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Editorial Comment

Does paediatric cardiology have a fuzzy future?

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In this editorial comment, I attempt to convey my limited understanding of fuzzy logic, and its potential applications in congenital cardiac practice, borrowing heavily from the wide range of disciplines which have utilised fuzzy based applications in clinical and industrial settings. Fuzzy logic appears to be a simple concept that makes inherent common sense, but which tends to be characterised by a plethora of complex jargon, to the degree that I am concerned that there is something I have missed, or am not entirely comprehending! I hope to provide some insight into the development and application of systems based on fuzzy logic, and leave Holzer and his colleagues, in this issue of the Journal,[1] to provide an excellent example of its potential application in an area relevant to many specialties, namely managing waiting lists.

Science and mathematics have been dominated for 2300 years by the Aristotelian dichotomous rubric that: "It is impossible for the same attribute at once to belong and not to belong to the same thing and in the same relation".[2] In the mid nineteenth century, George Boole further developed this two-valued logic into binary set theory. He produced a system of algebra that was to form the foundation of computer science, namely that a value is either 0 or 1, true or false, black or white, to the exclusion of that which might lie between.

Whilst powerful and extremely useful, this bivalent view is clearly an oversimplification of life, which thankfully is far more interesting, less precise, more qualitative, and comprises multiple shades of grey, and even other colours! One of the first challenges to binary logic was the "uncertainty principle", proposed by Heisenberg in 1927 for use in quantum physics. He established that it was impossible simultaneously to determine the position and velocity of subatomic particles. This incorporates uncertainty into reality itself, in that a choice has to be made between knowing one quantity or the other, but not both. Science continued to tolerate this uncertainty until 1965, when crisp logic was definitively challenged by Lotfi Zadek, from the University of California. He proposed the concept of fuzzy logic, presenting a multivalent, subjective, and seemingly less precise way of examining the world.[3] Fuzzy logic can be thought of as an extension of the theory of binary logic to areas where crisp definitions and distinctions are not required. Linguistic variables are used to show that the application of a concept previously thought of as either being true or false can be conceived as being, to differing degrees, partially true and partially false. The value of truth can be anywhere in between 0 and 1, whilst the binary option provides the extremities of the continuum. Fuzzy logic is, therefore, a methodology for computing with words to express qualitative data, rather than numbers, more naturally and accurately reflecting the processes of human intuition and thought.

When applied to set theory, fuzzy logic allows partial, rather than exclusive, membership of several sets, with the whole adding up to one. For example, a patient can be said to have both a partially "successful" outcome from a transcatheter intervention to relieve pulmonary valvar stenosis to a degree of 0.8, in terms of relief of the narrowing, and a partially "unsuccessful" outcome to a degree of 0.2. A separate determination, derived by experts, will have been made as to whether such an outcome is deemed clinically "successful" or not, at a particular level. This differs from probability, where the likelihood that something will or will not occur, is calculated. Here, the patient might have an 80 percent probability of having a good outcome,

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meaning that, of all patients undergoing the intervention, 80 percent will have a successful result, whilst 20 percent will not.

To utilise a fuzzy system, a series of "if-then" rules are created for modelling the relationships between the sets, usually by asking experts in the field in question, to produce a base of knowledge, known as the "rule base". In this case, *if* the balloon valvotomy reduced the gradient by approximately 80 percent, *then* the result would be judged as "successful" to a certain degree. This could be modulated by: *if* the valvotomy additionally produced moderate pulmonary regurgitation, *then* the result would be "less successful". In contrast, *if* the patient had Noonan's syndrome, *then* the result would be, in context, "more successful". In a traditional system, the rules would be structured as a decision tree, based on bivalent logic, in other words "successful" or not. In the modelling employed in a fuzzy system, partial memberships of several sets are applied as defined by the rule base. As the rule base needs to relate all possible values of the input variables to a value for a fuzzy output, its creation is the most labour and memory intensive part of the process, although far easier to generate than an exhaustive list of possibilities in a probabilistic system. Based on the degrees of membership of the input values to the input fuzzy sets, it is possible to create a series of mathematical relationships mapping inputs to outputs. For simplicity, most fuzzy systems use linear mapping between the limits of 0 and 1, leading to triangular or trapezoidal "membership functions", the fundamental building blocks of fuzzy systems.[4] The fuzzy output consists of a weighted average, based on degrees of membership of the fuzzy sets as influenced by the hierarchy of the rule base, which is then converted to a crisp output value or recommendation. The process, therefore, possesses four basic steps:

- conversion of real-world inputs to fuzzy sets, also called "fuzzification"
- creation of the fuzzy linguistic, hierarchical, if-then rule base
- application of the appropriate rules to the fuzzy sets to derive a weighted average, called the "inference engine"
- translation of the result back to a real-world as a "crisp" output value, or a recommendation for possible action, also called "defuzzification".

