OPTIMIZATION RESOURCE ALLOCATION MODEL FOR PAEDIATRICHEALTHCARE SYSTEMS DURING PATIENT REFERRAL

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Abstract
Patient referral is one of the strategies recommended for enhancing access to healthcare as stipulated by the Sustainable Development Goals Target 3 of the United Nations. However, the success of patient referral is directly dependent upon knowledge of the availability of requisite resources in the referral facility. Whereas several models based on heuristic search algorithms have been developed for healthcare system resource allocation, none seem to have been targeted at paediatric patients. This paper presents an intelligent distributed system resource allocation model based on Honey Bee Foraging theory for improving healthcare system provision to paediatric patients. The model was proved to be effective in enhancing healthcare service delivery due to informed decision making before a referral process was completed. More models should be designed which are capable of integrating patients and specialist data across county boundaries to facilitate wider referral options.

Key words: Resource Allocation; Healthcare System; Paediatric Patient Referral; Honey Bee Foraging; Heuristics;

1.1 Introduction

Efficient allocation of scarce healthcare resources forms one of the serious problems associated with complex and fragmented healthcare systems (Breuer, 2017). According to Youse, Hasankhani and Kiani (2020), timely allocation of specialist care, facilities as well as coordination of care has proved to be a permanent headache to health operation researchers. However, the rise in artificial intelligence including machine learning and data mining techniques has enabled pursuance of matching of patient demand and specialist care (Hao, Zhang, Liu and Goh, 2022). This notwithstanding, two questions remain: which hospital should receive the patient, and how should the patient be slotted?

One of the methods that has widely been deployed to obtain optimal or near-optimal solutions in complex situations is heuristics (Hoon, Singh, Han and Kee, 2013; Mijwel, 2015). A Greek word meaning “serving to find out or discover”, heuristics are experientially derived cognitive “rules of thumb” that serve as guides in problem-solving processes (Todd and Gigerenzer, 2000). Abel (2003) argues that problem solvers depend on heuristics which help them in simplifying choices regarding numerous complex and imperfectly understood factors that act simultaneously to shape problems, or the n-puzzle problem. According to Ahmed (2012), swarm-based decision-making in natural environments have recently emerged as a family of nature-inspired, population-based algorithms that are capable of producing low-cost, fast, and robust solutions to several complex problems. Consequently, the collective problem-solving capabilities of social animals have been used to model new optimization algorithms in the fields of engineering and mathematics (Rosenberg and Willcox, 2019). Amongst this collective behaviour of social animals, honey bee social foraging has been widely applauded for being robust and simply to adopt (Xu and Duan, 2010). This paper utilised the Honey bee foraging theory to develop a model for resource allocation in a paediatric healthcare system to aid patient referral in Kisumu City of Kenya.

Patient referral is a request from one doctor to another doctor, asking the latter to diagnose or treat a patient for a medical condition (Hao et al, 2022). Some of the reasons a patient might be referred to specialty care including diagnosis, management advice, and treatment beyond the scope of the primary care physician (Greenwood-Lee, Jewett, Woodhouse and Marshall, 2018). Therefore, effective patient flow control is an important means to balance the healthcare resource utilization in a disintegrated healthcare system (Mills, Argon, and Ziya, 2018). Agola and Raburu (2018) contend that for a referral to be successful, it is critical to know of the availability of the specialist doctor, his/her cost, time schedule in terms of patient workload, and the distance or his/her location from where the referral is being made. This is important in avoiding referring a patient to a doctor with many patients on the waiting queue which might end up delaying the treatment thus risking the life of the patient. Resource optimization researchers have considered distance and availability of hospital resources (Muriki, 2020) and background of the patient such as socio economic variables (Youse, et al, 2020) as important metrics in determining patient referral success. However, models developed to guide healthcare resource allocation have not comprehensively focused on paediatric health systems especially in regions with high rates of under five (U5) mortality rates such Kisumu County of Kenya.

Over the years, western Kenya region has had a significant contribution to the country's poor health indicators. For example, International Development Research Centre (IDRC, 2017) reports that the infant mortality rate in the region is 119 per 1,000, against the national rate of 72 per 1,000. Malaria is the most prevalent disease. The HIV infection rate sits at 15% (National AIDS & STI Control Programme, 20015), and prevention of mother-to-child transmission, as well as voluntary counseling and testing uptake, are low. The contraceptive prevalence rate sits at 46%, and only 44% of women deliver babies with skilled birth attendants present (UNICEF, 2012). A model to help situate key healthcare resources to aid referral of paediatric patients was considered as significant by these researchers.

1.2 Statement of the Problem

Kenya, like most developing countries South of the Sahara, has not attained the SDG target3:2 of achieving below 30 U5 mortality rate. The mortality rate of this population accounts for 45% of all deaths in the last five years, with Kisumu County contributing an average of 16% of such deaths during the same period. Whereas several models based on heuristic search with artificial intelligence have been developed for healthcare system resource allocation, none seem to have been targeted at paediatric patients. There was therefore need to develop a model capable of aiding resource allocation for quick response to paediatric patient during referral processes especially for the unique Kenyan system.

