



OPTIMIZATION OF WATER SUPPLY DISTRIBUTION NETWORK WITHIN MOUAU METROPOLIS USING GENETIC ALGORITHM

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Article information	Abstract
Article History Received 15 April 2026 Revised 28 April 2026 Accepted 02 May 2026 https://www.guujet.ng © 2026 guujet Pub All rights reserved	This study investigates the optimization of a water distribution network using an engineering management approach based on network analysis. The water supply distribution network pipe system of Michael Okpara University of Agriculture, Umudike, as analysed. This study used genetic algorithms (GA) approach to solve minimum spanning tree problem of a water supply network system of Michael Okpara University of Agriculture, Umudike. Computational experiment results show that the algorithm gave an optimal distance of 5151.9 m, using thirty-six (36) nodes, which was arrived at after 23 iterations (generations), using phyton programme environment. Hence, the study achieved a reduction in distance of distribution route and financial cost. Keywords: <i>Genetic Algorithm (GA), Python Program, Spanning Tree, Iterations, network, water supply, optimal distance</i>

1.0 Introduction

Network problems provide a unified approach to many applications because of its general structure, in which water distribution network is no exception. According to, Chao-Hsien *et al.*, (2000), the design and development of a reliable network infrastructure is a very critical activity, hence becomes a primary source for information creation, storage, distribution, and retrieval. Over the past few decades, there have been efforts to increase provision of domestic water for both rural and urban homes. Water is fundamental for life and essential for nearly every human endeavour. According to Cunningham *et al.*, (2005), the earth is endowed with approximately 1.4 billion kilometres and of these only about 2.5 percent (i.e. 35,000,000km³).

The availability of water varies greatly, while some people pay so dearly for domestic water, others have an easy access to adequate clean water and sanitation due to their location and social status. With increased urbanization, government cannot improve their infrastructure at the same pace, but changing the way they operate it can yield significant improvements, which might be critical especially in developing areas, Connor (2015). The water need of the rural population has been on the increase due to increases in the population and consumption rates, WHO and UNICEF (2012). According to Gandy (2006) and Water-Aid (2006), it was estimated that only 1% of the households of most the populated city in Nigeria were connected to sewers. As of 2010 only four wastewater treatment plants were rehabilitated and are situated in Lagos. The federal government is in charge of water resources management; state governments have the primary responsibility for urban water supply; and local governments together with communities are responsible for rural water supply, Gandy (2006). Such challenging issue with the Nigerian water supply sector is the traditional way in which citizens view the provision of water supply and services. This provision is as well regarded traditionally, a social responsibility of the government. Consequently, the costs of water infrastructure and service delivery is usually met largely from government allocations and aids, rather than from water tariffs and charges, thus leading to the long-standing practice of fixing water rates far below the full cost of service provision, Odigie and Fajemirokun, (2005). Ariyo and Jerome (2004), reveal that increased maintenance and operational costs, coupled with competing demands on public funds, government at the state and federal levels have proposed privatization of the drinking water supply sector, although have always met intense resistance. Critics of privatization have argued that the provision of safe drinking water is a fundamental human right, hence too crucial to the national welfare to be totally sold to the private sector. Private for-profit water services providers refer to individuals and/or small