An assessment of the predictive performance of the fuzzy model can be determined by comparing the known outputs of an independent data set to that predicted by the fuzzy system and the rules created by the experts involved. If appropriate, the rules can be adjusted to reflect such real data. Unsurprisingly, modelling based on fuzzy logic has less to offer when using crisp and precise variables, such as mortality, unarguably bivalent, or when dealing with missing data.

Although initially rejected by the scientific community, particularly in the West, fuzzy systems have been widely incorporated into industry for operational and process control. Examples where they have been used include automatic focussing cameras, washing machines, anti-skid brakes, and industrial processes such as water purification and waste combustion.[5] In the East, the application of fuzzy systems is well resourced, and far more widespread in industry and science. Allegedly, some 10,000 Chinese scientists are engaged in research related to fuzzy logic.[6] Perhaps part of our relative reluctance to embrace the concept lies in the terminology which implies imprecision. In fact, although the fuzzy process deals with imprecise data, capturing information expressed verbally, it allows computations which effectively incorporate common sense to produce unambiguous results, akin to the way a clinician assesses a patient to reach a diagnostic conclusion.

Fuzzy based systems in clinical practice

Medicine is characterised by a lexicon of vague and elastic terms, derived from natural language with imprecise boundaries (mis)applied daily in clinical practice, such as "unwell", "healthy", "heart failure", "cyanosis", "failure to thrive" and "chest pain", and so on. Clinical decision-making has long been viewed as a combination of art and science, yet we still strive for objectivity and precision when working with inherently imprecise and always incomplete data. Crisp parameters elude us for many aspects of medical assessment, such as measurement of the loudness of a heart murmur, or the degree of heart failure.

Over the last 20 years, the medical community has slowly begun to acknowledge and explore the potential usefulness of fuzzy systems. Over 1200 references are currently listed in PubMed with the search term "Fuzzy Logic". To date, medical applications of fuzzy systems have been categorised into pattern recognition or classification, devices for management control, and expert or fuzzy inference systems. In cardiology, devices for recognition of patterns have been successfully integrated into many areas including:

- analysis of different modes of imaging which assess borders: cross-sectional and Doppler echocardiograms, magnetic resonance imaging, coronary arteriograms[7,8]
- automated interpretation of electrocardiographic tracings, including differentiating maternal from fetal signals.[9,10]

Devices for management control measure changes in parameters within a system, using feedback loops to

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make a recommendation, which a health care worker considers before taking appropriate action in response to multiple qualitative variables. This produces an open system. In a closed system, the computer makes the changes without human intervention. The system may be programmed to react according to a particular reading, making it "proportional", or may take into account the rate or magnitude of the change, making it "derivative", or take account of a trend over time, minimising errors of overshoot, and making it "integrated", or may provide a combination of these models.[11] Such "smart alarm" systems have been used effectively in intensive care units, where large amounts of data of varying reliability are presented to health care workers. Intelligent systems to control the monitoring of patients using fuzzy logic are able automatically to detect and prioritise such data, sense and remove artefacts, and follow trends to trigger early warning systems which inform a knowledge-based management advisor, correlating well with recommendations made by clinicians.[11,12] Anaesthetic practice has also effectively incorporated fuzzy systems for control of ventilation and blood pressure, relief of post-surgical pain, and neuromuscular blockade.[13]

