# IMPLEMENTATION OF GENETIC ALGORITHM IN COMPLETION TRAVELING SALESMAN PROBLEM STUDY CASE OF GARUDA EXPRESS DELIVERY (GED)

<sup>1</sup>Syariful Alim, <sup>2</sup>Mahaputra Hidayat, <sup>3</sup>Bagus Damas Ardilestian, <sup>4</sup>Agus Bintoro

Informatics Engineering Study Program, Faculty of Engineering, Bhayangkara University Surabaya Jl. A Yani 114, Surabaya. Tel, 031-8285602 e-mail: <sup>1</sup>alim@ubhara.ac.id, <sup>2</sup>mahaputra@ubhara.ac.id, <sup>3a</sup>gusbintoro.14@gmail.com

## ABSTRACT

Indaily distribution activities, GED is a shipping service company. Always associated with couriers as inter mediaries. Where each courier will send a packagetoseveral different places. Surely they (couriers) want to immediately complete their tasks, by finding or determining the path that is traversed in order to shorten the work and return to the office and then make a report. This case is commonly called the Traveling Salesman Problem, which can be solved by several methods. One of them is by optimization of Genetic Algorithms. Genetic Algorithm methods can provide solutions to these problems by providing input (input) from several addresses that they will (courier) distribute. Then the input will be processed with several stages starting from initialization, selection, crossover, mutation and regeneration. The results are then displayed in graphical form which links the shipping addresses. The results of the study, obtained the fastest route with a maximum of 10 points or shipping address, which can be used by the courier in its distribution. In this study, the objective value is the value of the length of the road section taken from the Google Map. With termination rules or conditions that state that the smallest and largest fitness values must be the same or 60% of the fitness of the genetic algorithm population shows the greatest fitness. This rule will give the same and accurate results even though the number of generations produced is different.

#### Keywords: Genetic Algorithms, Shortest Path Problems, Crossovers, Mutations

## 1. INTRODUCTION

Genetic Algorithm is an optimization technique based on natural genetics. Toproduceanoptimalsolution, which can be used to solve heruistic problems. Such is the case with Garuda shipping service companies Express Delivery (GED). Where a courier must visit the customer's place, 1 place each onceand return to the place of origin (office). So that the total distance traveled to a minimum. In general, Genetic Algorithms are explained as Figure 1.1 below.



## Figure 1.1 General Algorithms

# 2.BASIC THEORY

Problems like the above are commonly known as Traveling Salesman Problem or (TSP). Which can be resolved premises Genetic Algorithm optimization method, with several stages as shown in Figure 2.1 below :



Figure 2.1 Stage On GA

## 2.1. Initialization

Thecodingprocessorencoding is oneofthedifficultprocesses Genetic Algorithms. This is due to the process encoding for every problem is different, because not all techniques encoding suitable for every problem. Process encoding produce the string which is then called a chromosome.Stringconsistsofasetofbitsknown as genes (Luke, et al., 2005: 1-2). Technique encoding used in TSP is permutation encoding. On permutation encoding, chromosomes are collections of numbers that represent positions in a series of selections. Inbrief, this chromosome representation can be explained in Figure 2.2

#### Figure 2.1.1 : Representation of chromosomes with $b_i \in \{ 0.1 \}$

## 2.2 Evaluation

The process of calculating and looking for values fitness from the smallest to the largest, which will aterbeused as chromosomes parent on the process crossover. Because TSP looks for a minimum value, then fitness is inverse of objective value. Where the agreed objective function is the distance between points  $\Sigma$  (b1, b2, b3, ... bn). While fitness is inverse of objective value  $f = \frac{1}{f(x)}$ 

## 2.3 Cossover

The process of cross breeding or better known as the crossover process (also known as crossing / recombination) is crossing two chromosomes to form a new chromosome that is expected to be better than it parent. There are several crossover techniques that can be used to Finishing TSP, one of which is Partially Mapped Crossover (PMX). For more clarity Can be seen illustration of this mutation method in Figure 2.3.1 and 2.3.2 as below :

Parent 1	J	0	E	V	F	С	L	В	Р	S
Parent 2	Р	S	J	F	E	0	В	C	V	L
Figure 2.3.1 Chromoson Parent										

Child 1	J	0	Е	V	F	0	В	С	V	L
Child 2	Р	S	J	F	E	С	L	В	Р	S

Figure 2.3.2 Crossover Ilustration

## 2.4 Mutation

The mutation process is carried out after the process crossover by selecting a chromosome to be randomly mutated then determining the mutation point on that chromosome randomly. Mutation technique used in this research is a technique Insertion Mutation. This technique begins by selecting two random numbers then the genes in the position of the first random number are exchanged for genes that are in these cond random number. Illustration as shown in Figure 2.4.1 below.