and micro-enterprises that generate, treat, and distribute water to households as commercial or business undertakings, Adeleye *et al.*, (2014). Against this backdrop, civil society groups and local communities have always mobilized and intensified their advocacy campaigns against privatization, since the process is perceived as more of concern for economic efficiency rather than ensuring the rights of the poor to access to safe drinking water, Odigie and Fajemirokun, (2005). The instruments and documents that govern and regulate water-resources in Nigeria are not sufficient to resolve the issues of control, ownership, management and protection of water resources. According to Nwankoala (2011); Omole (2015), the underperformance of these documents which govern and regulate water-resources in Nigeria is well known. The unsustainable nature of water services delivery is a major challenge which needs to be overcome if the rural economy, and more in the urban areas is to be transformed. Achieving this requires extensive research in order to select policies and strategies that are informed by clear scientific insight. The situation of water supply to citizens requires a pattern which could be represented in a spanning tree, hence minimum spanning tree algorithm. According to Wijaya *et al.*, (2016); Iswan *et al.*, (2016); Supiyandi *et al.*, (2017); Andysah *et al.*, (2018), The minimum spanning tree algorithm can calculate optimal usage. Optimization is a significant thing to achieve, as it also relates to the use of operational costs, and by optimization, some essential aspect will be saved and minimized. The economic factor in saving expenditure is a strong drive, in improving the water supply problem faced. There has been an increased interest in using Genetic Algorithm GA to resolve network distribution problems. GA has been applied in several network distributions in as to resolve vehicle routing which has been investigated by researcher for more than fifty years, Mazin *et al.*, (2017); Cortes *et al.*, (2017), in optimization of sensor network, Ehsan and Ali, (2011), piping network Eiger *et al.*, (1994); Fujiwara and Khang (1990). Furthermore, these have already been applied to different distribution network

optimization problems as may be seen in Murphy and Simpson, (1992); Boyd *et al.*, (1994); Savic and Walters, (1995). Also, according to Andysah *et al.*, (2018); Simpson *et al.*, (1994), a comparison of GA and other techniques has been provided. Michael Okpara University of Agriculture, Umudike has been bedevilled by the water supply challenges and one of the problems associated to the water supply is the distribution network. Hence, this study examines the use of GA in optimizing the distribution network of a water supply pipe.

2.0 Methodology

This research was carried out within the university premises of Michael Okpara University of Agriculture Umudike (MOUUAU). Umudike lies between latitudes 5° 25' and 5° 32' North and longitudes 7° 32' and 7° 35' East of the equator. It is in the tropical rainforest zone of Nigeria, and is one of the three universities of Agriculture established by the federal government of Nigeria.

