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An Implementation of Genetic Algorithm for Vehicle Routing Problem

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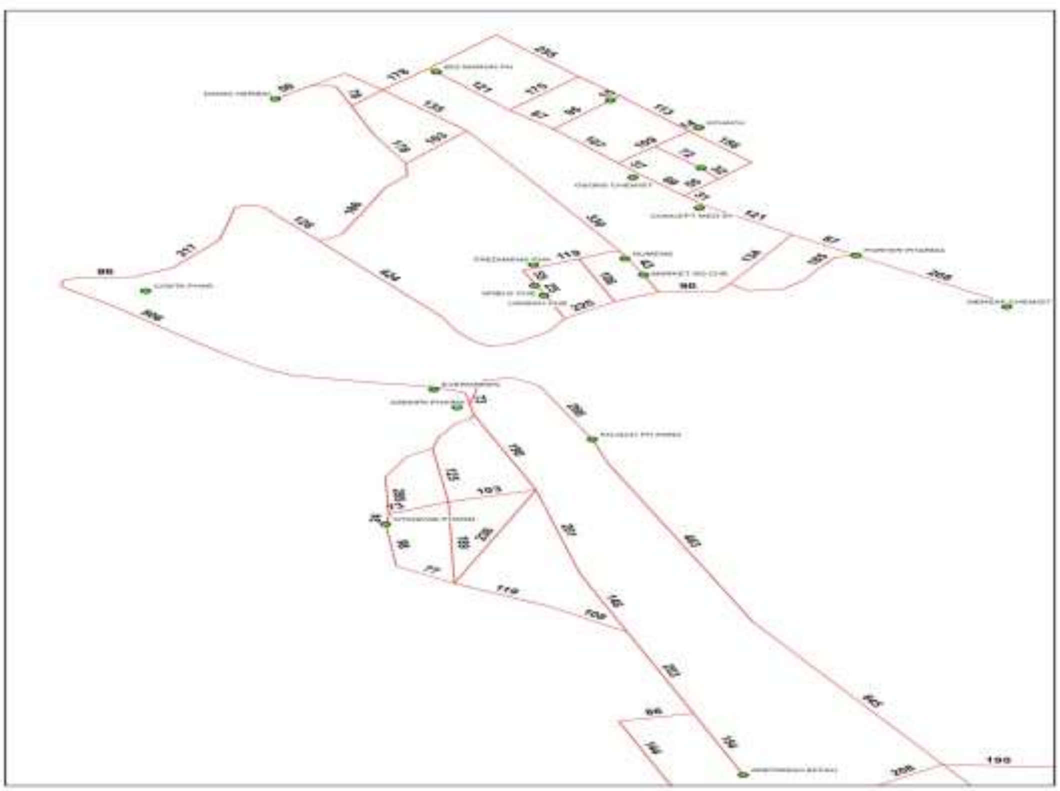
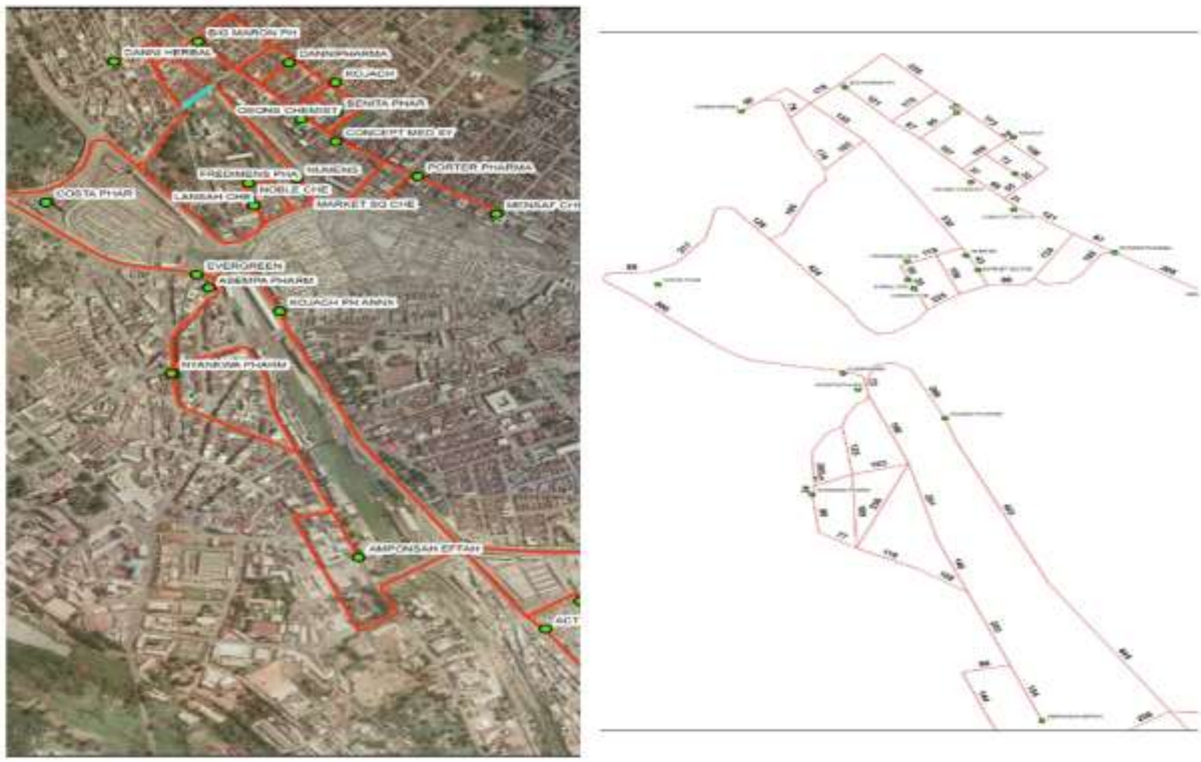
Abstract
*The Vehicle Routing Problem (VRP) can be solved using Genetic Algorithm (GA) because the wholesale points under focus here are random. The main objective or goal here is to find the minimum total distribution distance by the vehicle to **N** different wholesale locations. Upon studying the operations of Amponsah Effah Pharmaceutical Limited (Kumasi) carefully, the operations of this company is to distribute their medicine after production to their nineteen (19) wholesale points starting from their depot in Adum to different cities with their delivery vehicle. Since the wholesale points of the company are sited in random cities and the delivery vehicle have to distribute the medicines without passing through a specific route, their operations can be modeled by Vehicle Routing Problem. A data was collected from Amponsah Effah Pharmaceutical Limited which has been used to create a set of routes on which the company uses to minimize the total distribution distance of the vehicle. Testing every probability for N wholesale tour would be* $N!$. *This implies that testing 19 wholesale points including their main depot in Adum making it 20 tour, we would have to measure* $20! = 2.432902008 \times 10^{18}$ *different tours. To calculate the fittest of* $2.432902008 \times 10^{18}$ *tours for its minimum distance would take years. However, genetic algorithm can be used to find a solution in the shortest possible time, although it might not find the best solution, it can find a near perfect solution for a 100 wholesale tour in less than a minute. There are couples of basic steps to solving the vehicle routing problem using GA which has been discussed below.*