1.3 Objective of the paper

The purpose of the paper was to develop a model for the optimization of resource allocation for paediatric healthcare systems during patient referral. Specifically, the model aimed at improving paediatric healthcare system by aiding:

i. The referral of patients based on availability of specialists
ii. The referral of patients based on distance to specialists
iii. The referral of patient based on cost of specialist

2. Theory and Previous Literature on Resource Allocation Models

2.1 Theories for Resource Allocation

The model development was guided by the honey bee foraging theory. According to Ahmed (2012), the past several decades have witnessed biologists and natural scientists studying the behaviours of social insects because of the amazing efficiency of these natural collective decision making systems. Among the biological societies such as bees, ants, and birds, among others, the cooperation between individuals and self-organized groupings enable achievement of optimal efficiency in fundamental survival tasks such as predator avoidance and foraging, among others, feats which are not easy to make individually (Pham and Castellani, 2009). In consequence, computer scientists started proposing scientific insights or models of this natural collective behaviour into engineering into engineering (Rosenberg and Willcox, 2019). Yu, Wang, Han, Liu and Zhang (2015) assert that models adopting collective behaviour of such natural animals have practical characteristics which aim to improve the deficiencies of the algorithm and to improve the performance of the algorithm. Such characteristics include being strong and robust since they are distributed, and with no central control: their work environment is in a wide range hence one or some individual problems can not have an impact on the group, strong robustness. They are also simple and with operations which are easy to control; have better scalability since the amount of information of each individual sensing is limited; have strong self-organization since the complex behaviors exhibited by group are the result of individual interactions; and also have potentially parallelism and distributed features (Fritsche-Guenther et al, 2011). Due to its wide usage for informing decision making regarding resource allocation in various fields, this study adopted Honey Bee Social Foraging algorithm to guide the model development.

Bees have peculiar foraging behaviour for collecting their foods. According to Pham and Castellani (2009), the honey bee foraging framework is therefore suitable for modeling foraging efforts capable of performing a kind of exploitative neighbourhood search combined with random explorative search. Researchers (Tereshko and Loengarov, 2005; Yuce et al (2013) explains that the foraging behaviour of honey bee involves some bees known as employed bees being sent out to look for promising food sources in the first stage (Figure 1). After a good food source is located, bees return back to colony and perform a waggle dance to spread out information about the source. Three pieces of information are included in the dance: distance, direction, and quality of food source. The better the quality of food source, the more bees become attracted. Therefore, the best food source emerges (Lim, Jain and Dehuri, 2009).

After employed bees have shared information about food sources, onlooker bees probabilistically choose their destination accordingly. Usually, this is calculated depending on the fitness values provided by employed bees. The third kind of bees is the scout bees, which were usually employed bees abandoned by the algorithms because the quality of food sources they found was poor. Scout bees would again start from the beginning and search for other new food sources randomly (Karaboga and Ozturk, 2009).

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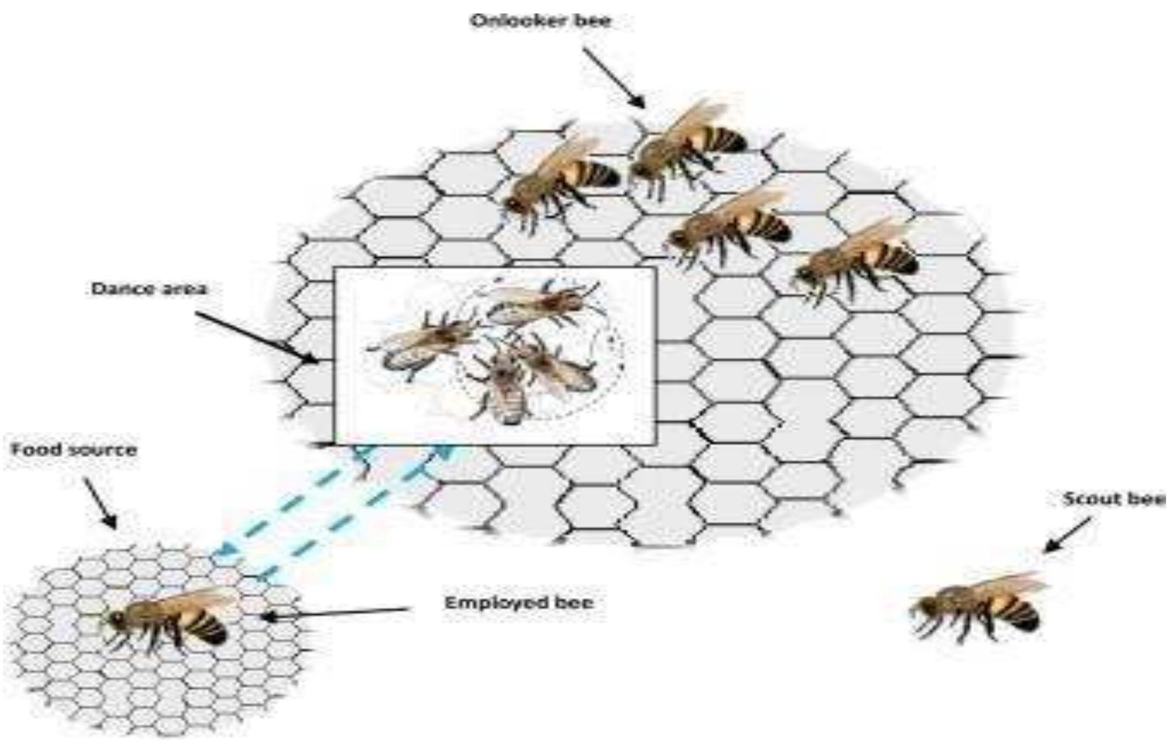


Figure 1: How bees work to find food sources

The meta-heuristic extracted from the foraging behaviors of bees can also be applied to solve combinatorial problems; especially problems involve global minimum or maximum. Indeed algorithms adopting the honey bee foraging theory have interesting applications in numerical optimizations, for example, it can be used to find global optimal solutions of functions. Moreover, recent studies suggest that the BCO algorithms can also be applied to problems in shop scheduling (Quijano and Passino, 2007), neural network training (Karaboga and Ozturk, 2009) and imaging processing (Xu and Duan 2010).

