Comparing Genetic Algorithms and Ant Colony in Optimizing Production Output Function in Dynamic Manufacturing Systems

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Abstract

Advance of technology and the increased quality of people's lives through industrial achievements has created an intense competition between manufacturers in providing high-quality products and services. Thus, if a manufacturing company cannot keep the quality and capability of its products up to certain standards, it will eventually have to leave this cycle of production and competition. Usually, reputable manufacturing companies require different techniques to enhance the reliability of their products in this competition. One of the most important elements of industrial products is the product's performance over time, in a way that it can perform its function properly. Considering that system performance over time is a random phenomenon, the role of probability and statistics in analyzing random characteristics of system performance is highlighted. Employing manufacturing systems without paying attention to their reliability increases the chance of sudden failures. Therefore, in this research and by considering time limits, we analyzed production in dynamic manufacturing systems with the aim of minimizing system costs, product's transfer time and pollutants. Sensitivity Analysis (SA) was carried out on Matlab for three different factories with small, medium and large sizes using metaheuristic genetic and ant colony algorithms. Results indicate that genetic algorithm is better than ant colony; because it leads to better, easier and faster optimization of time and cost in this research.

Key Words: Optimization, Output Function, Manufacturing Systems, Genetic Algorithm, Ant Colony.

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1- Introduction

Advance of technology and the increased quality of people's lives through industrial achievements has created an intense competition between manufacturers in providing high-quality products and services. Thus, if a manufacturing company cannot keep the quality and capability of its products up to certain standards, it will eventually have to leave this cycle of production and competition. Usually, reputable manufacturing companies require different techniques to enhance the reliability of their products in this competition. One of the most important elements of industrial products is the product's performance over time, in a way that it can perform its function properly. Considering that system performance over time is a random phenomenon, the role of probability and statistics in analyzing random characteristics of system performance is highlighted. Employing manufacturing systems without paying attention to their reliability increases the chance of sudden failures. Such failures in many industries such as aircraft manufacturing can have extremely dangerous and costly consequences for the economy, people's lives, politics, security and reputation. For instance, as it was noted above, 31 staff members died in Chernobyl accident in 1986, 200 people were affected by severe illnesses and it caused a 3-billion-dollar economic damage. Challenger Spaceship accident in the same year, Shuttle Spaceship in 2003 and oil leak accidents in the coasts of America and the explosion of Japan's Fukushima Power Plant in recent years and many other terrible accidents that occur every year in the world demonstrate the necessity to pay attention to the safety of systems. Like the rest of the world, we experience many terrible accidents such as crashes of aircrafts and ships, train and bus accidents and other driving incidents and we also witness accidents in the tools and equipment of factories in the country.

Considering that the main factor in many horrible accidents in our country is worn-out systems. In order to reach a desirable level, we need vast and comprehensive researches in this field (Sadesgh Fazel; 2014). It is noteworthy that the current research has been conducted with the goal of answering some of these issues and the researcher aims to solve some of the potential future problems and helps the country's industry take a small step towards growth and development. From a control and monitoring perspective, Niki and Davoodi (2009) presented a multistage multi-variate plan and design for control and monitoring and recognized the feasibility of remote-control signals. This approach considers several autocorrelation stages and several correlated qualitative characteristics inside a special stage. The first multistage approach is the development of multivariate autoregressive (MAR) model from the data of a multistage process in order to integrate the correlation and autocorrelation inside the stage and between the stages. Artificial neural network model is used to control and classify the mean intensity of changes in the multivariate autoregressive model. The suggested approach is a control process design for a multistage problem with multiple outputs instead of an optimization approach (Sasadhar , Bera and Indrajit, Mukherjee; 2015).

Employing manufacturing systems without paying attention to their reliability increases the chance of sudden failures. Therefore, in this research and by considering time limits, we analyzed production in dynamic manufacturing systems with the aim of minimizing system costs, product's transfer time and pollutants. Sensitivity Analysis (SA) was carried out on Matlab for three different factories with small, medium and large sizes using metaheuristic genetic and ant colony algorithms.