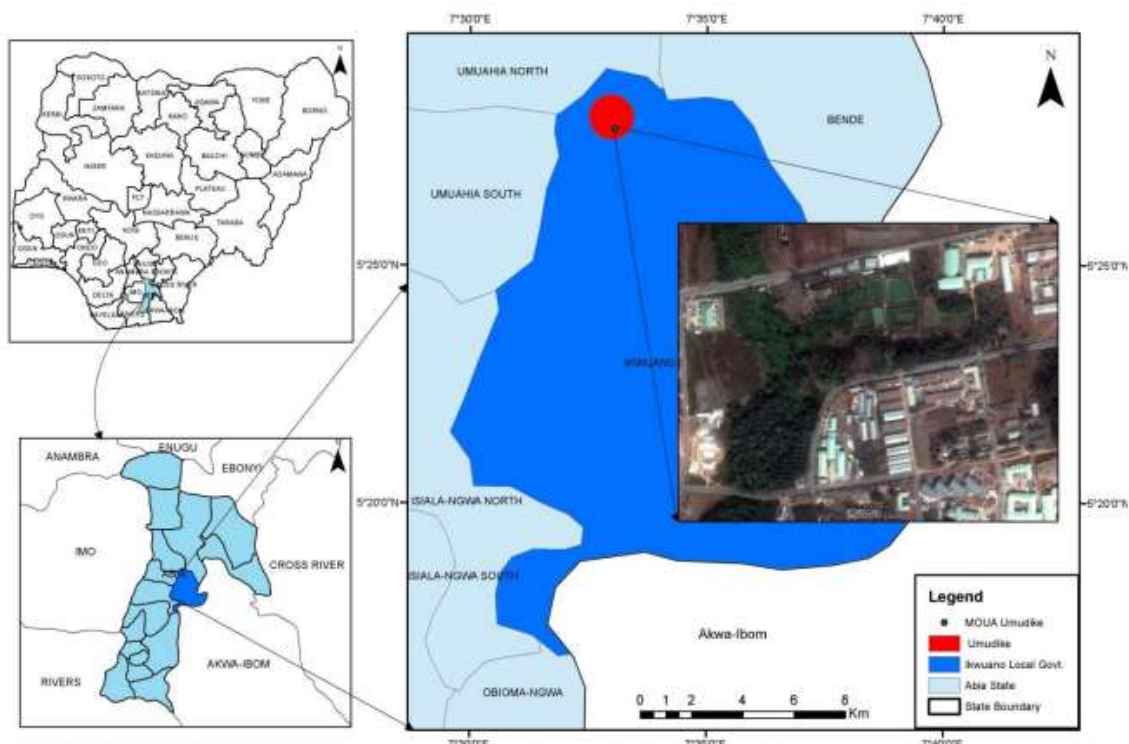


Figure 1: Map showing the location of MOUUAU in Abia State, Nigeria, with an aerial photograph of the study site. **Source:** Ministry of Lands and Survey, Abia State.

The source map (Umudike area) was extracted from the satellite imagery downloaded from Global Land Facility Cover Website, Google Earth. The map was geo-referenced using Arc Map 9.2 GIS software. The data was captured through heads-up digitizing in Arc Map 9.2. The final layout was prepared using the mapping functions of the same software (Amadi and Olasehinde, 2010). The source map (Umudike area) and borehole locations are shown in figure 2.

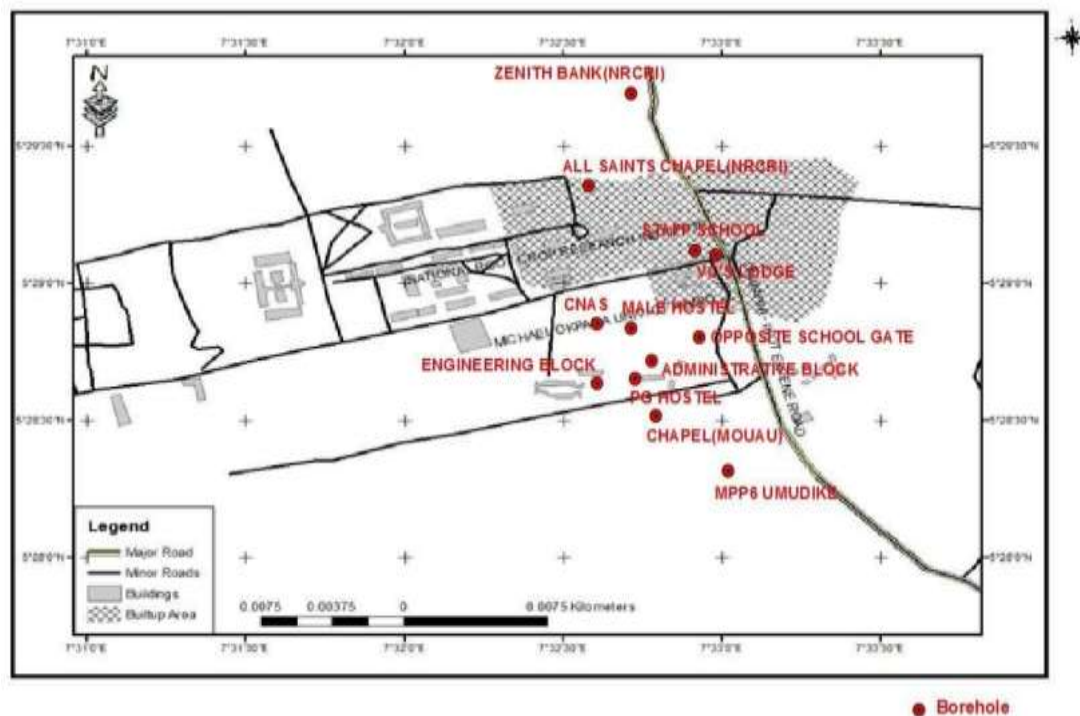


Figure 2: Source map of the study area showing borehole locations. **Source:** Akaninyene and Magnus, 2012

According to Akaninyene and Magnus, (2012), The source map of the area was registered into the software (ILWIS 2.1) through the steps of scanning, import, creation of coordinate system and georeferencing. The borehole locations captured using GPS were located on the digitized Umudike map (Table 1). The various spatial features (well location, elevation, contour lines) were digitized. Contour lines and elevation information were used to prepare the digital elevation model of the study area. Interpolation operation was used to prepare the vulnerability maps of different groundwater quality parameters and finally cross operation was used for the

preparation of the final hazard map of the area, (Igboekwe *et al.*, 2011; Akaninyene and Magnus, 2012).

