Application of Neuro-Fuzzy Modelling for Accurate Estimation of Oxygen Consumption from Heart Rate

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Abstract

Traditionally, oxygen consumption (VO_2), which reflects workload of physically demanding jobs, has been estimated from heart rate (HR) using the linear relationship between both variables. However, due to the presence of external factors, such as fatigue, emotional stress and fitness level, this relationship becomes nonlinear, especially at low workload intensity. This study presents a new method to estimate oxygen consumption from heart rates using adaptive neuro-fuzzy inference system (ANFIS), which is capable of handling uncertainties and nonlinearity. In a laboratory experiment, eight participants performed two step-tests in consecutive days during which oxygen consumption and heart rate were measured. Data from step-test 1 were used to develop individual ANFIS for each participant. The individual ANFIS were then tested and compared with traditional linear models using the dataset obtained from step-test 2. The results indicated increase in VO2 estimation accuracy of 38% (at low workload intensity, HR<90 bpm) and 21% (in general, throughout HR range). Individual ANFIS show potential to replace linear models at workplaces with small working population or when accurate estimation of physical workload is desired.

Keywords
Workload, Oxygen consumption, Heart rate and Fuzzy.

1. Introduction
Nowadays, many physically demanding jobs have been automated thanks to the development of new advanced technologies. Some industries, however, such as forestry, construction and mining, still involve tasks that are highly physically demanding. Human factors (HF) researchers have demonstrated the significance of designing jobs within the physiological capacity of a workforc. The balance between the energetic demands (workload) of the physical jobs and the physiological capacity of the workforce can significantly improve the workforce's safety and productivity (Malchaire et al. 1984; Abdelhamid 1999; Wu and Wang 2002; Dempsey et al. 2008; Kolus et al. 2018). The energetic demand of physical work can be accurately determined by measuring the amount of oxygen consumed (VO_2) by a worker during the physical activity (Malchaire et al. 1984; Wu and Wang 2002; Bridger 2003; Bouchard and Trudeau 2008; Smolander et al. 2008). However, the direct measurement of VO_2 in field is impractical because it is invasive and requires sophosticated and expensive equipment.

In 1907, Benedict was the first to observe a relationship between VO_2 and heart rate (HR). Later studies have reported that this relationship is roughly linear for a wide variety of activities (Wyndham et al. 1962; Poulsen and Asmussen 1962; McArdle et al. 1971; Rodahl et al. 1974; Evans et al. 1983; Gordon et al. 1983; Astrand and Rodahl 1986). Since then, the common practice has been to estimate VO_2 from HR, which can be measured easily in field (Smolander et al. 2008). This method is called "calibration process", which involves measuring an individual's HR and VO_2 while performing a graded exercise (i.e., step-test). Linear regression is used to model the linear relationship between HR and VO_2, called calibration curve. The model is then used to estimate VO_2 from HR data collected in field for the same individual.

This method, however, is criticised by many researchers due to the exsitance of external factors (e.g., emotional stress, high ambient temperature, high humidity, total amount of muscles, fatigue, physical fitness, caffeine, posture and illness) that may casue changes in HR without associated changes in VO_2 (Valanou et al. 2006). The impact of these factors is noticable especially at low workload intensity, which makes the relationship between HR and VO_2 nonlinear and deviates from the calibration curve (Abdelhamid 1999; Bouchard and Trudeau 2008; Smolander et al. 2008). In order to estimate VO_2 accurately, there is a need for a new technique that can handle the uncertainty and nonlinearity between HR and VO_2, especially at low workload intensity.

The objective of this study is to improve the current individual calibration process using computational intellegence. Neural networks, fuzzy systems and evolutionary computation are considered the three main pillars of computational intelligence (Zhu 2014). One of the computational intelegence techniques that has proven effective in pattern recognition and function approximation is the adaptive neuro-fuzzy inference system (ANFIS) (Güler and Übeyli 2004). ANFIS combines the ability of artificial neural networks (ANN) in automatic learning and adaptation from existence data and the ability of fuzzy logic in decision-making under uncertainties (Kaya et al., 2003). In 2014, Kolus and colleagues proposed a new approach based ANFIS to estimate VO_2 from HR. Their study focused on developing a general ANFIS model that can estimate VO_2 of forestry workers without the need to collect individual calibration data. The genearl ANFIS showed potential to be used in workplaces whith large poulation where one cannot afford to have each worker take step-test. This, however, may result in lower estimation accuracy (when compared to the traditional linear model) since individual calibration data are not used.