1	2	3	4	5	6	7	8		1	2	6	4	5	3	7	8
---	---	---	---	---	---	---	---	--	---	---	---	---	---	---	---	---

Figure 2.4.1 : Illustration Insertion Mutation

In the case of TSP it is not justified if there is more than one gene/city in common. For that, another mutation technique needs to be added so that in each chromosome results crossover do not have more than one same gene. Illustration like in Figure 2.6 below.



Figure 2.4.2: Illustration of chromosomes after mutation must be absent the same one

## 2.5 Regeneration

Regeneration is a selection process from the previous stage that produces the best chromosomes, to be used to the next generation, to find the expected generation. After going through all stages of population generation, evaluation, selection, crossover and mutation. Finally, the regeneration stage closes a generation process. Which already has all the data needed for the regeneration process, namely population, parent, child, mutants (chromosomes result from mutations).

## 3. RESULT AND DISCUSSION

Testing uses test data in the form of input data Shipment Delivery Record(SDR) courier and desired number of iterations. SDR input data are explained in the following table 3.1

No.	Cosignee Name	Cosignee Address
1.	Ali Fikri	Jl. Bratang Binangun Vi No 33 Rt
		001/07 Baratajaya Surabaya
2.	Gallery Itc Mega Grosir	Jl. Gembong No 20-30 (Itc Mega
		Grosir Lt 2 Blok 2/H 3A)
		Surabaya
3.	Cahaya Terang	Jl. Gembong Tebasan No. 29
		Surabaya
4.	Setiawan Sukses Bersama	Jl. Gembong Tebasan No. 34 A
		Surabaya
5.	Steven Gunawan	Jl. Kertopaten No 62 Kel
		Simolawang Kec Simokerto
		Surabaya
6.	Acacia It Service Surabaya	Jl. Kusuma Bangsa No 084 E
		Surabaya
7.	Surya Jaya Wira Sukses	JI. Pandan No. 3 Surabaya
8.	Citibank Surabaya	JI. Panglima Sudirman 66-68
		Surabaya (Bumi Mandiri Tower
9.	Pt Bank Uob Indonesia	JI. Panglima Sudirman No. 53
10	Cab Surabaya	Surabaya
10.	Maybank Kc Pemuda	JI. Pemuda 60-70 Surabaya
111	Bt Clobal Talashan This	Il Damuda No. 27.21 Embora
11.	Pt Global Teleshop Tok	JI. Femuda No 27-51 Embolig
	Surabaya	Lt 1 No 702 Surabava)
12	Smartfran Surabaya	II Pernuda No 60-70 Plaza Sinar
12.	Sinartifen Surabaya	Mae Surabaya
13	Makmur Abadi	II. Pencindilan No. 18 A
		Surabaya
14.	Tiahiono Tiondro Lukito	Jl. Plampitan 8 No.14 Rt.004
1	Tjuljono Tjonaro Zantio	Rw.002 Kel.Peneleh
		Kec.Genteng Surabaya
15.	Ibu Sjarleine	Jl. Sumatera No 103 Gubeng
	-	Surabaya
16.	Gadjah Mada	Jl. Undaan Wetan No. 16E
		Surabaya
17.	Cv Surya Sandang	Pengampon Square Blok C/ 32-
		33 Surabaya

Table 3.1 Shipment Delivery Record (SDR)

For more test plans can be seen in the table 3.2 bellow :

1	Tuble. 5.2 Testing Thins							
	No.	Number of Nodes	The amount of literacy	Number of Trials	Type of testing			
	1.	5	500	3x	Black Box			
	2.	6	500	3x	Black Box			
	3.	7	700	3x	Black Box			
	4.	8	800	3x	Black Box			
	5.	9	900	3x	Black Box			
	6.	10	1000	3x	Black Box			

T-1-1-	2 2	Tatina	D1
Table.	3.2	Testing	Plans

The application will produce the most optimal results then displayed in graphical form Google map. Complete with line which connects between places of visit. Some functions like how to get the distance between places and also make line in Google map, The application utilizes several features google api, that is Distance Matrix APIand geocode. Next is the application testing in detail.

