vertical lathe, a vertical CNC machining center and a drilling machine) and a toolbox containing eight cutters (T-01 to T-08) is selected for the machining. Car cost indicators, tool change and preparation are MCCI = 300 and TCCI = 10 and SCCL = 90, respectively. Other cost indicators such as machining and tool cost index are also listed in Table 8. Construction operations are all machining operations (cutting). The relationship between the operations and delay between the operations is shown in Table 8, which derives from a series of rules that include maintenance, tolerance factor, commodity production technique, and the need for operational processing steps to cut a compound.

Table 7-Feeding in Production Workshop

ID.	Type	Cost indices
M-01	Press drill	10
M-02	Vertical milling	35
M-03	Vertical CNC milling	60
M-04	Boring Machine	50
T-01	Drill Φ 0.2	3
T-02	Drill1Φ 1.2	3
T-03	Reamer	8
T-04	Boring tool	15
T-05	Milling cutter 1	10
T-06	Milling cutter 2	15
T-07	Slot cutter	10
T-08	Chamfer tool	10

MCCI: 300 *SCCI*: 90 *TCI*: 10

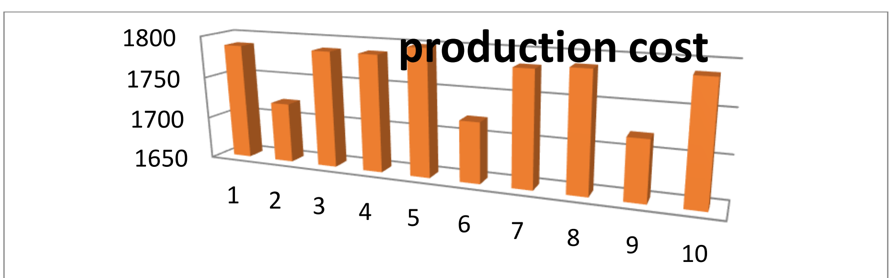
Table 6- Production Information

Feature-ID	Operations	TAD candidates	Machine candidates	Tool candidates
F1	Drilling (op1)	$+z, -z$	M-01, M-02, M-03	T-01
F2	Drilling (op2)	$+z, -z$	M-01, M-02, M-03	T-01
F3	Milling (op3)	$+z, -z$	M-02, M-03	T-08
F4	Milling (op4)	$+y, -z$	M-02, M-03	T-05, T-06
F5	Milling (op5)	$+y$	M-02, M-03	T-05, T-06
F6	Milling (op6)	$+y$	M-02, M-03	T-05, T-06
F7	Drilling (op7)	$+z, -z$	M-01, M-02, M-03	T-02
F7	Reaming (op8)	$+z, -z$	M-01, M-02, M-03	T-03
F7	Boring (op9)	$+z, -z$	M-03, M-04	T-04
F8	Drilling (op10)	$+z, -z$	M-01, M-02, M-03	T-01
F9	Drilling (op11)	$+z, -z$	M-01, M-02, M-03	T-02
F9	Reaming (op12)	$+z, -z$	M-01, M-02, M-03	T-03
F9	Boring (op13)	$+z, -z$	M-03, M-04	T-04
F10	Milling (op14)	$+x$	M-02, M-03	T-05, T-06
F11	Drilling (op15)	$-z$	M-01, M-02, M-03	T-01
F12	Drilling (op16)	$-z$	M-01, M-02, M-03	T-01
F13	Milling (op17)	$-y, -z$	M-02, M-03	T-05, T-07
F14	Milling (op18)	$-y, -z$	M-02, M-03	T-05, T-06
F15	Drilling (op19)	$+z, -z$	M-01, M-02, M-03	T-01
F16	Drilling (op20)	$+z, -z$	M-01, M-02, M-03	T-01
F17	Milling (op21)	$-y$	M-02, M-03	T-05, T-06
F18	Drilling (op22)	$-y$	M-01, M-02, M-03	T-01
F19	Drilling (op23)	$-y$	M-01, M-02, M-03	T-01

