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Using Metaheuristic Techniques to Optimize the Blood Assignment Problem

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Abstract—This paper presents the use of Meta-heuristic techniques to optimize the Blood Assignment Problem (BAP). The demand for blood is high leading to scarce blood resources and a need to minimize the total amount of blood resources imported from outside. A basic mathematical model has been designed as a good contribution to minimize the total amount of blood imported from outside the system. The problem was modeled as a knapsack problem and two Metaheuristics, Tabu search (TS) and Simulated Annealing (SA) were used separately to solve the problem. A hybrid of TS and SA was also tested. Experimental results show that the hybrid algorithm obtained better results compare to the individual algorithm.

Keywords—Metaheuristic Algorithm, Simulated Annealing, Tabu Search, Hybrid, Blood assignment

I. Introduction and Background

Blood donation campaigns may increase as blood supplies decrease and demand grows since the margin between donated blood supplies and blood demand have shrunk substantially over the last decade [1-4]. Although there are daily demands for blood by hospitals for different purpose, the case of emergency makes the demand to grow rapidly. Meanwhile, blood donations are made mainly from the four main types[1] of blood namely O, A, B and AB which each type having either Rh positive or Rh negative [2, 5, 6]. Blood type distribution in the population varies from country to country but O and A blood groups are the most dominant, followed by blood type B and AB [5]. For example, in South Africa, blood type proportion in the population is O-46%, A-37%, B-14%, and C-4% [6].

Blood products such as blood plasma, platelets, red blood cells (RBCs) and whole blood are necessary during blood transfusions. These products are stored for various usage in the blood bank and have varying life span for storage. The RBCs, the focus of this paper, are the most common blood components that deliver oxygen to the body tissues through the circulatory system [7]. The different type in human is based on the presence or absence of certain protein molecules called antigens and antibodies. Antigens are located on the surface of the BCs while antibodies are in the blood plasma. This lead to numerous genetically determined blood group systems among which, the ABO and Rh systems are the most prominent especially with respect to blood transfusions [8]. For transfusion purpose, not all blood groups are compatible thus transfusing or mixing incompatible blood groups can lead to serious medical dangers including blood clumping. Table 1 presents the compatibility between the various blood types. The cross (x) signifies incompatibility while the tick (√) signifies compatibility.

Ideally, a recipient should be allocated his/her own blood type safe for the shortage of such blood type in the blood bank. An imbalance can appear on the spur of the moment and blood of certain types may reach dangerously low levels. This is usually handled by given alternative but compatible blood type. Cases arise where blood bank has to depend on external supply (importing) for blood. Such cases need to be minimized especially in emergency situations.

TABLE I. Blood group Compatibility with Rhesus

Receiver/Donor	O-	O+	A-	A+	B-	B+	AB-	AB+
O-	✓	✗	✗	✗	✗	✗	✗	✗
O+	✓	✓	✗	✗	✗	✗	✗	✗
A-	✓	✗	✓	✗	✗	✗	✗	✗
A+	✓	✓	✓	✓	✗	✗	✗	✗
B-	✓	✗	✗	✗	✓	✗	✗	✗
B+	✓	✓	✗	✗	✓	✓	✗	✗
AB-	✓	✗	✓	✗	✓	✗	✓	✗
AB+	✓	✓	✓	✓	✓	✓	✓	✓

In an emergency case where the recipient blood type is unknown with little or no time to investigate this, the recipient are usually given the O negative blood hence donor with O negative blood are regarded as universal donors [5]. This makes the O negative blood to be in higher demand than the other blood types which can lead to shortage of in cases where there are more O negative recipients.

II. Related works

Literature is very limited with regards to the optimization of blood assignment. Most works are either not based on mathematical optimization or the author focused on related problems to blood distribution and allocation. Sahin et. al. [8] developed numerous mathematical models to solve the location-allocation decision problem in regionalization of

[1] The terms “blood type” and “blood group” can be used interchangeably to refer to classification of RBCs based on the presence (or absence) of inherited antigens in the red blood cells (see [5-7]).