2- Theoretical Basis and Literature Review

2.1- Dynamic Systems

Some social-industrial and management issues and problems are complex and cannot be solved by simple managerial assumptions. Dynamic system thinking is a way of modelling and exploring system factors and eventually finding the right solution.
Thinking and procedure of dynamic systems are a type of computer methodology, simulation and modelling to determine the framework, perception and discussion about some complex managerial, industrial, social and even medical issues. This thinking was proposed and started in the 1950s to help industrial managers focus on issues that exist in industrial companies. Using this type of thinking, managerial problems and issues such as instability in production, absence or instability of growth and development of companies, losing market share and etc. were addressed (Kahfi Ardekani & et al. 2012). This kind of thinking then entered other fields and subjects such as social problems, natural reources and even medicine; and the term "industrial dynamics" was changed to the broader term of "system dynamics" (Zhao & et al. 2006).
Systems Dynamics is an aspect of Systems Theory and is used as a method to understand the dynamic and continuous behavior is complex systems. Systems dynamics was invented in mid 50s by Jay Wright Forrester, a professor of Massachusetts Institute. During that time, Forrester faced a problem in General Electric (GE) Company. General Electric managers were surprised from the 3-year employment cycle in the factory in Kentucky. Commercial and managerial arguments could not justify the instability in employment and persistence of employees in the company. The drawing model of Forrester about the cycle of employment and the structure of decision-making in the company pointed to internal structures, workflow and feedbacks and showed the General Electric managers that the instability in hiring and persistence of employees is not due to external factors and is actually related to internal factors within the company. This representation and hand-drawn model became the beginning point of thinking about, studying, modeling, designing computer programmes and solving complex problems of dynamic systems. This thinking and procedure was gradually expanded and developed by Forrester and other professors and became more applicable in studying different systems (Defersha, F. and Chen, M; 2006)

2.2- Optimization

The objective of optimization is to find the best acceptable answer, considering the limitations and problem's requirements. There are different answers and in order to compare them and select the optimal answer, the objective function is defined. Selecting this function depends on the nature of the problem. For instance, time of travel or cost are among the common goals of optimizing transportation networks. Anyway, selecting the proper objective function is one of the most important steps of optimization. Sometimes, several objective are considered simultaneously in the optimization; these types of optimization which include several objective functions are called multi-objective problems. The simplest way to deal with these types of problems is to form a new objective function as a linear combination of the main objective functions. In this combination, the effectiveness of each function is determined by the weight assigned to it. Each optimization problem has a number of independent variables which are called design variables and are shown with a n-D vector x (Zhao; 2009). The goal of optimization is to determine the design variables, in a way that minimizes or maximizes the objective function. Optimization problems are divided into two following categories (Javadian; 2003):

A) Unlimited Optimization Problems: In these problems, the goal is to maximize or minimize the objective function without any restrictions on design variables.

B) Limited Optimization Problems: In most practical problems, optimization is done with considering some limitations; limitations in system behavior or performance are called behavioral limitations and limitations in the problem's physics and geometry are called geometrical or lateral limitations.

Equations representing limitations might be equal or unequal and in any case, the optimization method is different. Anyway, the limitations determine the acceptable area in design.

In general, optimization problems with limitations can be shown as the following:

Minimize or Maximize : F(X) (1)

Subject to : $g_i(x) \leq 0$ I = 1,2,3,…,p

$h_j(x) = 0$ j = 1,2,3,…,q

$X_k^{\min} < X_k < X_k^{\max}$ k = 1,2,3,…,n

In which X= (x_1, x_2, x_3,…, x_n), design vector and Equation 1are respectively the unequal limitations, equal limitations and the acceptable area for design variables.

2.3- Different Types of Metaheuristic Algorithms Derived from the Nature

A) Genetic Algorithm

Genetic Algorithm is a general method from metaheuristic methods for discrete optimization which solves timetable problems. Simulation method, which will be discussed in the following, is called the evolutionary strategy. This method was invented in 1975 by Holland and in 1989 by Goldberg.

This method is a method of searching for neighbors and performs like a gene. In natural, evolution occurs when the following conditions exist (Ghazanfari; 2009):

A) The animal should be able to multiply (Reproduction)

B) A population of this animal exists

C) Such situation should have diversity

D) These animals are differentiated by some capabilities in life.

