Volume 3, Issue 4, April 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

An Optimized Kidney Transplantation Based on Genetic Algorithm

Sakthivel.S
Department of Information Technology&Anna university
chennai, India.

Manimaran.S
Department of Information Technology&Anna university
chennai, India.

Abstract— ***Kidney paired donation (KPD) programs provide an innovative approach for increasing the number of available kidneys. In a Kidney transplantation program, willing but incompatible donor–candidate pairs may exchange donor organs to achieve shared benefit. Currently, most KPD programs focus on rule-based strategies of prioritizing kidney donation. In this paper, consider and compare two graph-based organ allocation algorithms to optimize an outcome-based strategy defined by the overall expected utility of kidney exchanges in a KPD program with both incompatible pairs and Altruistic Donors (Ads). Existing work present comparison to dialysis, kidney transplantation has been proven to be a more effective treatment for most patients with end-stage renal disease. Consider a graphical model to determine optimal matches for KPD program, in which both cycle and chain exchanges are involved. So it takes more time to perform optimal matching and it is not accurate. In graph based model, if any one of the chain connection is break the entire chain is rejected. So form a new chain to perform transplants. In proposed system the Genetic Algorithm is used to select the optimal matches among incompatible pairs based on the maximum number (or maximum utility) of transplants. GAs represents an intelligent exploitation of a random search used to solve optimization problems. The Genetic algorithm starts from the possible solution; it selects new population to provide the optimization solution so the solution is accurate.***

Keywords---* *Kidney Exchange; Optimal Matching; Computerized platform; Kidney Paired Donation; Altruistic Donors

I. INTRODUCTION

Kidney transplantation is typically the most effective treatment for patients with end-stage renal disease. Kidney Paired Donation (KPD) programs provide an innovative approach for increasing the number of kidney transplantation. In a KPD program, willing but incompatible donor-candidate pairs may exchange organs to achieve shared benefit. Recently, research on exchanges initiated by Altruistic Donors (ADs) because the resultant organ exchange mechanisms offer advantages that increase the effectiveness of kidney transplant. Graph based segmentation algorithms have become quite popular and mature in recent years. Unfortunately, biological incompatibility, such as ABO blood type mismatch or the presence of Human Leukocyte Antigen (HLA) antibodies prevents many intended living-donor transplants from being performed. The modern variations on graph-based segmentation algorithms are primarily built using a small set of core algorithms, graph cuts, random walker and shortest paths, which are reviewed shortly. An expected-utility-based graph model designed to increase the mutual benefits in kidney exchanges. Currently, most KPD programs focus on rule-based strategies of prioritizing kidney donation. Develop an interactive decision carry system to form, watch, and visualize a conceptual KPD program, which aims to support clinicians in the valuation of different kidney transplantation. Using this system, demonstrate empirically that an outcome-based strategy for kidney exchanges leads to improvement in both the quantity. A Genetic Algorithm (GA) is a search heuristic that mimics the process of natural evolution. This is routinely used to generate accurate solutions to optimization and search problems. Genetic Algorithm belongs to the larger class of Evolutionary Algorithms (EA), which generate solutions to optimization problems. The Genetic Algorithm starts from the possible solution; it selects new population to provide the optimization solution so the solution is accurate.

