A NONLINEAR MODEL FOR CONVERTING ACCELEROMETERS' SIGNALS INTO ENERGY EXPENDITURE: TOWARDS THE ARTIFICIAL PANCREAS WHICH WILL CONSIDER PHYSICAL ACTIVITY

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BACKGROUND AND AIMS

Problem: Physical activity (PA) has strong effects on glucose's dynamics [1]. Therefore, including PA information in artificial pancreas (AP) may improve glycemia regulation performance.
Existing solutions: Among a variety of PA indicators, energy expenditure (EE), computed from counts per minute (CPM), is the preferred physiological variable in AP applications [2,3]. However current models for converting CPM into EE are mostly linear [4-6].
Aim: In this work we propose a nonlinear model which improves EE estimation, and therefore may also improve AP performance.

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METHOD

A nonlinear model, based on the sigmoid neural network shown in Figure 1, is proposed for converting CPM into EE.

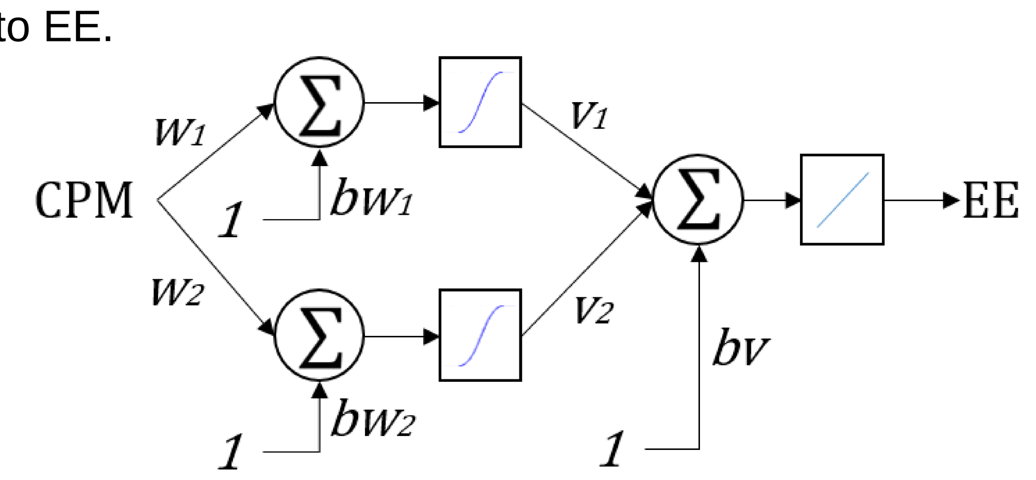

Figure 1. *Two-layer sigmoid neural network.*

The mathematical representation of such neural network is given by Eq. (1).

$$EE = v1 \times \sigma(AS \times w1 + bw1) + v2 \times \sigma(AS \times w2 + bw2) + bv \qquad (1)$$

where $v1 = -383.35$, $w1 = -0.0008$, $bw1 = 3.5964$, $v2 = 161.66$, $w2 = 0.0585$, $bw2 = 55.2162$, and $bv = 3.9365$ are the model parameters (synaptic weights), CPM are the counts per minute, and EE is the estimated energy expenditure.

This model is obtained from a database composed of 53 19-55-year-old subjects in which indirect calorimetry (SERVOPRO 4100, Servomex, UK) and CPM (hip-worn GT3X+, ActiGraph) were acquired, while the subjects performed a set of 24 5-min activities of various intensity (rest to vigorous) under lab-conditions.

