Bachelor's Thesis

Metabolic Cost of Traverses on Future Planetary Extra Vehicular Activities

Universitat Politècnica de Catalunya

Texas A&M University

Víctor Sainz Ubide

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Advisors:

Professor Ana Díaz Artiles, PhD

Professor Jaime Oscar Casas Piedrafita, PhD

ABSTRACT

Metabolic Rate (MR) is a fundamental magnitude during surface exploration traverses. Predicting energy expenditure during an upcoming traverse under specific conditions of speed, slope, gravity and suit characteristics can provide valuable information about the supply of consumables needed (i.e. oxygen and water), the most appropriate path to accomplish the exploration objectives, as well as information about workload, fatigue, and potential injuries.

In this project I did an overview of the existing methods and models developed to study metabolic rate during traverses, as well as the biomedical results of Apollo Missions and the current state of the art in the development of spacesuits.

I considered the use of machine learning predicting methods to determine MR as a way of improving current models for both Extravehicular Activities (EVAs) and Earth traverses.

I also made a prototype of a MR predictive tool and tested it with simulated data. The tool can be integrated into another app or used as a HTTP Application Programing Interface (API).

Keywords: Metabolism, Traverse, Exploration, Forecasting, Prediction, Human Factors, Human Performance, Extravehicular Activity, Neural Network, Machine Learning, Regression, API, Webapp, Biophysics, NASA, Space, Spacesuits.

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LIST OF ACRONYMS

ACSM	=	American College of Sports Medicine
API	=	Application Programming Interface
AWS	=	Amazon Web Services
BMR	=	Basal Metabolic Rate
CG	=	Center of Gravity
CO2	=	Carbon Dioxide
ECG	=	Electrocardiogram
EMU	=	Extravehicular Mobility Unit
EVA	=	Extravehicular Activity
EWT	=	EVA Walkback Test
HTML	=	Hyper Text Markup Language
HTTP	=	HyperText Transfer Protocol
ISS	=	International Space Station
JSC	=	NASA-Johnson Space Center
JSON	=	JavaScript Object Notation
LCG	=	Liquid Cooling Garment
MKIII	=	Mark III Advanced Space Suit Technology Demonstrator
NASA	=	National Aeronautics and Space Administration
NBL	=	Neutral Buoyancy Laboratory
NN	=	Neural Network
PLSS	=	Portable Life Support System
PTS	=	Preferred Transition Speed
SMR	=	Standing Metabolic Rate
VO2	=	Rate of oxygen consumption
xEMU	=	Exploration Extravehicular Mobility Unit

1 INTRODUCTION

The last time a human set foot on a planetary body other than Earth was on December 14th 1972, when Eugene A. Cernan and Harrison H. Schmitt lifted from the Moon on their Lunar Module during the Apollo 17 mission[1]. This was the sixth and last mission that landed on and returned from the Moon, achieving the United States long desired goal before the Russians did during the Space Race. After that achievement, high cost and low public interest prevented new missions, and space exploration was limited to Low Earth Orbit (LEO).

The human space program at NASA (National Aeronautics and Space Administration) has announced plans to send humans into deep space, with new landings on the Moon scheduled on the 2020 decade and eventually missions to Mars during the following decade[2]. The new program was given a name: Artemis[3]. Finally, after a hiatus of decades, there are serious plans to pursue deep space human exploration.

Although reaching the Moon during the Apollo Program was a remarkable human engineering achievement, only 28 Extravehicular Activities (EVAs) on the surface were performed. Current projections indicate that the next lunar exploration program will require thousands of EVAs[4]. An important factor of EVAs is the Metabolic Cost associated with the activities and duties performed, which has to be taken into account for mission planning, as this metabolic cost may impose restraints on the mission.

The focus of interest on this Thesis is the study of metabolic cost associated with planetary traverses and also on planet Earth.

2 OBJECTIVES

The first objective of this project is to do a literature review of the previous models that have been used in the past to estimate metabolic rate during traverses.

Second objective is to get insights about the challenges related to the metabolic expenses during Extravehicular Activities

Third and last objective is to propose a new tool to predict metabolic rate using a method adaptative to the individual, build a prototype, and test it.

3 METABOLIC COST MODELS

3.1 Fundamentals

Metabolic expenditure is a very important factor during an Extravehicular Activity, EVA, because it determines the expenditure of Oxygen, O_2, which is a consumable with a finite quantity and it is required to breath. That reserve imposes a hard constraint to EVA planning, because for how long an EVA can be conducted and the activities that can be reliable done. In the case of a surface EVA, distance from the spacecraft becomes a decisive factor, because the route of an EVA must allow a safe return to the hatch on all the points and instants of the traverse, in the case of a contingency. In particular, it has to be considered when using a rover or another vehicle, in case there is a broke down and the astronauts have to abandon it and return on foot[5].

Adequate cooling is also important during a spacewalk. During Apollo program, the maximum heat removal capability provided by the Liquid Cooling Garment (LCG) was about 590W[6].

Modern orbital EVA using the Extravehicular Mobility Unit, EMU on the Space Shuttle program an on the ISS usually lasts between 6 and 8 hours[7]–[9], the longest of which took place on mission STS 102, with 8 hours and 56 minutes[10]. During the 6 successful surface missions between 1969 and 1972 in the Apollo program there were 28 individual EVAs, with durations not exceeding 8 hours[11]. Maximum distances to the Lunar Module increased with the introduction of the Lunar Rover Vehicle, LRV, as well as because of longer lunar stays, because confidence was higher after previous mission successes and because there was a greater scientific interest on the later mission that required longer traverses.

Table 1 Extravehicular Activities During Apollo[11]

	Apollo 9	Apollo 11	Apollo 12	Apollo 14	Apollo 15	Apollo 16	Apollo 17
Earth Orbit EVA							
1st EVA Participant	Scott	---	---	---	---	---	---
1st EVA Duration	01:01	---	---	---	---	---	---
2nd EVA Participant	Schweickart	---	---	---	---	---	---
2nd EVA Duration	01:07:00	---	---	---	---	---	---
2nd EVA Dur. Outside LM	00:47:01	---	---	---	---	---	---
First Surface EVA							
Duration	---	02:31:40	03:56:03	04:47:50	06:32:42	07:11:02	07:11:53
Total Distance Traveled	---	~1,006 m	~1,006 m	~1,006 m	10.37 km	4.26 km	3.33 km
LRV Ride Time	---	---	---	---	01:02	00:43	00:33
LRV Park Time	---	---	---	---	01:14	03:39	---
Total LRV Time	---	---	---	---	02:16	04:22	---
Samples Collected (kg)	---	21.55	16.70	20.50	14.50	29.90	14.30
Second Surface EVA							
Duration	---	---	03:49:15	04:34:41	07:12:14	07:23:09	07:36:56
Total Distance Traveled	---	---	~1,311 m	~2,987 m	12.41 km	11.3 km	20.37 km
LRV Ride Time	---	---	---	---	01:23	01:31	02:25
LRV Park Time	---	---	---	---	02:34	03:56	---
Total LRV Time	---	---	---	---	03:57	05:27	---
Samples Collected (kg)	---	---	17.60	22.30	34.90	29	34.10
Third Surface EVA							
Duration	---	---	---	---	04:49:50	05:40:03	07:15:08
Total Distance Traveled	---	---	---	---	5 km	11.48 km	12.04 km
LRV Ride Time,	---	---	---	---	00:35	01:12	01:31
LRV Park Time	---	---	---	---	01:22	02:26	---
Total LRV Time	---	---	---	---	01:57	03:38	---
Samples Collected (kg)	---	---	---	---	27.30	35.40	62
Total Lunar Surface EVA							
Total Duration	---	02:31:40	07:45:18	09:22:31	18:34:46	20:14:14	22:03:57
Total Distance Traveled	---	~1,006 m	~2,316 m	~3,962 m	28 km	26.85 km	35.74 km
Total Samples Collected (kg)	---	21.55	34.35	42.28	77.31	95.71	110.52
Total LRV Ride Time	---	---	---	---	3:00	03:26	04:29
Total LRV Park Time	---	---	---	---	05:10	10:01	---
Total LRV Time	---	---	---	---	08:10	13:27	---
Maximum Distance Traveled From LM (m)	---	61	412	1,454	5,020	4,600	7,629
Transearth EVA							
Participant	---	---	---	---	Worden	Mattingly	Evans
Duration	---	---	---	---	00:39:07	01:23:42	01:05:44

Metabolic Rate (MR) is the energy released per unit of time estimated by food consumption, energy released as heat, or oxygen used in metabolic processes[12]. Metabolic Rate is measured in Watts, $1W = J \cdot s^{-1}$.

Metabolic Cost of Transport (MCT) is the energy required to move between two locations. It is usually declared as the energetic cost per meter $[J \cdot m^{-1}]$. It is equivalent to the Metabolic Rate divided by the Velocity.

$$MCT = \frac{MR}{V}; \qquad [J \cdot m^{-1}] = \left[J \cdot \frac{s^{-1}}{m \cdot s^{-1}} \right]$$

Under aerobic metabolic regime and submaximal effort, the energy spent by the body is proportional to the consumption of oxygen. The equation that relates both is determined by the American College of Sports Medicine, ACSM[13], [14]:

$$Metabolic\ Rate_{Measured} = \frac{\dot{V}_{O2} \cdot 5}{0.0143}$$

$\dot{V}_{O2}$ $[L \cdot minutes^{-1}]$ is the absolute oxygen consumption.

Basal Metabolic Rate

The Basal Metabolic Rate (BMR) is the amount of energy needed while resting in a temperate environment when the digestive system is inactive. This is the energy needed daily to maintain normal physiological function. It is the baseline of metabolic rate and Basal Metabolism is usually the largest component of the total caloric needs of a regular person[15]. BMR is measured after 8 hours of sleep and 12 hours of fasting. The sympathetic nervous system, which prepares the body for intense physical or mental activity and is often referred as the fight-or-flight response has to be deactivated.

Generally, BMR is estimated with equations summarized from statistical data. First remarkable equation is the Harris and Benedict first model (H&B) equation created in 1918[16] (see table 2). The equation was amended in 1984[17]. Another model widely used today is the Mi Mifflin-St Jeor formula[18] from 1990. Finally, Katch-McArdle Formula uses body fat percentage but not height nor age.

Resting Metabolic Rate (RMR) and BMR are similar concepts, but BMR is preferred because it is measured under more defined circumstances and thus it is more precise. BMR is measured after 12 hours of fasting, 8 hours of sleep and at rest. They are often interchanged.

Table 2 BMR Equations

	For men	For women
Mifflin-St Jeor Eq.	BMR = 10W + 6.25H - 5A + 5	BMR = 10W + 6.25H - 5A - 161
Revised Harris-Benedict Eq.	BMR = 13.397W + 4.799H - 5.677A + 88.362	BMR = 9.247W + 3.098H - 4.330A + 447.593
Katch-McArdle Eq.	BMR = 370 + 21.6·(1 - F)·W	

H: Height (in cm) W: Weight (in kg) A: Age (in years) F: Body Fat (0 to 1)

3.2 Earth-based metabolic cost models

The literature on traverse metabolic cost models on Earth is extensive, mainly due to the interest on military applications It is a good starting point to do a literature review of Earth-based models before proceeding to the more advance and less studied models for extravehicular activities.