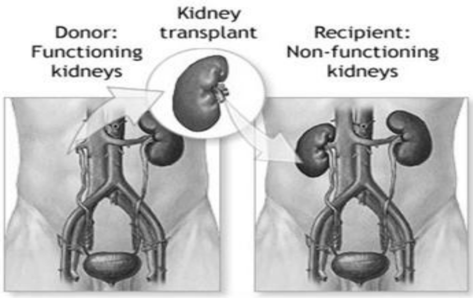

Figure1. Example of Kidney Exchange

II. LITERATURE SURVEY

In barter-exchange markets, agents seek to swap their items with one another, in order to improve their utilities. The author focuses primarily on the future national kidney-exchange marketplace, where patients with kidney disease can obtain compatible donors by exchange their own willing but mismatched donors [1]. It is contentious whether these chains should be performed simultaneously or nonsimultaneously. NEAD chains generate "bridge donors" whose mismatched recipients receive kidneys before the bridge donor donates, and so danger renege by bridge donors, but offer the chance to create more transplants by overcoming logistical barriers inherent in simultaneous chains [2]. The scheme does not presume any particular sprite scheme, or precedence standard. It offers the suppleness to the designer to select his desired fairness constraints and criteria under which patients are awarded points [3]. Usually the goal is to maximize the number of transplants, but sometimes the total benefit is maximized by considering the differences between suitable kidneys. These troubles match to computing cycle packing of maximum size or maximum weight in directed graphs [4]. It uses actual donor–recipient data taken into account all the hurdles and barriers that were encountered in real life. Examples are comorbidity of the patient necessitating temporary or definitely leaving the program, withdrawal of consent by the donor, and alternative kidney transplants [5]. A paired incompatibility, such that the donor from one pair gives an organ to a compatible recipient in the other pair and vice versa. KPD programs offer a unique and important platform for living incompatible donor-candidate pairs to exchange organs in order to achieve mutual benefit. Another primary contribution of this work is rooted in the development of a comprehensive micro simulation system for simulating and studying various aspects of an evolving KPD program. Allocations can be obtained using Integer Programming (IP) techniques and micro simulation models can allow tracking of the evolving KPD over a series of match runs to evaluate different allocation strategies [6]. There have started to be kidney exchanges involving two donor-recipients pairs such that each donor cannot give a kidney to the intended recipient because of immunological inappropriateness, but every patient can receive a kidney from the other donor. The exchanges are also completed in which a donor-patient pair makes a donation to someone waiting for a cadaver kidney, in return for the patient in the pair receiving high precedence for a well-matched cadaver kidney when one becomes available. There are strict legal/ethical constraints on how exchanges can be conducted [7]. Kidney exchange is likely to proceed incrementally, starting with the simplest cases (2-way exchange) and the patients who can benefit most (incompatible pairs). Roth, Sönmez, and Ünver (2005) show that most of the gain from larger than 2-way exchange comes from 3-way exchange, and so we are confident that it will be possible to achieve these gains in the near term also [8]. In the past decade, KPD has become the fastest increasing source of transplantable kidneys, overcome the barrier faced by living donors deemed incompatible with their proposed recipients. A number of different algorithms have been resourcefully implemented in the USA and elsewhere to transplant paired donors, each process exclusively contributing to the success of KPD [9]. The Organ Procurement and Transplantation Network (OPTN) Kidney Committee is considering a proposal for a new deceased donor kidney allotment system. Among the components under consideration is a strategy to position candidates in part by the estimated incremental years of life that are expected to be achieved with a transplant from a exact available departed donor, computed as the difference in expected median lifespan with that transplant compared with remaining on dialysis. This thought has been termed life years from transplant or LYFT [10].

