

# Deceased Organ Matching in Australia

Toby Walsh\*

UNSW Sydney, Data61, and TU Berlin  
Email: tw@cse.unsw.edu.au

**Abstract.** Despite efforts to increase the supply of organs from living donors, most kidney transplants performed in Australia still come from deceased donors. The age of these donated organs has increased substantially in recent decades as the rate of fatal accidents on roads has fallen. The Organ and Tissue Authority in Australia is therefore looking to design a new mechanism that better matches the age of the organ to the age of the patient. I discuss the design, axiomatics and performance of several candidate mechanisms that respect the special online nature of this fair division problem.

## Introduction

Kidney disease is a major problem in Australia. Thousands of people are on dialysis. Many spend years waiting for a transplant, each costing the health care budget hundreds of thousands of dollars. In addition, as dialysis takes up several days each week, many are unable to work and depend on support from the state. The total cost to the Australian economy runs into billions of dollars annually. In 2016, 85% of transplants involved a kidney coming from a deceased person, whilst only 15% of transplants came from a living donor. Whilst there has been considerable focus in the literature of late on increasing the supply of organs by developing mechanisms for paired exchange, only 2.5% of these living donations came from paired exchange. Most living donors were a spouse, family member or friend of the recipient.

Organs coming from deceased people still provide the majority of all transplanted kidneys. Many come from people killed in road traffic accidents. Matching such organs to patients on the waiting list is becoming more challenging as roads become safer. The mean age of donated organs has increased from 32 years in 1989 to 46 years in 2014. Advances in medicine mean that doctors are also now willing to transplant older kidneys. In 2014, the oldest organ transplanted came from a person who was 80 years old. This compares to 1989, the first year for which records are available, when the oldest organ transplanted came from a person aged just 69. The Organ and Tissue Authority of Australia, the government body charged with the task of allocating organs to patients fairly and efficiently, is therefore looking to develop a new matching mechanism. Their goal is to develop a new procedure which matches the age of the patients and organs.

## Organ matching mechanisms

The mechanism used at present in Australia does not explicitly take age of the patients or organs into account. As a result, young organs will be offered to old patients, and old

---

\* This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme under AMPLIFY 670077

organs to young patients. Neither are very desirable. Even if an old patient would like a young organ, from a societal perspective, this is not a very good outcome. The old patient will die from natural causes with an organ inside them that could have continued to function in a younger patient. And transplanting an old organ into a young patient is not a good outcome for both the individual or society. The graft will likely fail after a few years, meaning the patient will need a new transplant. In addition, the patient's immune system will now be highly sensitized, so that a new match will be more difficult.

The Organ and Tissue Authority is looking therefore to develop a new mechanism in which organs are ranked by the Kidney Donor Patient Index (KDPI). This is an integer from 0 to 100 that is calculated from the age of the donor, and a number of other factors like diabetic status. A donated organ with a KDPI of  $X\%$  has an expected risk of graft failure greater than  $X\%$  of all donated organs. Similarly the Organ and Tissue Authority wish to rank patients waiting transplant with the Expected Post-Transplant Survival (EPTS) score. This is also an integer from 0 to 100 that is calculated from the age of the recipient, and a number of other factors like diabetic status, and time on dialysis. A patient on the waiting list with a lower EPTS is expected to have more years of graft function from high-longevity kidneys compared to candidates with higher EPTS scores. Our goal is to provide the Organ and Tissue Authority with a new mechanism that is fair and efficient, matching organs so that the KDPI of an arriving organ is as close as possible to the EPTS score of their allocated patient.

## **Other applications**

This work fits into a broader research programme to design mechanisms for resource allocation problems that better reflect the complexity and richness of the real world [1,2]. Unlike traditional resource allocation problems [3], one of the fundamental features of the deceased organ matching problem is that it is online. We do not know when organs will arrive to be match. And we must match and transplant them shortly after they arrive, before we know what organs or patients will arrive in the future. At the end of the year, we could find an optimal allocation. However, we do not have the luxury of waiting till the end of the year as organs must be transplanted immediately. There are many other domains where resources are allocated in a similar online manner. A food bank might start allocating and distributing food to charities soon after it is donated [4]. An airport must start allocating landing slots before all demands are known. A particle accelerator might start allocating beam time before all requests have come in. An university might allocate rooms to students for the current term, not knowing what rooms might be wanted in future terms. This work offers a case study in how we can efficiently and fairly solve such *online* allocation problems. We study axiomatic properties of such online fair division problems, as well as run experiments on real world organ data [5]. Axiomatic analysis covers such properties as fairness and efficiency (e.g. [6]-[11]), as well as strategic behaviour and manipulation (e.g. [12]-[18]). Insights from this research may prove valuable in a range of other domains. In future, we plan to identify and study phase transition behaviour [19]-[24] which has proved valuable in a wide range of computational domains [25]-[33] including social choice [34,35,36].