First studies on determining energy expenditure and mechanical demands on traversing go back to the decade of 1960. Most studies are conducted using a sample of human test subjects composed by active military personnel, which are the beneficiaries of the research. These studies initially tried to find qualitatively dose-response curves, instead of finding general formulas.

Some authors focused on the cinematics of movement, finding relationship between walking speed, load and vertical displacement of center of mass[19], others chose to study the variability of metabolic cost with stride length and speed[20]. Finally, some biologists tried to scale up those models and apply them to larger mammals[21].

The Givoni-Goldman model[22], published on 1971 by a team of researchers at the US Army Research Institute of Environmental Medicine at Natick, Massachusetts, was the first attempt at finding a general equation arising from empirical data to predict metabolic rate. Using a pool of measurements obtained on previous studies, both published ([19], [23], [24], [25], [26]) and unpublished at the time, they were able to get an equation that took into account the effects of speed, grade, weight and load.

To obtain their formula, they began with two assumptions that they had deduced from their data. The first one is that metabolic cost of level walking is proportional to the total weight, so body weight plus clothing plus load, multiplied by a function of the current speed. The second assumption taken is related to the grade of the terrain: a new term has to be added to the original equation, containing a linear function of the grade and the traverse speed.

They managed to take into account the effect of terrain by multiplying by an arbitrary dimensionless terrain factor η.

The formula obtained was the following (figure 1):

$$MR = \eta \cdot (W + L) \cdot \left[2.3 + 0.32 \cdot (V - 2.5)^{1.65} + G \cdot \left(0.07 \cdot (V - 2.5)\right)\right]$$

MR: Metabolic Rate [kcal/hour].

W: Body weight, [kg].

L: External load, [kg].

V: Walking speed, [km/h]

S (or G): Slope (Grade), [%]

Their results had been obtained in a treadmill with walking speeds ranging from 2.5 to 9 km/h (0.7 to 2.5 m/s). This formula has a few limitations. For example, the fact that the pool of data was short at the time and composed by adults of good physical fitness and mostly male. Loads were not very big. According to the paper, if the multiplication of load and speed (in kg and km/h) ever exceeds 100, then a new term M^{+} has to be added to the equation, $M^{+} = 0.4 \cdot (V \cdot L - 100)$. All the measurements were performed on a stationary controlled environment, which required the use of a treadmill, so there is little insight about the quantitative effect of uneven or rougher terrains.

Table 3 Terrain factors

$\eta = 1.0$	Treadmill
$\eta = 1.2$	Hard-surface road
$\eta = 1.5$	Ploughed field
$\eta = 1.6$	Hard snow
$\eta = 1.8$	Hard snow

The biggest disadvantage of this equation is that the slope has always a linear effect, and so if the slope decreases, the metabolic cost decreases. This feature did not considerate that given a step hill there is a considerable effort when trying to keep balance, maintain speed and not fall forward.

Another insight provided is that the alleged transition speed from walking to running decreases with load and slope. According to the source[22], subjects changed gait mode when the Metabolic Rate is 900 kcal/hour, or 1046 Watts, being the point when the MR of walking equals the one of running. Using this insight, the corrected MR for running is the following equation:

$$MR_{running} = \left[MR_{wallking} + 0.47 \cdot (900 - M_{walking})\right] \cdot \left(1 + \frac{S}{100}\right)$$

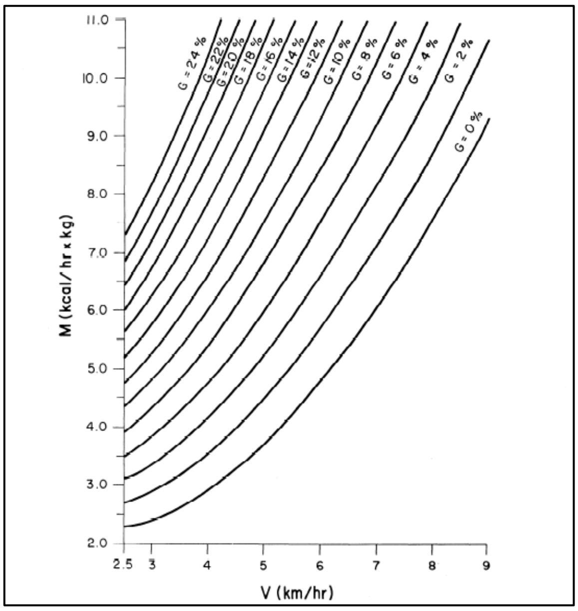


Figure 1 Givoni-Goldman 1971

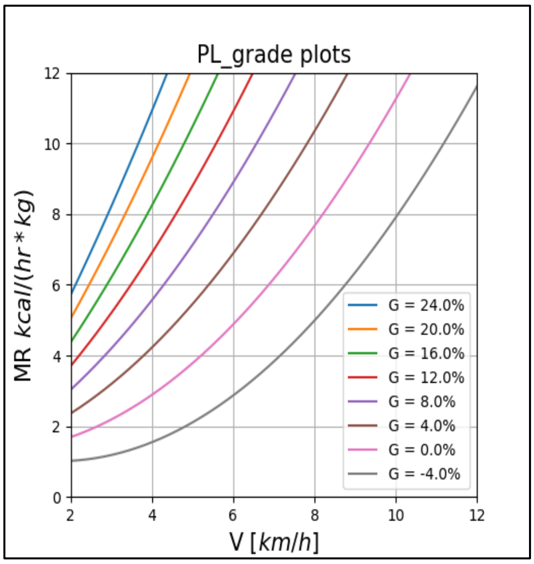


Figure 2 Givoni-Goldman-Pandolf, 1976

Since the objective is to get a model that works under an environment with different gravity, we should try to extrapolate this equation to a different gravity. Weight and load are combined in this equation and they have a multiplicative effect on the equation. A reasonable decision is to add a normalization factor $g/9.8$, where g is the gravity in m/s^2. To convert from kcal/hour to J/s it is necessary to multiply by another factor 4184/3600. The model is on figure 1. Using metric International System Units (SI), the resulting formula is for the predicted Metabolic Rate in Watts is:

$$MR = \frac{4184}{3600} \cdot \eta \cdot \frac{g}{9.8} \cdot (W + L) \cdot \left[2.3 + 0.32 \cdot (3.6V - 2.5)^{1.65} + S \cdot \big(0.07 \cdot (3.6 \cdot V - 2.5)\big)\right]$$

On 1976 a new model developed by the same team was introduced [27], which allegedly works better for slow walking and bigger loads (see figure 2).

The proposed equation is, in SI units:

$$MR = 1.5 \cdot W + 2.0 \cdot (W + L) \cdot \left(\frac{L}{W}\right)^2 + \eta \cdot (W + L) \cdot (1.5 \cdot V^2 + 0.35V \cdot S)$$

This model was consistent and was utilized decades after the publication of the formula, for example on Anthropology studying the movement of prehistoric hominids with the goal of developing archeological applications[28].

Nowadays it is still being used, as proven by the research that warns about its caveats, one of which is underpredicting the metabolic rate of contemporary military load carriage on two studies from different institutions[13][29].

Military work has also focused on the determination of acceptable slopes for military traverse. For uphill slopes it is observed an increment of metabolic cost that appears to be linear, whereas for downhill work the relationship appears to be harder to determine, as metabolic expense initially decrease and reaches a minimum at about a slope of - 9%[30], when more effort is put to maintain stability due to the increase on eccentric work.

Recent models have tried to incorporate this fact. In the case of the Pandolf-Load equation, it was proposed to add a new term only for downhill traverses[28][31].

$$Metabolic\ Rate = \begin{cases} M & \text{if:} \quad S \geq 0\% \\ M - C & \text{if:} \quad S < 0\% \end{cases}$$

Where M is the original equation and C the new term:

$$MR = 1.5 \cdot W + 2.0 \cdot (W + L) \cdot \left(\frac{L}{W}\right)^2 + \eta \cdot (W + L) \cdot (1.5 \cdot V^2 + 0.35V \cdot S)$$

$$C = \eta \left[\frac{\mathrm{S(W + L)V}}{3.5} - \frac{1}{W} \cdot \mathrm{(W + L)(S + 6)^2 + (25 - V^2)}\right]$$

In recent years, other simplified propositions have been made, such as William Santee's model proposed in 2001[31]. This model is based on the simplest proposition that the total work (W_T) required to transport a load equals the sum of the internal energy of cost of walking (W_L) plus the external cost of vertical displacement (W_V).

$$W_T = W_L + W_V$$

Using empirical results[32], the energy of level walking is:

$$W_L \;\; [Watts] = 3.28 \cdot (W + L) + 71.1$$

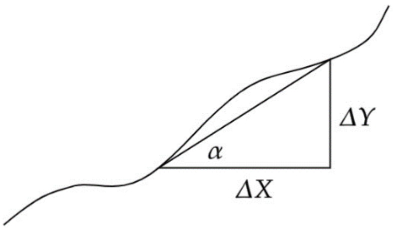
For the vertical displacement, it depends on whether the movement is up or down. If it is up, the increase is linear with the grade, while if the displacement is in the downward direction there is an exponential term that penalizes higher levels of downhill.

$$if\ \alpha \geq 0: \quad W_V\ [Watts] = 3.5 \cdot (W + L) \cdot g \cdot V \cdot \sin(\alpha)$$

$$if\ \alpha < 0: \quad W_V\ [Watts] = 2.4 \cdot (W + L) \cdot g \cdot V \cdot sin(\alpha) \cdot 0.3^{\frac{1}{7.65} \cdot |\alpha|}$$

where α is the angle of the slope, or in other words, the arctangent of the grade, and g is the gravity acceleration in meters per second squared.

$$\alpha = \arctan(S[\%]/100)$$



$$S = \frac{\Delta Y}{\Delta X} \cdot 100$$

$$\alpha = \arctan\left(\frac{S}{100}\right)$$

Figure 3 Slope

William Santee is still working on this topic along with other fellow researchers at the United States Army Research Institute of Environmental Medicine[33]. Their latest contribution is the Load Carriage Decision Aid (LCDA), a US Army planning tool.

For level walking (Slope = 0%), the equation is the following:

$$Energy\ Expenditure\ [W \cdot kg^{-1}] = 1.44 + 1.94 \cdot V^{0.43} + 0.24 \cdot V^4$$

This equation contains a term for standing Energy Expenditure. The other terms combine to model the initial elevation in energy costs of balance and stability between walking and standing, the maximization of walking economy at moderate speeds and the rise of EE at higher speeds. At level walking, the equation yields an optimal speed of 1.38m/s (4.95 km/h), shown on figure 4.