In nature, there are different kinds of one animal. These differences exist in the chromosomes of these animals and cause diversity in the structure and behavior of these animals.
This diversity in structure and behavior has effects on giving birth. Animals that have more abilities and capabilities to do different activities (more evolved animals) will have higher birth rate and obviously, animals that are less compatible with the environment will have lower birth rate. After several time periods and a few generations, population tends to be consisted of animals whose chromosomes are more compatible with the environment. Over time, the structure of people changes due to natural selection and this indicate the evolution of population.

B) Ant System

This method was suggested in 1991 by Maniezzo, Dorigo and Colorni which can be used in solving the Travelling Salesman Problem and multi-faceted allocation. Ant colony optimization algorithm uses simple factors which are called ant, in order to produce repetitive answers. Ants can find the shortest route from a food source to the nest using pheromone information. Ants pour pheromone on the ground as they walk and they follow the path by smelling the pheromone on the ground. If they reach a crossing, since they have no idea about the better path, they will choose the path randomly. It is expected that approximately half the ants choose the first path and the other half choose the second one (Kalami, 2008). It is assumed that all the ants walk with the same speed. Since one path is shorter than the other one, more ants pass that route and thus, more pheromones get accumulated on it. After a short while, the difference in pheromone between two routes reaches a point that affects their decisions in choosing the better way. After that, more ants are likely to use the shorter path, because they smell more pheromone from the smaller path. After a while, all the ants will select this path.

2.4- Genetic Algorithm and Optimization of the Problem

Genetic algorithms are one of random search algorithms and is derived from the nature. Genetic algorithms have been very successful for classic methods of optimization and in solving linear and convex and some other similar problems. But, genetic algorithms are even more efficient in solving discrete and non-linear problems. For example, we could mention the travelling salesman problem. In nature, better generations are created by combination of better chromosomes, In the meanwhile, some mutations occur in the chromosomes that can make the next generation better. Genetic algorithm uses this idea to solve problems.

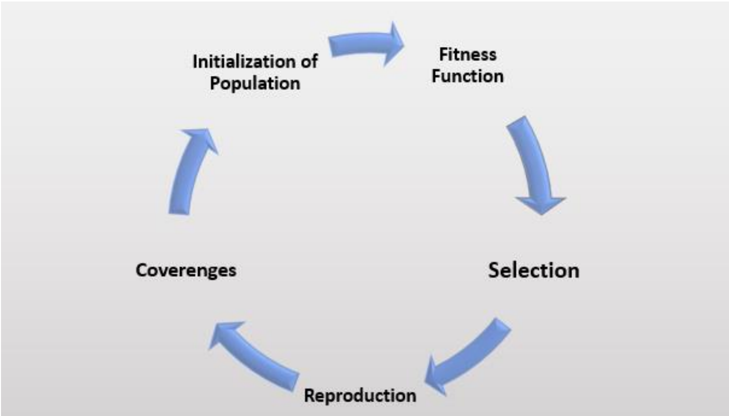


Figure 1: Genetic Algorithm Structure

The way genetic algorithm performance is deceptively simple, comprehensible and it is how animals have evolved. Each formula that follows the above-mentioned design is considered as a person from the population of possible formulas. In humans, genetic algorithm shows the variables that determine each given formula as a series of numbers which are equivalent to that person's DNA. In the genetic algorithm engine of an initial population, each person is tested against a series of data and the fittest one remains and the others are put aside. The fittest ones mate (exchanging DNA)(Random changes in DNA elements) and we can see that after the passing of a few generations, genetic algorithm tends to form more accurate formulas. The final formula will be observable by the human user and common statistic techniques can be applied to these formulas to reveal the reliability level. In modelling, it is briefly said that genetic algorithm is a programming technique that uses genetic evolution as a model to solve problems. The problem that needs to be solves has inputs that will turn into solutions through a process derived from genetic algorithm; these solutions are then evaluated as candidates by the fitness function and if the conditions to exit the problem exists, the algorithm ends. In each generation, the fittest are selected, not the best. One solution for the problem is shown by a list of parameters that are called chromosome or genome. Chromosomes are usually shown as a simple thread of data. Although, different structures of other data can also be used. At first, several characteristics are randomly created to form the first generation. During each generation, each characteristic is evaluated and the fitness value is measured by fitness function.