I. MODEL

Amponsah Efah Pharmaceuticals Limited has their main depot in Adum where it has all its vehicle located. A delivery van is used for the distributions in the northern sector to the depot. The nineteen (19) specific wholesale points for the northern sector including their depot Amponsah Efah located in different cities are:

- Action Pharmacy
- Amponsah Efah
- Asempa Pharmacy
- Benita Pharmacy
- Big Maron Pharmacy
- Concept Medical
- Costa Pharmacy
- Danni Herbal
- Evergreen Pharmacy
- Fredemens Pharmacy
- Nyankwa Pharmacy
- Kojach Pharmacy
- Kojach Pharmacy Annex
- Lansa Chemist
- Mensaf Chemist
- Noble Chemist
- Numens Chemist
- Oson's Chemist
- Panacea Pharmacy
- Porter Pharmacy





The delivery van has to set off from the central depot point. The schedule of the delivery van and its assigned route as partitioned is as follows:

Amponsah Efah $\rightarrow$ Action Pharmacy $\rightarrow$ Panacea Pharmacy $\rightarrow$ Nyankwa Pharmacy $\rightarrow$ Asempa Pharmacy $\rightarrow$ Kojach Pharmacy Annex $\rightarrow$ Evergreen Pharmacy $\rightarrow$ Costa Pharmacy $\rightarrow$ Lansah Chemist $\rightarrow$ Noble Chemist $\rightarrow$ Fredemens Pharmacy $\rightarrow$ Numens Pharmacy $\rightarrow$ Danni Herbal $\rightarrow$ Big Maron Pharmacy $\rightarrow$ Kojach Pharma $\rightarrow$ Benita Pharmacy $\rightarrow$ Oson's Pharmacy $\rightarrow$ Concept Medicals $\rightarrow$ Porter Pharmacy $\rightarrow$ Mensaf Pharmacy

The total distance travelled by the delivery van from the depot to all the nineteen (19) wholesale points and back to the depot was found to be 11336meters (11.3360km).