2.2 Related Literature

2.2.1 Patient Referral Models

In patient referral, a request from one doctor to another doctor is made, asking the latter to diagnose or treat a patient for a medical condition. In such a process, an effective patient flow control is a critical means to balance the healthcare resource utilization among the facilities in the system. Many scholars have documented steps taken in informing decisions regarding resource utilization in such systems. For instance, Mills, Argon and Ziya (2018) studied a hospital selection decision problem in which patients were transported from multiple disaster sites using a stochastic model. They proposed a Markov Decision Process (MDP) model, and developed two heuristic policies, Myopic and Policy Improvement. Geng et al (2017) studied patient assignments with a diversion penalty considering two types of patients and three time slots. An average-cost MDP model was developed to dynamically control the queue lengths of the two types of patients.

To achieve the wait-time targets in a cost-effective manner, Patrick, Puterman, andbetween the referral hospitals, to assess an agreement framework between the ULH and the LLH.

2.2.2 Heuristic Search Models

Heuristics have been widely used to readily obtain optimal or near-optimal solutions. To address the shortage of the emergency medical resources in MCI, Shin and Lee (2020) developed a heuristic policy for the stochastic dynamic model for patient transport prioritization and hospital selection. Chern, Chien and Chen (2008) proposed a heuristic to minimize the waiting time of patients and doctors for the patient health examination scheduling problem. Li, Pan, and Xie (2020) developed several strategies to determine the patient transfer time and the receiving hospital using simulation models and proposed a PSO-OCBA algorithm to find the best control threshold for each strategy. Hooshmand, MirHassani, and Akhavein (2018) proposed an improved Genetic Algorithm with a new chromosome assigning rule for solving the daily operating room scheduling problem with stochastic surgery duration. To minimize the hospital’s operating costs and improve patient satisfaction, Qiu et al. (2019) studied the scheduling problem of a single MRI facility of an uncertain service duration. A multi-objective evolutionary algorithm based on the decomposition framework was developed by combining an improved multi-objective evolutionary algorithm and a support vector regression surrogate model. To optimize hospital selection and treatment ordering for patients, Repoussis et al. (2016) proposed a mixed-integer programming model associated with an iterated Tabu Search algorithm to minimize the required time of completing the entire patient transport and treatment. To set the relationship among the medical process and resources of the patient scheduling problem, Li et al. (2019) presented a Petri net and developed a greedy heuristic to allocate the bottlenecked medical resources of an integrated hospital system.

3. Model Development

3.1 Proposed Model

The proposed model denotes the foraging behaviour of the bee colony. Under the Bee Colony Optimization, the employed bee searches the entire population of possible food sources for suitable foodstuffs. The search is terminated when a food source is found and the source is recommended for the entire colony. If a suitable source (specialist) is not found, a thorough search is conducted in the nearby hospitals. Again, the search is terminated if a suitable source is found and recommendation is made. In the event that a suitable source is not found, then further search is found among the surrounding population (hospitals). Figure 1 presents the proposed distributed model guided by the honey bee foraging theory.

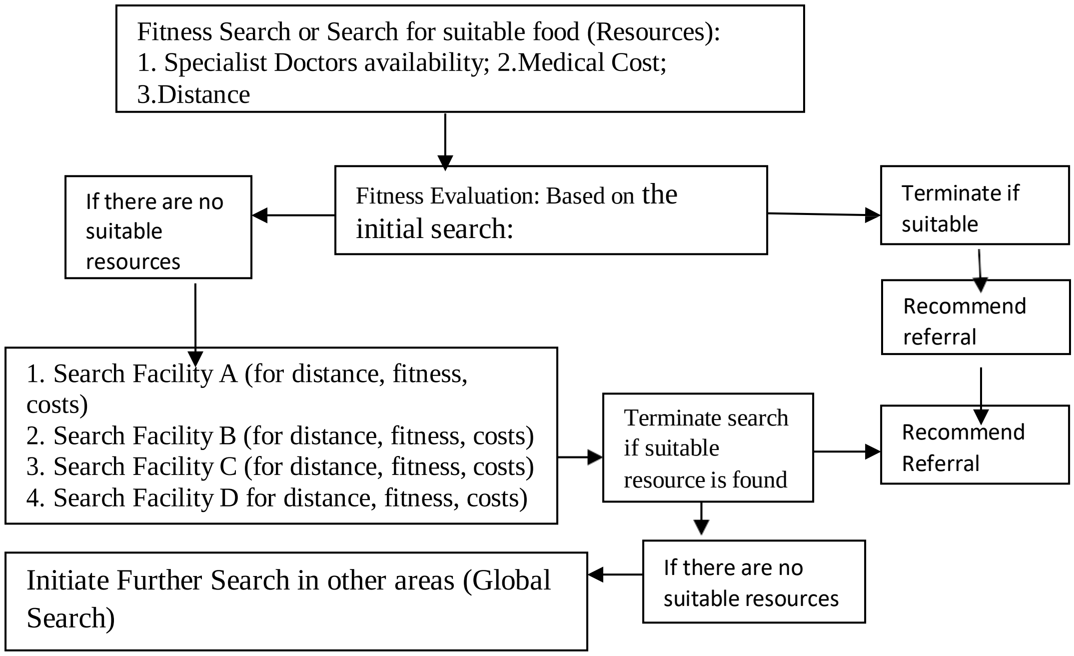


Figure 2: Search for Suitable Food Source under Bee Colony Optimization Principle

3.2 Model Development

Figure 3 presents the development layout of the resource allocation model.