Table 8- Matrix Priority and Deviation

Op	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1		1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0		1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	1		1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
6	0	0	0	1	0			0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
7	0	0	0	0	0	0		1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0		1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0		1	1	1	1	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	1		1	1	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	1	0		1	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	1	0	0		0	0	0	0	0	0	0	0	0	0
14	0	0	1	0	0	0	0	0	0	0	0	0	0		0	0	1	1	1	1	1	1	1
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0		1	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1		1	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0
21	1	1	1	0	0	0	1	1	1	1	1	1	1	0	0	0	1	1	1	0		1	1
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		1
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Since the implementation of genetic algorithms is not guaranteed and can never be evaluated on a single execution, the program is repeatedly implemented for ten times, and the cost of producing each optimal process plan is shown in Figure 9. As can be seen, the cost of production can be changed from 1739 to 1745. However, the production cost frequency (1742) is much higher than the other two. Therefore, the design of the process with the cost of production (1742), as the final design of the optimal process, is selected in this example, shown in Figure 13-11.



	1	2	3	4	5	6	7	8	9	10
production cost	1788	1721	1788	1788	1799	1721	1784	1788	1720	1788

Figure 9- Changes of Production Cost During Different Performances

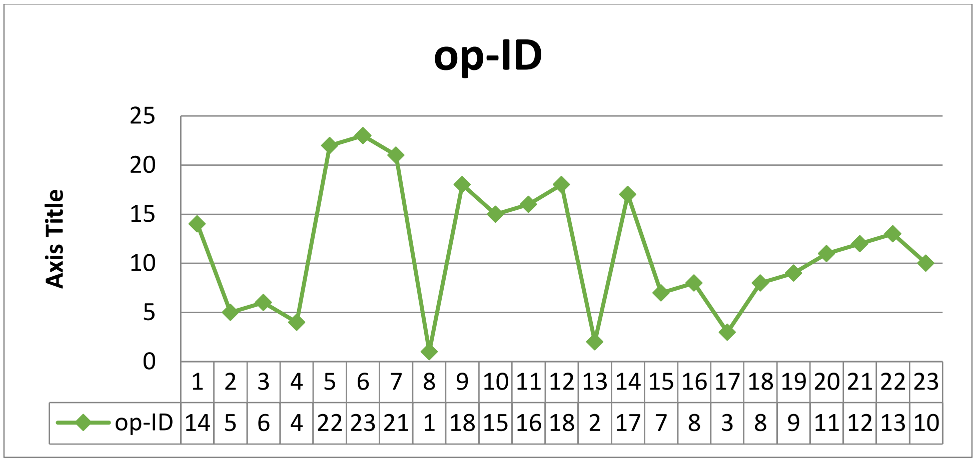


Figure 10 - Optimized op-ID process design

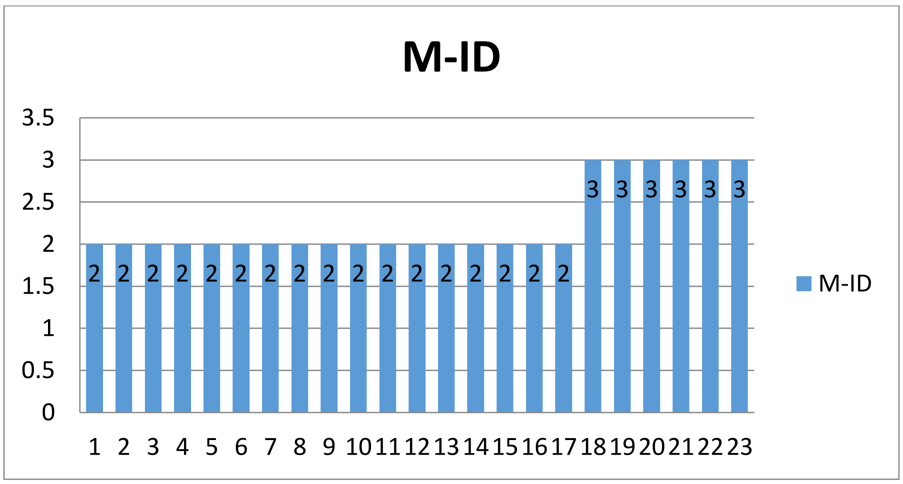


Figure 11- Optimized M-ID Process Design

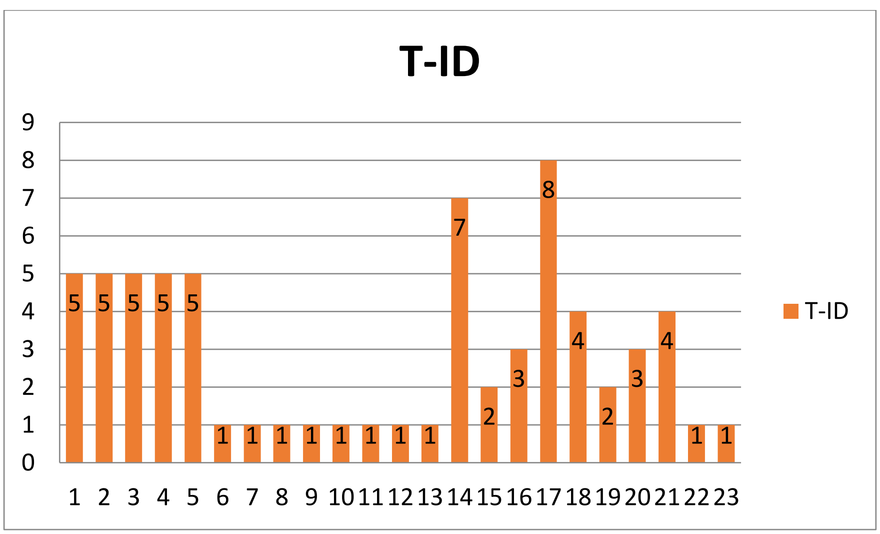


Figure 12- Optimized T-ID Process Design

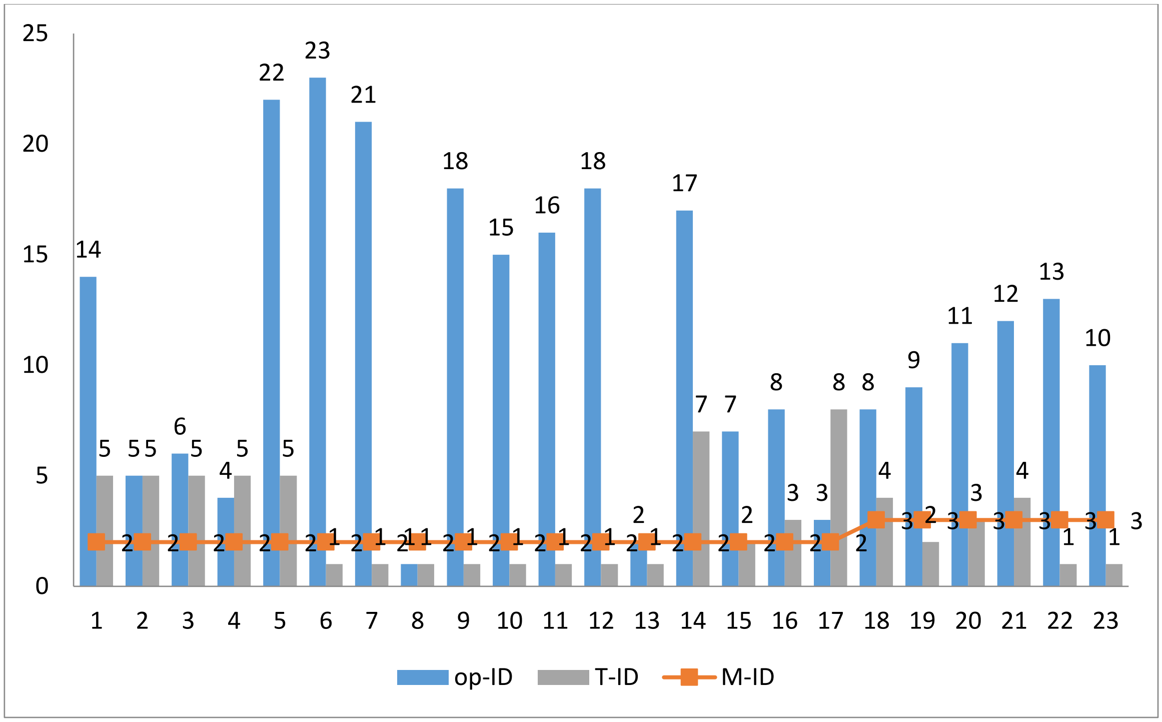


Figure 13- Case Study Process Design

According to the conclusion that the precedence relationships shown in Fig. 13 are preserved, as well as OP1 and OP2 before OP3 will be due to the product production technique. OP9 is after OP8 and after OP7 due to the need for operation floor. OP5 before OP21 is due to storage capability and so on. The number of repetitions to produce the optimal process design is not more than 50 times and the time was calculated on a Pentium 3 computer and with 500 MHz CPU and with a RAM of 64 M for about 40 seconds. The final design of the process produced by Zhang, which was selected as the best design with the least amount of preparation time after being evaluated by some exploration methods. The repetition was 8,000 generations and the calculation time on a computer with 133 MHz was about seven minutes.