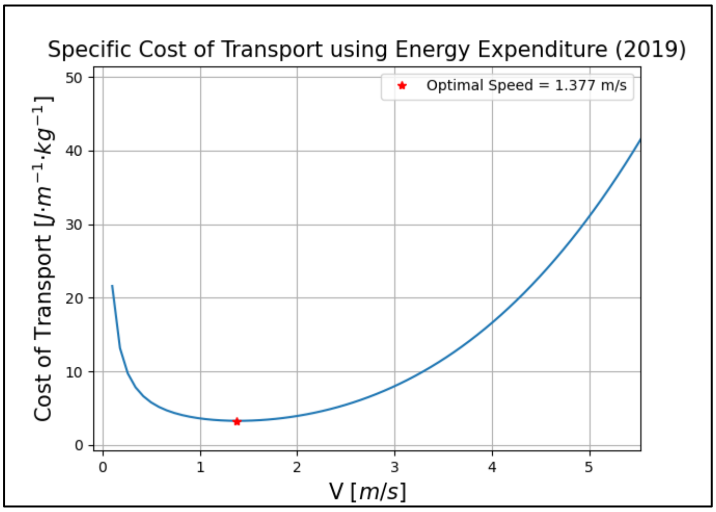


Figure 4 Specific Cost of Transport using Energy Expenditure and optimal speed

The LCDA graded walking equation was determined to be:

$$EE\ [W \cdot kg^{-1}] = 1.44 + 1.94 \cdot V^{0.43} + 0.24 \cdot V^4 + 0.34 \cdot V \cdot S \cdot \left(1 - 1.05^{1-1.1^{S+32}}\right)$$

The following figure 5 shows the MCT for the metabolic rate models seen until now. The conditions are $Slope\ = \ 0\%$, $Weight\ = \ 70kg$ and $Load\ = \ 0kg$.

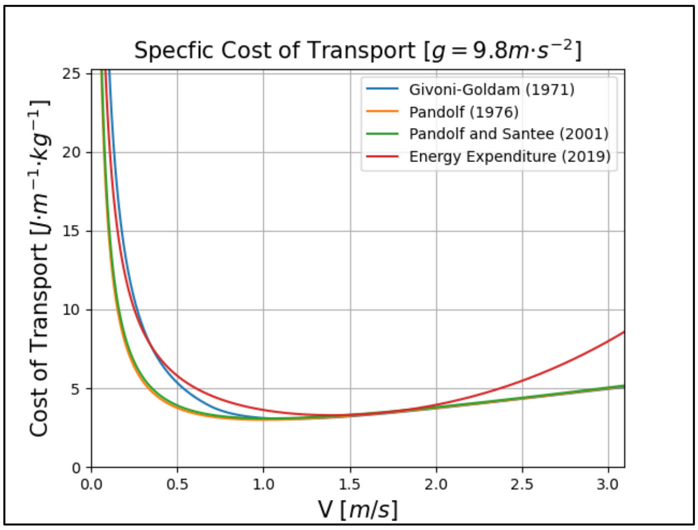


Figure 5 Cost of Transport for different Models

Table 4 Earth-based models

Models
Givoni-Goldman (1971)
$M = \eta \cdot (W + L) \cdot \left[2.3 + 0.32 \cdot (V - 2.5)^{1.65} + G \cdot \left(0.07 \cdot (V - 2.5)\right)\right]$
$M_{running} = \left[M_{wallking} + 0.47 \cdot \left(900 - M_{walking}\right)\right] \cdot \left(1 + \frac{S}{100}\right)$
$M = \frac{4184}{3600} \cdot \eta \cdot \frac{g}{9.8} \cdot (W + L) \cdot \left[2.3 + 0.32 \cdot (3.6V - 2.5)^{1.65} + S \cdot \left(0.07 \cdot (3.6 \cdot V - 2.5)\right)\right]$
Givoni-Goldman-Pandolf (1976)
$M = 1.5 \cdot W + 2.0 \cdot (W + L) \cdot \left(\frac{L}{W}\right)^2 + \eta \cdot (W + L) \cdot (1.5 \cdot V^2 + 0.35V \cdot S)$
Pandolf-Load equation (2001)
$Metabolic\ Rate = \begin{cases} M & \text{if: } S \geq 0\% \\ M - C & \text{if: } S < 0\% \end{cases}$
With $C = \eta \left[\frac{S(W+L)V}{3.5} - \frac{1}{W} \cdot (W + L)(S + 6)^2 + (25 - V^2)\right]$
Santee Energy Expenditure (2019)
$EE\ [W \cdot kg^{-1}] = 1.44 + 1.94 \cdot V^{0.43} + 0.24 \cdot V^4 + 0.34 \cdot V \cdot S \cdot \left(1 - 1.05^{1-1.1^{S+32}}\right)$

3.3 Non-Earth models

It is important to understand how well the astronauts are able to function while performing exploration responsibilities to improve the safety and efficiency of future lunar and martian sortie missions.

It is a different and considerably harder problem to study metabolic rate for surface EVAs. The challenges that make the research difficult are:

- Different Gravity and biomechanics.
- Spacesuit, whose effects are:
    - Increase load to the user
    - Displacement of the center of gravity.
    - Affected range of motion of the joints of the user.
    - Higher strength required because of pressurization the suit exerts reactive forces and torques at the joints of the user.

- It is hard to obtain data. Only 28 individual surface EVAs have been conducted. On Earth it is necessary to use imperfect analogs

3.3.1 Program Apollo data

The report with the Biomedical result of Apollo[6] was published in 1975, with information about the technology and countermeasures developed for the program, as well as astronaut health and performance data.

During the Apollo missions, spacesuits were custom made and were composed by two main elements: the Pressure Suit Assemble (PSA) and the Portable Life Support System (PLSS), with a total weight of around 81 kilograms[34].

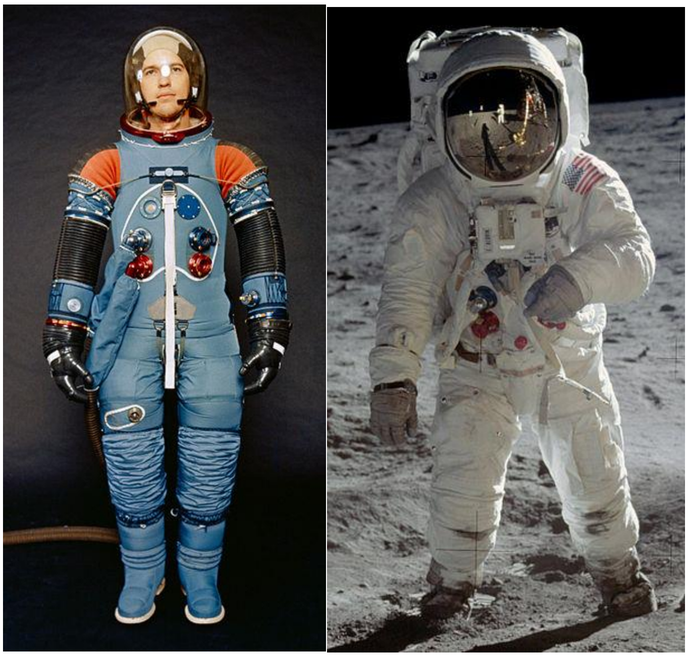


Figure 6 Apollo/Skylab A7L spacesuit: PSA and full suit.

A wealth of knowledge may be gained by searching the video archives from the extravehicular activities (EVAs) performed during the Apollo missions[35]. Video capturing technology improved dramatically during the Apollo program, with better cameras that obtained cleaner video and could be controlled from Houston Mission Control to zoom, pan and tilt, following the activity of astronauts. Cameras were usually located on the descent stage of the Lunar Landing Module, on the Lunar Rover, and the astronauts also used cameras on their chests. Using known references, such as the height of the Portable Life Support System (PLSS), it is possible to estimate the movement of the astronauts. Figure 7 shows examples of video analysis counting pixels using the software Dartfish™[35].

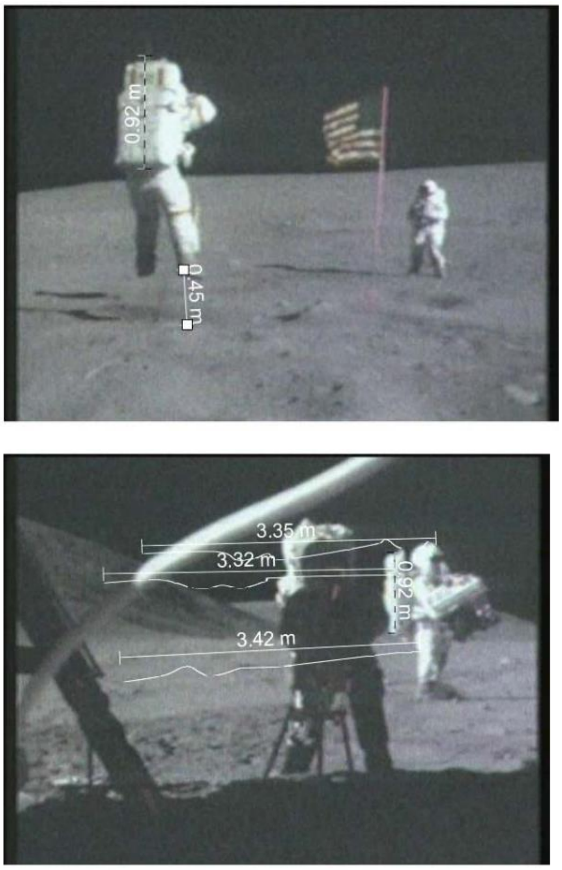


Figure 7 Analysis of recorded video using known distances

Metabolic data was obtained from two main sources. First, each astronaut had his own PLSS, which, among other functionalities, it provided temperature regulation (cooling) to the astronauts[36]. Astronaut wore the Liquid Cooled Garment (LCG), which had a closed circuit of hoses that distributed water to absorb the heating of the body of the astronaut. The PLSS had a dial that the astronaut could turn to adjust the total flow of fluid. Knowing the flow, the specific heat of the refrigerant and the temperature difference between the input fluid and the output, it was possible to determine the energy expelled by the astronaut in the form of heat.

$$\dot{Q}_{heat} = c \cdot \dot{V} \cdot (T_{out} - T_{in})$$

Where c $[J \cdot cm^{-3} \cdot K^{-1}]$ is the specific heat, $\dot{V}$ $[cm^3 \cdot s^{-1}]$ is the flow of coolant and T_{out}, T_{in} are the temperatures of the coolant. The following figure 8 shows the relationship between MR and $T_{out} - T_{in}$.