2.5- Ant Colony Optimization

Ant colony algorithm is inspired from studying and observing ant colonies. These studies have shown that ants are social insects that live in colonies and their behavior serves the survival of the colony and not just a part of it. One of the most important and interesting behavior of ants is their behavior to find food and especially the way they find the shortest path between the nest and a food source. This behavior is a result of a mass intelligence recently noticed by scientists. In the real world, ants are looking for food here and there and then they return home and leave a trace of pheromone. These traces can be observed after rain in white. When other ants discover such path, they stop strolling and follow that route. If they find food, they return home and leave another trace alongside the previous trace. In other words, they reinforce the path. Pheromone is gradually evaporated, which is good for three reasons:

- The path will have less attractiveness for the next ants; since an ant follows shorter paths more frequently in a long time and reinforces them. The shorter path between home and food will be reinforced more and the longer paths are less reinforced.
- If pheromone did not evaporate at all, paths taken several times will have become so attractive that a random search for food would be very limited.
- The trace would have remained even when the food was over.

Therefore, when an ant finds a short path from home to a food source, other ants are likely to follow the same path and by continuously reinforcing it and evaporation of other traces, all the ants will soon follow the same route. The goal of ant colony algorithm is to imitate this behavior by artificial ants moving on a graph. The problem is to find the shortest path and these artificial ants are the ones solving the problem. One of the applications of this algorithm is finding an almost optimal solution to the travelling salesman problem.

Research Background

In terms of optimization, researchers Hain & Shai (2019) presented a model to integrate and incorporate the variance error of each stage in dynamic systems with multiple outputs. The model's location had a linear structure and variance extension is considered to be due to deviations from the goals. Therefore, the suggested model provides us with a useful insight on different resources with product's efficient quality (Sasadhar, Bera. & Indrajit , Mukherjee; 2015). Other researches conducted by Hoang and Shai (2003) and Shai & Hou (2009) about variance extension in some independent stations of manufacturing process were studied and discussed. The research nature was related to a special stage of the spatial model whose main topic was about parts of the manufacturing processes. Anyway, in this model, the non-linear relation between input and output variables was not considered (Sasadhar, Bera. & Indrajit , Mukherjee; 2015). Also, Shai and Hou (2009) and Zantek & et al. (2002) suggested a systematic approach to measure the effect of variability of the previous stage on the next stages and also on the final stage of the product quality in a correlated manufacturing scenario. They determined the investment costs needed to improve the quality of each stage. They used this model of estimating the minimum squares to estimate model's parameters and its variance's components. They also studied deviation from goal in each stage and analyzed the model's effect on variance in the final stage of product's qualitative features. Their suggested approach was to distinguish the amount of resource variability in the quality of a better product from the optimization process parameter in different stages (Sasadhar, Bera. & Indrajit , Mukherjee; 2015).

Bowling, Khasawneh and Chou (2004) determined the optimization processes of objective function by employing Markov Chain in order to maximize the expected profit related to manufacturing systems. Certain restrictions were considered at upper and lower limits of each stage and it was assumed that each qualitative feature will be controlled and measured by normal distribution. Also, this study requires a 100% inspection in relation to the proper cost of expected information. In this research, waste reduction and rework for expected profit and moving towards optimal process of target values for each stage were on the agenda of these researchers and they showed the effect of waste sensitivity and rework costs on the expected profit. Assuming that manufacturing continues, it seems that a 100% inspection, constant cost of information and change is the process are among the key limitations of this research (Sasadhar, Bera. & Indrajit, Mukherjee; 2015). Finally, other researchers such as Koak, Kim and Lee (2010) suggested a method to optimize the manufacturing processes. They recommended continuous maximization of functions of each stage from the initial stage to the final stage that returns to the initial stage. They consider the relations between the stages and their approach is to determine the conditions to optimize the input variable without extracting the model prediction. In summary, Patient Rule Induction Method (PRIM) is used to investigate the sub-domains of the input variable space in order to improve output functions in order of preference from all the fields. Patient Rule Induction Method can provide help for input variable space with big dimensions and it has a low sensitivity to data outputs. Anyway, that depends on the number of observations with big data. Also, Patient Rule Induction Method is an approach type, similar to a black box and has not yet provided more in-depth insights on manufacturing process variables. Also, some models need to be confirmed and the solution needs to be proved (Sasadhar, Bera. & Indrajit, Mukherjee; 2015).

