Temporal Patterns: Smart-type Reasoning and Applications

Dineshen Chuckravanen
Jacqueline W. Daykin

Department of
Computer Science
Aberystwyth University
(Mauritius Branch Campus)
Mauritius
Email: dic4@aber.ac.uk
Email: jwd6@aber.ac.uk

Karen Hunsdale

Department of
Applied Management
Winchester Business School
University of Winchester
UK
Email: Karen.Hunsdale
@winchester.ac.uk

Amar Seeam

Department of
Computer Science
Middlesex University
(Mauritius Branch Campus)
Mauritius
Email: a.seeam@mdx.ac.uk

***Abstract*—Allen's interval algebra is a calculus for temporal reasoning that was introduced in 1983. Reasoning with qualitative time in Allen's full interval algebra is nondeterministic polynomial time (NP) complete. Research since 1995 identified maximal tractable subclasses of this algebra via exhaustive computer search and also other *ad-hoc* methods. In 2003, the full classification of complexity for satisfiability problems over constraints in Allen's interval algebra was established algebraically. Recent research proposed scheduling based on the Fishburn-Shepp correlation inequality for posets. We describe here three potential temporal-related application areas as candidates for scheduling using this inequality.**

***Keywords*–Allen's interval algebra, artificial intelligence; qualitative temporal reasoning; scheduling; smart-type reasoning.**

I. INTRODUCTION

Temporal reasoning is a mature research endeavor and arises naturally in numerous diverse applications of artificial intelligence, such as: planning and scheduling [1], natural language processing [2], diagnostic expert systems [3], behavioural psychology [4], circuit design [5], software tools for comprehending the state of patients in intensive care units from their temporal information [6], business intelligence [7], and timegraphs, that is graphs partitioned into a set of chains supporting search which originated in the context of story comprehension [8].

Allen [9] introduced an algebra of binary relations on intervals (of time), for representing and reasoning about time. These binary relations, for example *before*, *during*, *meets*, describe *qualitative* temporal information which we will be concerned with here. The problem of satisfiability for a set of interval variables with specified relations between them is that of deciding whether there exists an assignment of intervals on the real line for the interval variables, such that all of the specified relations between the intervals are satisfied. When the temporal constraints are chosen from the full form of Allen's algebra, this formulation of satisfiability problem is known to be NP-complete. However, reasoning restricted to certain fragments of Allen's algebra is generally equivalent to related well-known problems such as the interval graph and interval order recognition problems [10], which in turn find application in molecular biology [11][12][13].

TABLE I. [14] THE SET $\mathbf{B}$ OF THE THIRTEEN BASIC QUALITATIVE RELATIONS DEFINED BY ALLEN.

Basic Interval Relation	Symbol	Endpoint Relations
X precedes (before) Y	p ($\prec$)	$X^+ < Y^-$
Y preceded-by (after) X	$p\smile$ ($\succ$)	
X meets Y	m	$X^+ = Y^-$
Y met-by X	$m\smile$	
X overlaps Y	o	$X^- < Y^- < X^+ < Y^+$
Y overlapped-by X	$o\smile$	
X during Y	d	$X^- > Y^-,\ X^+ < Y^+$
Y includes X	$d\smile$	
X starts Y	s	$X^- = Y^-,\ X^+ < Y^+$
Y started-by X	$s\smile$	
X finishes Y	f	$X^- > Y^-,\ X^+ = Y^+$
Y finished-by X	$f\smile$	
X equals Y	$\equiv$	$X^- = Y^-,\ X^+ = Y^+$

A. Allen's Interval Algebra

Allen's [9] calculus for reasoning about time is based on the concept of *time intervals* together with *binary relations* on them. In this approach, time is considered to be an infinite dense ordered set, such as the rationals $\mathbf{R}$, and a *time interval* X is an ordered pair of time points (X^-, X^+) such that $X^- < X^+$.

Given two time intervals, their relative positions can be described by exactly one of the members of the set $\mathbf{B}$ of 13 basic interval relations, which are depicted in Table I; note that the relations $X^- < X^+$ and $Y^- < Y^+$ are always valid, hence omitted from the table. These basic relations describe relations between *definite* intervals of time. On the other hand, *indefinite* intervals, whose exact relation may be uncertain, are described by a set of all the basic relations that may apply.