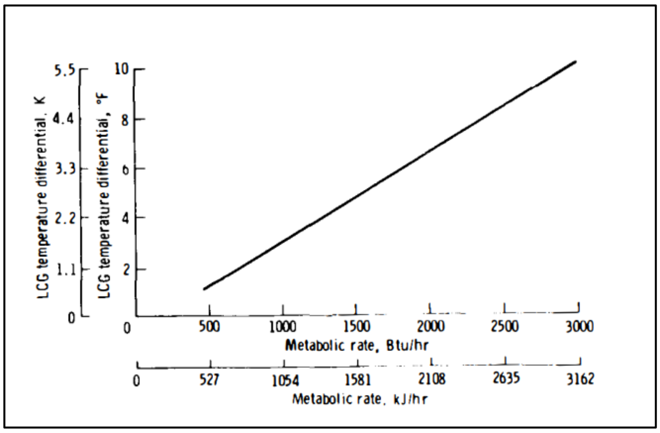


Figure 8 Temperature delta and Metabolic Rate

The total metabolic cost would be[37]:

$$\dot{Q}_m = \dot{W}_w + \dot{W}_{wc} + \dot{W}_{wr} + \dot{W}_{ws} + \dot{Q}_{heat} + \dot{Q}_s$$

where Q_m is the metabolic cost, W_w, is the external (useful) work (done by the system), W_{wc}, is the work done by the counterforce, W_{wr} is the work done to restore the body and limb position and orientation, W_{ws}, is the work done deforming the space suit, $\dot{Q}_{heat}$, is net heat lost, and $\dot{Q}_s$, is body heat storage. On average, $< \dot{W}_{wc} >, < \dot{W}_{wr} >, < \dot{W}_{ws} >, < \dot{Q}_s > = 0$, so the metabolic rate is about:

$$\dot{Q}_m = \dot{W}_w + \dot{Q}_{heat}$$

Another way to estimate metabolic rate was using Heart Rate. Each astronaut was equipped with sensors to obtain his electrocardiogram (ECG). Because the heart rate is an indicator of total physiological and psychological stress, it is not entirely dependent on metabolic rate. The heart-rate method was, however, the only method with a time-delay short enough to allow a minute-by-minute estimation of the energy expenditure. In addition to the inaccuracies (psychogenic factor, heat storage, and fatigue) usually associated with this method of metabolic-rate estimation, three unique problems were encountered during the Apollo missions: calibration-curve inaccuracies, crewmember deconditioning, and the technique used to determine heart rate. Control of the usual inaccuracies was not considered feasible because insufficient data were available during the EVA; however, as explained in the Apollo report[6], control of the unique sources of inaccuracy was attempted. Calibration curves (heart rate compared with metabolic rate) for each individual were determined before each mission by using standard ergometric calibration techniques. Heart-rate data were obtained under resting conditions and at several work rates; and least-squares analysis was used to determine a linear regression curve. Standard errors as large as 211 kJ/hr = 58 Watts were not unusual. Changes in test protocol (more data points at various work rates) did not significantly increase the accuracy, and it was concluded that this modification to the standard laboratory calibration procedures was not worthwhile.

The oxygen bottle of the PLSS pressure was telemetered from each EVA crewman and displayed in real time. It was not feasible to use oxygen consumption data as a reliable metabolic-rate indicator. For best accuracy of the oxygen method, a measurement of respiratory quotient (RQ) as well as oxygen consumption is required. The RQ is a ratio of the amount of carbon dioxide produced and the amount of oxygen consumed. There was no measurement of carbon dioxide production; therefore, the RQ had to be estimated. The maximum leakage of oxygen on the suit was equivalent to a metabolic rate of approximately 211 kJ/hour = 58 Watts[38], the same as the standard error.

Analysis results indicated that the Apollo astronauts fell 3% of their EVA time; walked, loped, or ran at speeds ranging from 1.3 km/h (0.36 m/s) to 5.5 km/h (1.53 m/s) and reached metabolic rates of more than 2 215 617.39 J/hour, or 615 Watts.

3.3.2 Locomotion

After the Apollo missions, there was not a lot of research. The new American spacesuit, the Extravehicular Mobility Unit, (EMU), was designed for use on microgravity EVA during the Space Shuttle and later on was used on the International Space Station, along with the Russian Orlan Spacesuit.

NASA funded research during the nineties shifted to increase the understanding of locomotion under partial gravity[39]. In the inverted pendulum model for walking, gravity provides the centripetal force needed to keep the pendulum in contact with the ground. The ratio of these two forces is known as the Froude number, Fr.

$$Fr = \frac{centripetal\ force}{gravitational\ force} = \frac{m \cdot v^2}{m \cdot gL} = \frac{v^2}{gL}$$

Where L is the length of the leg, g the acceleration of gravity and v the horizontal speed. Generally, when Fr>0.5, bipeds choose to switch from walking to running, independently of size[39]. At lower gravities, this transition occurs at lower speeds.

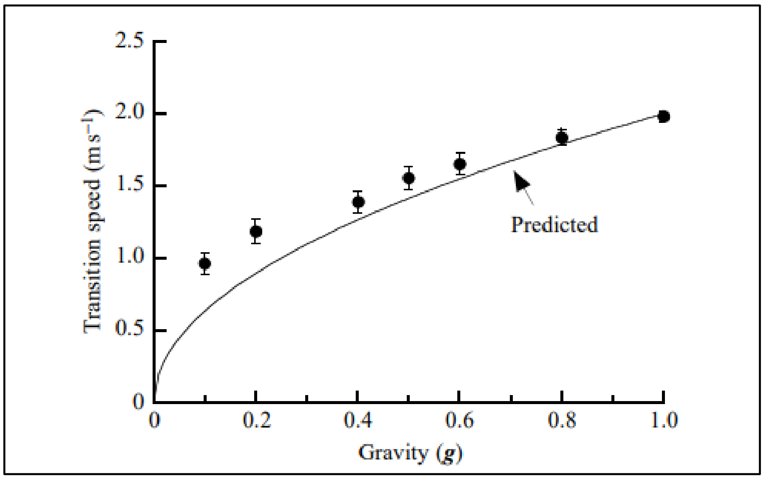


Figure 9 Preferred Transition Speed as a function of the gravity[39]

A big contributor to the understanding of the bioenergetics in Spacesuits was Christopher E. Carr, who wrote his PhD thesis on the subject in 2005[37]. He analyzed previous data and proposed a framework to estimate MR and also estimated the effect of suit pressure on the resistive nature of the suit. Other results include the conclusion that running on a spacesuit is always more efficient than walking, because the internal pressure makes the spacesuit legs behave like springs[40].

3.3.3 Modern state of spacesuits.

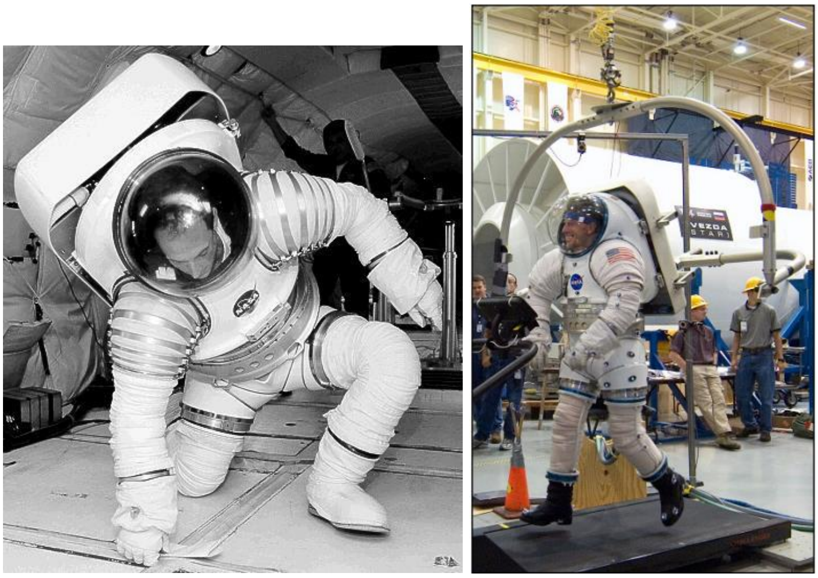


Figure 10 Mark III suit, 2010

Figure 11 Exploration EMU, public show on October 2019

On the last decade there have been three main suits: the Mark III technology demonstrator (figure 10), Z-series suit and finally the Exploration EMU (xEMU), which is the most advance suit that will be used on the Moon (figure 11). All of them feature rear back entry and a modular assembly of the lower torso, with circular bearings. Among the improvements on the new xEMU suit[41], it is worth noting the increase of mobility (thanks to the lower assembly, it is now possible to raise the legs or even to squat), the lower resistive torques when bending, and the lower weight.

Although the xEMU was revealed very recently, its lower assembly is similar to the previous MK III and all Z-series suits. Two exhaustive tests were conducted using the MK III suit, the EVA Walkback Test (EWT), which estimated the feasibility of performing a suited 10km ambulation on the Moon[5], and the Integration Suit Test (IST)[42].

The two following tables 6 and 7 contain partial gravity analogs, including cases that have not been used yet. In the case of the EWT and the IST the employed analog was overhead suspension using a partial gravity simulator known as POGO[43].

Table 5 Ground-Based analogs[44]

Name of analog	Species suitability	Exposure duration
Parabolic flight	Human	Acute
Head-up flight	Human	Acute
Supine or head-down tilted short-radius centrifugation	Human	Acute
Whole-body weighted-garment water immersion	Human	Acute
Lowe-body positive pressure (LBPP)	Human	Acute
Overhead suspension	Human	Acute
Head-out graded water immersion	Human	Acute
Head-out graded dry immersion	Human	Chronic
Long-radius centrifugation (upright, supine, or head-down tilted)	Human	Acute and chronic
Head-up bed rest	Human	Chronic
Computational modeling	Human, animal	Acute and chronic
Animal suspension	Animal	Chronic
Rotating-Wall Vessel (RWV)	Cells or tissue cultures	Chronic

Table 6 Space-Based analogs

Name of analog	Species suitability	Exposure duration
Short-radius human centrifugation	Human	Acute
Large-radius human centrifugation	Human	Chronic
Short-radius human centrifugation	Animal	Chronic
Rotating-Wall Vessel (RWV)	Cells or tissue cultures	Chronic

4 PROPOSAL OF A NEW APPROACH USING PREDICTIVE METHODS

On this chapter, I will describe a novel tool to predict metabolic rate during planetary traverses.

4.1 Approach

We have shown that it is hard to elaborate deterministic models that work under all circumstances. There are too many variables and factors that impact metabolic rate. There are variables related to the specific movement (velocity, slope), to the individual (weight, load, age, gender, suit/clothing) and to the environment (gravity, terrain type). All these variables have to be taken into account because each one of them may have an important impact on the final result. Thus, obtaining the data covering all conditions and validate a deterministic model becomes hard.

Instead of trying to find this ideal model, we are proposing a different approach. First fact is that the pool of astronauts is not very large, with only 58 NASA astronauts currently eligible for flight assignment[45], and only a few will get a chance to participate in a future planetary mission. The last graduated class of 11 NASA plus 2 Canadian astronauts, NASA Astronaut Group 22, was 37 years old on average at their time of graduation, in January 2020[46].