2.1 Assumptions

The following assumptions were made:

- i. The connectors (edges) are undirected i.e. there is no source node or sink node
- ii. Each chromosome formed is equivalent to a spanning tree and edges are genes within the chromosome
- iii. The weight is a restricted non-negative real number indices.
- iv. Increase in length is proportional to an increase in cost in naira.
- v. The nodes represent the respective colleges, hostels, engineering drawing studio, works department and the administrative block of the institution.

2.2 Network Representation

Figure 3 below shows Undirected digitalized network diagram of roads and 36 nodes with their corresponding interconnected distances (edges) in meters. It represents the paths in which the supply of water could be traced pass.

Let $G = (V, E)$ be a connected weighted undirected graph with n vertices, $V = \{1, 2, \dots, n\}$ is the set of nodes and $E = \{(i, j) : i, j \in V, i \neq j\}$ is the set of edges joining the node and W_{ij} represents the weight of each edge $(i, j) \in E$. Each edge $\in E$ with end points i and j is defined by an ordered pair $\{i, j\}$.

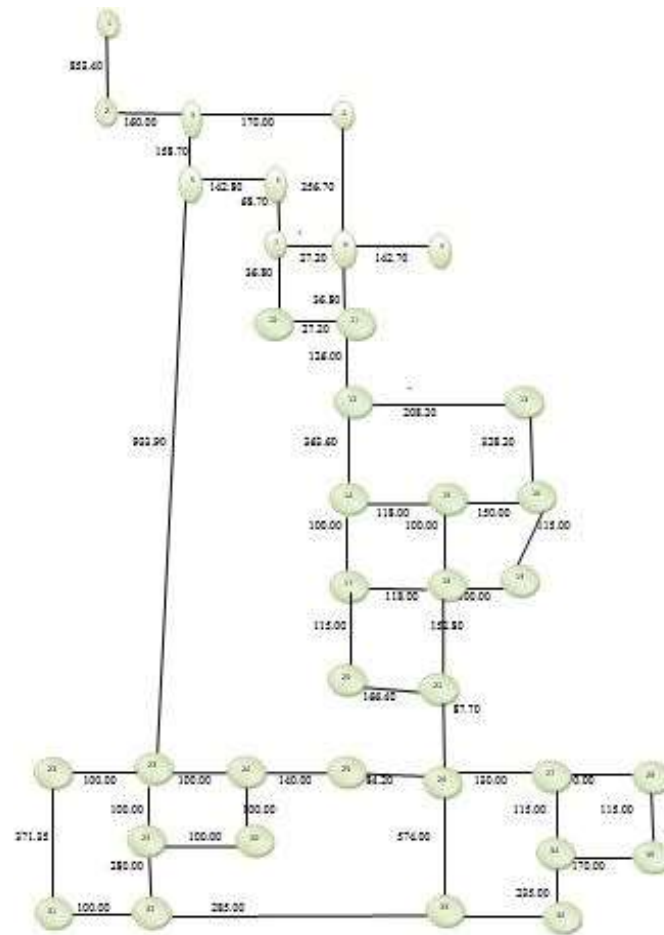


Fig. 3: Undirected graph showing Michael Okpara University of Agriculture, Umudike Nodal network

The Genetic algorithms (GA) was employed in solving the minimum spanning tree (MST) network optimization problem. Genetic Algorithm (GA) applied to an optimization problem is intimately related to a set of control parameters which must be appropriately determined by the designer of the GA in order to obtain high quality solutions in an efficient manner, (Goldberg, 1989; Hesser and Manner, 1990; Bernd and Michael, 1993). Genetic algorithms are commonly used to generate high-quality solutions to optimization problems through biologically inspired operators such as selection, crossover, and mutation. Genetic algorithm (GA) is a metaheuristic, inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA) in computer science and operations research, (Mitchell, 1996; Petrowski *et al.*, 2017). The flow diagram of the genetic algorithm for path optimization used is presented in Figure 1.