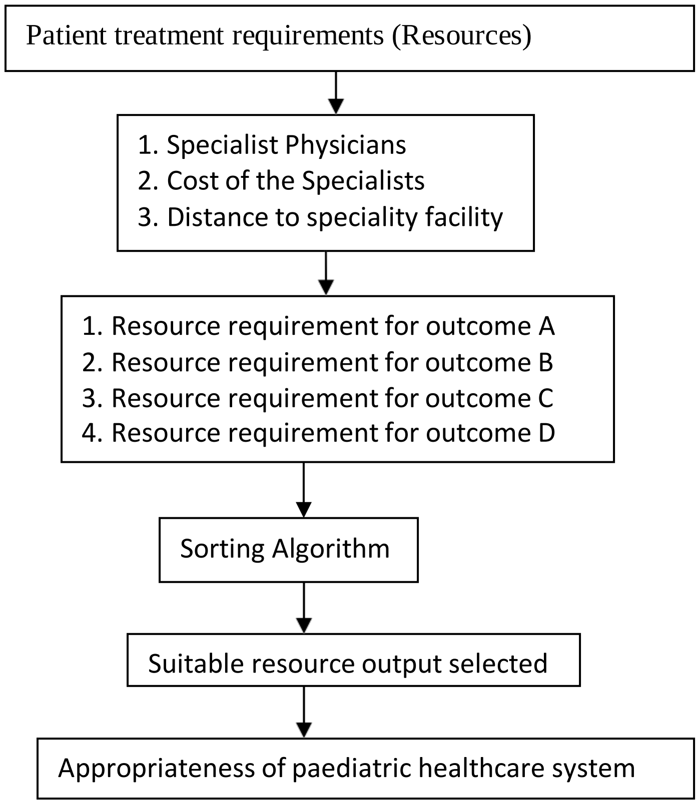


Figure 3: Development Layout for the proposed Resource allocation model based on Bee Colony Optimization

3.3 Search Process

The search process adopted for the model was A* Search Algorithm. This is an informed search algorithm, or a best-first search formulated in terms of weighted graphs capable of solving many kinds of problems. This algorithm also finds the shortest path through a search space to goal state using heuristic function. A* requires heuristic function to evaluate the cost of path that passes through the particular state. The A* algorithm adopted was described using following formula:

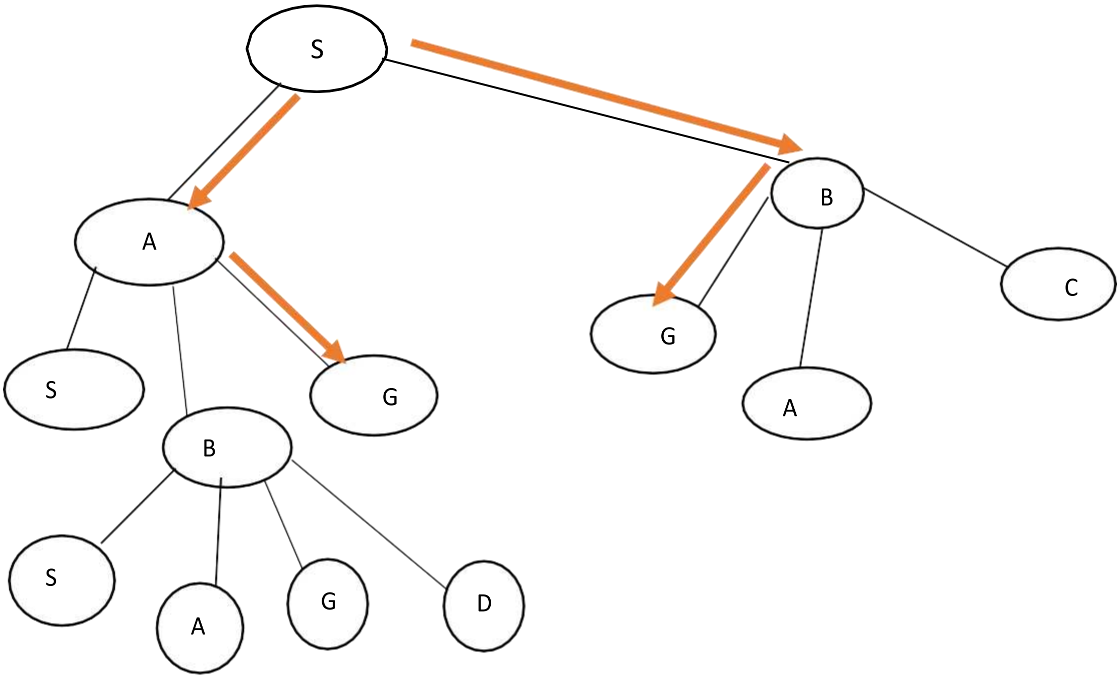
f (n) = g(n)+h(n)

Where:

g(n): The actual cost path from the start state to the current state.

h(n): The actual cost path from the current state to goal state.

The distance from the node (S) to the goal (G) was estimated as example given in figure



RESULT of A* Search: S->B->G, or S->A->G

Figure 4: A* Search Algorithm Process

Note: G is for Goal: S is for Node: A and D are available routs or distances

3.4 Sorting Process

For the purposes of coming up with the best solution in as far as decision making priorities are concerned, a sorting algorithm which requires less voluminous data and memory space was deemed suitable. According to Chauhan and Duggal (2020), the selection sort is the most simplistic sorting algorithms. Selection sort algorithm maintains two sub-arrays in a given array. The first sub-array which is already sorted and the second remaining sub-array which is unsorted. In ever iteration of selection sort, the slightest element from the unsorted secondary array is picked and moved to the sorted secondary array hence ensuring that sorting is done to every input data.

3.5 Choosing most appropriate outcome

This model provides the necessary information regarding requirements of health resources within shortest time possible which impacts overall performance of health information system, and health service delivery. The following flow chart describes the whole integrated process during the allocation of resources to paediatric patients during referral decision process.