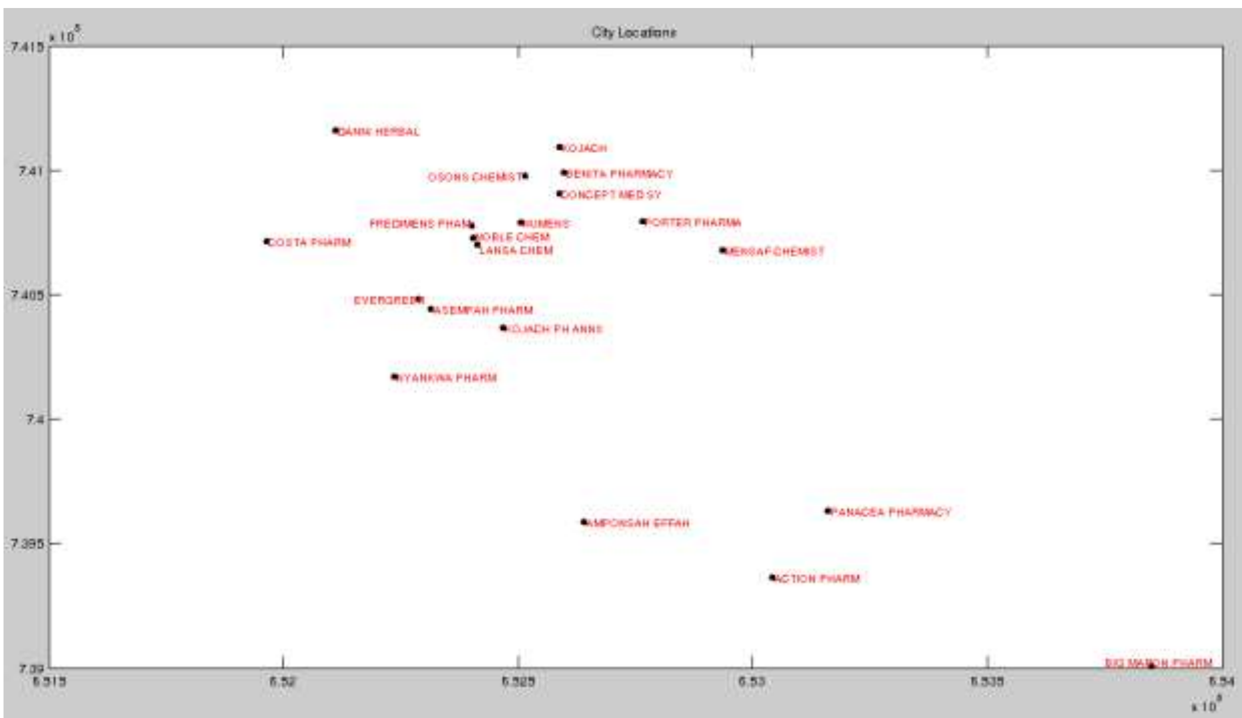
II. DATA

In using their local grid points (coordinates), all the 19 wholesale points and their depot are plotted in a graph using Matlab.

Table 4.2: (X,Y) Coordinates of wholesale points and depot

ID	X_m	Y_m
ASEMPA PHARMACY	652315	740442
BENITA PHARMACY	652597	740991
BIG MARON PHARMACY	652292	741221
CONCEPT MEDICAL	652589	740905

COSTA PHARMACY	651964	740712
DANNI HERBAL	652110	741159
EVERGREEN PHARMACY	652289	740483
FREDIMENS PHARMACY	652402	740774
KOJACH PHARMACY	652589	741092
LANSAH CHEMIST	652413	740702
MENSAF CHEMIST	652936	740676
NOBLE CHEMIST	652403	740725
NUMENS PHARMACY	652505	740787
NYANKWA PHARMACY	652235	740171
OSONS CHEMIST	652514	740976
PORTER PHARMACY	652766	740795
AMPONSAH EFFAH	652639	739588
ACTION PHARM	653042	739361
PANACEA PHARMACY	653161	739632
KOJACH PHARMACY ANNEX	652468	740367



Graph Showing The Coordinates

III. ENCODING

Permutation encoding is used. Numbers are assigned to all the 20 points as shown below.

Let WP represent Wholesale Point

WP 1 $\Rightarrow$ Amponsah Efah
WP 2 $\Rightarrow$ Nyankwa Pharmacy
WP 3 $\Rightarrow$ Asempa Pharmacy
WP 4 $\Rightarrow$ Evergreen Pharmacy
WP 5 $\Rightarrow$ Kojach Pharmacy Annex
WP 6 $\Rightarrow$ Costa Pharmacy
WP 7 $\Rightarrow$ Lansah Chemist
WP 8 $\Rightarrow$ Noble Chemist
WP 9 $\Rightarrow$ Fredemens Pharmacy
WP 10 $\Rightarrow$ Numens Pharmacy
WP 11 $\Rightarrow$ Benita Pharmacy
WP 12 $\Rightarrow$ Porter Pharmacy
WP 13 $\Rightarrow$ Mensaf Pharmacy
WP 14 $\Rightarrow$ Concept Medicals
WP 15 $\Rightarrow$ Action Pharmacy
WP 16 $\Rightarrow$ Oson's Pharmacy
WP 17 $\Rightarrow$ Kojach Pharmacy
WP 18 $\Rightarrow$ Panacea Pharmacy
WP 19 $\Rightarrow$ Big Maron Pharmacy
WP 20 $\Rightarrow$ Danni Herbal

The distance matrix is shown and the corresponding distance square matrix is plotted using Matlab as shown

Distance Square Matrix for Wholesale Points (WP)