In this study, we focus on estimating VO_2 at the individual level, where high estimation accuracy is desired. In physically demanding workplaces (e.g., mining, steel industry, firefighting and construction), the accurate estimation of VO_2 is crucial for maintaining the balance between the energetic demand of work and human capacity; hence improving human wellbeing and system performance. Therefore, individual adaptive neuro-fuzzy inference systems (called individual ANFIS) were developed for a group of eight participants in order to accurately estimate their VO_2 from HR. The developed models were then tested and compared with traditional linear calibration models. HR and VO_2 measurements were collected from the participants while performing two step-tests in a laboratory in consecutive days (step-test 1 data were used for models development and step-test 2 data were used for models testing and comparisons).

2. Methods

This research was based on a laboratory study where participants performed a submaximal step-test. The study used two data sets (i.e., training and test), both of which were obtained from the same set of participants (see Figure 1). Training data were obtained from the participants while performing the step-test in a laboratory. Similarly, test data were obtained from the same participants while performing the step-test in the laboratory, but on the next day in order not to accumulate fatigue. The training dataset was used for fuzzy model development for each participant. The test dataset was used to test the accuracy of the developed fuzzy models and compare their performance in estimating VO_2 with that of traditional linear models.

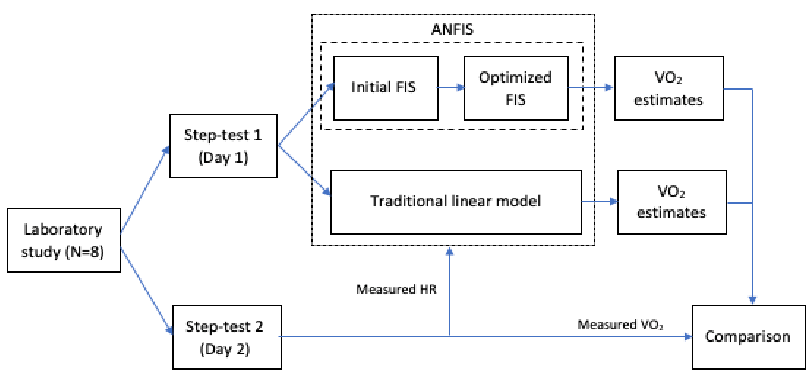

Figure 1. Schematic description of the study

2.1 Participants

Eight healthy males, from different background, aged from 28 to 45 years participated in this research. These participants were drawn from the local population in Montreal through advertisement. Table 1 shows the physical characteristics of the participants. Prior participating in the study, all participants had to pass the pre-activity readiness questionnaire (PAR-Q) (Chisholm et al. 1975; Shephard 1988). None of the participants were athlete, on a training program or medication. The study was approved by the Human Research Ethics Committee at University of Montreal. All participants signed a written informed consent form prior to their participation in the study.

Table 1. Physical characteristics of the participants

Characteristics	Participants (n = 8)	
	Mean (SD)	Range
Age (years)	35.67 (7.79)	[28, 45]
Body weight (kg)	80.29 (13.93)	[63.5, 104.33]
Height (cm)	175.92 (6.95)	[170.18, 187.96]
BMI ($kg.m^{-2}$)	25.14 (3.15)	[21.22, 29.53]
VO_2 max (ml/kg.min)	41.25 (5.18)	[30, 45]
HR_{max} (bpm)	184.33 (7.79)	[175, 192]
HR_{rest} (bpm)	71.8 (12.9)	[60, 87]

Note. SD: standard deviation; BMI: body mass index; VO_2 max: maximal oxygen consumption; HR_{max}: maximal heart rate; HR_{rest}: resting heart rate.

2.2 Procedure

The eight participants performed the Meyer and Flenghi (1995) step-test during the day in the Kinesiology laboratory of University of Montreal. Each participant performed the step-test twice (two sessions), with a 24-hour interval. The data obtained from the first session (step-test 1) were used to develop the proposed fuzzy model for each participnat. The data obtained from the second session (step-test 2) were used to test the accuracy of the fuzzy models, as well as make comparisons with traditional linear calibration models.

The Meyer and Flenghi step-test protocol was selectedbecause it is safe, simple, inexpensive and validated against benchmark submaximal exertion tests (Meyer and Flenghi 1995). In addition, it has been shown that the highest exertion level reached in this test is quite similar to the level of exertion generally measured in actual physical work, such as brushcutting (Imbeau et al. 2010).