2.3 Genetic Algorithm Concept and Consideration

The Genetic Algorithm (GA) was developed based on:

- i. The connectors (edges) are undirected i.e. there is no source node or sink node
- ii. Each chromosome formed is equivalent to a spanning tree and edges are genes within the chromosome
- iii. The weight is a restricted non-negative real number indices.
- iv. Increase in length is proportional to an increase in cost in naira.
- v. The nodes represent the respective colleges, hostels, engineering drawing studio, works department and the administrative block of the institution.

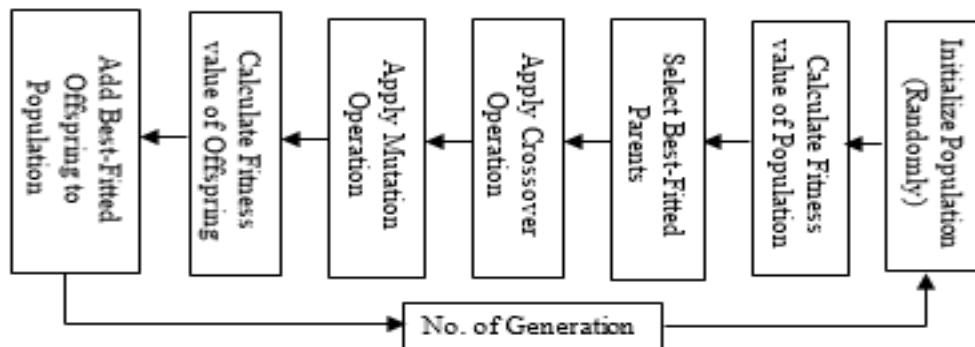


Fig. 4: flow diagram of the Genetic Algorithm for Path Optimization

2.4 Developed Program

The program developed was a python program, and the developed program is as shown below;

```

import random
import sys
sys.setrecursionlimit(2500)
class UFDS:
    def __init__(self,d):
        a=list(d.keys())
        c=[i.split('-') for i in a]
        s=set()
    for i in c:
        s.update(i)
        b=list(s)
        self.u=[{i} for i in b]
    def find(self,x):
        for i in self.u:
            if x in i:

```

```

return i
def union(self,x,y):
    self.u.remove(x)
    self.u.remove(y)
    a=x|y
    self.u.append(a)
    return self.u
def testing_solution(c,d):
    o=UFDS(d)
    for i in c:
        x,y=i.split('-')
        j=o.find(x)
        k=o.find(y)
        if j!=k:
            o.union(j,k)
        else:
            return False
        else:
            return True
def create_random_chromosome(d,s,e):
    o=UFDS(d)
    random.shuffle(s)
    a=[]
    for i in s:
        x,y=i.split('-')
        j=o.find(x)
        k=o.find(y)
        if j!=k:
            a.append(i)
            o.union(j,k)
        else:
            pass
        if len(a)==e:
            return a
def create_parent_solutions(d,s,n,e):
    p=[create_random_chromosome(d,s,e) for i in range(n)]
    return p

def computing_fitness_value(d,c):
    s=[d[i] for i in c]
    f=sum(s)
    return round(f,2)
def selecting_parent_solutions(d,s,n,e):
    p=create_parent_solutions(d,s,n,e)
    p.sort(key=lambda x: computing_fitness_value(d,x))
    ps=p[0:2]
    return ps
def crossover(d,a,e):
    ''' a is gotten from the selecting_parent_solutions function '''
    u=set(a[0])|set(a[1])