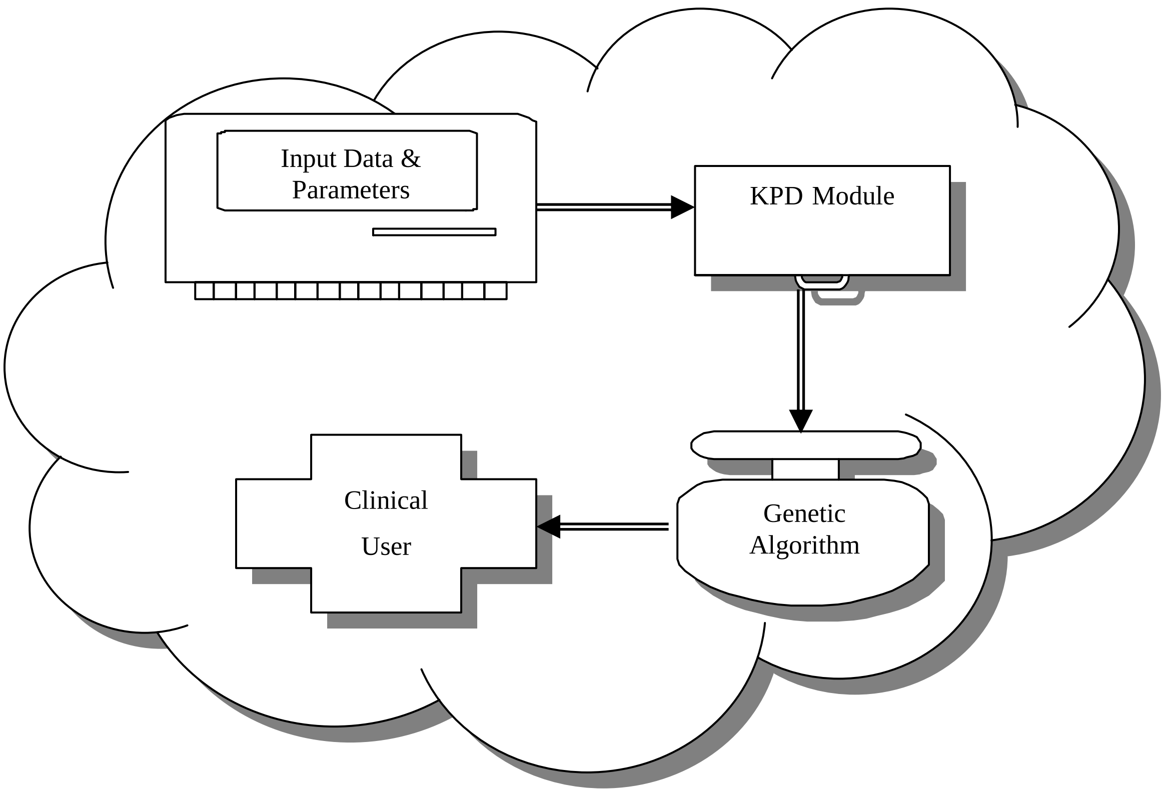

Figure2. Architecture Diagram

III. KPD ALGORITHM

The following are the phases involved in the proposed scheme

- Input Data and Parameters
- KPD Model
- Functional Parametric Relational Algorithm
- Clinical User

A. Input Data and Parameters

Data of candidates and donors are generated separately. Candidates are sampled at random from the University of Michigan kidney paired donation database, which currently has 187 incompatible donor-candidate pairs. This database provides us the important information of ABO blood type and HLA useful to characterize each sampled candidate. Donors, on the other hand, are generated by the population distributions of ABO and HLA. In particular, the distribution of ABO blood types for the US population is: O (44%), A (42%), B (10%), and AB (4%), according to Stanford Blood Center (2010) 1 and the distribution of HLA is derived from HLA haplotypes frequencies of the US population [7]. Through random sampling, we can appoint ADs directly from the set of drawn donors or construct an incompatible donor-candidate pair if either their ABO blood types mismatch or HLA incompatibility. In this way, simulated donors and candidates reflect real-world of data.

B. KPD Model

KPD parameters needed for data generation, including an initial pair number n and percentage of ADs, are specified for the first match run. The following are the important KPD parameter identification.

- Initial number of people
- Arrival rate
- Altruistic donor percentage

C. Functional Parametric Relational Algorithm

Use the initial population to evaluate the chromosomes fitness. The parallel processing is used to assign the fitness. An implementation of genetic algorithm begins with a population of (typically random) chromosomes. Then evaluates these structures and allocated reproductive opportunities in such a way that these chromosomes which represent a better solution to the target problem are given more chances to `reproduce' than those chromosomes which are not as good as solutions. The 'goodness' of a solution is typically defined with respect to the current population. It is used to find the possible solutions.