The step-test uses a portable bench with adjustable step height of 11.5, 21.5, 31.5 and 41.5 cm. The protocol of the Meyer and Flenghi step-test can be described as follows. The participant was asked to sit on a chair for 5 min to obtain his resting heart rate (HR_{rest}), and then asked to stand in front of the bench for 2 min. Then, the participant was asked to step on and off the lowest step height (11.5 cm) for 3 min. This was followed by 30 sec standing rest during which the experimenter increased the step height to the next level. This 3.5-min cycle was repeated for the remaining step heights. More details about the test protocol can be found in Meyer and Flenghi (1995).

Heart rate and oxygen consumption were continuously measured and monitored during both step-test sessions using an automated metabolic cart (MOXUS Metabolic System, AEI Technologies, Pittsburgh, PA). HR and VO_2 data were measured every second by the metabolic cart. Prior to each test, the gas sensor and the flowmeter of the metabolic cart were calibrated by a qualified technician. Heart rate was continuously monitored during the test to ensure that it did not exceed 85% of the participant's age-predicted maximum heart rate (HR_{max}) (Fox et al., 1971). The test was terminated whenever a participant exceeded his age-predicted HR_{max}. The complete step-test took 21 min, followed by a sitting rest to allow participant's heart rate to return to resting.

The learning dataset included HR and VO_2 measurements collected from all participants at rest and for each step height of step-test 1. The test dataset included HR and VO_2 measurements collected from all participants at rest and for each step height of step-test 2.

2.3 Adaptive neuro-fuzzy inference system (ANFIS) development

ANFIS is a fuzzy model put in the framework of adaptive systems (i.e., ANN) in order to able to learn from existing data and then optimize the model parameters accordingly. This section describes the development of ANFIS, which consists of two steps: deciding on the architecture of ANFIS (network design) and learning algorithm.

The structure of ANFIS can be identified by developing an initial fuzzy inference system using the fuzzy set theory (Jang et al. 1997). This step involves: selecting input variables, selecting the type of fuzzy model, determining the rule-base and determining the membership functions for the variables.

In this study, an individual fuzzy model was developed for each participant based on the participant's HR and VO_2 measurement collected during step-test 1. Measured HR and HR_{rest} constituted the input variables to the fuzzy model, while measured VO_2 constituted the output variable. A total of 41 data samples obtained from a participant were used to train the corresponding individual fuzzy model. Optimal subtractive clustering parameters were determined based on enumerative search. The optimal parameters were: cluster radius (r) = 0.5; squash factor (η) = 1.25; accept ratio ($\overline{\epsilon}$) = 0.5 and reject ratio ($\underline{\epsilon}$) = 0.15. As a result, three clusters were identified each of which corresponded to a fuzzy IF-THEN rule. The three fuzzy IF-THEN rules constituted the initial FIS, which were then embedded in ANN framework in order to optimize the rules parameters (premise and consequent).

The combination of back-propagation gradient descent method and the least squares method was used to train the fuzzy model for 1000 epochs (MATLAB version 7.5.0 with fuzzy logic toolbox). The developed fuzzy model consists of three fuzzy IF-THEN rules, three Gaussian membership functions assigned to each input variable and 21 modifiable parameters (12 premise and 9 consequent parameters).

2.4 Traditional linear models development

The traditional linear model is a linear regression equation of the form: $y = ax + b$, where y and x denote VO_2 and HR measurements respectively and a and b denote the slope and intercept of the first-order linear equation, respectively. Training dataset (328 data samples of HR and VO_2 measurements obtained from step-test 1) were used to develop individual linear calibration models. The first-order linear equations were developed using Excel 2013 (Microsoft Corporation, Redmond, WA).

2.5 Models testing and comparisons

The accuracy of the developed models (ANFIS and traditional linear calibration) in VO_2 estimation were compared using the test dataset over all participants. The comparisons were made throughout the HR range, as well as for three HR ranges: <80 bpm (very light work); 80-100 bpm (light work); and >100 bpm (moderate to heavy work), according to (Smolander et al. 2008).

2.6 Statistical analysis

The accuracy of the developed models (traditional linear and ANFIS) in VO_2 estimation and the comparisons among them were evaluated at the individual level using the root mean square error (RMSE) between the measured and estimated VO_2. In addition, limits of agreementbetween the measured VO_2 values and the values estimated by the traditional linear and ANFIS models were determinedusing the Bland-Altman plot, which examines the estimation accuracy of the developed models (Bland and Altman 1986).