```

```

o=list(u)
try:
    c=create_random_chromosome(d,o,e)
    assert computing_fitness_value(d,c)<computing_fitness_value(d,a[0])
except RecursionError:
    return a[0]
except AssertionError:
    return crossover(d,a,e)
else:
    return c
def mutation(d,s,e,b):
    ''' b is gotten from the crossover function '''
    r=random.random()
    if r<0.15:
        try:
            c=create_random_chromosome(d,s,e)
            assert computing_fitness_value(d,c)<computing_fitness_value(d,b)
        except AssertionError:
            return mutation(d,s,e,b)
        except RecursionError:
            return b,computing_fitness_value(d,b)
        else:
            return c,computing_fitness_value(d,c)
        else:
            return b,computing_fitness_value(d,b)
    def ga(d,g,e):
        s=list(d.keys())
        offsprings=[]
        a=selecting_parent_solutions(d,s,4,e)
        h=crossover(d,a,e)
        f= mutation(d,s,e,h)
        offsprings.append(f)
        for i in range(g):
            try:
                a=selecting_parent_solutions(d,s,4,e)
                a=[offsprings[0][0],a[0]]
                h=crossover(d,a,e)
                f= mutation(d,s,e,h)
            offsprings.sort(key=lambda x: x[1])
            offsprings=offsprings[:1]
            if offsprings[0][1]>f[1]:
                print('The total distance after {} iterations is {}'.format(i, offsprings[0][1]))
            offsprings.append(f)
        except RecursionError:
            solution=offsprings[0]
        print(solution)
    else:
        print('total distance after {} iterations is {}'.format(g, offsprings[0][1]))
        solution = offsprings[0][0]
        print(solution)

```

```

for edge in solution:
print(f'{edge} \t {d[edge]}')
network = {'1-2': 853.4, '2-3': 160, '2-23': 933.9, '3-4': 170, '3-5': 158.7, '5-6': 142.8, '4-8': 256.7, '6-7': 68.7, '7-8': 27.2, '8-9': 142.7, '7-10': 36.8, '10-11': 27.2, '8-11': 36.8, '11-12': 126, '12-13': 208.2, '12-14': 363.6, '14-15': 118, '13-16': 328.2, '15-16': 150, '14-17': 100, '15-18': 100, '18-19': 100, '18-17': 118, '16-19': 115, '20-21': 166.4, '18-21': 152.8, '21-26': 170, '26-25': 84.2, '26-27': 130, '27-28': 170, '28-35': 115, '35-34': 170, '27-34': 115, '34-36': 235, '36-33': 72, '33-26': 574, '25-24': 140, '24-23': 100, '23-22': 100, '22-31': 371.35, '24-30': 100, '23-29': 100, '29-30': 100, '29-32': 170, '32-33': 285, '32-31': 100, '17-20': 115}, 40, 35)

```

The algorithm was iterated using varying chromosome populations until the optimal solution was obtained. The result is shown in Appendix E. These results are discussed in chapter four.

3.0 RESULTS AND DISCUSSION

There was a reduction in total distance from 6501.95m to 5537.00m, when the number of generations increases from 5 to 8. A slight increase occurs at the 10th generation which decreases slightly and stabilizes at the 23 generation with the value 5151.9 m. Figure 5 shows the variation of randomly generated generations with the overall distance covered, and Figure 6 shows the minimum spanning tree graph formation for the genetic algorithm. The optimal network has the following edge combinations:

['34-36', '24-23', '14-15', '8-9', '15-18', '7-8', '1-2', '3-4', '16-19', '12-13', '17-20', '26-25', '3-5', '21-26', '10-11', '29-32', '6-7', '13-16', '23-22', '28-35', '18-19', '25-24', '7-10', '35-34', '29-30', '5-6', '2-3', '26-27', '11-12', '36-33', '14-17', '18-21', '27-34', '23-29', '32-31']".