The universe of Allen's interval algebra consists of all the binary relations on time intervals which can be expressed as disjunctions of the basic interval relations. These disjunctions are written as sets of basic relations, leading to a total of $2^{13} = 8192$ binary relations, including the *null relation* $\emptyset$ (also denoted by $\perp$) and the *universal relation* $\mathbf{B}$ (also denoted by $\top$). The set of all binary relations $2^{\mathbf{B}}$ is denoted by $\mathcal{A}$; every temporal relation in $\mathcal{A}$ can be defined by a conjunction of disjunctions of endpoint relations of the form $X < Y, X = Y$ and their negations.

The operations on the relations defined in Allen's algebra are: unary *converse* (denoted by $\smile$), binary *intersection* (denoted by $\cap$) and binary *composition* (denoted by $\circ$), which are defined as follows:

$$\begin{aligned} \forall X, Y: \quad & X r^{\smile} Y \leftrightarrow Y r X \\ \forall X, Y: \quad & X(r \bigcap s) Y \leftrightarrow X r Y \bigwedge X s Y \\ \forall X, Y: \quad & X(r \circ s) Y \leftrightarrow \exists Z: (X r Z \bigwedge Z s Y), \end{aligned}$$

where X, Y, Z are intervals, and r, s are interval relations. Allen [9] gives a composition table for the basic relations.

Fundamental *reasoning problems* in Allen's framework have been studied by a number of authors, including Golumbic and Shamir [15] [16], Ladkin and Maddux [17], van Beek [18] and Vilain and Kautz [19].

B. Posets and the Fishburn-Shepp Inequality

We now consider novel research proposed in [20], namely to specify heuristics for scheduling based on representing a collection of intervals of time with constraints as a poset, and applying the Fishburn-Shepp inequality to guide a scheduling algorithm. In [20], applications are sought for this approach: we address this first step here by describing potential applications which are also related to smart-type reasoning. First, we commence with overviews of the scheduling problem and the Fishburn-Shepp inequality.

Generally, a *schedule* of tasks (or simply schedule) is the assignment of tasks to specific time intervals of resources, such that no two tasks occupy any resource simultaneously – additionally, a requirement can be that the capacity of resources is not exceeded by the tasks. A schedule is *optimal* if it minimizes a given optimality criterion. However, our ultimate interest is in providing an algorithm to solve, or schedule, temporal constraint satisfaction problems; since we also consider indefinite qualitative temporal information, the solution may assign events simultaneously to intervals.

Let Q be a finite *poset* (partially ordered set) with n elements and C be a chain $1 < 2 < \cdots < c$. For (Q, C), a map $\omega : Q \to C$ is *strict order-preserving* if, for all $x, y \in Q$, $x < y$ implies $\omega(x) < \omega(y)$. Let $\lambda : Q \to \{1 < 2 < \cdots < n\}$ be a *linear extension* of Q, that is, an order-preserving injection.

A poset Q is equivalently a *directed acyclic graph (DAG)*, $G = (V, E)$; for temporal reasoning, the vertices represent time intervals, and edges between vertices are labeled with relations in Allen's algebra which satisfy the partial ordering. For scheduling problems, a linear extension λ of Q (or G) can be used to schedule tasks: λ must respect interval constraints, that is relations between comparable elements. Algorithmically, a linear extension of a DAG, G, can be determined in linear time by performing a depth-first search of G; while G (Q) can be represented by an adjacency matrix.

The Fishburn-Shepp inequality [21] [22] is an inequality for the number of extensions of partial orders to linear orders, expressed as follows. Suppose that x, y and z are incomparable elements of a finite poset, then

$$P(x < y)P(x < z) < P((x < y) \wedge (x < z)) \qquad (1)$$

where P(*) is the probability that a linear extension has the property *. By re-expressing this in terms of conditional probability, $P(x < z) < P((x < z) \mid (x < y))$, we see that $P(x < z)$ strictly increases by adding the condition $x < y$. The problem posed in [20] concerns applying the Fishburn-Shepp inequality to efficiently find a favourable schedule under specified criteria, where a naive scheduling algorithm is also given together with an illustrative example. However, our focus here is in introducing application scenarios. The rest of the paper is structured as follows.

In Section II, we describe various applications in temporal reasoning that include applications in smart homes, applications in intelligent conversational agents, and also applications in exercise physiology followed by Section III which describes conclusion and future work.