Since the group of future subjects is so small, there is no need to find a general and universal model. Instead, the approach will be to create an adaptable model for each individual astronaut adapted to their unique characteristics.

Current path planning tools, such as SEXTANT (Surface Exploration Traverse Analysis and Navigational Tool)[47] try to calculate metabolic cost using a deterministic approach[48] and it is taken as an inspiration for this thesis. Significant efforts have been made in the last years to develop SEXTANT, and it was integrated in the Exploration Ground Data Systems (xGDS) developed at NASA Ames[49], which has been used for planning, executing and post processing the simulated EVAs in analog environments on Earth.

The advantage of embedding SEXTANT within their user interface is that this puts the planning capability at the disposal of the Extravehicular (EV), Intravehicular (IV) and science backroom team during the several phases of simulated EVA. During the planning phase, it allows scientist to select the areas where they want to go during the deployment, and automatically plan the traverses which can give them further information on the time required for moving. It was used in the analog mission series of BASALT, in Hawaii 2016 and 2017. Unfortunately, energetic data were not collected during those analog missions[50].

The main assumption they take is that the speed of an astronaut depends only on the slope of the terrain, using a function determined by Jessica Marquez on her PhD thesis from Apollo traverses[51]. This estimated speed is then used to calculate the energy cost with Santee's proposed model for load carriage on sloped terrain[31]. That simplifies their calculation of Metabolic Cost per meter, as it now becomes a function of slope alone, but it is an oversimplification nonetheless. The relationship can be seen on table 7, on figure 12 and the Metabolic Cost per meter on figure 13.

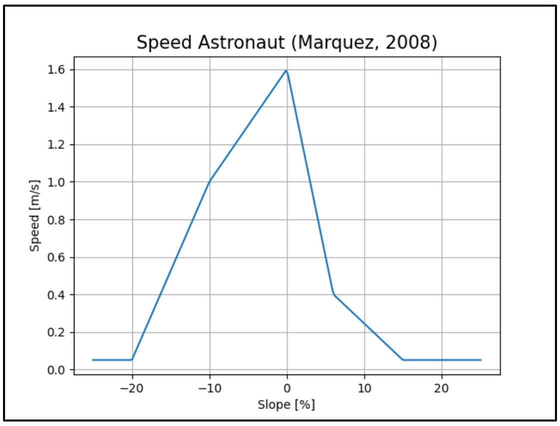


Figure 12 Astronaut Moon Speed (Marquez 2008)

Table 7 Slope and speed

Slope [%]	Speed [m/s]
$S \leq -20$	0.05
$-20 < S \leq -10$	$0.095 * S + 1.95$
$-10 < S \leq 0$	$0.06 * S + 1.6$
$0 < S \leq 6$	$-0.2 * S + 1.6$
$6 < S \leq 15$	$-0.03 * S + 0.634$
$15 < S$	0.05

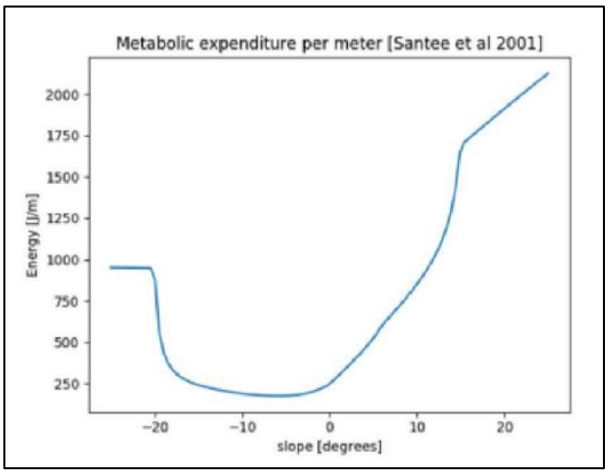


Figure 13 Metabolic expenditure per meter

The new model we proposed has the following requirements. The model should be able to replicate measured metabolic and fatigue data, it should be easy to update when new data ~~becomes~~ available, it needs to be flexible, reliable, and lastly the model has to be implemented in such a way that it becomes possible to be used for mission planning, system requirements and design equipment.

4.2 Architecture of the model

As I previously stated, the objective is to create a model capable of predicting metabolic expenditure for different subjects. For that reason, each subject has its own regression problem.

4.2.1 Inputs and Outputs

In a regression problem the goal is to estimate the relationships between a dependent variable and one or more independent variables. This relationship is studied using a set of existing data, where the independent variable is known for some cases.

For this problem in particular, some of the inputs and outputs are the following:

<u>INPUTS</u>

- TRAVERSE DATA.
    - Load [kg]
    - Velocity [kg]
    - Changes in elevation, Slope [%]
- INDIVIDUAL DATA.
    - Weight [kg]
    - Age [scalar]
    - Gender [Male, Female]
    - Height [cm]

<u>OUTPUT</u>

- Metabolic Rate [W]

Given the complexity of the interactions of the variables in the previously studied metabolic models, we have to accept that it may not be possible to yield a simple formula using only a few of common mathematical operations. Instead, I will use a supervised model in a more advance tool, an Artificial Neural Network (ANN).

4.2.2 Formulation

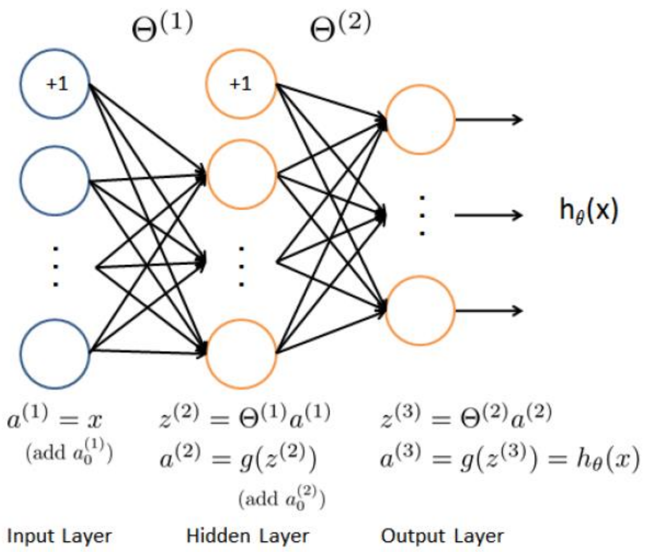


Figure 14 Neural Network diagram

A Neural Network is a series of mathematical operations composed by layers of neurons[52]. Each neuron has an activation function, the inputs of that function are a linear combination of the activations of the neurons of the previous layers plus a bias[53]. A diagram can be seen on figure 14.

Layer k has n_k neurons, the activation potentials are $\boldsymbol{a}^{(\boldsymbol{k})} = \left(a_1^{(k)}, a_2^{(k)}, a_3^{(k)}, \dots, a_{n_k}^{(k)}\right)'$. Then, for layer $k+1$:

$$\boldsymbol{z}^{(\boldsymbol{k}+\mathbf{1})} = \boldsymbol{\Theta}^{(\mathbf{k})} \begin{pmatrix} a_0^{(k)} = 1 \\ a_1^{(k)} \\ a_2^{(k)} \\ \vdots \\ a_{n_k}^{(k)} \end{pmatrix}; \qquad a_j^{(k+1)} = h\left(z_j^{(k+1)}\right)$$

Where $\boldsymbol{\Theta}^{(\mathbf{k})}$ is a matrix of dimensions $(n_k + 1) \cdot (n_{k+1})$, the activation of neuron j on layer $k + 1$ is $a_j^{(k+1)}$ and the activation function is $h(z)$.

Before the first layer, $\boldsymbol{a}^{(\mathbf{0})} = \boldsymbol{x}$, where **x** is a vector with all the input variables.

For this particular regression problem there is one output, Metabolic Rate, and the last layer only has one neuron.

The inputs of this model are the traverse data: Velocity, Slope, Load and Weight. Given the fact that a model is trained for each individual subject, the personal data of a user do not convey any information, since all personal variables (age, gender, etcetera) remain constant. The reason we keep Weight as an input variable is because its relationship with Load is quite direct.

It is reasonable to assume from the models on the literature that there are interactions between the input variables. For example: multiplication of Velocity times Slope. In order to manage to replicate these interactions on a Neural Network it would be necessary to have at least 4 layers[54]. However, with only 4 input variables it is not advisable to have many layers, because this would involve many parameters and thus the model would overfit the data, which is not acceptable.

Therefore, a better approach is to combine features. The model will be able to take combinations of the input variables. In particular, multiplication between features. For example: $Velocity * Slope$, $Load * Velocity$, etcetera. The list of input variables has to be specified; the final number of input variables is left to the user to decide.

Another consideration that I took is to normalize the input and the output, with the purpose of making them of similar magnitude. For this problem, I decided to make the following arbitrary transformations, to make the input values have a value around 1:

$$Weight' = Weight/90kg$$

$$Load' = Load/50kg$$

$$Slope' = Slope/20\%$$

$$Velocity' = Velocity/(3.0\, m \cdot s^{-1})$$

If the output of the NN is $Metabolic\ Rate'$, then:

$$Metabolic\ Rate = Metabolic\ Rate' \cdot 2000\, W$$

I experimented with different layer configurations: between 2 and 4 layers, with a number of neurons per layer that decreases, with only one layer in the last layer to yield the final value.

For all the layers except the last, the activation function will be a hyperbolic tangent, $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$, with a range between -1 and 1. The reason for that is because it introduces nonlinearities in the network, it is a symmetric function and it is easy to compute.

The last layer will have a Rectified Linear Unit, $Relu = \max(0, x)$. This is interesting because for the last layer it is important to keep as much linearity as possible, but physically the Metabolic Rate cannot be less than 0, and so it is useful to keep this hard constraint.

4.2.3 Learning characteristics

Since the target values are numerical, the cost function that the optimization algorithm will try to minimize will be be Mean Squared Error (MSE). For a dataset of examples N examples $(\boldsymbol{X_0}, Y_0)$, where $\boldsymbol{X_0}$ is a matrix with the features and Y_0 a vector of the measured Metabolic Rates the cost function will be:

$$MSE(Model_{ID}) = \frac{1}{N} \cdot \sum_{Examples} (Model_{ID}(\boldsymbol{X_0}) - Y_0)^2$$

For this problem, the optimizer I chose is Stochastic Gradient Descent (SGD)[55].

4.3 Implementation

This model was developed in Python3 [56], a high level and open source programming language that is used on many applications because it is very versatile and programs need less lines that other languages such as JAVA or C++, and it also allows quick development and maintainability of code.

The code necessary to run the project on this Thesis is available on a repository on the code sharing website GitHub[57]; (https://github.com/visaub/metabolic-predictor).

In the following sections, I will briefly explain the main components of the project.

4.3.1 Explorer

The explorer is an individual subject of whom data are stored and analyzed. Each subject has a specific 'ID' which is its unique identifier throughout the application.