	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7	WP 8	WP 9	WP 10	WP 11	WP 12	WP 13	WP 14	WP 15	WP 16	WP 17	WP 18	WP 19	WP 20
WP 1	0	759	894	967	1160	1400	2253	2278	2333	2521	2478	2753	2961	2823	2941	2923	3083	3211	2431	2321
WP 2	759	0	309	382	575	888	1741	1766	1821	2009	1966	2241	2449	2311	2429	2411	2571	2650	1859	1809
WP 3	894	309	0	73	266	579	1432	1457	1512	1700	1657	1932	2140	2002	2120	2102	2262	2341	1559	1500
WP 4	967	382	73	0	339	592	1359	1384	1439	1627	1584	1859	2067	1929	2047	2029	2189	2268	1555	1427
WP 5	1160	575	266	339	0	845	1612	1637	1692	1880	1837	2112	2320	2182	2300	2282	2442	2521	1816	1766
WP 6	1400	888	579	592	845	0	767	792	847	1035	992	1267	1475	1337	1455	1437	1597	1676	885	835
WP 7	2253	1741	1432	1359	1612	767	0	25	80	199	242	500	708	570	688	670	830	909	664	714
WP 8	2278	1766	1457	1384	1637	792	25	0	55	174	217	492	700	562	680	662	822	901	630	689
WP 9	2333	1821	1512	1439	1692	847	80	55	0	119	162	437	645	507	625	607	767	846	584	634
WP 10	2521	2009	1700	1627	1880	1035	199	174	119	0	43	318	526	388	506	488	160	239	465	515
WP 11	2478	1966	1657	1584	1837	992	242	217	162	43	0	275	483	345	463	445	605	684	508	558
WP 12	2753	2241	1932	1859	2112	1267	500	492	437	318	275	0	208	208	326	308	468	547	640	896
WP 13	2961	2449	2140	2067	2320	1475	708	700	645	526	483	208	0	416	534	516	676	755	848	1154
WP 14	2823	2311	2002	1929	2182	1337	570	562	507	388	345	208	416	0	118	100	260	339	432	738
WP 15	2941	2429	2120	2047	2300	1455	688	680	625	506	463	326	534	118	0	156	202	316	556	862
WP 16	2923	2411	2102	2029	2282	1437	670	662	607	488	445	308	516	100	156	0	160	239	332	638
WP 17	3083	2571	2262	2189	2442	1597	830	822	767	160	605	468	676	260	202	160	0	142	382	688
WP 18	3211	2650	2341	2268	2521	1676	909	901	846	239	684	547	755	339	316	239	142	0	270	576
WP 19	2431	1859	1559	1555	1816	885	664	630	584	465	508	640	848	432	556	332	382	270	0	306
WP 20	2321	1809	1500	1427	1766	835	714	689	634	515	558	896	1154	738	862	638	688	576	306	0