II. Applications in Temporal Reasoning

A. Applications in Smart Homes

Buildings consume a considerable amount of energy. Managing that energy is challenging, though is achievable through building control and energy management systems. These systems will typically monitor, measure, manage and control services for the lighting, heating, ventilation and air conditioning (HVAC), security, and safety of the building. They also permit a degree of scheduling, albeit they are often limited by static programming and may have no awareness incorporated of external events. For example, a building's HVAC system may heat rooms that are unoccupied as the setpoint has been programmed to be a certain temperature for a specified interval of the day. Clearly this is quite inefficient, and though motion detectors can play a role in actuating lights during periods of room occupancy, maintaining a comfortable indoor climate using similar sensors to detect people cannot provide the same benefits. Furthermore, the indoor climate is impacted by outdoor thermodynamic processes, as well as internal heat gains which can be unaccountable (e.g., people, mobile equipment, etc). However, most modern non-residential building's energy management systems will be configured to turn building services on and off throughout the day using a pre-programmed schedule (e.g., a repeating daily pattern of heating use) and can also employ intelligent start-up controllers with external temperature compensation to delay the turning on of heating for example. Modern heating controllers (i.e., programmable thermostats) in homes can also have setpoints configured in a daily schedule (e.g., 6-8am: increase setpoint to 20°C, representing a waking-up phase; 9am - 4pm: heating deactivated or set to a maximum (e.g., 15°C); and from 5pm - 6pm: 21°C, representing a heating-up phase to anticipate arrival of an occupant from a workplace, and so forth).

Aside from heating control, homes can now also employ smart home systems to perform some degree of energy management and appliance automation. These systems are becoming more commonplace, particularly as the Internet of Things (IoT) paradigm is gaining more traction, whereby humans are bypassed, and machine to machine communication takes place (e.g., Smart Homes communicating with Smart Grids [23]). This gives rise to smart automation and reasoning where decision making can take place and determine when home appliances can be scheduled, particularly in the case of peak-load shaving [24] or demand response optimization [25]. In these cases, consumption patterns can be shifted to times of lower cost electricity. Appliance scheduling can be further classified by, for instance, their minimum required periods of operations, whether or not their operations can be interrupted, and if a human occupant is involved (i.e., in climate control scenarios). For instance, washing machines will have varying periods of operation depending on the program (wash, spin, dry) and cannot (typically) be interrupted if scheduled. Heating or cooling systems will have optimum start-up times to turn on in anticipation of occupants requiring the temperature of the house to be at a preset setpoint upon arrival. The Internet of Things has even enabled this particular scenario to be influenced by the distance an occupant is from the home or building, whereby the driving time is estimated via tracking of a Global Positioning System (GPS signal) [26]. In [27], driving patterns were analysed, and a programmable thermostat augmented with GPS control enabled energy savings of 7%.

The emerging Internet of Things in this respect will be responsible for huge volumes of temporal pattern data (i.e., timestamped sequences of events, be it a change in temperature, or a light being turned on and off, or the duration of activity of an entertainment system, etc), thus also incorporating quantitative temporal information. In the smart home, the ability to detect user behaviour or house activities from this kind of temporal pattern data can provide a better understanding of how to identify patterns of energy use and thus determine when or how to gain energy savings. Naturally, the accumulative savings factor is increased many-fold in the smart city concept. Temporal pattern event detection inspired by Allen's relations has proved useful in smart environments: for anomaly detection in assisted living applications [28], and in activity monitoring [29]. In these examples, intervals represent the sensed data (cooking would imply the stove being on while an inhabitant is present in the kitchen [30]). Such kinds of recognition are useful for determining normal behaviour of elderly occupants, and thus, for instance, detecting any onsets of dementia [31].

Clearly, efficient, or ideally optimized, scheduling of events can lead to enhanced savings of time and energy – it is with this goal that we propose applying the Fishburn-Shepp inequality, possibly to a specified subset of events in a larger complex system.

B. Applications in Intelligent Conversational Agents

Intelligent conversational agents (CA) enable natural language interaction with their human participant. Following an input string, the CA works through its knowledge-base in search of an appropriate output string. The knowledge-base consists of natural language sentences based on a specific domain. Through the use of semantic processing using a lexical database with grouped sets of cognitive synonyms, word similarity is determined, with thus the highest semantically similar ranked string returned to the user as output.

Scripts consist of contexts that relate to a specific theme or topic of conversation. Each context contains one or more rules, which possess a number of prototype natural language sentences. An example of a scripted natural language rule is shown below, where s is a natural language sentence and r is a response statement.

<Rule-01>

s: I am having problems accessing my email account.
r: I'm sorry to hear that. Have you tried contacting IT support?