An explorer is initiated by calling the class Explorer() located on explorer.py

For each explorer, its traverse data and energy data are stored into Comma Separated Values (CSV) files that are managed using Python Pandas library.

There are two directories for these data:

- **traverse/temp/:** in this directory traverse data are stored. The headers are explicit on each CSV file and are the following:

  TIME, X, Y, Weight, Load, Velocity, Slope, Eta, Gravity

  - **TIME:** Timestamp in seconds of each moment. Throughout this project, a delta of 60 seconds between samples is the standard, but it can be modified if needed.
  - **X:** Position on the horizontal axis, in meters. Traverses are considered to have a constant horizontal direction.
  - **Y:** Position on the vertical axis, in meters. Elevation.
  - **Weight:** Weight of the explorer, in kilograms.
  - **Velocity:** Speed of the explorer, in meters per second.
  - **Load:** Load carried by the explorer, in kilograms.
  - **Slope:** This is the rate of change of elevation, in percentage. It is defined as the increment of Y divided by the increment of X. It is also the tangent of the slope angle α.
  - **Eta:** Terrain factor.
  - **Gravity:** Gravity on the specific environment, in meters squared per second.

- **energy/temp/:** this directory contains traverse data and also energetic data. The headers are:

  TIME, Weight, Load, Velocity, Slope, Eta, Gravity, Rate, Fatigue

  - **Rate:** Metabolic rate at a given instance, in Watts, Joules per second.
  - **Fatigue:** Energy spent since the start of the traverse. It is the result of integrating the Rate over time.

$$Fatigue(t) = \int_{t_0}^{t} MR(\tau)d\tau$$

Given the fact that we work with discrete values, the Fatigue is actually calculated as a convolution of all Metabolic Rates with the difference of time between samples.

$$Fatigue[T] = \sum_{i=1}^{T} MR[i] \cdot (TIME[i] - TIME[i-1])$$

On both **traverse/temp/** and **energy/temp/** there are subdirectories for every explorer that contain traverse data and energy data. Each traverse has its own filename, which should ideally be a numeral. For example, *traverse/temp/subject1/5.csv* is traverse *5* for user *subject1.*

The class Explorer() supports several methods and functions that allow easy management and interaction of the raw traverse and MR information. A few of the features of this class are:

- Instantiate object of this class. The identity of the subject is denoted by the parameter *ID*. It automatically loads all the traverse information of that subject into the object. If there exist no subject with that *ID* then a new one is generated.
- Get information and data of the traverses. All data of a subject can be retrieve using queries on its object.
- Set and modify data on the subject. For example, to add new traverses.
- There are utility functions that are useful to simulate data for testing purposes. Uses include generate traverses, which creates random traverses according to parameters and limits that can be customized. On figure 15 there are examples of height profile. The way these simulated traverses could be generated will be discussed in chapter 5.

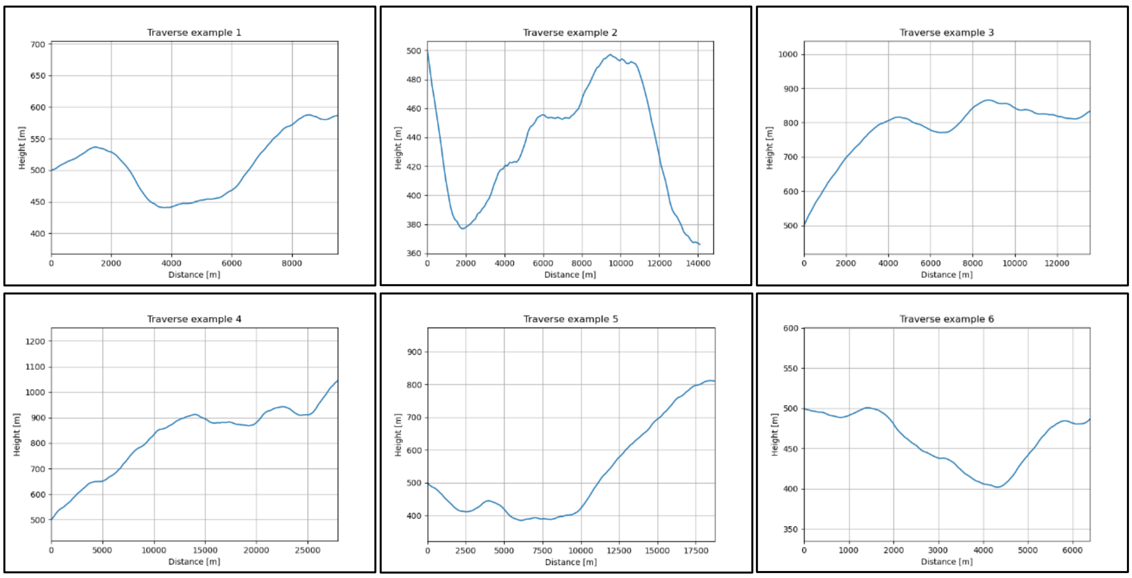


Figure 15 Traverse examples

4.3.2 Utilities

There are classical MR models implemented in the models.py file, along with utility functions for tasks such as storing traverses on csv files or obtaining the MR given a traverse and a model.

Another useful script is plotstuff.py, which is used to generate the plots that appear thorough this thesis.

4.3.3 Predictive model

For each subject there is a predictive model that is trained with its individual data. When new data are added, this model is updated to accommodate the new data.

The model is a simple neural network. In Python, it is recommended to use libraries to manage models, tensors, activation functions and the training process.

This is a Machine Learning regression problem, where there are a few numerical inputs and the output is a quantity.

This project uses Keras, a high level Application Programming Interface for Machine Learning (ML) and Deep Learning (DL) models in Python[58]. The tensor library that works as backend for Keras is Theano. I choose Theano over the more popular Tensorflow for two reasons. First, Theano occupies less space than Tensorflow, and the second is that Theano has less compatibility issues.

Functions to create, train, save and load NN models are located on the file learn.py. The desired layers and neurons-per-layer are customable.

The models are saved with a file name of '*ID*.h5'.

This code also handles the normalization of inputs and outputs.

4.4 Application Programming Interface (API)

In order to facilitate access to the main functionalities on the source code I made an API that runs on a HyperText Transfer Protocol (HTTP) server.

APIs are intended to allow different Applications to send information and do actions between them. HTTP is the protocol that all websites use. This is a Representational State Transfer (REST) API, diagram is shown on figure 16. Client sends HTTP request to a server, which after doing the action requested sends back a Response to the Client. In a POST request and on the HTTP a JSON with appropriate format is required.

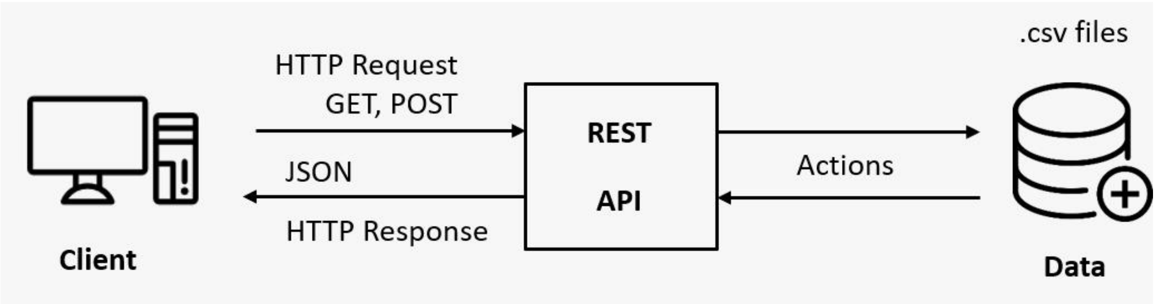


Figure 16 RESTful API diagram

It is possible to download and use the API locally, using local data too.

A comprehensive guide for the installation and utilization of this API is available on Appendix A. There are methods to get lists with the existing subjects and the traverses for each subject, to get the information of a specific traverse, to add a new subject, to add new traverse, to train the models for a specific user and finally to predict MR from an input traverse.

I made version available online. The link is the following: https://metabolic.visaub.com. The online application is running on a server of PythonAnywhere[59], which is a company that runs its client websites on Amazon Web Services (AWS)[60]. The parent domain visaub.com is owned by me.

5 ANALYSIS

In this chapter I use the prototype MR predictive tool and observe its performance.

5.1 Testing using simulated data

This a step to check the correct behavior of the model with data generated by a simulation, not a real human being. The objective is to check that this tool learns from the input data, even if we use simulated data.

Example using Earth gravity:

Let us first define a subject with ID = 'User1' and Weight = 70kg. For that user, we generate 30 traverses of 120 minutes of duration. The acceleration is set to $g = 9.8\, m \cdot s^{-2}$. On each traverse the weight and load are kept the same, whereas the velocity and slope change. The load is different on every traverse, randomly generated from a uniform distribution from 0 to 30kg. Every traverse has a measured Metabolic Rate provided by a deterministic model, for this example I choose the Pandolf Load equation modified by William Santee.

$$Metabolic\ Rate = \begin{cases} M & \text{if:} \quad S \geq 0\% \\ M - C & \text{if:} \quad S < 0\% \end{cases}$$

$$M = 1.5 \cdot W + 2.0 \cdot (W + L) \cdot \left(\frac{L}{W}\right)^2 + \eta \cdot (W + L) \cdot (1.5 \cdot V^2 + 0.35V \cdot S)$$

$$C = \eta \left[\frac{\mathrm{S(W+L)V}}{3.5} - \frac{1}{W} \cdot \mathrm{(W+L)(S+6)^2 + (25 - \ V^2)}\right]$$

For this example, terrain factor $\eta = 1.0$.

To add some distortion, let us multiply each sample of MR by a normal distribution of mean 1 and standard distribution of 0.02.

$$MR^* = MR \cdot normal(\mu = 1.0, \sigma = 0.02)$$

The slope and velocity are modified slowly. With $S = Slope[i]$ and $V = Velocity[i]$,

$$Slope[i+1] = S + UniformDistribution(-S/20 - 2, -S/20 + 2)$$

$$Velocity[i+1] = V + UniformDistribution(-0.5 - (V - 2.5)/5, 0.5 - (V - 2.5)/5)$$

The goal of these modifications is to get a diverse set of datapoints to be able to train the network. With the limits of the random uniform distributions, the intervals of slope and velocity are $-20 < S < +20$ and $0 < V[m \cdot s^{-1}] < 5m \cdot s^{-1}$.

$5m \cdot s^{-1} = 18km \cdot h^{-1}$ is a high but achievable speed on Earth.