3. Results and Discussion

3.1 Initial fuzzy inference system (FIS)

In order to develop an initial FIS for each participant, corresponding HR-VO_2 data (obtained from step-test 1) were clustered using the subtractive clustering algorithm. Optimal subtractive clustering parameters were determined based on enumerative search. The optimal subtactive clustering parameters for each participant are summarized in Table 2. In addition, the number of resultant initial fuzzy rules (that construct the initial FIS), as well as the quality of fit of the initial FIS (based on RMSE) were shown in Table 2. For example, the enumerative search showed that the optimal subtractive clustering parameters for participant 1 are as follows: $r = 0.1$, $\overline{\epsilon} = 0.9$, $\underline{\epsilon} = 0.7$ and $\eta = 1.5$. The resultant initial FIS for participant 1 consisted of four fuzzy IF-THEN rules and had a RMSE of 1.102 ml/kg.min. The same subtractive clustering parameters were found to be optimal for participant 5. However, the resultant initial FIS for participant 5 consisted of three fuzzy IF-THEN rules and had a RMSE of 1.348 ml/kg.min.

The developed initial FISs consisted of four fuzzy IF-THEN rules for all participants, except for participants 5 and 7 (their FISs consisted of three fuzzy IF-THEN rules). This is due to the insignificant impact of the increased of number of rules on the RMSE.

Table 2. Optimal subtractive clustering parameters based on enumerative search

Participant	Sample size	Subtractive clustering					
	n	r	$\bar{\epsilon}$	$\underline{\epsilon}$	η	Rules	RMSE
P1	41	0.1	0.9	0.7	1.5	4	1.102
P2	41	0.3	0.9	0.5	0.9	4	1.177
P3	41	0.5	0.3	0.1	1.1	4	1.115
P4	41	0.3	0.9	0.3	1.5	4	1.609
P5	41	0.1	0.9	0.7	1.5	3	1.348
P6	41	0.1	0.9	0.5	0.7	4	1.553
P7	41	0.3	0.9	0.3	1.5	3	1.011
P8	41	0.3	0.9	0.1	1.5	4	1.127

3.2 Adaptive neuro-fuzzy inference systems

The developed initial FISs were trained (by learning from existing data) in order to improve their performance. The initial FISs were embedded in ANN framework, constituting adaptive neuro-fuzzy inference systems (ANFIS), in order to optimize the rules parameters (premise and consequent parameters). Table 3 summarizes the number of training epochs applied on initial FISs and the resultant RMSE.

Table 3. Training the initial FISs using adaptive neuro-fuzzy inference systems (ANFIS)

Participant	Sample size	ANFIS training	
	n	Epochs	$RMSE_{trn}$
P1	41	110	0.987
P2	41	10	1.160
P3	41	100	1.114
P4	41	500	1.580
P5	41	100	1.337
P6	41	100	1.549
P7	41	300	0.960
P8	41	100	1.120

The optimal parameters of the trained FIS (i.e., ANFIS) for each participant are shown in Table 4. The ANFIS models associated with each participant can be presented as follows:
For participant i:
Rule j: IF HR is A_{ij} THEN $VO_2 = a_{ij}$ (HR) + b_{ij}
, where i is an index of the participant (i = 1, …, 8) and j is an index of the fuzzy rule (j = 1, …, 4)

The antecedent parameters (μ_{ij} and σ_{ij}) associated with the fuzzy sets A_{ij} as well as the consequent parameters (a_{ij} and b_{ij}) can be found in Table 4. Figure 2 shows the optimized Gaussian membership functions of heart rate for each participant. For example, the ANFIS model for participant 1 is as follows:

Rule 1: IF (HR is A_{11}) THEN VO_2 = 0.870 (HR) - 71.189
Rule 2: IF (HR is A_{12}) THEN VO_2 = 0.263 (HR) - 15.127
Rule 3: IF (HR is A_{13}) THEN VO_2 = 0.377 (HR) - 24.537
Rule 4: IF (HR is A_{14}) THEN VO_2 = 0.826 (HR) - 62.649

The Gaussian membership functions characterizing the fuzzy sets (A_{11}, A_{12}, A_{13} and A_{14}) are as follows:

$$\mu_{A_{11}}(HR) = e^{-\frac{1}{2}\left(\frac{HR-94.77}{2.39}\right)^2}$$

$$\mu_{A_{12}}(HR) = e^{-\frac{1}{2}\left(\frac{HR-77}{1.91}\right)^2}$$

$$\mu_{A_{13}}(HR) = e^{-\frac{1}{2}\left(\frac{HR-106}{1.91}\right)^2}$$

$$\mu_{A_{14}}(HR) = e^{-\frac{1}{2}\left(\frac{HR-86.66}{1.12}\right)^2}$$

Table 4. Optimal parameters of the fuzzy IF-THEN rules associated with the developed ANFIS for each participant