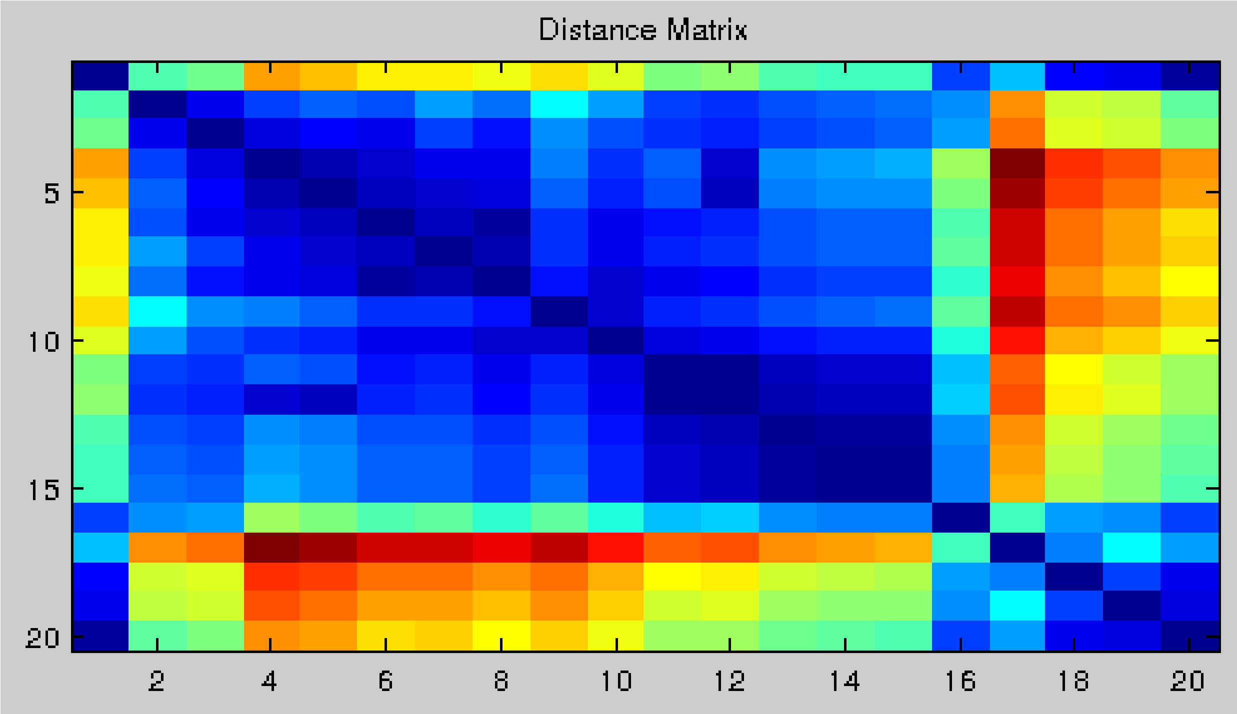


Fig. 4.24 Plot of Distance square matrix

IV. INITIAL POPULATION

A group of many random tours called an initial population is created where a population is a combination of chromosomes. We represent the population as array of 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 chromosomes which represent all the different wholesale locations and the main depot as 20. For each chromosome we calculate the length that is coded into it, actually this is the fitness of the tour. Fitness function is nothing but the minimum cost. Initially the fitness function is set to the maximum value and for each tour the cost is calculated and compared with the fitness function. The new fitness value is assigned to the minimum cost. Initial population is randomly chosen and taken as the parent.

V. CROSSOVER AND MUTATION

There are two main problems associated with the use of GA to solve VRP. These problems are the choosing of proper methods of crossover and mutation that is used to combine the two parent tours to make the child tours. The two point crossover is used. Given a random population of 12 16 6 9 2 15 11 5 18 10 13 14 4 1 3 8 19 17 7 20. This means that we start from the depot 1, the van goes to wholesale point 3 to point 8 to point 19 to point 17 to point 7 to point 20 or from the depot 1, the van goes to in the opposite direction, thus from 1 it goes to wholesale point 4 to point 14 to point 13 to point 10 to point 18 to point 5 to point 11 to point 15 to point 2 to point 9 to point 6 to point 16 and then to point 12. To reduce bias and the endpoint effect, two-point crossover is used in which two positions in the parents are chosen at random and the segments between them are exchanged.
If our parents with the two random points chosen are

Parent 1 $\Rightarrow$ 18 16 3 12 20 7 6 1 17 M15 4 2 14 11 M9 13 10 8 19 5

Parent 2 $\Rightarrow$ 12 13 3 19 7 10 1 11 18 M16 2 15 6 4 M8 20 9 11 14 5

Then after the crossover, the offspring produced will be

Offspring 1 $\Rightarrow$ 18 16 3 12 20 7 6 1 17 M16 2 15 6 4 M9 13 10 8 19 5

Offspring 2 $\Rightarrow$ 12 13 3 19 7 10 1 11 18 M15 4 2 14 11 M8 20 9 11 14 5

The problem of not being trapped in a local optimum could be solved by mutation after crossover. Due to the randomness of the process we will occasionally have chromosomes near a local optimum but not the global optimum. Therefore the better the fitness the less chance of hiding the global optimum. So mutation is a completely random way of getting to a possible solution that would otherwise not be found.

Mutation is performed after crossover. The mutation index must decide whether to perform mutation on this offspring or not. We then choose a point to mutate and switch that point. Like we had

Offspring 1 $\Rightarrow$ 18 16 3 12 20 7 6 1 17 M16 2 15 6 4 M9 13 10 8 19 5

Offspring 2 $\Rightarrow$ 12 13 3 19 7 10 1 11 18 M15 4 2 14 11 M8 20 9 11 14 5

If we decide to choose the mutation point in offspring 1 to be 3 and 10, and that of offspring 2 to be 7 and 9, then the two offspring would become

Offspring 1 $\Rightarrow$ 18 16 10 12 20 7 6 1 17 16 2 15 6 4 9 13 3 8 19 5

Offspring 2 $\Rightarrow$ 12 13 3 19 9 10 1 11 18 15 4 2 14 11 8 20 7 11 14 5

The process makes a strict verification of the chromosome after the mutation process to ignore non legal chromosome.

The product finds a solution to the Vehicle Routing Problem. For this purpose of VRP of finding the minimum total tour, we use cities, chromosomes and populations, where our cities are the wholesale points, chromosomes are the individual tours and the population is the combination of all the individual tours, ie., 20! =

Each wholesale point is situated on coordinates (x,y) on the map. In the working process a defined number of wholesale points are being created. Then the program solves the vehicle routing problem foe these wholesale points in different cities.

VI. FITNESS FUNCTION

To decide if a chromosome (tour) is good and how good it is, is the purpose of the fitness function. The criteria for good chromosome (tour) in VRP is the length of the chromosome. Thus, the longer the chromosome that is coded, the better the chromosome. Calculation takes place during the creation of the chromosome. Each chromosome is created and then its' fitness function is calculated. The length of the tour is measured in pixels by the scheme of the tour.

$$\text{Fitness tour} = \sum_{i=1}^{n} d_i$$

where n is the number of wholesale points and d_i is the distance between a wholesale point and the depot.