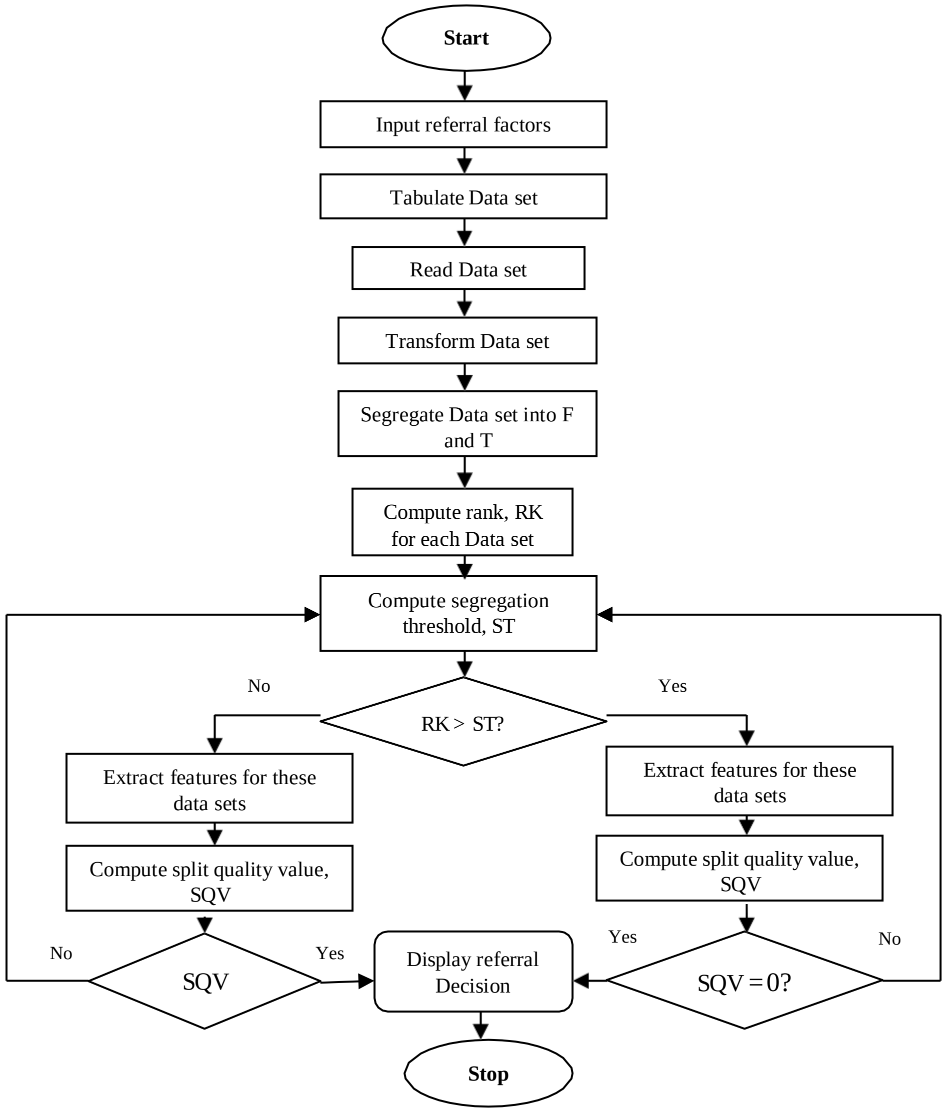


Figure 5: Data flow for the referral decision process

4 Model Simulation

4.1 Data Description

The dataset used was from New York City Regional Electronic Adoption Centre (NYC - REACH) Members data set initially provided by the Department of Health and Mental Hygiene (DOHMH). It entails particulars of doctor. The details can be accessed by various people like when there is need for a specialist to diagnose a certain kind of condition.

4.2 Setup of the environment

This model was simulated on Anaconda3 2021.11 (64-bit) alongside Python programming language version 3.9.7. The Anaconda application deployed in this model was Jupyter Notebook, a web-based integrated development environments (IDEs) that uses diverse default web browsers and enable creation and sharing of assorted documents or textx simultaneously (Rolon-M´erette, et al, 2020). The code for the project was written in the Jupyter Notebook Python 3 IPython Notebook (IPYNB). Below is the interface of Anaconda application deployed in the simulation of this model.