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blood services. Based on a real life case from Turkey, the authors decomposed the problem into three sub-problems as follows:

(i) A medium location model that minimizes the total number of population weighted average distances among the service facilities and between the service facilities and the demand points.

(ii) A set covering model that locates the supporting facilities, like the blood stations.

(iii) The mobile units to each service region were redistributed.

Few literature that has considered BAP as an optimization problem can be found in [1-4, 9]. Chapin and Adewumi [9] designed a basic continuous mathematical optimization model to manage blood allocation to donors in a blood bank. The model assumed the amount of blood needed for each blood type to be proportional to the representation of the blood types in the general population. Angelis et al. [1] proposed a multi-objective linear programming model that minimizes the amount of blood imported from outside the system, and redistributing the blood more evenly among the days of the month for the BAP. The model was applied to the CRI (Italian Red Cross) system in Rome with promising results reported. The model did not handle the global request of different blood types at the same time. The applicability and efficiency of metaheuristics for handling the BAP has been examined in [2-4] but none has reported a comparative study of Tabu Search (TS) and Simulated Annealing (SA). Adewumi et. al. [2] presents a multiple knapsack models of the BAP and compared the performance of hill climbing (HC) and Genetic Algorithm (GA) with some its variants and hybrids. They reported that the HC algorithm provided the best overall results. Similarly, Dufourq et. al. [3] improved on the work of [3] by testing various mutation operators for GA and compared the results with that of SA with the improved GA doing better. Finally, Igwe et. al. [4] further tested the performance of the Greedy Random Adaptive Search Procedure (GRASP) and dynamic programming for the BAP with the latter doing better.

This paper is based on the same mathematical model of [1] while we test the efficiency of TS and SA in handling the global request for different blood types. The TS was benchmarked with SA as well as a hybrid that incorporate both algorithms. The global request for a given day is required to carry out simulations. The current work only considers RBCs without emphasize on the Rhesus factor, emergency allocation of blood and the validity date of the blood products.

III. THE MODEL

The model used in this paper is based on the variable representing the units of blood coming from inside and outside the blood bank system. The objective is to minimize the total amount of blood imported from outside the system.

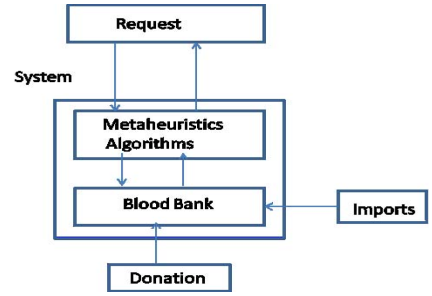

Fig. 1. *Model of Blood request and allocation in a blood bank*

Fig.1 shows a block diagram model of how metaheuristic algorithm can be incorporated to manage the allocation of blood based on request and availability in a blood bank. When a request is made, it goes through the algorithm which obtains information about the blood types and their respective volume requested in order to efficiently meet the request while it minimizes the volume of blood that should be imported from outside the blood bank.

The problem is modeled as a knapsack problem as represented in equations (1) – (3) where x_{ij} is a binary variable that denote a request for blood type. The objective function is shown in equation (1) with the constraints presented in equations (2) and (3).

Objective function:

$$\min \sum_{i=0}^{m} \sum_{j=0}^{n} p_j \, x_{ij} \tag{1}$$

subject to:

$$\sum t = s + \sum_{j=1}^{n} p_j \qquad i = 1 \ldots \text{m} \tag{2}$$

$$x_{ij} = \{0,1\} \qquad \text{i = 1...m, j =1...n} \tag{3}$$

where:

t: total amount of red blood cell units supplied, from inside and/or outside the system

s: positive integer representing total amount of red blood cell units supplied from inside the system, for a given day.

p_j: amount of blood type j coming from outside the system

m: positive integer representing the number of requests (number of hospitals requesting blood)

n: positive integer representing number of blood types

Equation (2) ensures that the total amount of blood units supplied is exactly the amount coming from both inside and outside the system. Equation (3) indicates is the binary variable that indicates whether there is a supply of blood or not from outside.

IV. METHODS AND TECHNIQUES

A. Metaheuristic Techniques

This paper implements TS metaheuristic for the BAP based on the model presented above. The TS is also benchmarked with SA and its hybrid with TS.