3- Research Method

Due to the fact that the research subject has its own special complications in different stages of dynamic manufacturing systems that cause the formation of many dependent and independent variables in each stage and in the part under study, i.e. optimization of manufacturing's output function in dynamic manufacturing systems, the researchers will have to use data analysis methods of different pieces of software such as Matlab and by using different methods of optimization such as genetic algorithm and ant colony ,which is one of the best optimization methods, they aim to analyze and optimize the subject in order to reach the research goals. The researcher intends to consider one of the country's industrial companies as the statistical population in terms of geographical location. In the qualitative part of data collection, non-random and judgmental sampling is used and by which 25 experts are selected for interview and 10 experts will be used for group discussions. In the quantitative part, sampling will take place from all the data of recent 5 years as daily data for one of the main manufacturing processes.

4- Modelling

Problems relating to output function of dynamic manufacturing systems are a part of hard-NP problems. Therefore, we can conclude that the research problem is one these problems. In hard-NP problems, as the problem size increases, the solving time will slightly increase as well. In this research and in order to solve the mathematical model and to solve the problem, two metaheuristic algorithms, ant colony and genetic algorithms, are developed and then by presenting a number of numerical examples, the efficiency of the given algorithms will be evaluated. We consider the number of demands to be between 1-30 in a small factory, 30-80 in a medium-size company, and 250-1000 in a big factory. By doing the repetitions and reviewing the answers of the objective function is different vicinities, the best answer in each state is achieved and we will see the results in the following.

5- Simulation Results

Here, we show the output results. The following figures show the results of applying ant colony and genetic algorithms.

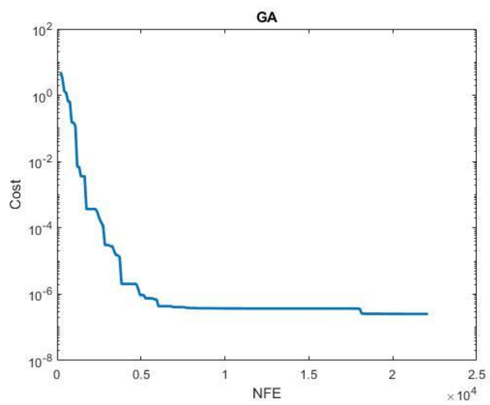


Figure 3: The results of genetic algorithm

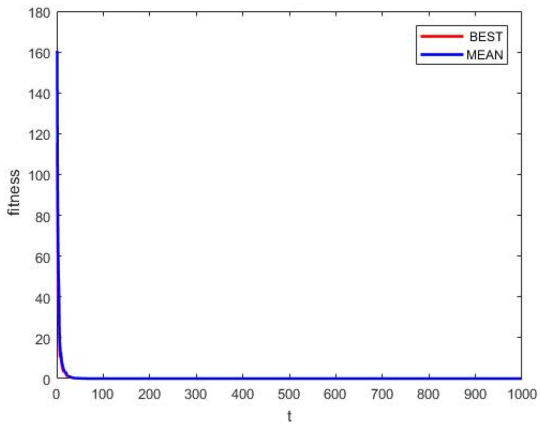


Figure 2: Convergence result of ant colony algorithm

Considering the coding and the used algorithm, the best time and best cost between the manufacturing system and customers are determined. In order to review it, we considered this procedure to have 5000 repetitions. As we can see on Matlab and in the command window, the cost processing will reduce by repeating the procedure and in the 5000th repletion, it will yield the minimum output amount. Table 1 to 3 review 10 models in factories using the suggested algorithm.

Table 1: Samples, number of products and orders in small, medium and large factories

Sample	Number of orders			Number of products		
	Large	Medium	Small	Large	Medium	Small
1	250	31	1	20	6	2
2	300	35	5	20	6	2
3	400	40	7	25	7	2
4	510	45	10	30	7	3
5	600	57	12	32	8	3
6	650	61	17	38	8	4
7	730	65	20	41	9	4
8	800	70	23	45	12	4

9	900	75	27	50	14	5
10	1000	80	30	60	16	5

Table 2: Results of delay time, cost and emission of pollutants in small, medium and large factories (genetic algorithm)