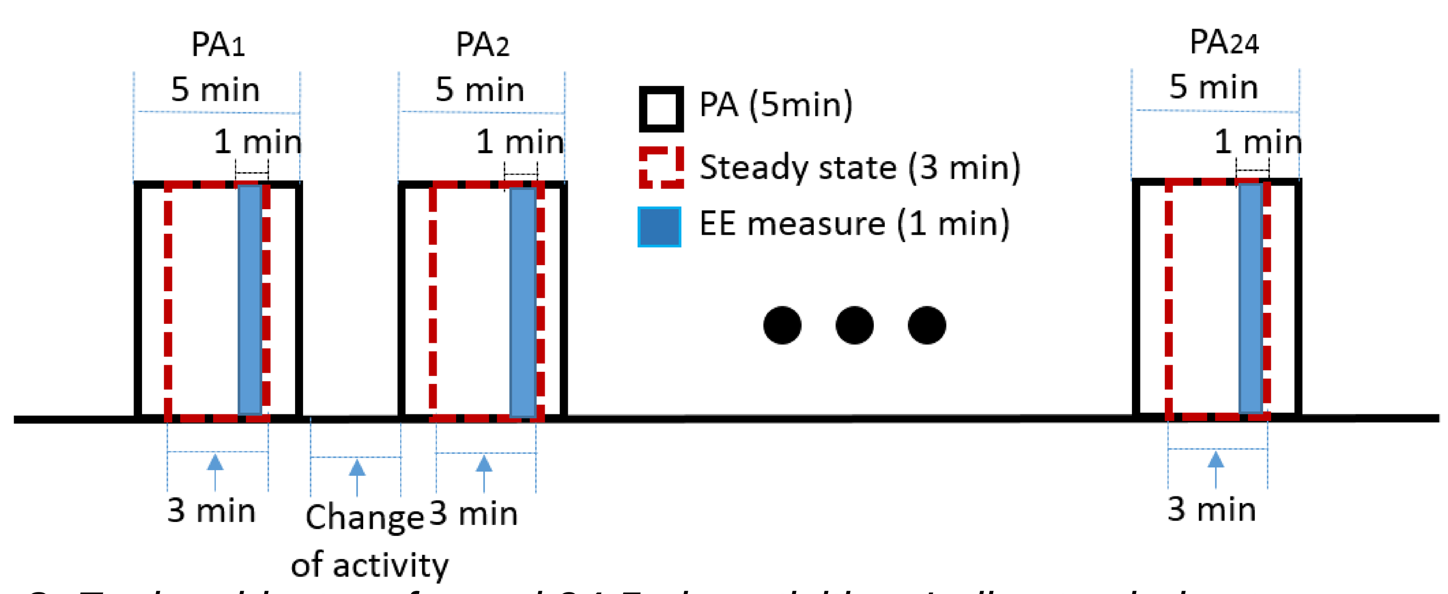

Figure 2. *Each subject performed 24 5min-activities. Indirect calorimetry was measured during 1 min.*

The proposed model is compared with 1 linear model trained on the same data and 1 classical linear model for converting CPM (counts per minutes from Actilife®) into EE. A leave-one-subject-out (LOSO) approach and the classical performance indicators were chosen for comparison purposes.

RESULTS

Table 1 displays performance obtained by each model. The linear and nonlinear models were evaluated via a LOSO approach. No cross validation was applied on the classical linear model (Freedson), where the parameters are given in [6].

Table 1. *Performance on 53 subjects performing 24 5-min activities of various intensity (rest to vigorous).*

Model	R2	r2	RMSE
Proposed model	0.6374	0.7019	88.64
Linear model	0.5686	0.5686	89.30
Classical linear model (Freedson)	0.3740	0.5140	107.75

R2 = coefficient of determination, r2 = correlation coefficient, and RMSE= root-mean-square error.

Figure 3 shows EE estimation achieved by the three models on one subject.