An expert medical system can be defined as a computer program that simulates the judgment and decision making of a clinician, with expert knowledge and experience in a particular field. Expert systems for diagnosis and derived management, using fuzzy inference systems, are appealing, as they are able to deal with imprecise and non-parametric data, such as observations in medical practice which rely on perception, self report, and clinical judgement. Symptoms, signs, and investigational data often conflict, particularly if several disease processes coexist. For example, we found that an algorithm based on expert knowledge, with probabilistic refinement created for the diagnosis and initial management of neonatal congenital heart disease, had problems with comparable cases falling into incorrect diagnostic categories, although rarely with incorrect derived management.[14] This was in part related to the fact that the characteristics of, and data from, an individual patient did not exactly match the expert-derived predictions for a particular congenital cardiac lesion, due to inter-patient variability and the fuzzy nature of the disease profile itself. Diagnostic certainty in the neonate with congenital cardiac disease is confounded by the heterogeneity of the pathology, the fact that degrees of heart failure and cyanosis often co-exist, the presence of comorbid conditions, such as prematurity or a chest infection, and the difficultly of distinguishing different patterns of pulmonary vascular markings on a neonatal chest x-ray. Such "greyness" naturally lends itself to a solution based on fuzzy logic, and invites further research and development.

In this issue of the Journal, Holzer et al.[1] have explored a novel application of fuzzy logic in an expert medical system with wide relevance across specialities, namely management of the waiting list. Prioritising any group of patients with similar conditions is fraught with conflicting factors, some of which may be related to the patient, their disease, or the presence of comorbid conditions. Other extrinsic factors are less tangible, such as the need to fulfil targets, including financial ones, imposed by government. As the authors emphasise, these factors need to be weighed against the risks of a pre-procedural adverse event, the best timing of the procedure to minimise mortality and morbidity, and immediate and long term benefits of the procedure. This is particularly true with a profile of disease as diverse as seen in the setting of congenital cardiac malformations, where anatomical and physiological factors play a crucial role in optimising the timing of a procedure and its impact on the quality of life. Not carrying out surgery in a patient with an atrioventricular septal defect with common valve and significant ventricular shunting beyond the age of six months will not only increase the operative risk, but is likely to prolong the post-operative stay, due to pulmonary hypertensive crises and other complications; increasing morbidity as well as the cost of care. Fewer symptoms in this scene indicate added, rather than less, urgency, as pulmonary vascular damage develops and the extent of left-to-right excessive pulmonary blood flow decreases. By augmenting fuzzy linguistic data with crisp objective facts to produce a comprehensive rule base derived from the knowledge of experts, the authors have produced a robust system which performed as well as the "expert" paediatric cardiologists themselves. Potentially, this could therefore be used by coordinators of waiting lists who are not physicians with minimal subsequent "expert" input. The ability to update the system with new data relating to the patients, as it becomes available, strengthens its utility, enabling priorities to be updated as frequently as the hospital infrastructure allows.

Will this system revolutionise the way we admit patients for their procedures, minimising risks and adverse events, whilst optimising bed occupancy? Perhaps not yet, as there remain multiple variables to take into account that are not related to the patients, and which are difficult to factor in with appropriate rules. These would potentially sabotage the attempts made by the fuzzy system to prioritise, and make it impossible simply to leave the solution to the machine. Chief among these are:

- human factors, such as individual variations of operator/surgical performance with particular lesions or the availability of the specific surgeon

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best able to perform a procedure who may additionally require a specific anaesthetist or perfusionist to be present
- unit factors, such as availability of beds due to emergency admissions, in-house infections, or shortages of expert nurses
- family factors, such as the needs of a sibling, or the persuasive powers of a family who choose to use the media or political influence to highlight and promote their case
- conflict of interests between clinical need and externally imposed waiting list or financial targets, or even the need to provide for private patients
- factors specific to the country or health service, such that wider healthcare constraints and prioritisations come into play.

This study provides an interesting approach to an essential area of care in which all clinical paediatric cardiologists are involved, and uses a novel system based on the knowledge of experts and the use of computers. The system now requires prospective testing against the current clinician driven, inherently fuzzy "system", utilised by most units to derive priorities for waiting lists. The rule base needs to be examined in detail to create a system which incorporates some of these unit and national factors that are not related to the patients. Ideally, the decision on when to perform surgery in a patient with a particular lesion should also incorporate a measure of the complexity of the lesion, for instance, intramural coronary arteries in a patient awaiting an arterial switch procedure, and co-morbid factors, such as weight, prematurity, pre-procedural acidosis, and so on. A system for grading complexity, such as the Aristotle Score for congenital cardiac surgery,[15] which attempts to address some of these issues, could be incorporated into the rule base.