One such CA, as proposed by O'Shea *et al.* ([32] [33] [34]), uses semantics as a means to measure sentence similarity. The CA is organized into contexts consisting of a number of similarly related rules. Through the use of a sentence similarity measure, a match is determined between the user's utterance and the scripted natural language sentences. Similarity ratings are measured in the range from 0 to 1, in which a value of 0 denotes no semantic similarity, and 1 denotes an identical sentence pair. The highest ranked sentence is fired and its associated response is sent as output. The following algorithm describes the application:

1. Natural language dialogue is received as input from the user.

2. Semantic-based CA receives natural language dialogue from the user which is sent to the sentence similarity measure.

3. Semantic-based CA receives natural language sentences from the scripts files which are sent to the sentence similarity measure.

4. Sentence similarity measure calculates a firing strength for each sentence pair which is returned and processed by the semantic-based CA.

5. The highest ranked sentence is fired and its associated response is sent as output.

Natural language interaction between two participants (human or otherwise) can be modeled using Allen's interval algebra: the intervals of speech could satisfy the basic relation p, if one speaks before the other, or the relation o if their speech overlaps, and so on. In terms of scheduling a set of speech events with specified relations, that is constructing a linear extension by applying the Fishburn-Shepp inequality, we envisage an application for the learning impaired which schedules the events sequentially to reduce confusion from simultaneous speech. This could then be integrated with a CA facility.

C. Applications in Physiology

In exercise physiology, the study of complex rhythms arising from the peripheral systems (for example, the cardiovascular system) and the central nervous system of the human body is important to optimize athletic performance while using a suitable type of pacing. Pacing plays an important part during athletic competition so that the metabolic resources are used effectively to complete the physical activity in the minimum time possible, as well as to maintain enough metabolic resources to complete that task [35]. Moreover, according to the Central Governor Model (CGM) [36], there is a central regulator that paces the peripheral systems during physical activity to reach the endpoint of that physical activity without physiological system failure. This central governor model of fatigue is a complex integrative control model which involves the continuous interaction, in a deterministic way, among all the physiological, and that of the central systems.

In this context, the decision making process involved when an athlete changes his or her pacing strategy during a particular race (and especially during endurance exercise) seems quite complex. However, the change in the decision making process could be simply explained by the basic relations in Allen's interval algebra. Consider the following scenario where an athlete or runner needs to complete a 20-km race. An experienced runner will subconsciously be aware of the amount of energy resources they will need during the race so that they can effectively complete the race without catastrophic failure. During the race, there are both exogenous and endogenous factors which will influence the optimal performance of the runner, and therefore she or he has to make important decisions as to when, or when not, change their pacing during the race so that they can complete the race in the minimum time possible.

For instance, there may be three major changes in the patterns of the running speed, power output, or pacing strategies that the runner could adopt for a long distance race such as the 20-km race [37]. Initially, on the first stage of the race, he or she will accelerate from a resting standing (or crouching) position to reach a constant optimal speed as determined by the runner's physical ability; meanwhile their heart rate (HR) will accelerate as well as their volume of oxygen consumption (VO2). In the second stage, they will maintain the same constant running speed for most of the race while their heart rate will be quite steady; moreover, the volume of oxygen consumption will be kept practically constant throughout the race. Finally, in the third stage of the race, the runner will accelerate or sprint in order to complete the race, which will at the same time, increase their heart rate as well as the rate of volume of oxygen consumption.

This represents one possible scenario that may occur during a race, which illustrates that Allen's temporal relations can be exploited to more clearly express the complex decision-making processes related to the human body during physical exertion, and hence allow for scheduling the pacing strategy adopted by a runner during a particular race. Furthermore, smart-type devices can be worn by an athlete which can also feed into the decision-making process in real time.

III. CONCLUSION AND FUTURE WORK

Previous research in temporal pattern reasoning surrounding smart homes has largely focused on activity recognition of inhabitants, and gaining an understanding from sensor data retrieved from indoor environments (such as electricity, temperature, light, or motion). The Internet of Things, however, will provide further dimensions of data from people (wearable sensors, tracking of GPS, etc.). This kind of outdoor data will provide additional context to the smart home and enable it to make better and more informed decisions as to how to actuate and control building services.