Comparing the Zhang process design, it is observed that the proposed genetic algorithm approach can produce the most optimal process design with the same quality as Zhang, but with less repetition than 8,000 repetitions, only 45 replications. In addition, the improvement for the algorithm is suggested that it can also optimize the distributed CAPP issue in addition to optimizing the CAPP issue in a production unit.

6-2- Distributed CAPP

The genetic algorithm was used to evaluate the capability of the genetic algorithm. The cuts were used by Chi-Cong and Rajit to test a law-based approach to minimize preparation time in which the RS1-RS6 surface covered with raw materials. The precedence relationship of the parts is shown in Table 9, which shows column 2 operations that must be completed before column 1 operation, and column 3 shows the operation that must be completed when the first column operation is completed.

In this case, it is assumed that each piece feature can be completed by executing a production operation TAD. Each piece feature is listed below:

F1(-y), F2(-y), F3(-z), F4(+x, -x), F5(-x), F6(+x, -x), F7(-x).

It is also assumed that there are three factories: 001, 002 and 003 that have different devices, tools as well as different production facilities in distributed manufacturing systems. Table 10 shows the cost of car costs, tools and preparation changes (MCCL, TCCL and SCCCL) and the time index of machines and tools and preparation changes in each factory. All production resources available in the three factories are shown in Table 11 and are parentheses, car cost indicators and tools. In order to create an easy and understandable case study, the cost or time index is intentionally higher or lower than others. From Table 11 and 12 it is seen that the factory 001 has the highest time index but the lowest cost index compared to the other two factories, and the factory 002 has the highest cost index, but the lowest time index of 001 and 003. At the same time, cost and time indicators in the factory 003 are lower than the other two factories, so a process plan with the least cost of production and the least processing time can be produced from factories 001, 002 and 003, which indicates that the distributed CAP system can use multiple targets and determine the most appropriate factory for work.

In this case, it is assumed that for a certain type of manufacturing operation, all machining time indicators (MTLs) are the same for different machines that can perform the production operation. All the information information is shown in Table 13 that column shows 3 types of operations to create each feature and column 4 volume to make each feature, and MTL is shown in column 5.

Table 9- Priority Relationship for Case Study

Operation ID	Predecessor	Successor
Op1	op3	op2 op4
Op2	op1	op4 op6 op7
Op3	—	op1 op4
Op4	op1 op2 op3 op5 op6	—
Op5	—	op4
Op6	op2	op4 op7
Op7	op2 op6	—

Table 10- Time and Cost Indicators in three factories

Factory-ID	*MCCI*	*TCCI*	*SCCI*	*MCTI*	*TCTI*	*SCTI*
001	**70**	**25**	**30**	60	55	45
002	90	40	60	**25**	**25**	**15**
003	80	30	40	25	30	20

Table 11- Resources used in three factories

Factory-ID	Available machines	Available tools
001	M-01(20), M-02(26),M-03(15)	T-01(3), T-02(2), T-03(4), T-04(6), T-05(5)
002	M-04(40), M-05(30), M-06(35), M-07(40)	T-06(15), T-07(10), T-08(12), T-09(9), T-10(13)
003	M-08(25), M-09(30), M-10(15)	T-11(4), T-12(3), T-13(5),T-14(7), T-15(6)

Table 12- Describe seven main operations

Feature-ID	Operation-ID	Operation type	Removed volume	Machining time index
F1	Op1	Milling	4	3
F2	Op2	Milling	7	3
F3	Op3	Milling	6	3
F4	Op4	Milling	9	3
F5	Op5	Drilling	4	5
F6	Op6	Milling	6	3
F7	Op7	Drilling	4	5