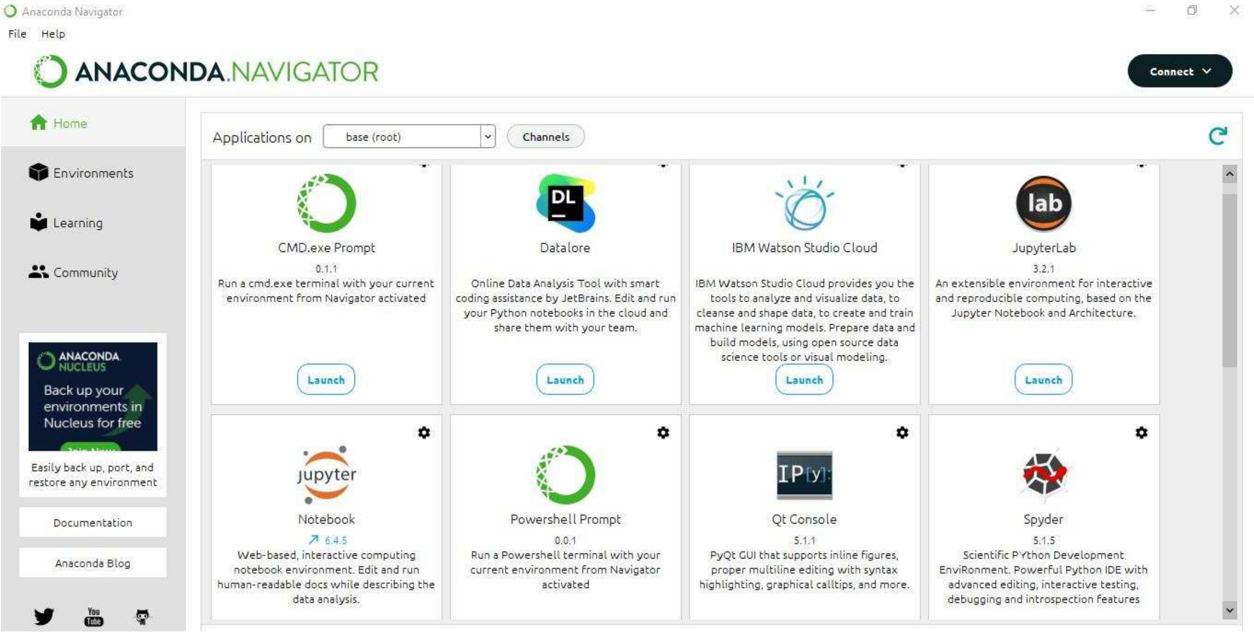


Figure 6: The interface of the Anaconda application

Anaconda has been applauded to provide access to different environments known as known as integrated development environments (IDEs) which allow coding in either Python or other programs hence greatly ease the development of code. The screenshot of a sample of notebook directory structure interface of the libraries that are commonly used in various models is presented in Figure 7.

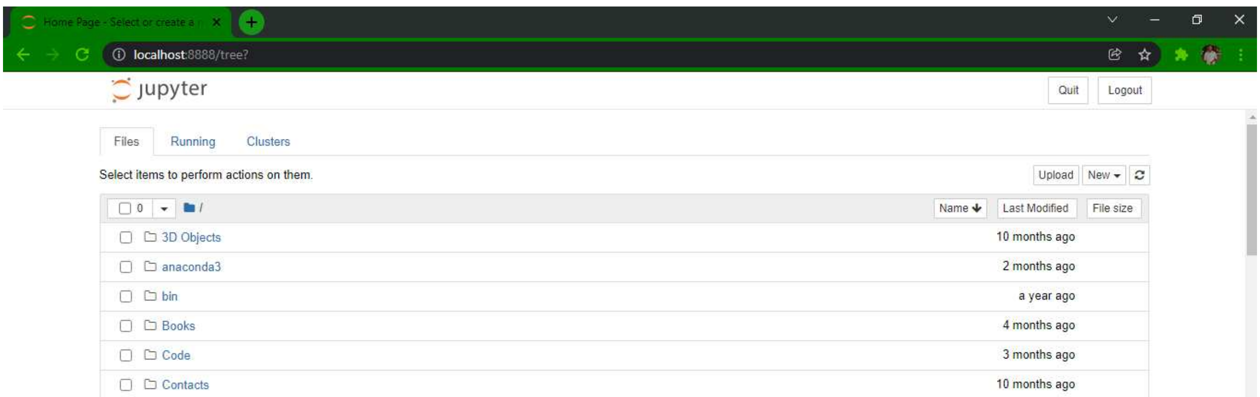


Figure 7: Sample of Notebook directory structure interface

4.3 Importation of libraries and modules

Importation of libraries and modules for the model simulation was performed using Pandas. Tabular data such as data stored in spreadsheets or databases are best handled with a tool which helps to explore, clean, and process such data. Pandas is the right tool. Pandas is an open source, BSD-licensed library providing high performance, easy-to-use data structure and analysis tools for the python programming language (Harrison, 2016). In pandas, a data table is called a DataFrame. For purposes of implementation of K-Nearest Neighbourhoos search algorithm in Python programming language, the sklearn (Scikit-learn) library was used. In addition, to enable visualization of data in the form of treemaps or proportional rectangular structures, the model adopted the Squarify library. Figure 8 presents the importation of libraries.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import sklearn.neighbors
#If squarify is not installed, try installing it using the command below:
#pip install squarify
import squarify
```

```
#pip install squarify
```

```
#pip install geopy
```

Figure 8: Importation of libraries and Modules

5 Optimization of Specialist during Patient Referral

5.1 Referral of patients based on availability of specialists

The flow chart in Figure 9 shows how the Patient referral was simulated based on the availability of a specialist.

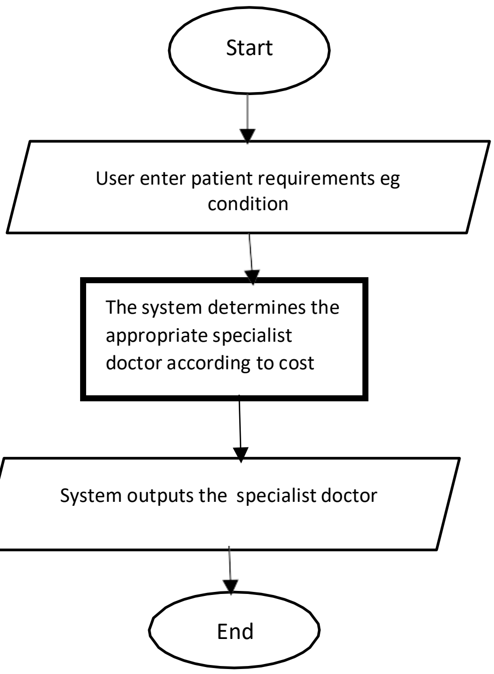


Figure 9: Flowchart for predicting data according to availability of specialist

Codes were generated through simulation as presented in Figure 10. The parameters x for the ailment expected to be diagnosed and y for the location were used. Thereafter the prediction from the algorithm was mapped to the solution dataset with consideration to the values of x and y. After that process, the values obtained were sorted by the average treatment cost and distance (avg_trt_fee and final_dist) respectively.