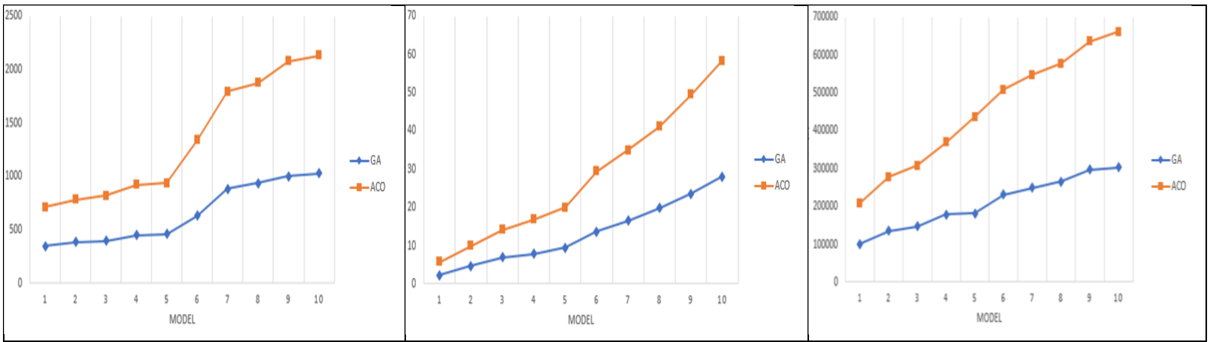
	CO_2 emission (ppm)			System's total cost ($)			Time (s)		
Sample	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
1	13526	1178	350	101254	375995	100254	68.542	8.6652	2.35
2	13658	1208	384	112352	379551	135662	72.332	11.472	4.65
3	14002	1321	399	163251	404124	146882	81.402	15.985	6.998
4	14230	1342	450	175895	423554	179302	88.484	18.663	7.885
5	15200	1574	459	188547	468596	181332	90.441	29.874	9.551
6	16210	1622	632	192332	496554	231021	93.221	32.412	13.74
7	16890	1700	885	202114	521447	249704	95.3325	39.994	16.475
8	17532	1765	935	218774	547758	265995	99.718	42.412	19.770
9	18050	1932	1002	229663	598664	297302	102.332	48.990	23.542
10	19850	2120	1027	236562	635975	302665	110.475	51.062	28.102

Table 2: Results of delay time, cost and emission of pollutants in small, medium and large factories (ant colony algorithm)

	CO_2 emission (ppm)			System's total cost ($)			Time (s)		
Sample	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
1	13526	1299	362	101254	379887	108623	68.542	10.221	3.40
2	13658	1368	397	112352	388654	142387	72.332	12.032	5.32
3	14002	1401	421	163251	410214	159902	81.402	17.087	7.105
4	14230	1433	469	175895	433625	190021	88.484	19.221	8.998
5	15200	1687	479	188547	478850	255570	90.441	20.145	10.421

6	16210	1710	704	192332	502327	276352	93.221	34.775	15.636
7	16890	1788	910	202114	536270	296653	95.3325	42.745	18.462
8	17532	1822	936	218774	569985	310224	99.718	44.247	21.332
9	18050	1997	1074	229663	612352	337470	102.332	50.664	25.948
10	19850	2241	1102	236562	647805	358721	110.475	53.212	30.229

In the above table, we reviewed and solved the problem in small scales. As it was shown in the above table, genetic algorithm has had a better and more significant performance than ant colony algorithm. This is evident is all three items: time, system's total cost and CO_2 emission. In order to compare them more precisely, the comparison graphs for cost, time and pollutant emission of both algorithms are shown in figures 4 to 7 for small, medium and large companies.



C B A

Figure 4: Comparison between the cost, time and CO_2 emission using the two algorithms in a small factory

As it is clear from Figure 4(A) which compares the two algorithms in terms of system's total cost for a manufacturing system model in small scale, ant colony algorithm has improved total costs by 8.7% and was better. Based on Figure 4(B), it is clear that any colony algorithm is faster than genetic algorithm by 9%. In case of CO_2 emissions, based on Figure 4(C) for small factories, genetic algorithm was better than ant colony algorithm by 4%.