1) Tabu Search

TS [10] is an established metaheuristic algorithm applied especially for combinatorial optimization problems. It is an iterative improvement procedure that starts from any initial solution and attempts to determine a better solution by avoiding being trapped in a local optimal point through the use of flexible memory or search history stored as a tabu list. The tabu list stores some solutions that have been previously visited. If a newly generated solution is found on this list, it is rejected right away. Details on TS can be found in [10]. Algorithm 1 shows the basic TS algorithm used in this paper.

Algorithm 1: tabu search

```
Data: generate random data
Data: create requests
Data: currBestSol, current solution
Data: newSol, new solution
Result: best solution found
begin
    While termCriterion     terminator do
            newSol      mutate(currBestSol)
            newSol = calTotal(newSol)
            if! isTabu(newSoltnTot) then
               if newSoltnTot < currSoltnTot then
                        currSoltnTot      newSoltnTot
                        termCriterion      0
               else
                        termCriterion      termCriterion + 1
               end
            end
            if tabulist:size()     n then
               tabulist.remove(0)
            end
            tabulist.add(newSoltnTot)
  end
  return currBestSoltnTot
end
```

2) Simulated Annealing

SA [11,12] is a probabilistic metaheuristic that is based on the principle of thermodynamic, popular for locating a good approximation to the global optimum of a given function in a large search space [11]. It guarantees to find an acceptably good solution in a fixed amount of time without being trapped in local optimum point as a result of the metropolis criteria which allows some controlled probability of accepting worse solutions. SA has been applied earlier to BAP [2, 3]. Similar to the principle of metallurgy, the annealing process [11, 12] allows a search process with a temperature parameter raised to a very high value to cool very gradually and slowly until an equilibrium state is reached, at which point the solution is deemed to have reached an acceptable (near optimum) point. Details on SA algorithms and implementation can be found in [10-12]. Algorithms 2 presents overview of the SA implemented for the BAP in this paper.

Algorithm 2: Simulated Annealing

```
Data: generate random data
Data: create requests
Data: currBestSol, current solution
Data: newSol, new solution
Result: best solution found
begin
    delta E ← 0
    While temp > coolTemp do
         For t times do
             delta E ← newSoltnTot – currBestSoltnTot
             if delta E ≤ 0 then
                newSoltnTot ← currBestSoltnTot
             end
             if currBestSoltnTot < bestSoltnTot then
                 bestSoltnTot ← currBestSoltnTot
             else
                rnd ← random (0,1)
                exp ←
                if rnd < exp then
                   currBestSoltnTot ← newSoltnTot
                end
                newSoltnTot ← calculateTot(newSol)
             end
             decrement temp
      end
   return bestSoltnTot
 end
```

3) Hybrid Algorithm

Generally, hybrid algorithms seek to exploit the good characteristics of incorporated techniques in order to have an better and efficient solution to an optimization problems. This paper implements a hybrid algorithm which incorporates TS and SA. TS is used to obtain the initial solutions to the BAP which is then passed unto the SA for better exploitation and refinement. The hybrid algorithm as implemented in presented in algorithm 3.

Algorithm :3 Hybrid of TS and SA for BAP

```
Data: generate random data
Data: create requests
Data: currBestSol, current solution
Data: newSol, new solution
Result: best solution found
begin
    While termCriterion     terminator do
            newSol      mutate(currBestSol)
            newSol = calTotal(newSol)
            if! isTabu(newSoltnTot) then
               if newSoltnTot < currSoltnTot then
                        currSoltnTot      newSoltnTot
                        termCriterion      0
               else
```

```
                termCriterion      termCriterion + 1
            end
          end
          if tabulist:size()     n then
             tabulist.remove(0)
          end
          tabulist.add(newSoltnTot)
  end
  Simulated annealing (currBestSoltnTot)
end
```

A bottom-up approach is used in assigning blood to meet given request based on blood compatibility since compatible blood types can be given whether there is shortage or not. If where R_{type} represent the amount requested and V_{type} is the amount available, a situation where $R_{type} > V_{type}$, where R_{type} is the amount requested and V_{type} is the amount available implies shortage of blood type to meet the demand. Using the bottom-up approach, whenever blood is to be assigned, the requested blood type is considered first; in case of shortage, the next available compatible blood type is assigned until the request is met. The blood assignment is ordered based on availability and importance with blood type O being the last resort. Where the request cannot be satisfied fully, blood will be imported to the blood bank from outside the system relative to the request(s).