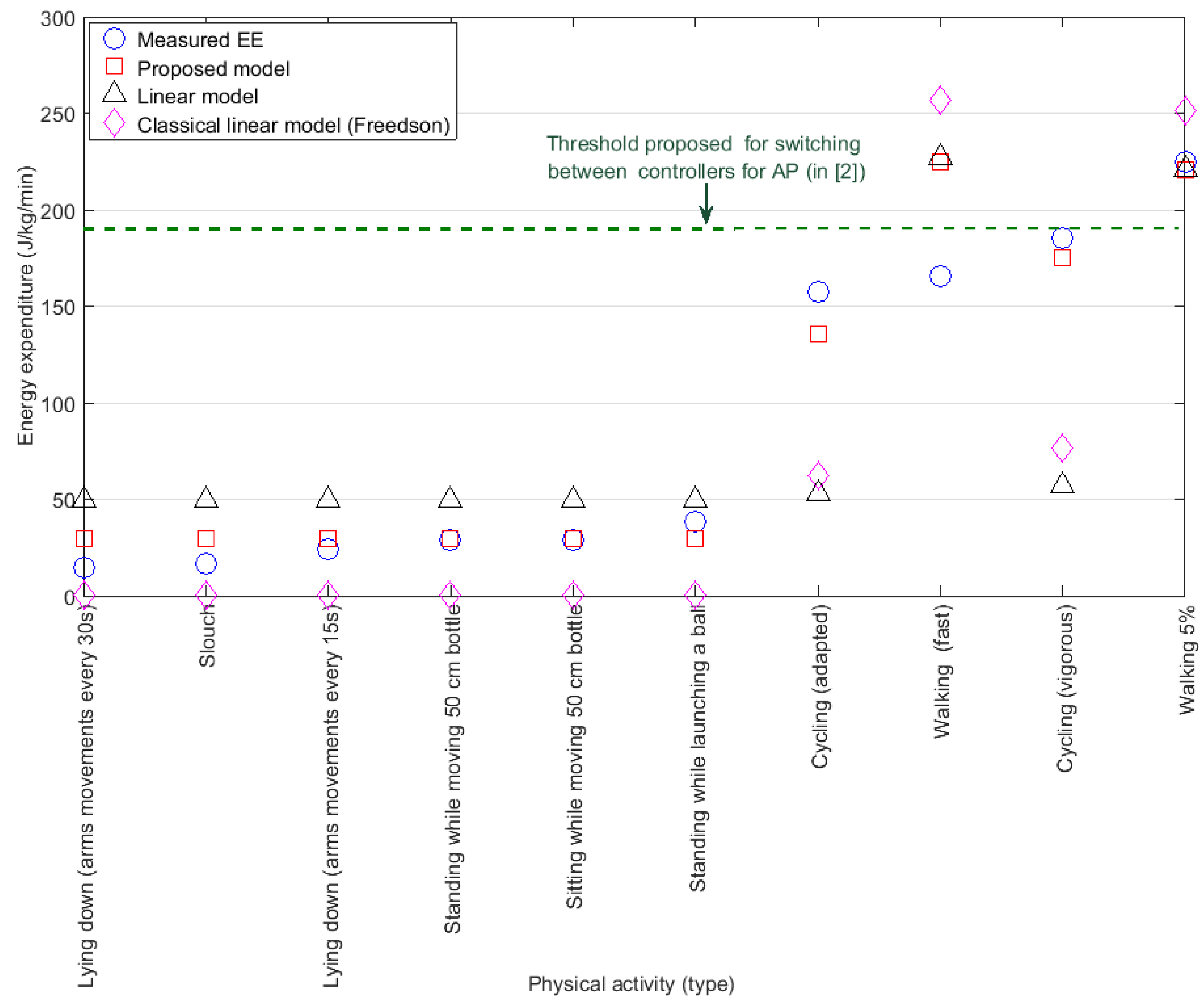

Figure 3. *EE estimations during activities where the proposed model reaches better results. Estimations of the three models are shown.*

CONCLUSIONS

- The proposed model yields better performances than the two linear models (see Table 1 and Figure 3).
- The proposed non linear model allowed accurate EE computation for activities where linear models failed (see Figure 3, cycling vigorous and adapted).
- Performance of the AP developed by our research group may be further improved by including other non-linear structural equations to obtain more accurate EE estimations. For instance, in [2] a threshold set to 4 kcal/min was proposed for switching between two control modes, i.e., PA or non-PA modes. As a future work, an approach including EE into a validated physiological model will be implemented in our artificial pancreas.

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