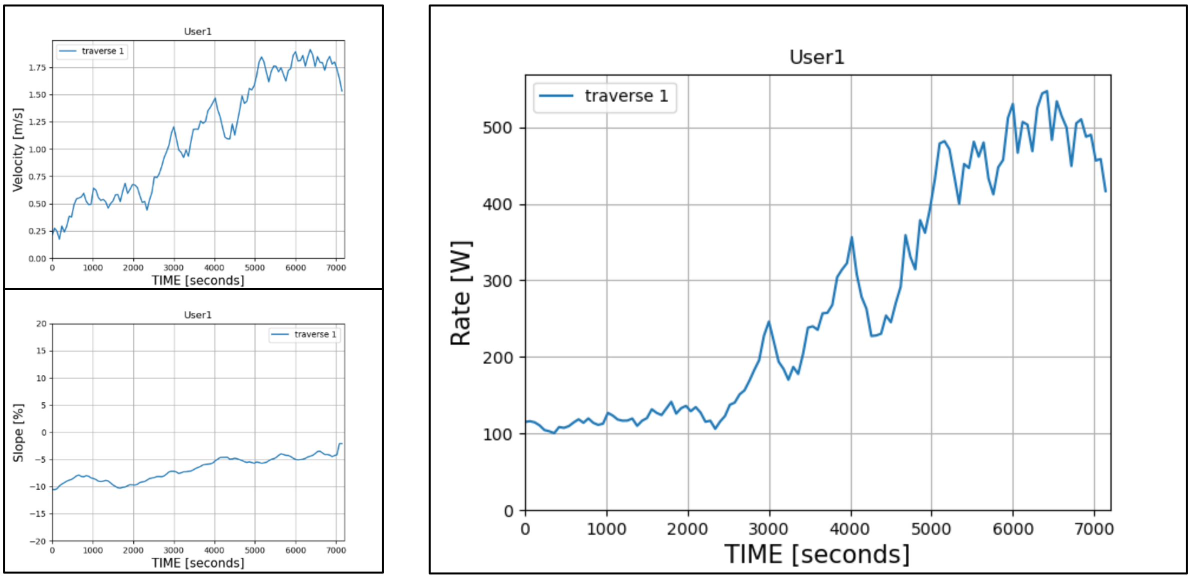


Figure 17 Example of Velocity, Slope and Metabolic Rate of a traverse

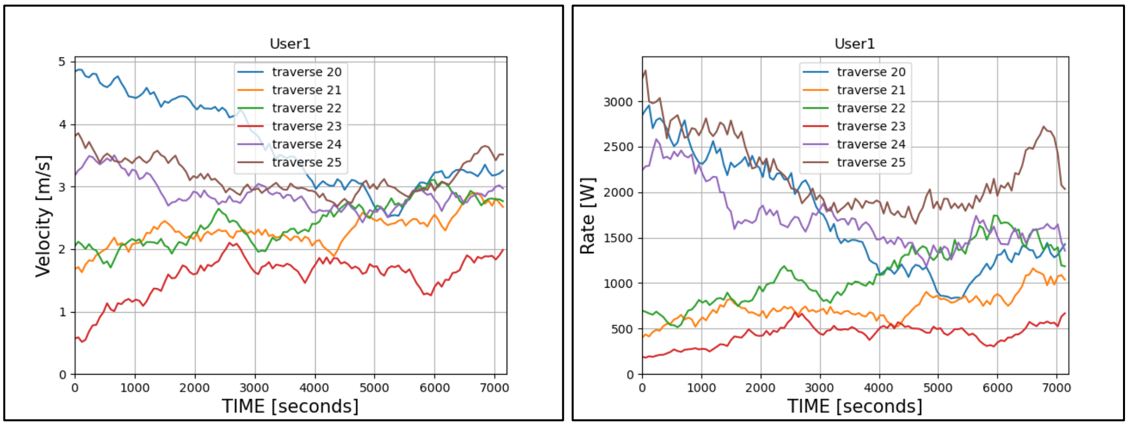


Figure 18 Example of velocities and metabolic rates of traverses 20 to 25

Figure 17 and figure 18 contain visualizations of the simulated data as an example.

I divide the dataset of 30 traverses into a training-set of 10 and a test-set of 20. The training-set is utilized to optimize the Neural Network, whereas the test-set shows how well the NN is performing. The number of layers and neurons-per-layer can be adjusted. Using a neural network with 200 neurons on the first layer, 50 on the intermediate layer and one final neuron, with 4 inputs variables, $Input\ variables : [Weight, Load, Velocity, Slope]$, the performance of the NN on the train-set and the test-set is depicted on figure 19.

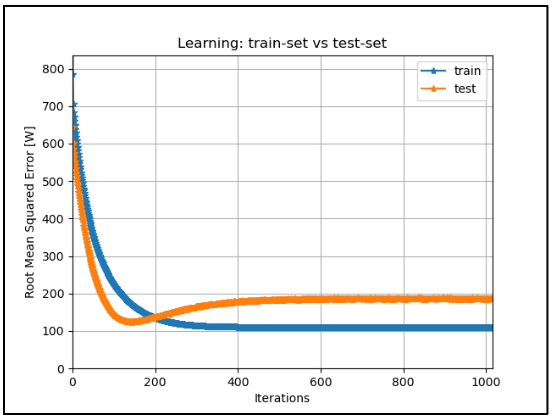


Figure 19 Root Mean Squared Error during training

The Root Mean Squared Error, $RMSE = \sqrt{\frac{1}{N} \cdot \sum(Model(\boldsymbol{X}) - Y_0)^2}$, is about $\sim 180\ Watts$ for the test set at the minima of the function, achieved after about 500 iterations. This is a metric of error for the NN. On figure 20 there is a comparison between test data that has not been used to optimize the NN and the prediction of the model on that data.

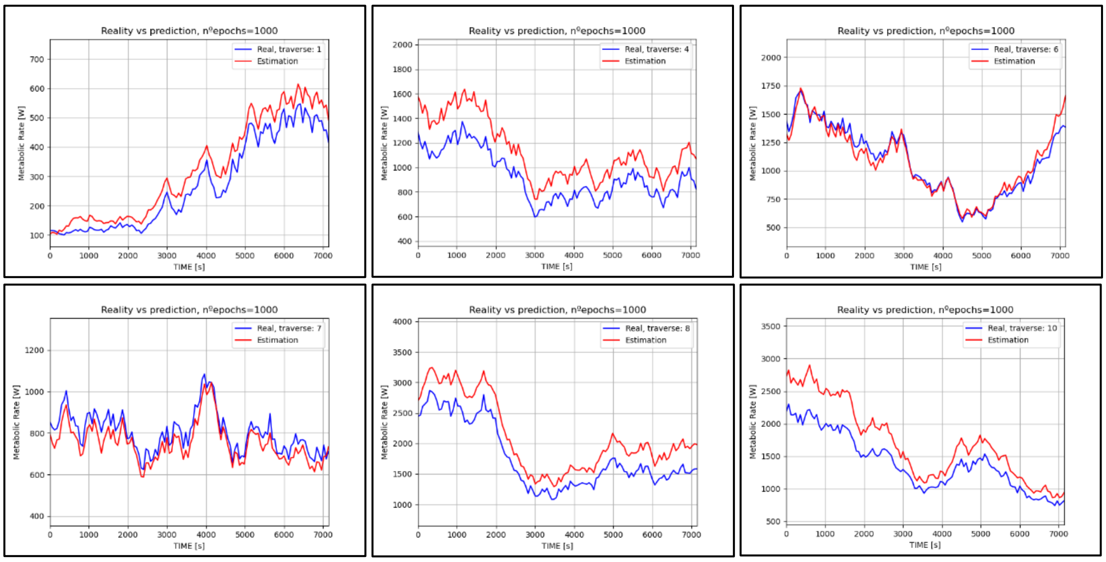


Figure 20 MR estimated for various test traverses

Even though it can be appreciated that the NN is roughly estimating data which it has not been trained on, 180W is a remarkable error, comparable to the BMR of an individual of about 40 kilograms. To decrease the error, the first attempt involves the generation of more input variables. If the variables that we add are multiplications between the initial set of $[Weight, Load, Velocity, Slope]$ and n is the polynomial order of the feature recombination, then there are $N(n) = \frac{(n+3)!}{n! \cdot 3!}$ input variables of order n. For $n = 1$ there are the initial 4 input variables; $N(n = 2) = 10$, the set of input variables of order 2 is: $[Weight * Weight, Weight * Load, Load * Load, Weight * Velocity, Load * Velocity, Velocity * Velocity, Weight * Slope, Load * Slope, Velocity * Slope, Slope * Slope]$.

The final set of input variables is the combinations of variables of $n = 1, n = 2 \ldots$ up to the specified degree. On figure 21 there is a comparison of the learning curves for different polynomial recombination of features.

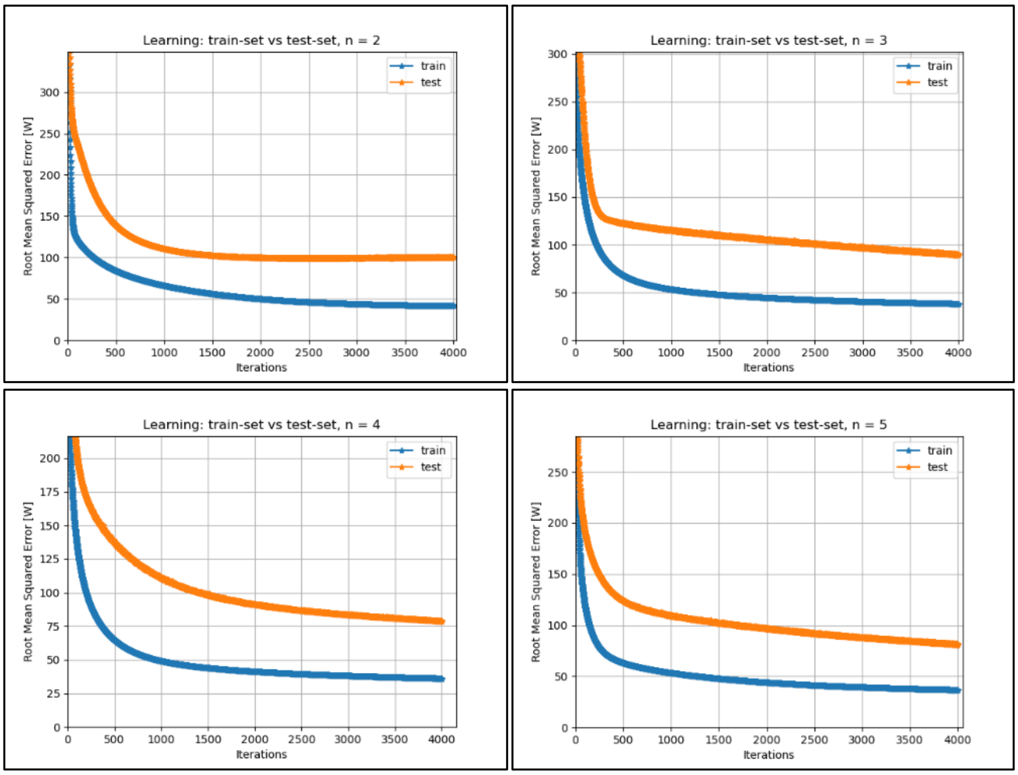


Figure 21 Learning curves for different n

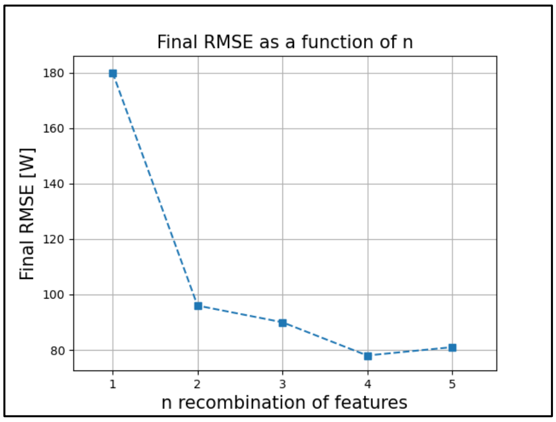


Figure 22 Final Root Mean Squared Error on the test-set for different polynomial recombinations of input variables.