## References

1. Walsh, T.: Allocation in practice. In: Proceedings of 37th German Conference on Artificial Intelligence (KI-2014). Lecture Notes in Artificial Intelligence, Springer (2014) 13–24
2. Walsh, T.: Challenges in resource and cost allocation. In: Proceedings of the 29th AAAI Conference on AI, Association for Advancement of Artificial Intelligence (2015) 25–30
3. Chevaleyre, Y., Dunne, P., Endriss, U., Lang, J., Lemaître, M., Maudet, N., Padget, J., Phelps, S., Rodríguez-Aguilar, J., Sousa, P.: Issues in multiagent resource allocation. *Informatica (Slovenia)* **30**(1) (2006) 3–31
4. Aleksandrov, M., Aziz, H., Gaspers, S., Walsh, T.: Online fair division: analysing a food bank problem. In Yang, Q., Wooldridge, M., eds.: Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, (IJCAI 2015). (2015) 2540–2546
5. Mattei, N., Saffidine, A., Walsh, T.: Mechanisms for online organ matching. In: Proceedings of the 26th International Joint Conference on AI, International Joint Conference on Artificial Intelligence (2017)
6. Bouveret, S., Lang, J.: A general elicitation-free protocol for allocating indivisible goods. In Walsh, T., ed.: Proceedings of the 22nd International Joint Conference on Artificial Intelligence (IJCAI 2011), IJCAI/AAAI (2011) 73–78
7. Kalinowski, T., Narodytska, N., Walsh, T.: A social welfare optimal sequential allocation procedure. In: Proceedings of the 23rd International Joint Conference on Artificial Intelligence (IJCAI-2013), International Joint Conference on Artificial Intelligence (2013)
8. Baumeister, D., Bouveret, S., Lang, J., Nguyen, N., Nguyen, T., Rothe, J., Saffidine, A.: Axiomatic and computational aspects of scoring allocation rules for indivisible goods. In: 5th Int. Workshop on Computational Social Choice (COMSOC), (2014)
9. Aziz, H., Gaspers, S., Mackenzie, S., Walsh, T.: Fair assignment of indivisible objects under ordinal preferences. In Bazzan, A., Huhns, M., Lomuscio, A., Scerri, P., eds.: International conference on Autonomous Agents and Multi-Agent Systems, AAMAS '14. (2014) 1305–1312
10. Aziz, H., Walsh, T., Xia, L.: Possible and necessary allocations via sequential mechanisms. In Yang, Q., Wooldridge, M., eds.: Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI 2015. (2015) 468–474
11. Aziz, H., Kalinowski, T., Walsh, T., Xia, L.: Welfare of sequential allocation mechanisms for indivisible goods. In Kaminka, G., Fox, M., Bouquet, P., Hüllermeier, E., Dignum, V., Dignum, F., van Harmelen, F., eds.: ECAI 2016 - 22nd European Conference on Artificial Intelligence. Frontiers in Artificial Intelligence and Applications, IOS Press (2016) 787–794
12. Roos, M., Rothe, J.: Complexity of social welfare optimization in multiagent resource allocation. In: Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems. AAMAS10 (2010) 641–648
13. Kalinowski, T., Narodytska, N., Walsh, T., Xia, L.: Strategic behavior when allocating indivisible goods sequentially. In: Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence (AAAI 2013), AAAI Press (2013)
14. Aziz, H., Walsh, T., Xia, L.: Possible and necessary allocations via sequential mechanisms. In Yang, Q., Wooldridge, M., eds.: Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, (IJCAI 2015). (2015)
15. Aziz, H., Gaspers, S., Mackenzie, S., Mattei, N., Narodytska, N., Walsh, T.: Manipulating the probabilistic serial rule. In Weiss, G., Yolum, P., Bordini, R., Elkind, E., eds.: Proc. of Int. Conference on Autonomous Agents and Multiagent Systems, AAMAS 2015. (2015)
16. Nguyen, N., Baumeister, D., Rothe, J.: Strategy-proofness of scoring allocation correspondences for indivisible goods. In: Proceedings of the 24th International Joint Conference on Artificial Intelligence (IJCAI 2015), IJCAI (2015)