Genetic Algorithm

1. [Start] Generate random population of n chromosomes (suitable solutions for the problem)
2. [Fitness] Evaluate the fitness f(x) of each chromosome x in the population
3. [New population] Create a new population by repeating following steps until the new population is complete
   a. [Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
   b. [Crossover] With a crossover probability, cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
   c. [Mutation] With a mutation probability mutate new offspring at each locus (position in chromosome).
   d. [Accepting] Place new offspring in a new population
4. [Replace] Use new generated population for a further run of algorithm
5. [Test] If the end condition is satisfied, stop, and returns the best solution in current population
6. [Loop] Go to step 2

D. Clinical User

Genetic Algorithm begins with a set of solutions called the population. Solutions from one population are used to form a new population. This is motivated by the chance that the new population will be better than the old one. Solutions are chosen according to their fitness to form new solutions; more suitable they are more probability they have to reproduce. This is repeated until some condition (e.g. number of populations or improvement of the best solution) is satisfied.

- *Crossover* – Crossover is a genetic operator used to vary the programming of a chromosome or chromosomes from one generation to the next. Cross over is a process of taking more than one parent solutions and producing a child solution from them.
- *Selection* – the application of the fitness criterion to choose which individuals from a population will go on to reproduce
- *Replication* – the propagation of individuals from one generation to the next generation
- *Mutation* – the modification of chromosomes for single individuals

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, performance of Kidney Paired Donation is evaluated for Functional Parametric Relational Algorithm through J2EE implementation. One of the major contributions of this work is the design of a Kidney Paired Donation. To confirm the analytical results, Genetic Algorithm in the network simulator ns-2 is implemented and the performance is evaluated.

The performance of Functional Parametric Relational Algorithm is evaluated by the following metrics.

- Accuracy of Optimal Matches
- Time to Perform Optimal Matches

Figure 3 demonstrates the Accuracy of Optimal Matches. X-axis represents the number of pairs whereas Y-axis denotes the Accuracy percentage using both the Graph Based Optimization Algorithm and the proposed Functional Parametric Relational Algorithm. When the number of pairs increased, Accuracy percentage gets increase accordingly. The accuracy is illustrated using the existing Graph Based Optimization Algorithm and proposed Functional Parametric Relational Algorithm. Figure 3 shows better performance of Proposed Functional Parametric Relational Algorithm in terms of Optimal matches than existing Graph Based Optimization Algorithm. Functional Parametric Relational Algorithm achieves 10% to 20% more accuracy when compared to existing system.

TABLE I. ACCURACY OF OPTIMAL MATCHES

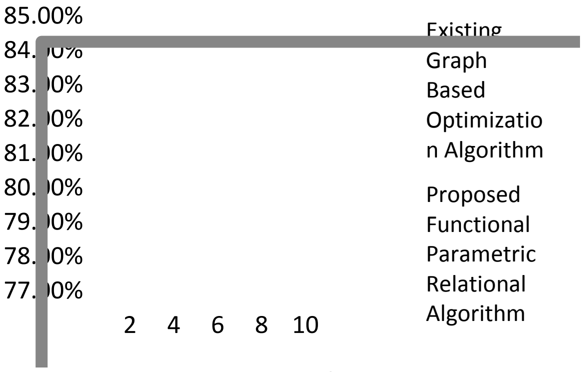

Figure 3. Accuracy of optimal matches

TABLE II. TIME TO PERFORM OPTIMAL MATCHES

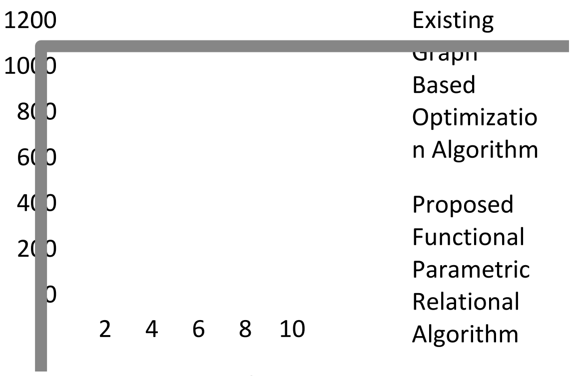

Figure 4. Time to Perform Optimal Matches

Number of Pairs	Existing Graph Based Optimization Algorithm	Proposed Functional Parametric Relational Algorithm
2	798 ms	728 ms
4	816 ms	769 ms
6	896 ms	799 ms
8	912 ms	812 ms
10	976 ms	856 ms