Table 13- The sources in the machining operation

Operation-ID	Machine candidates			Tool candidates		
Op1	M-02 M-03	M-04 M-05	M-08 M-10	T-03 T-05	T-07 T-09	T-12
Op2	M-02 M-03	M-04 M-05	M-08 M-10	T-03 T-04	T-07 T-09 T-10	T-12 T-13
Op3	M-02 M-03	M-04 M-05	M-08 M-10	T-03	T-07 T-09	T-12 T-13
Op4	M-02 M-03	M-04 M-05	M-08 M-10	T-01 T-03	T-07 T-10	T-12 T-15
Op5	M-01 M-02 M-03	M-04 M-07	M-08 M-09 M-10	T-02	T-06 T-08	T-11 T-14
Op6	M-02 M-03	M-05 M-06	M-08 M-10	T-01 T-03	T-09 T-10	T-12 T-13
Op7	M-01 M-02 M-03	M-04 M-07	M-08 M-09 M-10	T-02	T-06 T-08	T-11 T-14

Given that Table 13 columns 2 and 3 of the candidates and tools for each operation are shown in which machines and tools from different factories are separated by columns, such as M-02, M-03, M-05, M-08, and M-08 and M-100, respectively, 001 and 002 and 003.

In this case, the lowest cost of production and the shortest time the process will be selected separately as the optimization goal to test the most appropriate factory for the specific work by the proposed CAP system and produce the optimized or close -up process plan, which varies according to the desired purposes. Assessment of Optimized Process Plans discussed in Table 4

Table 14-Process Design in accordance with minimizing production costs

Factory-ID: 001

Operation-ID	Machine-ID	Tool-ID	TAD-ID
Op3	M-03	T-03	−z
Op1	M-03	T-03	−y
Op2	M-03	T-03	−y
Op6	M-03	T-03	−x
Op7	M-03	T-02	−x
Op5	M-03	T-02	−x
Op4	M-03	T-01	−x

Number of machine change: 0 Number of tool change: 2 Number of set up change: 2

The total processing time is 336
The total production cost is 238

The first criterion

The lowest cost of production: The final process plan with the overall cost of its production, the process time and the number of devices, tools, and the change in preparation are shown in Table 14 that the prerequisite relationship in Table 9 is observed. From Table 13 it can be seen that all operations can be completed on M-02 and M-03, since the cost index of M-03 is slightly lower, instead of the M-02. Using the equations (3-1) to (3-5), the final cost of production and process process process time can be achieved, if the production cost is selected as the optimization goal, the distributed CAP system of the factory 001 with the lowest index chooses the cost instead of the 002 and 003 factories, indicating the most appropriate genetic algorithm.

Table 15- Process Design by Minimizing Process Time

Factory-id: 002

Operation-ID	Machine-ID	Tool-ID	TAD-ID
Op3	M-05	T-09	−z
Op1	M-05	T-09	−y
Op2	M-05	T-09	−y
Op6	M-05	T-09	−x
Op7	M-04	T-08	−x
Op5	M-04	T-08	−x
Op4	M-04	T-07	−x

Number of machine change: 1 Number of tool change: 1 Number of set up: 2

The total processing time is 216
The total production cost is: 560

- Criterion 2

The lowest process of the process: Table 15 shows the final production design based on the second criterion and it is observed that the factory 002 has been selected for this because its cost index has the lowest value among the three factories. The process time is much lower than the project 1, although the cost of producing it is much higher due to the high cost index and more replacement of the car. This process design may seem a little useful in practice, but it shows that the genetic algorithm can respond to the criterion. The results mentioned above show that the proposed genetic algorithm can be divided into different criteria, provided that the optimized or close to the optimized process plan is effectively and efficiently for a distributed manufacturing system in accordance with the selected criteria.

In the fundamental approach, the process design is based on the information available in the production and process data database. In this approach, the process design system acts as a DSS system in the form of knowledge -based and artificial intelligence system, and in some cases, the details of the part in question, the types of available operations available and their ability to be accurate and tolerance, the experience of the previous components, and the experience. In a distributed industrial environment, different factories and different machines and tools in different geographical locations are often combined to achieve the highest production efficiency. This research offers an emerging genetic algorithm to design the process with the help of data obtained from the process that has a successful use of distributed CAPP (ie, a traditional and traditional environment). The application of genetic algorithm for CAPP in distributed manufacturing systems was developed geographically based on the distribution of machines and tools. This can compare the production of an optimal or close -up process design with other key approaches for single production. The most suitable manufacturing plant can be set up when the distributed production problems are investigated. In addition, this approach is capable of performing multiple optimization targets based on the lowest cost of production or the least production time. Based on the selected goals, solutions close to the optimal can be obtained by using genetic algorithm. By performing the experiment showed that developed techniques are better or comparable to other CAPP systems