B. ***Experimental Set-up***

This section reports the parameter set-up for the algorithms implemented as well as the data generation for simulation purpose.

1) Parameters Setting

The tabu list for the TS was set to 100 while the parameters for SA algorithms are as follows: the coolest temperature was set to 0.1, the highest temperature was set to 100; the energy function was calculated as

$$\Delta E \leftarrow newsolution - currentsolution$$

2) Data generation

The algorithms were tested on randomly generated data. The total amount of donated blood of various types in the blood bank is assumed to be proportional to the blood type distribution for the country. Using South Africa as case study [5], 46% of the value generated was assigned to blood type O, 37% to blood type A, 14% to blood type B and 4% to blood type AB. The requests were also generated randomly such that there will be shortages in the blood bank, in order to evaluate the efficiency of the algorithms. The amount of blood needed for each blood type is proportional to the representation of blood types in the population.

V. RESULTS AND DISCUSSION

Simulation experiments were run for different number of blood requests. For each simulation the total amount of blood available was calculated and the total amount of blood needed for each blood type was calculated and the algorithms were applied to try to minimize the total amount of blood resources imported from outside the system in case there is shortage of blood resources in the blood bank.

Table II shows the generated total amount of each blood type available in the system, as well as the total quantity of each blood type requested for a different number of requests, number of requests is the number of hospitals making the requests for blood, so number of requests equal to 300 means that there are 300 hospitals making requests for each of the blood types. From table II we observe that there will be a shortage of blood resources during the assignment process and hence the need to import blood from outside the system.

TABLE II. RESULTS OBTAINED BY THE DIFFERENT ALGORITHMS

		Blood Bank Volume = 1, 500		Blood Bank Volume = 3, 000	
No. of request	*Algorithm*	*Best Solution*	*Time (ms)*	*Best Solution*	*Time (ms)*
300	TS	272	2042	20	2578
	SA	260	7973	20	20029
	Hybrid	260	6165	18	17464
400	TS	443	3684	200	2317
	SA	433	7290	184	15715
	Hybrid	426	5962	186	14495
500	TS	636	4900	380	3608
	SA	614	17441	358	16687
	Hybrid	604	15264	361	14056
600	TS	817	12401	564	7022
	SA	790	15195	534	15605
	Hybrid	784	14488	530	14517
700	TS	986	5878	738	10408
	SA	969	15351	717	15940
	Hybrid	963	14655	710	14533
800	TS	1179	6889	913	4718
	SA	1143	15306	887	16509
	Hybrid	1153	14933	884	15023
900	TS	1358	5625	1103	9802
	SA	1323	15758	1064	17289
	Hybrid	1329	15486	1072	15839
1000	TS	1530	13774	1274	6486
	SA	1499	16697	1250	17363
	Hybrid	1497	15987	1254	16468

Table 2, Fig. 2 and Fig. 3 shows the results obtained with the TS, SA and hybrid techniques. The performance of the algorithms are measured based on the amount of blood imported from outside the system as well the time taken by these algorithms to reach a desirable solution. From table 2, we observe that when the number of requests is 300, which is low in this case, TS found the better solution that is lower than the solutions obtained by SA and the hybrid algorithm, the best solution being the least total amount imported. TS also took the longest time to get to the best solution compared with the other two algorithms. As the number of requests increases, the total quantity imported from outside also increase as expected but the SA and the hybrid algorithm tried to keep this quantity as low as possible compared with the TS algorithm. From Fig. 2, it is observed that the ratio between the total amounts imported to number of requests increase when the number of requests is set to 500. The results obtained by the hybrid algorithm were not far off from the results obtained by SA, and at some instances they were equal, this can be seen from Table II especially when the number of requests is 500. In the overall, the hybrid algorithm gives better results with using the TS algorithm alone. It also took the least amount of time to find a solution than the individual algorithm for the different number of requests. It should be noted that the *y*-axis is the ratio of total imported to number of requests in Fig. 2 and 3.