Parameters			**Participants**							
			P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**
			i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i = 7	i = 8
Antecedent	j=1	c_{i1}	94.77	88	71.6	71.18	52.92	93	88.83	60.05
		σ_{i1}	2.39	5.30	8.32	6.71	1.41	1.62	4.84	4.9
	j=2	c_{i2}	77	105	91.1	92.2	71.77	97	106.65	77.55
		σ_{i2}	1.91	5.30	7.47	5.93	1.47	1.64	3.45	3.99
	j=3	c_{i3}	106	109	105.88	100.08	82.07	105	124.05	89.79
		σ_{i3}	1.91	5.30	8.17	5.9	1.27	1.63	5.73	4.54
	j=4	c_{i4}	86.66	118	82.9	122	0	95.01	0	99.83
		σ_{i4}	1.12	5.30	7.36	6.03	0	1.61	0	4.85
Consequent	j=1	a_{i1}	0.87	-0.14	-1.79	-0.03	-0.03	1.18	0.04	0.14
		b_{i1}	-71.19	16.48	117.7	6.23	6.64	-98.98	0.39	-3.46
	j=2	a_{i2}	0.26	-4.18	-1.01	-0.58	0.31	4.03	0.53	0.04
		b_{i2}	-15.13	389.27	134.1	59.63	-11.64	-395.53	-43.95	6.92
	j=3	a_{i3}	0.38	-4.32	0.55	-1.01	0.56	0.32	0.37	-0.08
		b_{i3}	-24.54	544.93	-38.33	123.14	-31.68	-20.92	-28.8	22.54
	j=4	a_{i4}	0.83	0.26	-4.12	0.14	0	11.15	0	0.31
		b_{i4}	-62.65	-10.93	346.65	6.69	0	-1046.28	0	-9.07