How important, therefore, is fuzzy logic and its derived systems to the future of paediatric cardiology? Whilst the proposal that fuzzy theory "will constitute the universal disciplinary matrix in all areas of science, humanities, technology, and human reasoning"[5] may be extreme, it has to be at least acknowledged that it has made a significant contribution across science and industry. Fuzzy systems have proved to have the power and versatility to characterize effectively imprecise, ambiguous, and incomplete information. As a result, systems for recognition of patterns and classification are already in place across medical disciplines. Fuzzy based control systems have demonstrated clinical usefulness in their ability readily to automate nonlinear systems, without the need for a detailed mathematical model, and at relatively low cost. I am confident that the effectiveness of such systems in intensive care and other medical environments will become increasingly recognised and developed.

Despite this, expert knowledge-based fuzzy inference systems, as proposed by Holzer and associates,[1] are unlikely to be universally accepted in the near future. The potential clinical usefulness and appeal of the intuitive simplicity of fuzzy logic may be resisted by many clinicians, as they perceive that their ability to make diagnostic and management decisions is being undermined. The many examples of expert assessment, measurement, and enhancement of decision-making by computer technology, nonetheless, suggest that we do indeed have a fuzzy future. Fuzzy systems will increasingly provide intelligent assistance for highly specialised, complex problems, with the intention of improving performance and minimising the potential for human error in the expert.

References

1. Holzer R, Ladusans E, Kitchiner D, Peart I, Gladman G, Miles G. Prioritization of congenital cardiac surgical patients using fuzzy reasoning – a solution to the waiting list problem? Cardiol Young 2006; 16: 289–299.
2. Aristotle. The Metaphysics. Book IV, 1005 b 19–25. ~340 BC [Engl. Translation: Hugh Tredennick]. William Heinemann, London, 1961.
3. Zadeh LA. Fuzzy sets. Inform Control 1965; 8: 338–353.
4. Sugeno M, Yasukawa T. A fuzzy-logic based approach to qualitative modeling. IEEE Trans Fuzzy Syst 1993; 1: 7–31.
5. Sadegh-Zadeh K. The Fuzzy Revolution: goodbye to the Aristotelian weltanschauung. Artif Intell Med 2001; 21: 1–25.
6. Kay R. Fuzzy Logic. Computer Science 2004. Available from http://www.computerworld.com/databasetopics/data/software/story/0,10801,95497,00.html?from=story_package (accessed 16 February 2006).
7. JC Bezdek JC, Hall LO, Clark MC, Goldgof DB, Clarke LP. Medical image analysis with fuzzy models. Stat Meth Med Res 1997; 6: 191–214.
8. Guler I, Hardalac F, Necaattin B. Application of FFT analyzed cardiac Doppler signals to fuzzy algorithm. Comp Biol Med 2002; 32: 435–444.
9. Deganl R. Computerized electrocardiogram diagnosis: fuzzy approach. Meth Inform Med 1992; 31: 225–233.
10. Al-Zaben A. Extraction of foetal ECG by combination of singular value decomposition and neuro-fuzzy inference system. Phys Med Biol 2006; 51: 137–143.
11. Vitez TS, Wada R, Macario A. Fuzzy Logic: Theory and Medical Applications. J Cardiothorac Vasc Anesth 1996; 110: 800–808.
12. Belal SY, Taktak AFG, Nevill A, Spencer A. An intelligent ventilation and oxygenation management system in neonatal intensive care using fuzzy trend template fitting. Physiol Meas 2005; 26: 555–570.
13. Grant P, Naesh O. Fuzzy logic and decision-making in anaesthetics. J R Soc Med 2005; 98: 7–9.
14. Franklin RCG, Spiegelhalter DJ, Macartney FJ, Bull C. Evaluation of a diagnostic algorithm for heart disease in neonates. Brit Med J 1991; 302: 935–939.
15. Lacour-Gayet F, Clarke D, Jacobs J, et al. The Aristotle score for congenital heart surgery. Semin Thorac Cardiovasc Surg Pediatr Card Surg Annu 2004; 7: 185–191.

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