Matlab code is used to find the optimal route (tour) which is given as

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

and its corresponding graph is shown below in Fig. 4.26

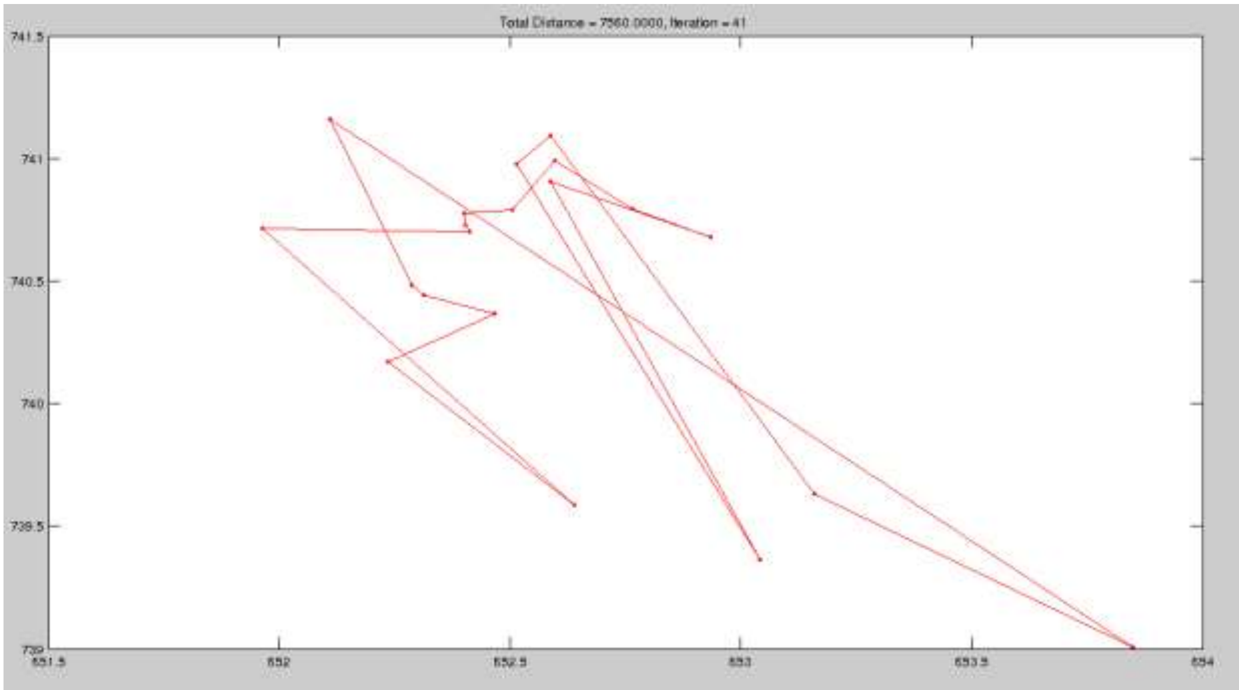


Fig. 4.26

Bearing it in mind that Amponsah Efah Pharmaceuticals Limited uses one delivery van, the optimal route is rearranged for the one vehicle as represented below.

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

Rearranged

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

VII. OPTIMAL ROUTE WITH DELIVERY POINTS

The optimal routes after they have been rearranged is as follows. This is done together with the main depot point as

Amponsah Efah → Nyankwa Pharmacy → Asempa Pharmacy → Kojach Pharma → Evergreen Pharmacy → Lansa Chemist → Noble Chemist → Fredemens Pharmacy → Numens Pharmacy → Benita Pharmacy → Porter Pharmacy → Mensaf Pharmacy → Concept Medicals → Action Pharmacy → Oson's Pharmacy → Kojach Pharmacy → Panacea Pharmacy → Big Maron Pharmacy → Danni Herbal → Costa Pharmacy

Total distance for the delivery van (for the northern sector) is calculated to be 7560metre (7.5600km). The fitness tour was calculated based on the following assumptions being used by Amponsah Efah Pharmaceutical Limited, Kumasi.

- One delivery van is used to make the distributions in the northern sector.
- The van picks up all the wholesale points demand from only one source which is the depot, Amponsah Efah Pharmaceutical Limited, Adum.
- The van is big enough to contain the requested demands of all the wholesale points in a single distribution without shortage for more.
- There are no traffic and other constraints after a tour has been established.

Then the optimal tour from the population depends on

- The shortest distance from the starting point which is the depot, to any of the wholesale points.
- All the distances from the depot to the wholesale point locations gives the minimum fitness value.

VIII. CONCLUSION

Genetic Algorithms can be applied to solve combinatorial optimization problems (COPs) such as VRP. Optimal solutions among the search space can be found by Genetic algorithm with the use of the operators like crossover and mutation. They are not instantaneous, but can perform an excellent search. In this work, Genetic algorithm is tested to find the optimal route for the VRP which shows the superiority of Genetic Algorithm over the company's normal route.