For example, returning to the case of augmented heating control using GPS - an occupant leaves the house and goes for a short jog (automatically disabling the heating as they leave) - as they run their own body temperature rises. The wearable sensors will be monitoring their temperature and their GPS coordinates. As they return and approach their home, the augmented heating control with the GPS system will turn on the heating, but will also take into account the occupant's current body temperature, and accordingly apply the appropriate heating control strategy (i.e., reducing the return-to-home setpoint from a previously higher setting and actuation time). In this case, the quantitative temporal information between arrival and heating activation will be lengthened as the temperature setpoint requirement will be reduced. This is just one of a myriad of possibilities that can be realized from the abundance of potential sensor data generated from the Internet of Things. We believe the relation between indoor and outdoor sensing (as well as any other sensing source for that matter) and reasoning strategies requires further exploration, and as part of our future research strategy we will investigate smart home event and action temporal reasoning from multiple data streams beyond enclosed indoor scenarios. In particular, smart-type scheduling is a key factor in energy-related issues.

We envisage enhanced synergy in the smart-environment by integrating intelligent conversational agents. Useful responses to even simple sentences such as *Where are my keys?* can have impact on human energy and stress levels and allow for more efficient use of time.

To date, physiological research into pacing strategies has focused on the amount of energy resources that are available for a runner to complete a long distance race. We propose that the future area in which the exercise physiology field should endeavour to concentrate more on, is the optimal time in switching between the different types of pacing strategies, so that a race is completed successfully and in the minimum time possible without homeostatic failure. In order to achieve this, the various changes in pacing, namely, increasing, constant or decreasing pace, depends on each individual's resource capacity and endurance for each type of pacing so as to achieve the target in the least possible time. Moreover, we suggest that the decision-making process underlying the choice of the various pacing strategies can be informed through the application of Allen's algebra, and the resulting scheduling can be applied to promote and improve world elite athletic performance.

REFERENCES

[1] J. F. Allen, "Temporal reasoning and planning.in j.f. allen, h.a. kautz, r.n. pelavin and j.d. tenenberg (eds.)," in Reasoning about Plans. Morgan Kaufman, 1991, pp. 1–67.

[2] F. Song and R. Cohen, "The interpretation of temporal relations in narrative," National Conference on Artificial Intelligence (AAAI-88), 1988.

[3] K. Nökel, Temporally distributed symptoms in technical diagnosis. Springer Science & Business Media, 1991, vol. 517.

[4] C. H. Coombs and J. Smith, "On the detection of structure in attitudes and developmental processes." Psychological Review, vol. 80, no. 5, 1973, p. 337.

[5] S. A. Ward and R. H. Halstead, Computation structures. MIT press, 1990.

[6] J. Juarez, M. Campos, A. Morales, J. Palma, and R. Marin, "Applications of temporal reasoning to intensive care units," Journal of Healthcare Engineering, vol. 1, no. 4, 2010, pp. 615–636.

[7] H.-U. Krieger, B. Kiefer, and T. Declerck, "A framework for temporal representation and reasoning in business intelligence applications." in AAAI Spring Symposium: AI Meets Business Rules and Process Management, 2008, pp. 59–70.

[8] A. Gerevini, L. Schubert, and S. Schaeffer, "Temporal reasoning in timegraph i–ii," ACM SIGART Bulletin, vol. 4, no. 3, 1993, pp. 21–25.

[9] J. F. Allen., "Maintaining knowledge about temporal intervals," Commun., vol. 26, no. 11, 1983, pp. 832–843.

[10] I. Pe'er and R. Shamir, "Satisfiability problems on intervals and unit intervals," Theoretical Computer Science, vol. 175, no. 2, 1997, pp. 349–372.

[11] M. C. Golumbic, H. Kaplan, and R. Shamir, "On the complexity of dna physical mapping," Advances in Applied Mathematics, vol. 15, no. 3, 1994, pp. 251–261.

[12] R. M. Karp, "Mapping the genome: some combinatorial problems arising in molecular biology," in Proceedings of the twenty-fifth annual ACM symposium on Theory of computing. ACM, 1993, pp. 278–285.

[13] I. Mandoiu and A. Zelikovsky, Bioinformatics algorithms: techniques and applications. John Wiley & Sons, 2008, vol. 3.

 ISBN: 978-1-61208-534-0

[14] B. Nebel and H.-J. Bürckert, "Reasoning about temporal relations: a maximal tractable subclass of allen's interval algebra," Journal of the ACM (JACM), vol. 42, no. 1, 1995, pp. 43–66.

[15] M. C. Golumbic and R. Shamir, "Algorithms and complexity for reasoning about time," in AAAI, 1992, pp. 741–747.

[16] G. Martin Charles and R. Shamir, "Complexity and algorithms for reasoning about time: A graph-theoretic approach," Journal of the ACM (JACM), vol. 40, no. 5, 1993, pp. 1108–1133.