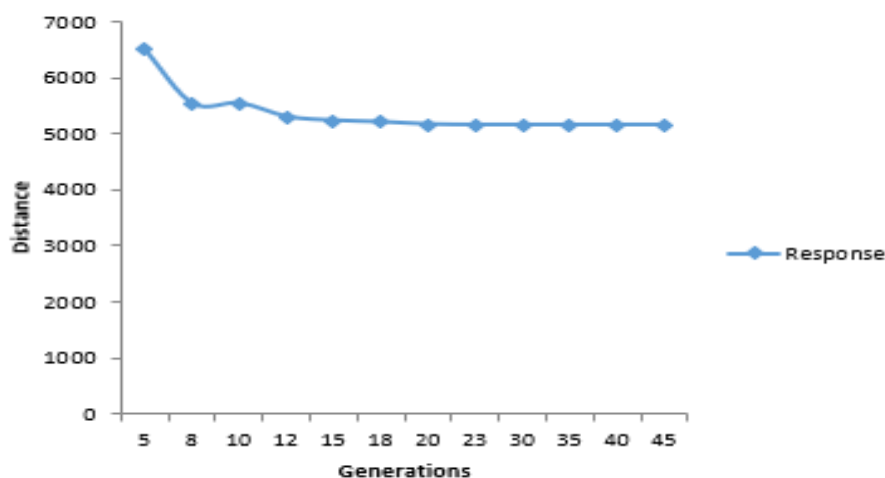


Fig. 5: variation of randomly generated generations with distance

REFERENCE

- Adeleye B., Medayese S., Okelola O. (2014). "Problems of water supply and sanitation in Kpakungu Area of Minna, Nigeria". *Journal of Culture, Politics and Innovation*. Iss. 2 p. 1–9.
- Akaninyene O. A. and Magnus U. I., (2012). Application of Geographic Information System in Mapping of Groundwater Quality for Michael Okpara University of Agriculture Umudike and its Environs, Southeastern Nigeria. *Archives of Applied Science Research*, Vol.4 (3), pp. 1483-1493.
- Amadi A. N. and Olasehinde P. I., (2010). Application of remote sensing techniques in hydrogeological mapping of parts of Bosso Area, Minna, North-Central Nigeria. *International Journal of the Physical Science*, Vol.5(9), pp. 1465-1474.
- Andysah P. U. S., Rusiadi, Phak L. E. K., Ku Nurul F. K. A., Amiza A., (2018). Prim and Genetic Algorithms Performance in Determining Optimum Route on Graph. *International Journal of Control and Automation* Vol. 11, No. 6, Pp.109-122.
- Ariyo, A. and A. Jerome (2004), 'Utility Privatization and the Poor: Nigeria in Focus', Global Issue Papers No. 12, The Heinrich Böll Foundation. Available online at <http://www.boell.de/internationalepolitik/africa-3361.html>, accessed on 25 November 2011.
- Bernd F., and Michael H., (1993). "Optimization of Genetic Algorithms by Genetic Algorithms". *Artificial Neural Nets and Genetic Algorithms*, Springer-Verlag/Wien, Pp. 392-399.
- Boyd I. D., Surry E. D., Radcliffe N. J., (1994). Constrained gas network pipe sizing with genetic algorithms, Technical Report EPCC-TR94, Edimburg Parallel Computing Center.
- Chao-Hsien C., Premkumar G., Hsinghua C., (2000). Digital data networks design using genetic algorithms. *European Journal of Operational Research* 127. Pp. 140-158.
- Connor R, (2015). 'The United Nations world water development report 2015: Water for a sustainable world'. *Technical report, UNESCO publishing*, 201.
- Cortes P., Montoya G. R. A., Munuzuri J., Espinal C. A., (2017). A tabu search approach to solving the picking routing problem for large and medium size distribution centres considering the availability of inventory and K heterogeneous material handling equipment. *Appl. Soft Comput*, 53: 61-73.
- Cunningham, W. P.; Cunningham, M. A., Siago, B. (2005). Environmental science: a global concern. New York: McGraw-Hill.
- Ehsan H., Ali M., (2011). An Efficient Method Based on Genetic Algorithms to Solve Sensor Network Optimization Problem. *International journal on applications of graph theory in wireless ad hoc networks and sensor networks*, (GRAPH-HOC) Vol.3, No.1, Pp. 18-33.
- Eiger G., Shamir U., Ben-Tal A., (1994). Optimal design for water distribution networks, *Water Resources Research* 30 (9), Pp. 2637-2646.