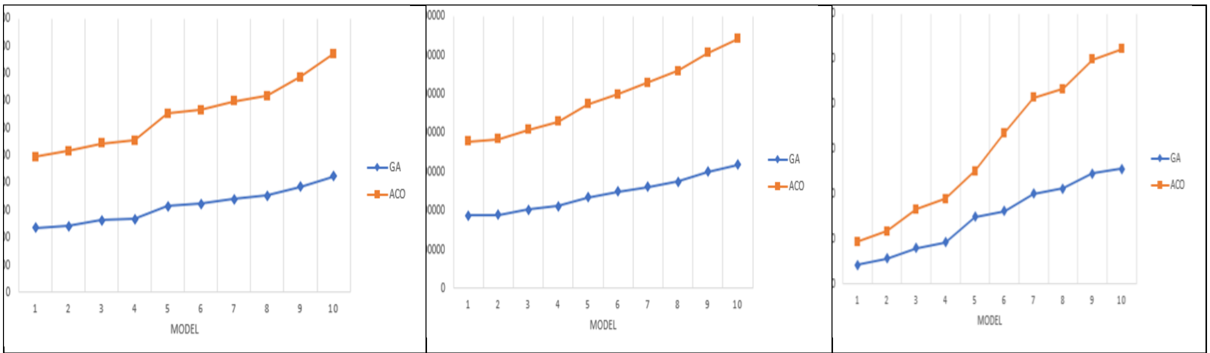


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Figure 5: Comparison between the cost, time and CO_2 emission using the two algorithms in a medium factory

In a medium size factory and considering that the model was solved in medium measurements, genetic algorithm is better than ant colony algorithm in determining the total manufacturing cost by 6 percent. In delay time, genetic algorithm is faster than ant colony algorithm by 1.5%. Finally, genetic algorithm has improved CO_2 emissions by 4.5% compared to ant colony algorithm.

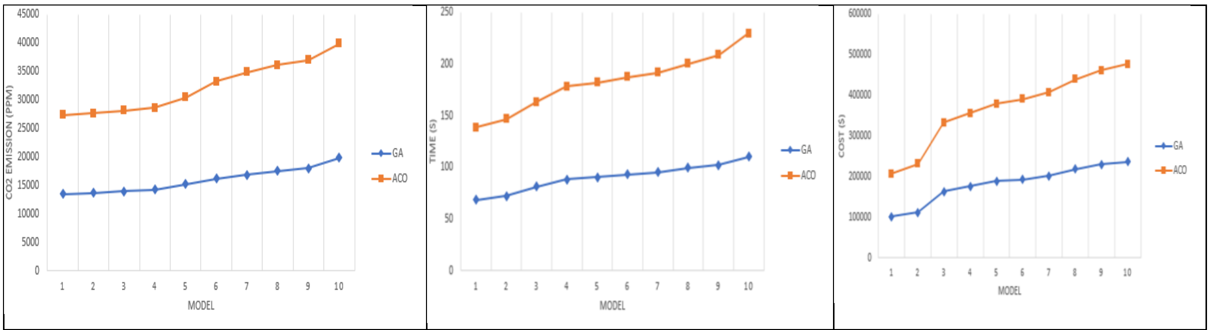

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Figure 6: Comparison between the cost, time and CO_2 emission using the two algorithms in a large factory

Based on the comparison made between two algorithms in big dimensions, it became clear that genetic algorithm, by a 2% improvement over ant colony algorithm, has led to reduced total cost. On the other hand, with a mean time of 90.227s when the algorithm is implemented, genetic algorithm is faster than ant colony algorithm by 2%. According to Figure 6(C), it is clear that genetic algorithm has been effective in reducing CO_2 emissions by 2.2%.