It is also proven that if Amponsah Effah Pharmaceutical Limited in retrospective uses this work, they would be able to reduce their operational distance by 3776m (3.7760km) thereby reducing their cost of fuelling their delivery vans which intend reduces the cost of operations of the company. We are of the view that this work if adopted would increase the profit margin of the company y and as well help the company to improve remuneration of all staff members of the company.

As an efficient tool for combinatorial optimization problems, Genetic Algorithm is very useful for solving problems which can be modeled as the VRP, thereby finding the optimal distance. In light of this capacity of Genetic Algorithm, it is recommended that GA should be used to solve Vehicle Routing Problem (VRP) instead of other traditional heuristic methods.

The following recommendations should be considered by the company,

- It is recommended that the deliveries of Amponsah Effah Pharmaceutical Limited (distributions of medicines) should be done before 07:00am or after 06:00pm where there will be no traffic congestions.
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References

A. Leon and J. Pozo, Using a genetic algorithm to study properties of minimum energy states and geometrical frustration in artificial ''spin ice'' systems, Journal of Magnetism and Magnetic Materials 320, pp. 210–216, (2008).

A. A. Ghanbari, A. Broumandnia, H. Navidi, A. Ahmadi, Brain Computer Interface with Genetic Algorithm, International Journal of Information and Communication Technology Research Vol. 2 No. 1, (2012).

A. Ghosh and S. Dehuri, Evolutionary algorithms for Multi-Criterion Optimization: A Survey, International Journal of Computing and Information Sciences, vol.2, pp 35-62, (2004)

Arifovic, J., Evolutionary algorithms in macroeconomic models. Macroeconomic Dynamics 4 (5): pp 373-414, (2000).

Birchenhall, C., N. Kastrinos, and J. Metcalfe, Genetic algorithms in evolutionary modeling, Journal of Evolutionary Economics 7 (4): pp 375-393, (1997).

Bremermann, H. J., The evolution of intelligence. The nervous system as a model of its environment, Technical Report No. 1, Department of Mathematics, University of Washington, Seattle, WA, (1958).

Carlsson, C., and E. Turban, DSS: Directions for the next decade. Decision Support Systems 40 (1): pp1-8, (2002).

Cassaigne, N., Aversi, R., G. Dosi, G. Fagiolo, M. Meacci, and C. Olivetti, Demand dynamics with socially evolving preferences. IIIASA Working Paper, Luxemburg, Austria, (1997).

C. Darwin, The Origin of Species, Dent Gordon, London, (1973).

C. Basnet, A. Weintraub, A Genetic Algorithm for a Bicriteria Supplier Selection Problem,(2001) Chia-Feng Juang. A TSK-type recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithm, IEEE Transactions on Fuzzy Systems, 10(2), pp. 155-170, (2002)

Chuan-Yin T. and Li-Xin G. Research on Suspension System Based on Genetic Algorithm and Neural Network Control, The Open Mechanical Engineering Journal, pp. 72-79, (2009).

Dosi, G., L. Marengo, A. Bassanini, and M. Valente., Norms as emergent properties of adaptive learning. Journal of Evolutionary Economics 9 (1): pp 5-26, (1999).

D. B. Fogel, 'Evolutionary Computation: Toward a New Philosophy of Machine Intelligence', IEEE Press, Piscataway, NJ, (1995).

D. B. Fogel, 'Evolving Artificial Intelligence', Ph.D. Thesis, University of California, San Diego, CA, (1992).

D. E. Goldberg, Sizing populations for serial and parallel genetic algorithms. In Schaffer, J. D. (editor) Proceedings of the Third International Conference on Genetic Algorithms. San Mateo, CA: Morgan Kaufmann Publishers Inc. (1989).

D. E. Goldberg, 'Genetic Algorithms in Search Optimization and Machine Learning', Addison-Wesley, Reading, MA, (1989).

D. Goldberg and R. Lingle, Alleles, loci and traveling salesman problem, In J.J. Grefenstette, editor, Proceedings of International Conference on GAs, Lawrence Erlbaum, (1985).

D. E. Goldberg, B. Korb, K. Deb, Messy Genetic Algorithms: Motivation, Analysis, and First Results, Complex Systems 3, pp. 493-530, (1989).

D. E. Goldberg, Genetic algorithms in search, optimization, and machine learning, Addison Wesley Longman, Inc., ISBN 0-201-15767-5, (1989).

Dawid, H. Adaptive learning by genetic algorithms: Analytical results and application to economic models. Berlin: Springer, (1999).

Davis, L., Applying algorithms to epistatic domains, in: *Proc. Int. Joint Conf. on Artifical Intelligence*, pp. 162–164, (1985).

Davis, Lawrence (editor), *Genetic Algorithms and Simulated Annealing*. London: Pittman, (1987).

Davis, Lawrence, *Handbook of Genetic Algorithms*. New York: Van Nostrand Reinhold, (1991).

De Jong K., An Analysis of the Behaviour of a Class of Genetic Adaptive Systems, PhD Dissertation, Department of Computer and Communication Sciences, University of Michigan, Ann Arbor, (1975).