Number of Pairs	Existing Graph Based Optimization Algorithm	Proposed Functional Parametric Relational Algorithm
2	80.1%	80.6%
4	80.5%	80.9%
6	80.9%	81.8%
8	81.5%	82.8%
10	81.9%	84.4%

Figure 4 demonstrates the time to perform optimal matches. X-axis represents the number of pairs whereas Y-axis denotes the time for using both the Graph Based Optimization Algorithm and the proposed Functional Parametric Relational Algorithm. When the number of pairs increased the time to perform optimal matches is also increased. Figure 4 shows minimum time to perform optimal matches of Functional Parametric Relational Algorithm. Functional Parametric Relational Algorithm achieves 20% to 30% less time to perform optimal matches.

V. CONCLUSION

In this paper, the Genetic Algorithm is investigated and designed to increase the mutual benefits in kidney exchanges. The real application of a computerized exchange system, have suggested that utilizing both paired donors–candidates, and ADs can increase both quantity and quality of kidney transplants. Compared to the existing system, it increases the speed of transplants. In the future, plan to conduct practical studies to solicit feedbacks so that the software can be improved with more user-friendly features for clinical convenience. All algorithms discussed in this paper have been fully integrated into a novel GUI software package, which will be released to the public through the necessary

Institutional Review Board (IRB) regulations on the website. Finally, this system helps to improve both the quality and quantity of kidney transplantation and improve the speed of kidney transplantation.

REFERENCES

[1] D. Abraham, A. Blum, and T. Sandholm, "Clearing algorithms for barter exchange markets: Enabling nationwide kidney exchanges," in Proc. Electron. Commerce, 2007, pp. 295–304.

[2] G. Ashlagi, A. Roth, and M. Rees, "Nonsimultaneous chains and dominos in kidney paired donation-Revisited," Amer. J. Transplant., vol. 11, no. 5, pp. 984–994, 2011.

[3] D. Bertsimas,V. Farias, and N. Trichakis. (2011, Oct.). Fairness, efficiency and flexibility in organ allocation for kidney transplantation [Online]. Available: http://hbswk.hbs.edu/item/6622.html.

[4] P. Bir´o, D. Manlove, and R. Rizzi, "Maximum weight cycle packing in directed graphs, with application to kidney exchange programs," Discrete Math., Algorithms Appl., vol. 1, 2009.

[5] M. Klerk, W. Deijl, M. Witvliet, B. Hasse-Kromwijk, F. Claas, and W. Weimar, "The optimal chain length or kidney paired exchanges: an analysis of the Dutch program," Transpl. Int., vol. 23, pp. 1120–1125, 2010.

[6] Y. Li, J. Kalbfleisch, P. Song, Y. Zhou, A. Leichtman, and M. Rees. (2011, May). Optimization and simulation of an evolving kidney paired donation (KPD) program [Online]. Available:http://www.bepress.com/umichbiostat/paper90.

[7] A. Roth, T. Sonmez, and M. Unver, "Kidney exchange," Q. J. Econ., vol. 119, no. 2, pp. 457–488, 2004.

[8] A. Roth, T. Sonmez, and M. Unver, "A kidney exchange clearinghouse in New England," Amer. Econ. Rev., vol. 95, no. 2, pp. 376–380, 2005.

[9] C. Wallis, K. Samy, A. Roth, and M. Rees, "Kidney paired donation," Nephrol. Dial. Transplant., vol. 0, pp. 1–9, 2011.

[10] R.Wolfe, K. McCullough, D. Schaubel, J. Kalbfleisch, S.Murray, M. Stegall, and A. Leichtman, "Calculating life years from transplant (LYFT): Method for kidney and kidney-pancreas candidates," Amer. J. Transplant., vol. 8, pp. 997–1011, 2008.