## **3.1 Initialization**

Population generation is done by selecting a delivery point from the SDR data, to fill in the value of genes on each chromosome and done as many as the population determined is at least 5, a maximum of 10 points. Like Figure 3.1 below.

	NEXT						
•••••							
5	۲						
	ACAK						
Ali Fikri	Gallery Itc Mega Grosir						
🔲 Cahaya Terang	🖉 Setiawan Sukses Bersama						
Steven Gunawan	Acacia It Service Surabaya						
📄 Surya Jaya Wira Sukses	Citibank Surabaya						
Pt Bank Uob Indonesia Cab Surabaya	Maybank Kc Pemuda Surabaya						
Pt Global Teleshop Tbk Surabaya	<ul> <li>Smartfren Surabaya</li> </ul>						
Makmur Abadi	Tjahjono Tjondro Lukito						
🗷 Ibu Sjarleine	🔲 Gadjah Mada						
Cv Surya Sandang							

Figure 3.3.1: Selecting a delivery point

The selected point will be the gene for each chromosome then generate population as in Figure 3.2.2 below:

				PREVIOUS	NEXT				
_									
<pre>empatierpuin A. Jl. Gembong Tebasan No. 34 A Surabaya (Setiawan Sukses Bersama) B. Jl. Penuda No 60-70 Plaza Sinar Mas Surabaya (Smartfren Surabaya) C. Jl. Pencindilan No. 18 A Surabaya (Makmur Abadi) D. Jl. Sumatera No 103 Gubeng Surabaya (Ibu Sjarleine) E. Pengampon Square Blok C/ 32-33 Surabaya (Cv Surya Sandang) A = B = C = D = E </pre>									
ABCDE									
CREATE POPULASI									
No.	Populasi	Σ Objektif	Fitness						
1	BEADC	16200	0.000061728	3950617284					
2	BCEDA	16900	0.000059171	597633136094					
3	DBAEC	10400	0.0000961538	34615384615					
4	ECADB	11200	0.000089285	71428571429					
5	DCBAE	16100	0.0000621118	30124223603					
6	AEDCB	16100	0.0000621118	30124223603					
7	BEACD	10500	0.0000952380	9523809524					
8	BEADC	16200	0.000061728	3950617284					
9	ADEBC	17400	0.0000574712	26436781609					
10	DCAEB	11400	0.0000877192	29824561403					

Figure 3.3.2: Population generation

## 3.2 Selection

Furthermore, each chromosome undergoes an evaluation process to get an objective and fitness value from each chromosome. From the previous stage the application only needs to choose which chromosome will be selected to become the parent chromosome. As in Figure 3.2.1

	PREVIOUS NEXT					
•••						
Se	eleksi					
Populasi						
1.BEADC[16200]	2.BCEDA[16900]					
3.DBAEC[10400]	4.ECADB[11200]					
5.DCBAE[16100]	6.AEDCB[16100]					
7.BEACD[10500]	8.BEADC[16200]					
9.ADEBC[17400]	10.DCAEB[11400]					
Keterangan						
Cari 2 kromosom terbaik untuk dijadikan indukan (PARENT) Untuk menghasilkan anakan (CHILD) dari proses crossover 2 kromosom terbaik ya itu pada index 3:DBAEC dan 7:BEACD						

Figure 3.2.1: Process of selecting the best chromosome

## 3.3 Crossover

Pair some parts of the genes from the parent chromosome to become a new chromosome, the child chromosome. In accordance with the agreement above as shown in Figure 3.3 below.

Seleksi	
3.DBAEC	
7.BEACD	
Hasil	
DBACD	

Figure 3.3.1 Crossover Process

#### 3.4 Mutation

Next chromosome results from crossover mutated according to the agreement above. Because the problem faced is TSP, each chromosome may not have a gene that is repeated. So the function of mutation here is to make sure there are no identical genes / twins in each chromosome. This application mutation process can be seen as Figure 3.4.1 below.