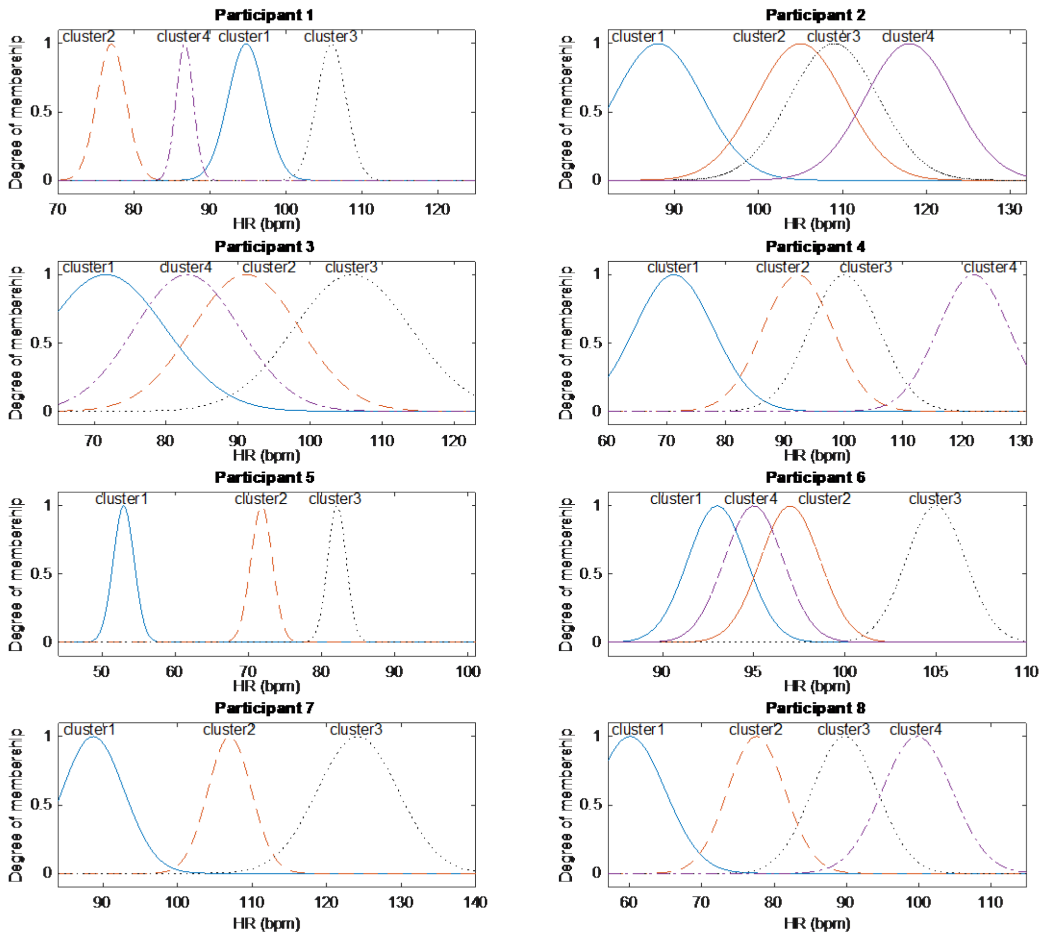

Figure 2. Optimized membership functions associated with HR for each participant

3.3 Test and comparisons

The accuracy of the developed individual ANFIS models were tested based on the test dataset (data obtained from step-test 2). The measured HR data were plugged into the developed ANFIS models as well as traditional linear models in order to estimate VO_2 for each participant. Figure 3 shows the measured VO_2 values along with estimated values obtained from both ANFIS and linear models. It clearly shows the outperformance of the ANFIS models over the traditional linear models in VO_2 estimation. This was obvious especially during the first 10 minutes of the step-test, which correspond to low intensity levels. The results show that the VO_2 estimation accuracy, during the first 10 minutes, significantly increased for participants 4 and 5 (by 72% and 59%, respectively). For participants 3, 2, 7 and 1, the increase in the estimation accuracy of VO_2 was moderate (about 28.8%, 27%, 20.3% and 17.5%, respectively). Lower improvements in VO_2 estimation accuracy were reported for participants 8 and 6 (about 7.84% and 5.23%, respectively).