```
def pred_sorted_cost(x, y):
    solution = data[(data.speciality == x)]\
    .sort_values(['avg_trt_fee', 'final_dist'], ascending = (True, True))
    return solution
```

Figure 10: Code for predicting the availability of a specialist

After that process, a specialist and his/her location were provided to obtain the output in Figure below.

```
pred_sorted_cost('Surgeon', 'Kisumu')
```

	specialist_name	speciality	facility_name	phone_no	available_days	time	location	facility_type	consultation_fee	min_trt_fee	max_trt_fee	avg_trt_fee
0	Dr. Ongonga	Surgeon	JOOTRH	720474745.0	Monday and Friday	8-12pm	Kondele Kisumu	Referral Hospital	50.0	10000.0	30000.0	20000.0
1	Dr. Atieno	Surgeon	KCHR	723484737.0	Tuesday	6-11am	Kisumu Town	Referral Hospital	50.0	10000.0	30000.0	20000.0
6	Dr. Ongonga	Surgeon	OASIS	724384374.0	Sunday and Monday	9-1pm	Kisumu Town Centre	Referral Hospital	500.0	200000.0	250000.0	112500.0
5	Dr. Atieno	Surgeon	St. Jairus	723636464.0	Wednesday and Sunday	8-2pm	Kondele Kisumu	Referral Hospital	1500.0	150000.0	200000.0	175000.0
11	Dr. Ongonga	Surgeon	Avenue	724734938.0	Monday and Friday	7-2pm	Kibuye Market, Kisumu	Referral Hospital	3000.0	200000.0	200000.0	200000.0
85	Dr. Ongonga	Surgeon	Kisumu Specialist	720474745.0	Monday and Tuesday	2pm to 4pm	Kisumu Town Centre	Referral Hospital	3000.0	80000.0	600000.0	340000.0

Figure 11: Outputs (Availability of specialist) in accordance to Location

5.2 Referral of patients based on Distance to specialists

The flowchart in Figure 12 was used to predict possible referral for a patient based on the distance to the referred specialist with regards to sorting parameter:

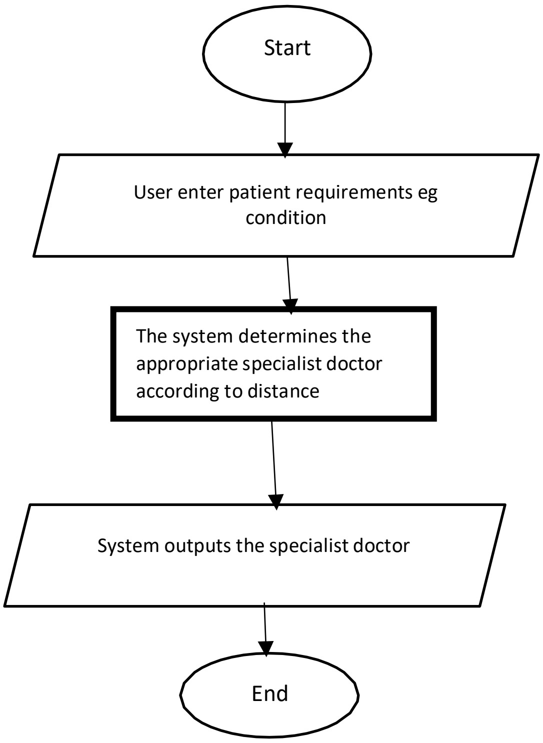


Figure 12: Flowchart for sorting predictions according to distance

As reflected in Figure 12, the simulation code presented in Figure 13 demonstrates how specialist sorting prediction was simulated according to distance. The function pred_specialist takes the parameters x and y respectively representing the name of the specialist and his/her. Consequently, the output dataset column order are sorted in sequence of various distances in the ascending order. The code then takes up the specialist’s name and maps it in the prediction to get a final output named the output dataset in Figure 13.

```
def pred_specialist(x, y):
    solution = data[(data.specialist_name == x)]\
    .sort_values(['final_dist', 'avg_trt_fee'], ascending = (True, True)).head(5)
    output = solution[['specialist_name', 'speciality', 'facility_name', 'phone_no',
                       'available_days', 'time', 'location', 'final_dist',
                       'avg_trt_fee', 'min_trt_fee', 'max_trt_fee']]
    return output
```

Figure 13: Code for sorting predictions according to distance

After the process of sorting specialists based on distance, the next input was the specific name of the specialist, in this case Dr. Ongonga (as shown in Figure 14). This specialist was located within different health facilities in the area of Kisumu as provided in the screenshot in Figure 14 when sorted according to distance.