[17] P. B. Ladkin and R. D. Maddux, On binary constraint networks. Kestrel Institute Palo Alto, CA, 1988.

[18] P. Van Beek, "Reasoning about qualitative temporal information," Artificial intelligence, vol. 58, no. 1-3, 1992, pp. 297–326.

[19] M. B. Vilain and H. A. Kautz, "Constraint propagation algorithms for temporal reasoning." in Aaai, vol. 86, 1986, pp. 377–382.

[20] J. W. Daykin, M. Miller, and J. Ryan, "Trends in temporal reasoning: Constraints, graphs and posets," in International Conference on Mathematical Aspects of Computer and Information Sciences. Springer, 2015, pp. 290–304.

[21] P. C. Fishburn, "A correlational inequality for linear extensions of a poset," Order, vol. 1, no. 2, 1984, pp. 127–137.

[22] L. A. Shepp et al., "The xyz conjecture and the fkg inequality," The Annals of Probability, vol. 10, no. 3, 1982, pp. 824–827.

[23] K. M. Tsui and S.-C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," IEEE Transactions on Smart Grid, vol. 3, no. 4, 2012, pp. 1812–1821.

[24] G. T. Costanzo, J. Kheir, and G. Zhu, "Peak-load shaving in smart homes via online scheduling," in 2011 IEEE International Symposium on Industrial Electronics. IEEE, 2011, pp. 1347–1352.

[25] J. Zhu, F. Lauri, A. Koukam, and V. Hilaire, "Scheduling optimization of smart homes based on demand response," in IFIP International Conference on Artificial Intelligence Applications and Innovations. Springer, 2015, pp. 223–236.

[26] A. B. John Krumm, "Learning time-based presence probabilities," in Pervasive 2011. Springer Verlag, June 2011. [Online]. Available: https://www.microsoft.com/en-us/research/publication/learning-time-based-presence-probabilities [retrieved 2/2017].

[27] M. Gupta, S. S. Intille, and K. Larson, "Adding gps-control to traditional thermostats: An exploration of potential energy savings and design challenges," in International Conference on Pervasive Computing. Springer, 2009, pp. 95–114.

[28] V. Jakkula and D. J. Cook, "Anomaly detection using temporal data mining in a smart home environment," Methods of information in medicine, vol. 47, no. 1, 2008, pp. 70–75.

[29] J. Ullberg, A. Loutfi, and F. Pecora, "Towards continuous activity monitoring with temporal constraints," in Proc. of the 4th Workshop on Planning and Plan Execution for Real-World Systems at ICAPS09, 2009, pp. 3833–3860.

[30] F. Palumbo, J. Ullberg, A. Štimec, F. Furfari, L. Karlsson, and S. Coradeschi, "Sensor network infrastructure for a home care monitoring system," Sensors, vol. 14, no. 3, 2014, pp. 3833–3860.

[31] P. C. e. a. Roy, "A possibilistic approach for activity recognition in smart homes for cognitive assistance to alzheimers patients," in Activity Recognition in Pervasive Intelligent Environments. Springer, 2011, pp. 33–58.

[32] K. O'shea, Z. Bandar, and K. Crockett, "Towards a new generation of conversational agents using sentence similarity," in Advances in Electrical Engineering and Computational Science, L. N. in Electrical Engineering, Ed. Sio-Long Ao and Len Gelman, Ed. Netherlands: Springer, 2009, vol. 39, pp. 505–514.

[33] K. O'shea, Z. Bandar, and K. A. Crockett, "Application of a semantic-based conversational agent to student debt management," in World Congress on Computational Intelligence, I. International, Ed. Conference on Fuzzy Systems, Barcelona: 978-1-4244-6917-8, 2010, pp. 760–766.

[34] K. O'shea, "An approach to conversational agent design using sentence similarity measures," International Journal of Artificial Intelligence, 2012, pp. 558–568.

[35] H. Ulmer, "Concept of an extracellular regulation of muscular metabolic rate during heavy exercise in humans by psychophysiological feedback," Experimentia, vol. 52, 1996, pp. 416–420.

[36] E. Lambert, A. St Clair Gibson, and T. Noakes, "Complex systems model of fatigue: integrative homeostatic control of peripheral physiological systems during exercise in humans," B J Sports Med, vol. 39, 2004, pp. 52–62.

[37] D. Chuckravanen and S. Rajbhandari, "Management of metabolic resources for a 20-km cycling time-trial using different types of pacing," Journal of Human Sport and Exercise, vol. 10, no. 1, 2015, pp. 95–103.