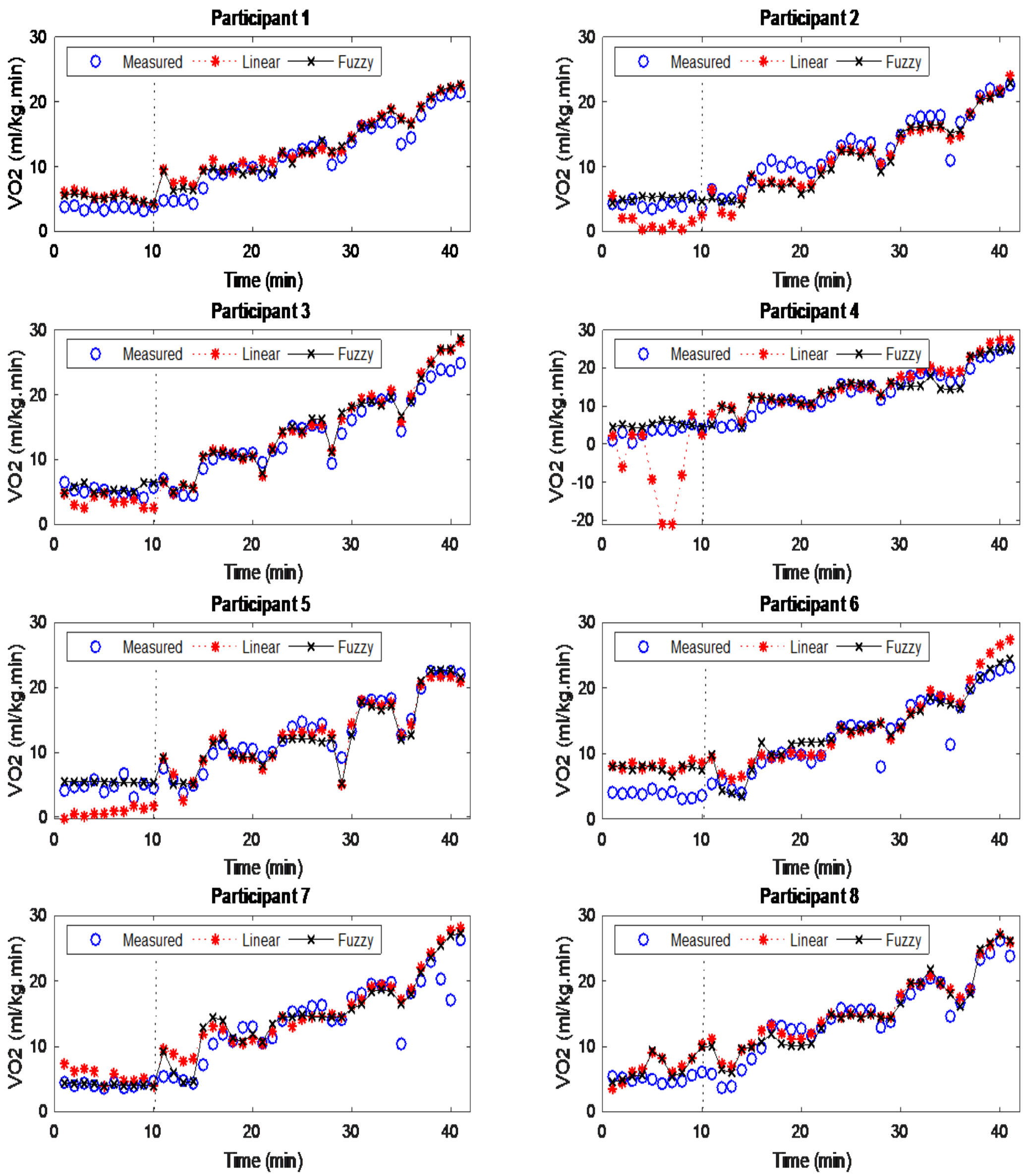

Figure 3. The performance of the developed fuzzy models for each participant in VO_2 estimation using the test dataset

Table 5 summarizes the results obtained for VO_2 estimation using both models (linear and ANFIS). It reports the average VO_2 estimation per participant per model and the corresponding mean RMSE throughout HR range. Results show that both linear and ANFIS models overestimated the measured VO_2 with overall mean differences of 0.33 and 0.6 ml/kg min, respectively. In terms of model estimation error, the results indicated the outperformance of the developed ANFIS models (average RMSE = 1.98 ml/kg.min) over traditional linear models (average RMSE = 2.84 ml/kg.min). The VO_2 estimation accuracy significantly increased for all participants (by 21.3%, on average) when using ANFIS models. The highest increase in estimation accuracy was obtained for participants 4 and 5 (by 66.2% and 38.94%, respectively). The least increase in estimation accuracy was obtained for participant 8 (about 5.59%).

Table 6 summarizes the results obtained for VO_2 estimation using both models (linear and ANFIS) during low intensity levels (HR<90 bpm). It reports the average VO_2 estimation per participant per model and the corresponding mean RMSE. Results show that the linear model underestimated the measured VO_2 (with mean difference of 0.58 ml/kg.min), while the ANFIS model overerestimated the measured VO_2 (with mean difference of 0.62 ml/kg.min).

In terms of model estimation error, the results indicated the outperformance of the developed ANFIS models (average RMSE = 1.56 ml/kg.min) over traditional linear models (average RMSE = 3.14 ml/kg.min). It is clear that the estimation accuracy of linear modelling deacreases at low intensity level (HR<90 bpm) (by 10.56%) comparing to its accuracy throuought HR range. The VO_2 estimation accuracy significantly increased for all participants (by 37.81%, on average) when using ANFIS models. The highest increase in estimation accuracy was obtained for participants 4 and 2 (by 73.18% and 62.45%, respectively). The least increase in estimation accuracy was obtained for participant 8 (about 7.13%).

Table 5. Estimated VO_2 using traditional linear and fuzzy calibration methods with associated RMSE and percentage reduction in RMSE when using fuzzy calibration instead of traditional linear (throughout HR range)

Participant	Measured VO_2 (ml/kg min)	Traditional linear model		Fuzzy model		% reduction in RMSE
		Estimated VO_2 (ml/kg min)	RMSE (ml/kg min)	Estimated VO_2 (ml/kg min)	RMSE (ml/kg min)	
1	10.27	11.68	1.88	11.38	1.62	13.90
2	11.01	9.55	2.13	10.27	1.78	16.46
3	12.01	12.35	1.67	12.83	1.56	6.88
4	11.51	10.75	6.66	12.37	2.25	66.20
5	11.18	10.00	2.36	10.98	1.44	38.94
6	10.92	12.82	3.02	12.43	2.72	9.81
7	11.81	13.09	2.88	12.53	2.52	12.64
8	12.46	13.59	2.11	13.21	1.99	5.59
Average	11.40	11.73	2.84	12.00	1.98	21.30
Std. Dev.	0.69	1.49	1.61	1.01	0.47	20.93

Table 6. Estimated VO_2 using traditional linear and fuzzy calibration methods with associated RMSE and percentage reduction in RMSE when using fuzzy calibration instead of traditional linear (during low intensity level HR<90 bpm)