		PREVI	OUS NEXT					
	$\bullet \bullet \bullet \bullet \bullet \bullet \bullet \bullet$							
	Mutasi							
-lasil Cr	rossover							
DBACE	D							
Hasil	lasil							
No.	Keterangan	Mutasi	$\Sigma$ Objektif					
1	DBACD (Kanan) => D   B   A   C   0.D-E	DBACE	11000					
	Jika angka random 1 maka yang akan dirubah muli Jika angka random 2 maka yang akan dirubah muli Jika sudah tidak ada yang sama, maka dimutasi de gennya	ai sebelah k ai sebelah k ingan pinda	iri anan h tempat					
Mutasi	Manual							
Jika tidak ada yang sama 🔻								
DBACD								
MUTASI								
ABCDE gen-3[C] ≻ gen-5[E] ⇒ ABEDC								

Figure 3.4.1 Mutation Procress

#### 3.5 Regeneration

The mutated chromosome will be used to replace the chromosome with a value fitness Lowest. For previous data manipulation, can be seen in Figure 3.4.1 above. From the old population data, there will be a change or replace according to agreement. Namely the chromosome with the smallest fitness value will be replaced with the chromosome that results from the mutation process. So there generation process can be seen in Figure 3.5.1 below:

Populas	'opulasi baru						
No.	Populasi	Σ Objektif	Fitness				
1	BEADC	16200	0.0000617283950617284				
2	BCEDA	16900	0.000059171597633136094				
3	DBAEC	10400	0.00009615384615384615				
4	ECADB	11200	0.00008928571428571429				
5	DCBAE	16100	0.00006211180124223603				
6	AEDCB	16100	0.00006211180124223603				
7	BEACD	10500	0.00009523809523809524				
8	BEADC	16200	0.0000617283950617284				
9	DBACE	11000	0.000090909090909090909				
10	DCAEB	11400	0.00008771929824561403				

Figure 3.5.1 New Population

Which will then be continued to the next generation with a new population. And will stop regenerating until the specified iteration limit or stop conditions are completed. With several stop conditions, namely:

- 1. Minimum and maximum values are the same
- 2. The amount of regeneration has reached 500 or in accordance with the maximum recursive input that is required.

From 1st generation to specified generation limit or predetermined stop condition. The resulting graph is shown in Figure 3.5.2 below.



Figure 3.5.2 : 1st to n generation graphs

Because the highest and lowest chromosomes are the same, then that is considered the best coromosome produced by the Genetic Algorithm Optimization system. Namely chromosomes **ECDBA** with an objective value **10400** and will be converted into a graph Google map as in figure 3.5.3



Figure 3.5.3 Graph Google map

After testing the system 3 times the experiment in each group of genes used, produces the following analysis:

- 1. Number of genes or points, affect total generation produced. The more genes, the more generations are produced.
- 2. The best chromosome in a generation lastly, have significant objective value differences from the first generation raised.
- **3.** In experiment no.4 with 8 gene inputs, no Stop on condition or rules for termination of iteration. But it stops at the maximum number of iterations given. Minimum value of fitness/the objective value produced by each experiment is the same and does not increase in size during the next trial. The results of all experiments are summarized in a table, can be seen in table 3.5.1 as below.

Node	Boundary generation Experiment			Generations are complete at Experiment			Minimum value Experiment		
	Ke-1	Ke-2	Ke-3	Ke-1	Ke-2	Ke-3	Ke-1	Ke-2	Ke-3
5	100	100	100	91	62	70	19700	19700	19700
6	1000	1000	1000	249	351	300	11100	11100	11100
7	1000	1000	1000	420	310	497	21000	21000	21000
8	5000	5000	5000	374	5000	5000	14500	14500	14500
9	5000	5000	5000	730	872	839	16600	16600	16600
10	5000	5000	5000	565	1314	940	22600	22600	22600

Table 3.5.1 Result Testing

From table 3.5.1 above, 83% of applications run quite optimally in completing the CSR program in the Garuda case study Express Delivery. Because the optimization process with the genetic algorithm method goes according to plan and stops at the desired stop criteria. That is when all the objective values of chromosomes in the population are the same. Although 2 of them stop at the maximum limit of iteration, the resulting objective value remains and will change if one of the chromosomes has a better fitness value than before.