```
pred_specialist('Dr. Ongonga', 'Kisumu')
```

	specialist_name	speciality	facility_name	phone_no	available_days	time	location	final_dist	avg_trt_fee	min_trt_fee	max_trt_fee
11	Dr. Ongonga	Surgeon	Avenue	724734938.0	Monday and Friday	7-2pm	Kibuye Market, Kisumu	61.425496	200000.0	200000.0	200000.0
6	Dr. Ongonga	Surgeon	OASIS	724384374.0	Sunday and Monday	9-1pm	Kisumu Town Centre	63.095331	112500.0	200000.0	250000.0
0	Dr. Ongonga	Surgeon	JOOTRH	720474745.0	Monday and Friday	8-12pm	Kondele Kisumu	63.126547	20000.0	10000.0	30000.0
85	Dr. Ongonga	Surgeon	Kisumu Specialist	720474745.0	Monday and Tuesday	2pm to 4pm	Kisumu Town Centre	73.120836	340000.0	80000.0	600000.0

Figure 14: Predictions of Specialists according to sorted distances

5.3 Referral of Patients based on cost of Specialist

Referral was also predicted according to the costs of accessing the specialists, that is, charges levied by the doctor. The simulation run utilised the data on the condition of the patient, matched it with the available specialists and sorts the output according to the cost as illustrated in the flowchart in Figure 15.

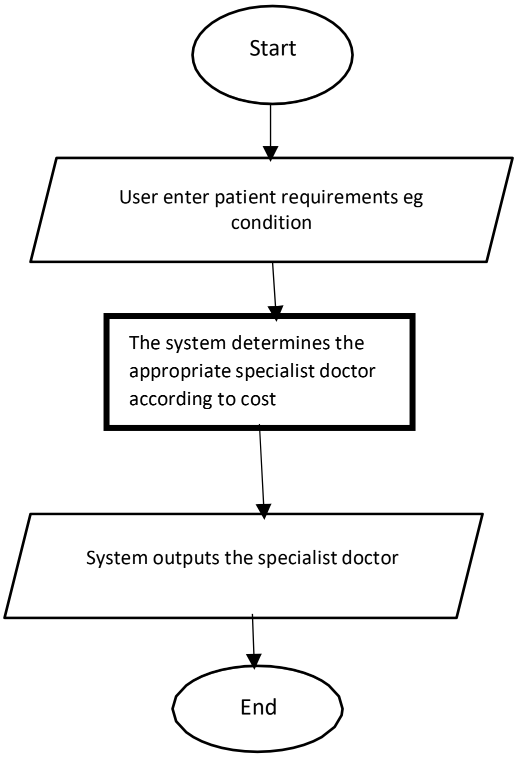


Figure 15: 1Referral of patients based on costs of available specialists

To obtain the flowchart presented in Figure 15, the codes presenting a function pred_speciality_cost was used to simulate prediction of availability of the sought specialist based on the needs of the patients (Figure 16). Sorting of the availability of the needed specialist was based on his/her average treatment fee denoted by avg_trt_fee which were categorised in ascending order. In the event that treatment fee happens to be equal for two specialists or facilities, the next factor considered in the sorting process was the distance to the referred specialist or facility. The output would then be returned in a dataset for solutions. Figure 16 presents codes for prediction of specialist based on charges or costs.

```
def pred_speciality_cost(x, y):
    solution = data[(data.speciality == x)]\
    .sort_values(['avg_trt_fee', 'final_dist'], ascending = (True, True)).head(5)
    return solution
```

Figure 16: Prediction of a specialist according to cost

Based on the codes generated in Figure 16, the outputs were sorted in according to the average treatment cost that is in the data of the last column in the screenshot in Figure 17.

```
pred_speciality_cost('General Paediatrics', 'Kisumu')
```

	specialist_name	speciality	facility_name	phone_no	available_days	time	location	facility_type	consultation_fee	min_trt_fee	max_trt_fee	avg_trt_fee
14	Dr. Ochido	General Paediatrics	JOOTRH	726388728.0	Thursday and Saturda	6-11am	Kondele, Kisumu	Referral Hospital	50.0	15000.0	15000.0	15000.0
19	Dr. Awuonda	General Paediatrics	JOOTRH	729448487.0	Tuesday	8-2pm	Kondele, Kisumu	Referral Hospital	50.0	2000.0	30000.0	16000.0
22	Dr. Walter	General Paediatrics	OASIS	729494957.0	Wednesdayand Saturday	7-12pm	Kibuye Market, Kisumu	Referral Hospital	2000.0	60000.0	100000.0	70000.0
12	Dr. Walter	General Paediatrics	Avenue	724854893.0	Wednesday	7-11am	Kibuye Market, Kisumu	Referral Hospital	500.0	200000.0	250000.0	112500.0

Figure 17: Prediction of Patient Referral according to sorted costs of Specialist

6 Discussions and Conclusion

6.1 Discussions

The researchers developed a model for the optimization of resource allocation for paediatric healthcare systems during patient referral, specifically for enhancing referral of patients based on availability of specialists, distance to specialists, and cost of specialist. The social foraging behaviour of honey bee, being one of the widely utilised swarm intelligence methods in resource allocation processes, was adopted. As had been articulated by Yu et al (2015), the search for suitable specialist in the model was robust, and failure to get the right referral in one facility did not limit it from foraging the environment (other hospitals). Earlier researchers (Karaboga and Ozturk, 2009; Quijano and Passino, 2007; Xu and Duan 2010) had also achieved optimization in models applying honey bee social foraging such in shop scheduling among other fields.

The application of the model for resource allocation enabled sorting of the specialists based on the distances of their locations, their availability (including specific time during the day), and their respective costs or charges. These were tailored to the capabilities and needs of the patients. Indeed better integration between primary healthcare and specialty care simulation of ICT developed model has also been revealed in chen et al (2016), Greenwood-Lee et al (2018), Breuer (2017), and Zhao et al (2021) among others. In their work, Agola and Raburu (2018), developed a model which enabled knowledge of availability and workload of consultant doctor during referral process. It is therefore critical that the model developed in this paper is a step in the direction of solving the problem of under-five mortality in Kisumu County and, by far, the entire Kenya.

6.2 Conclusion

This paper concludes that swarm intelligence is an appropriate algorithm for locating resources in complex and distributed environments. Such models, including the one presented in this paper, are robust, simple, and are controlled by one centre. In this paper, bee colony model developed for allocating resources in paediatric healthcare system was found to enhance referral based on distance, availability, and cost of the specialist doctors. This in turn stands to ensure that each patient has access to healthcare irrespective of their socio economic backgrounds.

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