Participant	Measured VO_2 (ml/kg.min)	Traditional linear model		Fuzzy model		% reduction in RMSE
		Estimated VO_2 (ml/kg.min)	RMSE (ml/kg.min)	Estimated VO_2 (ml/kg.min)	RMSE (ml/kg.min)	
1	4.96	7.00	2.33	6.62	1.91	18.06
2	4.55	2.19	2.79	5.02	1.05	62.45
3	7.07	6.48	1.47	7.38	1.06	28.10
4	3.95	-0.19	10.79	6.09	2.89	73.18
5	9.70	8.44	2.50	9.43	1.52	39.15
6	2.16	2.59	2.20	2.14	1.50	31.91
7	2.01	2.12	0.75	2.00	0.43	42.50
8	9.25	10.43	2.31	9.93	2.15	7.13
Average	5.46	4.88	3.14	6.08	1.56	37.81
Std. Dev.	2.95	3.71	3.16	2.96	0.76	21.85

The Bland-Altman plot (Figure 4) shows the limit of agreement between the measured and estimated (by linear calibration and ANFIS models) VO_2 values. The differences between measured and estimated (using ANFIS) VO_2 values at various intensity levels were within ±10%, which is the acceptable range when estimating the metabolic rate based on HR measurements (ISO 8996, 2004). These differences were remarkably/slightly smaller than those associated with the linear calibration method at low intensity/high intensity levels.

On the other hand, the differences between measured and estimated (using linear calibration) VO_2 values exceeded the ±10% acceptable range (often) at low intensity (indicated with dashed arrows in Figure 4) and (rarely) at high intensity levels (indicated with a solid arrow in Figure 4). This indicates that the linear calibration model may produce inaccurate VO_2 estimation especially during low intensity levels. At moderate intensity levels, the differences between the measured and estimated (by linear and ANFIS) VO_2 values were both within the ±10% acceptable range. The results clearly indicate the superior performance of ANFIS method in VO_2 estimation, especially at low and high intensity levels.

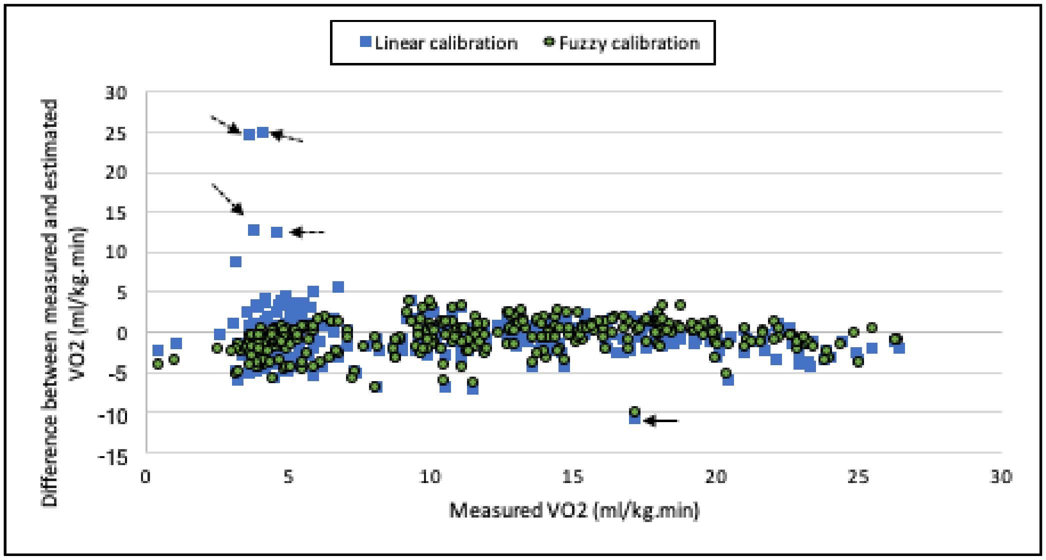

Figure 4. Bland-Altman plot to test the agreement between measured and estimated VO_2 values

4. Conclusion

This study presented a new methodology for VO_2 estimation of individuals based on HR measurements. Individual ANFIS models were proposed for VO_2 estimation to better capture the nonlinearity between HR and VO_2, especially in low intensity levels. Results indicated the outperformance of the individual ANFIS models over the linear calibration models throughout the HR range and in the lower HR range (HR<90 bpm), where intensity level is low. Therefore, the proposed ANFIS approach can be used at work environments where high accuracy of VO_2 estimation at the individual level is desired.

Acknowledgment

The author would like to acknowledge the support of King Fahd University of Petroleum and Minerals and the Interdisciplinary Research Center of Smart Mobility and Logistics. In addition, the author would like to thank Professor Daniel Imbeau for the valuable discussions and Dr. Philippe-Antoine Dubé for his help in data collection.

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Biography

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