Blood Bank volume = 3,000

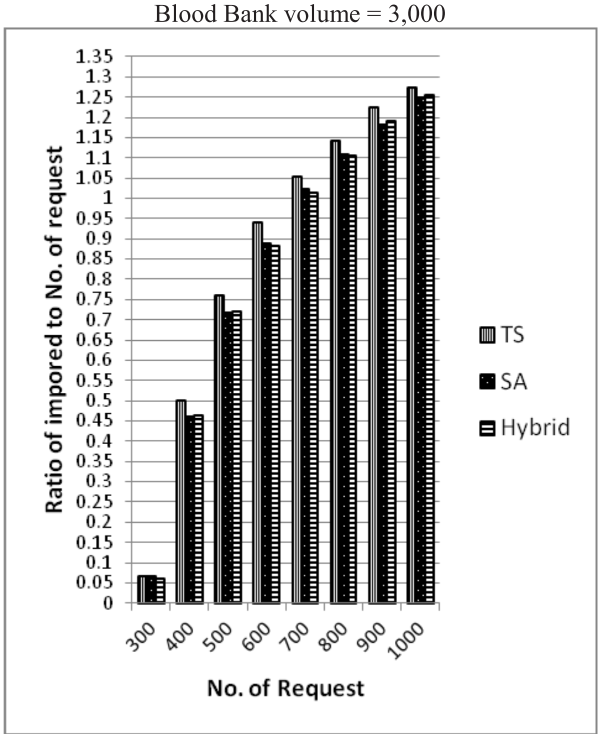

Fig. 2. Graph showing perfomance of algorithms for blood volume = 3000

VI. CONCLUSION AND FUTURE WORK

This paper present the BAP model as a mathematical optimzation problem seeking to minimize the importation of blood from outside the blood bank. TS, SA and their hybried are applied to obtained solutions that achieve the stated objective. Results obtained shows that the standard TS might not be give an efficient solution fo the BAP hence there is need to further study the inner workings of the algorithm with the view of improving it for better results. Results obtained with the hybrid algorithm serve to justify such further study, although the SA seems to be competiting with the hybrid algorithm in our experimental studies. Further work would therefore also be needed in trying other forms of hybrids of the two algorithms. There is also room for more assumption which might change the mathematical model used in this work especially when considering real-life study with data rather than randomly generated data. BAP is still at the infancy and hence the various objectives function can be considered such as minimizing blood loss due to expiration on storage.

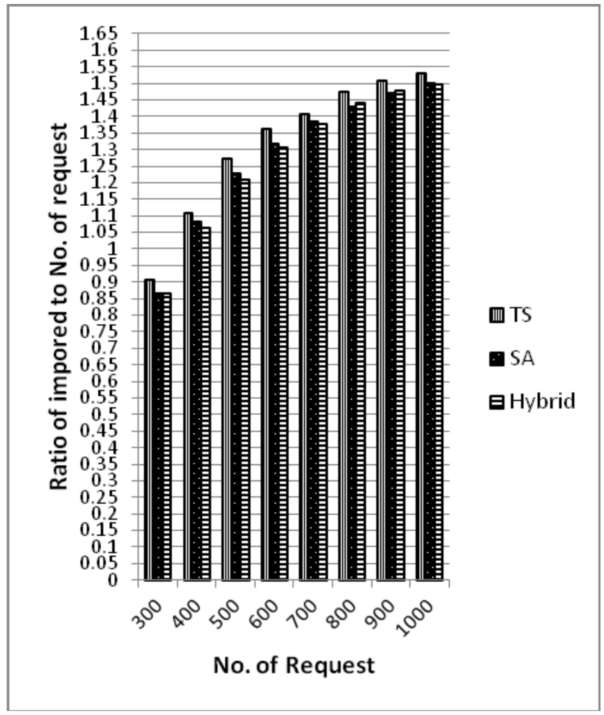

Fig. 3. Graph showing perfomance of algorithms for blood volume = 1500

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