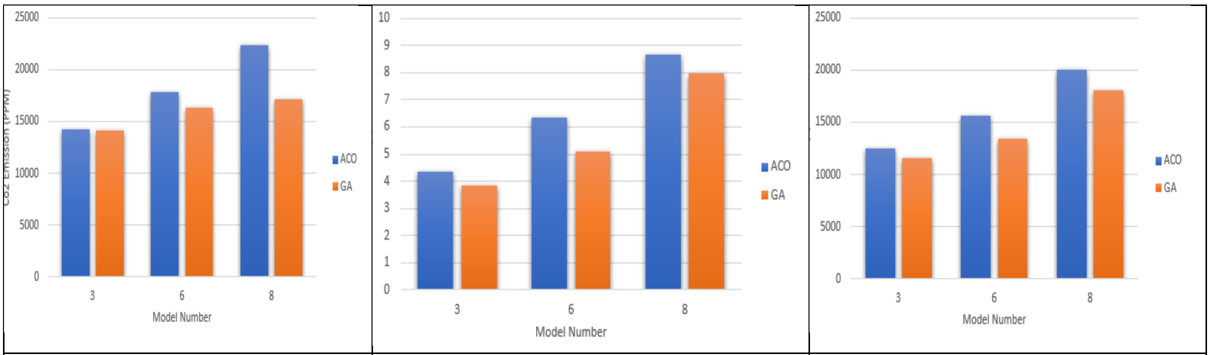
Sensitivity Analysis

Considering that acceptance or rejection of projects are the most important part of investments, main parameters should be analyzed in order to obtain the amount of acceptable changes in them. Meanwhile and considering engineering economic problems, time value of money should also be considered. Therefore, sensitivity analysis should be done by methods of engineering economics; the most important of which is considering the current value of investment and invest return rate. In order to analyze sensitivity, we analyze the model for factories with small, medium and large sizes. We analyze the results from ant colony algorithm and genetic algorithm for different modes of time, CO_2 emissions and costs.

Table 4: Results of time, cost and CO_2 emission

Size	item	GA			ACO		
		Cost	Emission	Time	Cost	Emission	Time
Small	3	11550	14152	3.854	12524	14300	4.36
	6	13454	16332	5.102	15636	17878	6.323
	8	18047	17120	7.968	19985	22307	8.662
Medium	12	23665	20352	11.021	23656	25588	12.328
	16	24141	24665	15.001	26859	285970	16.874

	18	27898	26681	17.232	29987	302114	19.885
Large	20	30652	28968	20.384	33663	321225	23.332
	24	34875	32078	26.363	36874	365247	28.968
	28	37745	34585	29.885	40985	381124	31.204



C B A

Figure 7; Comparing the results of cost, time and CO_2 emission in the small factory

Results indicate the high efficiency of genetic algorithm in all three fields of time, emission and cost. They also show that the problem has been stable during all sensitivity conditions and genetic algorithm has yielded better results which show its high ability and great memory is solving complex problems.

6- Conclusion

In this research and by considering time limitations, the subject of product manufacturing in dynamic manufacturing systems was analyzed with the goal of minimizing total system costs, product transfer time and reducing pollutant emissions. For this purpose, after studying resources and references related to designing manufacturing systems and considering the determined limitations and assumptions, this problem was modelled using Mixed Integer Nonlinear Programming (MINLP). Then, in order to achieve a universal optimal solution by using linearization techniques, problem's mathematical model was turned into using Mixed Integer Linear Programming (MILP). According to this, the objective function was reviewed using genetic and ant colony algorithms on Matlab and the results for this problem were presented for manufacturing companies with different sizes (sensitivity analysis): small, medium and large. Based on the results, it was shown that genetic algorithm has a better and more optimal solution compared to ant colony algorithm and the implementation time is also less.
Considering the simulation in this research and the results, we can conclude that the convergence of ant colony algorithm reaches the optimal mode after several repetitions of this algorithm on specified functions and objectives. And considering the results of genetic algorithm, we can conclude that we succeeded in achieving the best time and cost between manufacturer and the customer. The best mode created will become its best version after 250 repetitions.

Sensitivity analysis was conducted on three different factories with small, medium and large sizes using metaheuristic genetic and ant colony algorithms on Matlab. By increasing the problem size, the time needed to precisely solve the given mathematical model increases significantly. Therefore, in order to solve the problem with medium and large sizes, two metaheuristic ant colony and genetic algorithms were developed. The results of solving the problem with small size showed that both algorithms are efficient enough to solve the small problems. In the following, the performances of suggested algorithms were compared in solving medium and large problems. It should be mentioned that three criteria of cost, CO_2 emission and delay time were evaluated in both methods and the results revealed that genetic algorithm had a better performance than ant colony algorithm. Also, it becomes clear, in reviewing the presented results, that genetic algorithm is better than ant colony algorithm because it leads to better, easier and faster optimization of time and cost in this research.

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