7-CONCLUSION

This research offers an emerging genetic algorithm that has a successful use of distributed CAP (ie a multipurpose environment) and traditional. The application of genetic algorithm for CAPP in distributed manufacturing systems was developed geographically based on the distribution of machines and tools. This can compare the production of an optimal or close -up process design with other key approaches for single production. The most suitable manufacturing plant can be set up when the distributed production problems are investigated. In addition, this approach is capable of performing multiple optimization targets based on the lowest cost of production or the least production time. Based on the selected goals, solutions close to the optimal can be obtained by using genetic algorithm. It has been shown that the developed techniques are better or comparable to other CAPP systems.

REFRENCES

[1] Bernabei, M., Eugeni, M., Gaudenzi, P., & Costantino, F. (2023). Assessment of smart transformation in the manufacturing process of aerospace components through a data-driven approach. Global Journal of Flexible Systems Managment, 24(1), 67–86. doi:10.1007/s40171-022-00328-7

[2] Shiva Khalili Gheidari. (2025). Design and Training a Routing Model for Predicting E-Commerce Logistics Distribution Systems in Transportation and Delivery of Educational Goods for Students Using Existing Algorithms, Big Data Analysis, and Machine Learning Methods . Pegem Journal of Education and Instruction, 15(3), 330–360. Retrieved from https://www.pegegog.net/index.php/pegegog/article/view/4161.

[3] Eshaghali Saberi & Bita Aramesh (2018) Computed tomography evaluation of root canal transportation using ProTaper, Race and Sendoline rotary systems: an ex vivo study, Clinical, Cosmetic and Investigational Dentistry, , 93-98, DOI: 10.2147/CCIDE.S160054.

[4] Bita Aramesh, Impact of Nanotechnology on Improving the Performance and Lifespan of Implants, Journal of Electrical Systems, 20(10), 3150-3166, 2024.https://journal.esrgroups.org/jes/article/view/5732

[5] Bita Aramesh, INVESTIGATION OF THERMODYNAMIC MODELS AND HEAT TRANSFER DURING LASER RADIATION IN TEETH TISSUE, Journal of Population Therapeutics & Clinical Pharmacology,31 (09), 1362-1377, 2024 . https://doi.org/10.53555/kqp0mj79.

[6] Bita Aramesh, Artam Enayat, Melika Espahbodi, Akram Mona Ghannadpour, Shahab Honar, Presenting a New Method for Reconstructing and Revealing Metal Areas in Real Raw Data (Cyanogram Improved with Tooth Filling Materials) To Reduce the Effect of Various Distortions in Two-Dimensional Scan Images of Spiral-Shaped Metal Implants and Dental P, Power System Technology, Vol. 48 No. 3

[7] (2024).https://powertechjournal.com/index.php/journal/article/view/811.

[8] Badri M, Kazemi S M, Rahimi H, (2025), Presenting the behavioral model of citizens in selection of trip vehicle with emphasis on how to go to work, Case Studies on Transport Policy Volume 19 , 101304. https://doi.org/10.1016/j.cstp.2024.101304

[9] Erkip, N. K. (2023). Can accessing much data reshape the theory? Inventory theory under the challenge of data-driven systems. European Journal of Operational Research, 308(3), 949–959. doi:10.1016/j.ejor.2022.08.024

[10] J.P. Reddy, S. Kumanan, and O.V.K. Chetty. Application of Petri Nets and a Genetic Algorithm to Multi-Mode Multi-Resource Constrained Project Scheduling .International Journal of Advanced Manufacturing Technology, 17(4):305–314, 2001.

[11] A.J.M.M. Weijters and W.M.P. van der Aalst. Rediscovering Workflow Models from Event-Based Data using Little Thumb. Integrated Computer-Aided Engi -neering, 10(2):151–162, 2003.