17. Aziz, H., Schlotter, I., Walsh, T.: Control of fair division. In Kambhampati, S., ed.: Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI 2016, IJCAI/AAAI Press (2016) 67–73
18. T, W.: Strategic behaviour when allocating indivisible goods. In Schuurmans, D., Wellman, M., eds.: Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI Press (2016) 4177–4183
19. Huberman, B., Hogg, T.: Phase Transitions in Artificial Intelligence Systems. *Artificial Intelligence* **33** (1987) 155–171
20. Hogg, T.: Refining the phase transition in combinatorial search. *Artificial Intelligence* **81**(1–2) (1996) 127–154
21. Cheeseman, P., Kanefsky, B., Taylor, W.: Where the really hard problems are. In: Proceedings of the 12th IJCAI, International Joint Conference on Artificial Intelligence (1991) 331–337
22. Mitchell, D., Selman, B., Levesque, H.: Hard and Easy Distributions of SAT Problems. In: Proceedings of the 10th National Conference on AI, Association for Advancement of Artificial Intelligence (1992) 459–465
23. Gent, I., Walsh, T.: The SAT phase transition. In Cohn, A.G., ed.: Proceedings of 11th ECAI, John Wiley & Sons (1994) 105–109
24. Gent, I., Walsh, T.: Easy problems are sometimes hard. *Artificial Intelligence* (1994) 335–345
25. Gent, I., Walsh, T.: Phase transitions from real computational problems. In: Proceedings of the 8th International Symposium on Artificial Intelligence. (1995) 356–364
26. Gent, I., Walsh, T.: Phase transitions and annealed theories: Number partitioning as a case study. In: Proceedings of 12th ECAI. (1996)
27. Gomes, C., Selman, B.: Problem structure in the presence of perturbations. In: Proceedings of the 14th National Conference on AI, Association for Advancement of Artificial Intelligence (1997) 221–226
28. Gomes, C., Selman, B., Crato, N.: Heavy-tailed distributions in combinatorial search. In Smolka, G., ed.: Proceedings of Third International Conference on Principles and Practice of Constraint Programming (CP97), Springer (1997) 121–135
29. Gomes, C., Selman, B., McAloon, K., Tretkoff, C.: Randomization in backtrack search: Exploiting heavy-tailed profiles for solving hard scheduling problems. In: The Fourth International Conference on Artificial Intelligence Planning Systems (AIPS'98). (1998)
30. Gent, I., Walsh, T.: The TSP phase transition. *Artificial Intelligence* **88** (1996) 349–358
31. Gent, I., Walsh, T.: Beyond NP: the QSAT phase transition. In: Proceedings of the 16th National Conference on AI, Association for Advancement of Artificial Intelligence (1999)
32. Bailey, D., Dalmau, V., Kolaitis, P.: Phase transitions of PP-complete satisfiability problems. In: Proceedings of the 17th IJCAI, International Joint Conference on Artificial Intelligence (2001) 183–189
33. Walsh, T.: From P to NP: COL, XOR, NAE, 1-in-k, and Horn SAT. In: Proceedings of the 17th National Conference on AI, Association for Advancement of Artificial Intelligence (2002)
34. Walsh, T.: Where are the really hard manipulation problems? The phase transition in manipulating the veto rule. In: Proceedings of 21st IJCAI, International Joint Conference on Artificial Intelligence (2009) 324–329
35. Walsh, T.: An empirical study of the manipulability of single transferable voting. In Coelho, H., Studer, R., Wooldridge, M., eds.: Proc. of the 19th European Conference on Artificial Intelligence (ECAI-2010). Volume 215 of Frontiers in Artificial Intelligence and Applications., IOS Press (2010) 257–262
36. Walsh, T.: Where are the hard manipulation problems? *Journal of Artificial Intelligence Research* **42** (2011) 1–39