E. Alba and J. M. Troya, A Survey of Parallel Distributed Genetic Algorithms, Journal of Information and Operations Management
ISSN: 0976–7754 & E-ISSN: 0976–7762 , Vol. 3, pp 38-42, (2012).

E. Correa, R. Goodacre, A genetic algorithm-Bayesian network approachfor the analysis of metabolomics and spectroscopic data: application to the rapid identification of Bacillus spores and classification of Bacillus species, Correa and Goodacre BMC Bioinformatics, (2011) Forrest, S., Genetic algorithms: Principles of natural selection applied to computation, *Science* **261**:872–878,(1993).

F. Oliveira, M.R. Almeida and S. Hamacher, Genetic algorithms applied to scheduling and optimization of refinery operations, **(2001).**

Frenke, R., Co-evolution and stable adjustment in the cobweb model, Journal of Evolutionary Economics 8 (4): pp 383-406, (1998).

Fraser, A. S., Simulation of genetic systems by automatic digital computers II: Effects of linkage on rates under selection, Austral. J. Biol. Sci. 10: pp 492–499, (1957).

Forel, D. B., and Atmar, W., eds., Proceedings of the second on Evolutionary Programming. Evolutionary Programming Society, (1993)

Fogel L. J., Autonomous automata. Industrial Research 4: pp 14–19, (1962).

Fogel L. J., Owens A. J. and Walsh M. J., Artificial Intelligence through Simulated Evolution, Wiley, New York, (1966).

G. Kannan, P. Sasikumar and K. Devika, A genetic algorithm approach for solving a closed loop supply chain model: A case battery recycling Journal of Applied Mathematics, vol.34, pp. 655-670, (2010)

Goldberg, D. E., Deb, K., and Korb, B. Messy genetic algorithms revisited: Studies in mixed size and scale. Complex Systems 4. pp. 410-470, (1990)

Goldberg, D. E. Genetic Algorithms and the minimal deceptive problem. In L. D. Davis, ed., Genetic Algorithms and Simulated Annealing. Morgan Kaufmann, (1987)

Goldberg, D. E. A note on Boltzman tournament selection for genetic algorithms and population-oriented simulated annealing. Complex Systems 4, pp. 445-460.

Goldberg, D. E. Genetic Algorithms and Walsh Functions: Part I, A gentle introduction. Complex Systems 3: pp. 130-155 (1998).

Goldberg, D. E., Genetic algorithms and Walsh functions: Part II, deception and its analysis, *Complex Syst.* **3**:153–171, (1989a).

Goldberg, D. E., 1989b, *Genetic Algorithms in Search Optimization and Machine Learning,* Addison-Wesley, Reading, MA, (1989b).

Goldberg, D. E., Sastry, K. and Latoza, T., On the supply of building blocks, in: *Proc. of the Genetic and Evolutionary Computation Conf.*, pp. 336–342, (2001).

Goldberg, D. E. and Lingle, R., Alleles, loci, and the TSP, in: *Proc. 1st Int. Conf. on Genetic Algorithms,* pp. 154–159, (1985).

Gen, M. and Cheng, R., Genetic algorithms and engineering optimization, John Wiley, New York, (2000).

Holland, John H., Escaping brittleness: The possibilities of general-purpose learning algorithms applied to parallel rule-based systems. In Michalski, Ryszard S., Carbonell, Jaime G. and Mitchell, Tom M. Machine Learning: An Artificial Intelligence Approach, Los Altos, CA: Morgan Kaufman, vol II. P. 593-623, (1986).

Hong Y. Y. and Li C. . Genetic algorithms based Economic Dispatch for Cogeneration Units Considering Multiplant Multibuyer Wheeling, IEEE Power Engineering Review, 22(1), pp. 66-69, (2002).

H.-P. Schwefel, 'Numerical Optimization of Computer Models', Wiley, Chichester, (1981).

H. G. Beyer and H. P. Schwefel, Evolution strategies: A comprehensive introduction, Natural Computing 1, pp. 3-52, (2002).

H. P. Schwefel. Evolutions strategies and Numeric Optimization, Dr.-Ing. Thesis, Technical University of Berlin, Department of Process Engineering, (1975).

H. R. Kanan, M. H. Moradi, A Genetic Algorithm based Method for Face Localization and pose Estimation, 3rd International Conference: Sciences of
Electronic, Technologies of Information and Telecommunications, (2005)

Hidalgo, J., F. Soltero, D. Bodas-Sagi, and P. Fernandez-Blanco, Technical market indicators optimization using evolutionary algorithms. Paper presented at the thirteenth IEEE International conference on evolutionary computation, Atlanta, Georgia, USA, (2008).

Holland J. H., Outline for a logical theory of adaptive systems. JACM 9: pp 297–314, (1962).

J. Blazewicz, M. Szachniuk and A. Wojtowicz, Evolutionary algorithm for a reconstruction of NOE paths in NMR spectra of RNA chains, Bulletin Of The Polish Academy Of Sciences Technical Sciences, Vol. 52, No. 3, pp. 8-33, (2004).