- Fujiwara O., Khang D. B., (1990). A two-phase decomposition method for optimal design of looped water distribution networks, *Water Resources Research* 26 (4), Pp. 539-549.
- Gandy, M., (2006). The bacteriological city and its discontents. *Histor. Geogr.* 34 (2006), 4–25.
- Goldberg D. E., (1989). 'Sizing Populations for Serial and Parallel Genetic Algorithms', *Proc. of the 3rd Int. Conference on Genetic Algorithms and their Applications*, pp. 70-79.
- Hesser J and Manner R, (1990). 'Towards an Optimal Mutation Probability for Genetic Algorithms', *Proc. of the 1st Int. Workshop on Parallel Problem Solving from Nature*, pp. 23-32, *Lecture Notes in Computer Science* 496, Springer-Verlag.
- Igboekwe M. U., Akankpo A. O., Udoinyang I. E., (2011). Hydrochemical evaluation of groundwater quality in Michael Okpara University of Agriculture, Umudike and its environs, southeastern Nigeria. *Journal of Water Resource and Protection*, Vol. 3(12), pp. 925-929.
- Iswan M., Perangin-angin, Khairul and Siahaan A. P. U., (2017). "Fuzzy Logic Concept in Technology, Society, and Economy Areas in Predicting Smart City", *Int. J. Recent Trends Eng. Res.*, vol. 2, no. 12, (2016), pp. 176-181.
- Mazin A. M., Mohd K. A. G., Omar I. O., Salama A. M., Dheyaa A. I., Burhanuddin M. A., (2017). "A Review of Genetic Algorithm Applications in solving Vehicle Routing Problems". *Journal of Engineering and Applied Sciences* 12(16); Pp. 4267-4283.
- Mitchell, M., (1996). *An Introduction to Genetic Algorithms*. Cambridge, MA: MIT Press. ISBN 9780585030944.
- Murphy L. J., and Simpson A. R., (1992). "Genetic algorithms in pipe network optimization", *Research Report No. R93*, Department of Civil and Environmental Engineering, University of Adelaide.
- Nwankoala H. O. (2011). The role of communities in improved rural water supply systems in Nigeria: Management model and its implications for vision 20:2020. *Journal of Applied Technology in Environmental Sanitation. Vol. 1. Issue. 3 p. 295–302.*
- Odigie, D. and Fajemirokun, B., (2005). *Water Justice in Nigeria: Crisis or Challenge*. International Workshop on Water Poverty and Social Crisis, Dec. 12-15, Agadir, Morocco, 198-198.
- Omole D. O., (2015). Sustainable groundwater exploitation in Nigeria. *Journal of Water Resources and Ocean Science. Vol. 2. Iss. 2 p. 9–14.*
- Pérowski, Alain; Ben-Hamida, Sana (2017). *Evolutionary algorithms*. John Wiley & Sons. p. 30. ISBN 978-1-119-13638-5.
- Savic D.A., Walters G.A., (1995). Genetic Operators and constraint handling for pipe network optimization, in: T.C. Fogarty (Ed.), *Evolutionary Computing*, vol. 2, Springer-Verlag, New York. Pp. 154-165.

- Simpson A.R., Dandy G.C., Murphy L.J., (1994). Genetic algorithms compared to other techniques for pipe optimization, ASCE Journal of Water Resources Planning and Management 120 (4). Pp. 423-443.
- Supiyandi S., Perangin-angin M. I., Lubis A. H., Ikhwan A., Mesran and Siahaan A. P. U., (2017). “Association Rules Analysis on FP-Growth Method in Predicting Sales”, Int. J. Recent Trends Eng. Res., vol. 3, no. 10, (2017), pp. 58-65.
- WaterAid USA. (2006). Giving shares: Give shares - share water. Available online at http://www.wateraid.org/usa/donate/giving_shares/default.asp.
- WHO and UNICEF (2012). Progress on drinking water and sanitation 2012 Update. WHO/UNICEF Joint Monitoring Programme (JMP) for water Supply and Sanitation. Geneva. World Health Organization. ISBN 978-92-4-150329-7 pp. 59.
- Wijaya R. F., Tondang Y. M. and Siahaan A. P. U., (2016). “Take Off and Landing Prediction using Fuzzy Logic”, Int. J. Recent Trends Eng. Res., vol. 2, no. 12, (2016), pp. 127-134.