## **4.CONCLUSION**

After doing the optimization system development Traveling Salesman Problem with Genetic Algorithms and implementing the system, the conclusions of this study are:

- 1. In experiments with 8 genes as input, process optimization does not stop at the first condition, i.e. if the maximum and minimum values are the same. But the application stops at a predetermined generation limit. But the final result or objective value and fitness which is fixed and unchanged after 3 times the experiment.
- 2. From 18x testing with various input node, 83% stop at the first stop rule. That is when the maximum and minimum values of the objective value are the same. Then by 16%, the application stops at the given iteration limit. Experimental data has been summarized in tabular form, such as table 6.9 in the previous chapter.
- 3. Each trial will stop according to 2 criteria, which are first if the objective value is minimal and maximum at the same value. Or the second stops at the given iteration limit.

# REFERENCES

- [1] Agus Wahyu Widodo, Wayan Firdaus Mahmudy (2010), Application of Genetic Algorithms in Culinary Tourism Recommendation System, Journals Scientific COURSE, Vol. 5, No. 4, p. 205-211.
- [2] Medrio Dwi Aksara Cipta Hasibuan, Lusiana (2015), Finding the Best Route in Traveling Salesman Problem (TSP) Using Genetic Algorithms at Pekanbaru City Sanitation and Landscaping Service, SATIN - Information Science and Technology, Vol. 1, No.1, pp.35-46.
- [3] Putri Yuli Utami, Cucu Suhery, Ilhamsyah (2014), Application Shortest Route Search Using Genetic Algorithms (Case Study: Shortest Route Search for Fire Extinguishers in Pontianak City Area), Journal of Untan Computer System Coding, Volume 02, No. 1, pp. 19-25.
- [4] William Tanujaya, Dian Retno Sari Dewi, Early Endah (2011), Application of Genetic Algorithms to Resolve Vehicle Routing Problemsat PT.MIF, **WIDYA TEKNIK**, Vol. 10, No. 1, p.(92-102).

- [5] Samaher, Wayan Firdaus Mahmudy (2015), Implementation Genetic Algorithm for Maximizing Profit Production Hijab, Journal of Environmental Engineering and Sustainable Technology, Vol. 02, No. 01 pg 06-11.
- [6] Najirah Umar (2014), Application of Genetic Algorithms for Resolving Traveling Salesman Problem (TSP), **JTRISTE**, Vol. 1, No. 2, pp. 50-57.
- [7] Evi Nur Azizah, Imam Cholissodin, Wayan Firdaus Mahmudy (2015), Optimization Fuzzy Membership Function Tsukamoto Uses Genetic Algorithms for Pricing Selling Home, Journal of Environmental Engineering & Sustainable JEEST Technology, Vol. 02, No. 02, p. 79-82.
- [8] Wiga Ayu Puspaningrum, Arif Djunaidy, Retno Aulia Vinarti (2013), Course Scheduling Using Genetic Algorithms in ITS Information Systems Department, JOURNAL OF POMITS ENGINEERING, Vol. 2, No. 1, p. 2337-3539.
- [9] Rahman Erama, Retantyo Wardoyo (2014), Modifications Genetic Algorithms for Solving School Scheduling Problem Problems, **IJCCS**, Vol.8, No.2, p. 111-120.
- [10] Sella Erary, Beni Irawan, Ilhamsyah (2014), Schedule Application Lectures with Genetic Algorithm Methods Using Visual Basic.net (Case Study: Faculty of Mathematics and Natural Sciences), Journal of Computer System Coding at Tanjungpura University,
- [11] Wayan Firdaus Mahmudy, Muh. Arif Rahman (2011), Optimasi Fungsi Multi-Obyekif Berkendala Menggunakan Algoritma Genetika Adaptif Dengan Pengkodean Real, Jurnal Ilmiah KURSOR, Vol. 6, No. 1, hal. 19-26. Zukhri, Zainudin. (2014), Algoritma Genetika Metode Komputasi Evolusioner untuk Menyelesaikan Masalah Optimasi, Edisi 1, Andi Offset: Yogyakarta. Vol 02 No. 3, p. 30 – 39.
- [12] Riska Ayu Permata, Dedi Triyanto, Ilhamsyah (2016), Application Food Compiler for Prevention of Hypercholesterolemia Using Genetic Algorithms, Journal of Untan Computer System Coding, Vol 04, No.2, p. 96-106. Totok Ruki Biyanto1 (2015), Genetic Algorithms for Mengoptimasi Penjadwalan Pembersihan Jaringan Penukar Panas, Jurnal Teknik Industri, Vol. 17, No. 1, hal. 53-6