[12] Narges Farhad-Mollashahi, Eshagh Ali Saberi, Bita Aramesh, Farnaz Faramarzian, Effect of photobiomodulation on pain following single visit non-surgical root canal treatment of molar teeth with symptomatic irreversible pulpitis, Pesquisa Brasileira em Odontopediatria e Clínica Integrada, 23, 2023. https://doi.org/10.1590/pboci.2023.087

[13] W.M.P. van der Aalst. Business Process Management Demystified: A Tutorial on Models, Systems and Standards for Workflow Management. In J. Desel, W. Reisig, and G. Rozenberg, editors, Lectures on Concurrency and Petri Nets, volume 3098 of Lecture Notes in Computer Science, pages 1–65. Springer-Verlag, Berlin, 2004.

[14] W.M.P. van der Aalst and M. Song. Mining Social Networks: Uncovering Interac- tion Patterns in Business Processes. In J. Desel, B. Pernici, and M. Weske, editors, International Conference on Business Process Management (BPM 2004),volume 3080 of Lecture Notes in Computer Science, pages 244–260. Springer-Verlag, Berlin, 2004.

[15] W.M.P. van der Aalst, B.F. van Dongen, J. Herbst, L. Maruster, G. Schimm, and A.J.M.M. Weijters. Workflow Mining: A Survey of Issues and Approaches. Data and Knowledge Engineering, 47(2):237–267, 2003.

[16] W.M.P. van der Aalst, A.J.M.M. Weijters, and L. Maruster. Workflow Mining: Discovering Process Models from Event Logs. IEEE Transactions on Know ledge and Data Engineering, 16(9):1128–1142, 2004

[17] Gandhi, S., Kiwelekar, A., Netak, L., & Shahare, S. (2023). A blockchain-based data-driven trustworthy approval process system. International Journal of Information Management Data Insights, 3(1), 100162. doi:10.1016/j.

[18] Ma GH, Zhang F, Zhang YF, Nee AYC. An automated process planning system based on genetic algorithm and simulated annealing. Proceedings of the ASME design engineering technical conference, vol. 3. 2002. p. 57–63

[19] Li WD, Ong SK, Nee AYC. Hybrid generic algorithm and simulated approach for the optimization of process plans for prismatic parts. Int J Prod Res 2003;4(8):1899–922.

[20] A. Alharbi, A. Bulpitt, O. Johnson, Improving pattern detection in healthcare process mining using an Interval-based event selection method International Conference on Business Process Management (2017(

[21] E. HelmTowards process mining in radiology: utilization of IHE SOLE Biomedical Informatics for Health and Care: Proceedings of the 14th Health Informatics Meets Digital Health Conference (2020)

[22] R. Lira, J. Salas-Morales, R.d. l. Fuente, R. Fuentes, M. Sepúlveda, M. Arias, V. Herskovic, J. Munoz-Gama Tailored process feedback through process mining for surgical procedures in medical training: the central venous catheter case International Conference on Business Process Management (2019)

[23] Mandl, C., & Minner, S. (2023). Data-driven optimization for commodity procurement under price uncertainty . Manufacturing & Service Operations Management, 25(2), 371–390. doi:10.1287/msom.2020.0890

[24] Nadim, K., Ragab, A., & Ouali, M.-S. (2023). Data-driven dynamic causality analysis of industrial systems using interpretable machine learning and process mining. Journal of Intelligent Manufacturing, 34(1), 57–83 . doi:10.1007/s10845-021-01903-y

[25] Alam MR, Lee KS, Rahman M, Zhang YF. Process planning optimization for the manufacture of injection moulds using a generic algorithm. Int J Comput Integr Manuf 2003;16(3):181–91

[26] .Peng, Y., Ahmad, S. F., Irshad, M., Al-Razgan, M., Ali, Y. A., & Awwad, E. M. (2023). Impact of digitalization on process optimization and decision-making towards sustainability: The moderating role of environmental regulation. Sustainability (Basel), 15(20), 15156. doi:10.3390/su152015156

[27] Bhashara RSV, Shunmugam MS, Narendran TT. Operation sequencing in CAPP using genetic algorithms. Int J Prod Res 1999;37(5):1063–74.

[28] L.O. Elkhovskaya, A.D. Kshenin, M.A. Balakhontceva, M.V. Ionov, S.V. Kovalchuk Extending process discovery with model complexity optimization and cyclic states identification: application to healthcare processes Algorithms, 16 (1) (2023)