It is clear that for this particular problem a good choice could be either $n = 2, 3\ or\ 4$, using the information on figure 22. The RMSE for $n = 4$ is about 80W, less than half of what it was previously.

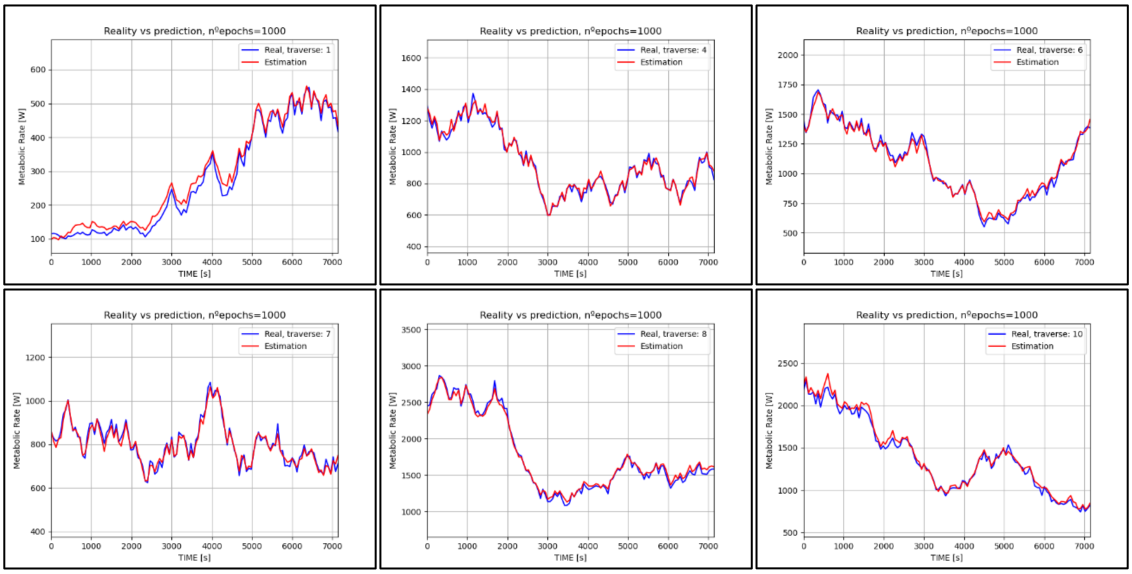


Figure 23 Metabolic Rate estimated for various test traverses, n=4

On figure 23 the NN there is a comparison between test data and predictions, using the same traverses of figure 20. The latter model does comparatively better.

With a trained model it is possible to obtain insights for the particular subject that can be used on a deterministic tool. For example: curves for the metabolic cost of transport at different inclinations, depicted on figure 24.

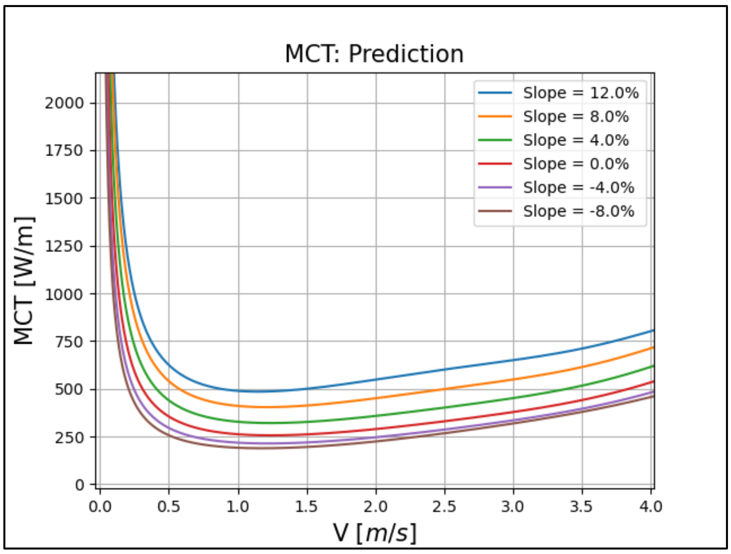


Figure 24 Prediction of the Metabolic Cost of Transport at different inclinations.

6 DISCUSSION AND FUTURE WORK

Finally, this is the chapter where I discuss the findings on each chapter and propose future steps.

6.1 Metabolic expenses models future exploration missions

There are a few caveats of past MR models for locomotion under 1g unsuited, starting with the input variables. Terrain factor is a non-dimensional factor that is supposed to add information about the terrain. The problem is that each model has its own definition and tables of this factor, its values are determined after the model has been proposed, which is circular reasoning. Slope does not consider lateral inclination, only longitudinal. It is not the same to walk on an edge between two mountain peaks than to walk with the mountain to one side and an abyss on the other, using the legs asymmetrically.

For extravehicular missions, one of the main challenges that needs to be addressed is that longer missions result in bone loss, muscle loss and balance loss. That makes harder to extrapolate the data obtained on Earth. Currently, bed-rest studies are the best way to induce these changes into the human body in a controlled environment, the feasibility of performing partial gravity suited locomotion experiments should be considered.

With the introduction of the new xEMU spacesuit new opportunities for development of MR models open. The step-by-step development from the MK III and Z-series suits that concluded with the modern suit will be helpful to leverage the previous research.

A lot of work is still needed to develop and use MR models. Here is a list of studies compiled from Christopher Carr research[37] and the last experiments on Johnson Space Center[5], [42].

Table 8 Sources of data of Metabolic Rate

Reference	Description	Suit or Load	Independent Variables	N
[Streimer et al., 1964]	Treadmill locomotion	Three unk. suits	s, p	4
[Harrington et al., 1965]	Treadmill locomotion	Unk. ILC Dover Suit	v, a	4
[Wortz et al., 1967]	Treadmill locomotion	Gemini G2C	v, altitude	8
[Haaland, 1968]	Treadmill locomotion during simulated lunar mission	A5L, A6L, or A7L	v, a	2
[Robertson et al., 1968]	Partial gravity locomotion	A5L and RX-2 Suits	s, g, p	6
[Annis & Webb, 1971]	Treadmill locomotion	Space Activity Suit	v, s	2

[Kubis et al., 1972]	Apollo 16 Time and motion study	A7LB Suit	V	2
[Johnston et al., 1975]*	Apollo 14, 2nd Lunar EVA	A7L Suit	v, a	2
[Bishop et al., 1999]	Emergency Shuttle egress simulation	LES Suits	p	12
[Lee et al., 2001]	Emergency Shuttle egress simulation	LES & ACES Suits	s	4
[Wortz et al., 1966]	Partial gravity locomotion	Unsuited	v, g	8
[Sanborn, 1967]	Partial gravity locomotion	Unsuited	v	9-10
[Fox et al., 1975]	Partial gravity locomotion	Unsuited	v, g	2-4
[Webbon et al., 1981]	Treadmill liquid cooling garment tests	CPG	s	5
[Stauffer et al., 1987]	Load carrying at different velocities	Unsuited	v, m, gender	24
[Newman et al. 1994]	Partial gravity locomotion (water tank)	Unsuited	v, g	3-6
[Patton et al., 1995]	Load carrying during grade walking	Unsuited; CPG	a, m	14
[Santee et al., 2001]	Load carrying during grade walking	Unsuited	a, m	16
[Norcross et al., 2006]	Emergency Walkback Test	Mark III	a, m, v, s	6
[Norcross et al., 2010]	Load carrying during grade walking	Mark III	a, m, v, s	6

Independent variables in the original study: v=velocity, a=slope angle, s=suit, g=gravitv,dof=simulator degrees of freedom, m=mass, p=suit pressure, others as noted.

6.2 Metabolic rate prediction tool

It is possible to create and implement a MR prediction tool. The current prototype could be developed further. There are three branches for improvement.

- User experience. At the moment the application can only be used by orders on a command line interpreter or by requests to the HTTP API. It is necessary to start using a user interface with visualization of terrain, paths and points of interest. There are a few options:
    - Use as a black-box plugin on an existing platform, like xGDS or Sextant. Initially, I tried to start using Sextant but I was unsuccessful because I could not install GDAL and OSGeo4W, two of the libraries required. Also, there was no documentation about the program and the public source code had not been updated in one and a half years. But now there is a new opportunity, because on March 2020 development has been resumed by Nicholas Anastas from

MIT[61], who has already upgraded the application from Python2 to Python3, among other improvements.

- Build this application with a new frontend. It could be built from scratch or on top of a 3rd party app, for example https://www.carto.com, which is a mapping tool that works well with Python. https://cesium.com/ is an open source alternative, although it runs on Javascript.

- A better Machine Learning model. The current model is a standard feedforward Sequential Neural Network and the training examples are treated independently, and so there is no information conveyed into the model from the fact that the data is a time series. For example: the model those does not detect acceleration $[m \cdot s^{-2}]$ as a factor, which in reality has a significant effect on the final Metabolic Rate[62]. A Recurrent Neural Network with feedback connections might be able to overcome the impairment, for example a Long Shor-Term Memory (LSTM).
- Data management. In the future, it would be more adequate to store the traverse and metabolic data on a different SQL and on a different server. It is also necessary to build the pipeline to obtain Digital Elevation Models (DEM), as well as the methods to work with that new data.

Figure 25 Pnoe Portable Metabolic Cart

Currently there is a lack of metabolic data on long traverses on the field. Most experiments take place on a controlled environment on a treadmill, with a duration that does not exceed 20 minutes. To get relevant data it would be necessary to go outdoors and measure metabolic rate using a portable metabolic cart and a position tracking device to record the movement data. Nowadays there are companies that have launched lightweight metabolic carts, for example PNOE analytics (https://www.mypnoe.com/), whose product (figure 25) has already been tested against the stationary well-established COSMED – Quark CPET without statistical significance[63].

It is likely that in the future ML applications will become more widespread in the near future. There is current interest in physiological for soldiers on the battlefield.[64]

REFERENCES

[1] W. Sam, “Apollo 17 Mission Report Jsc-07904,” no. March, 1973.

[2] Office of Inspector General, “NASA’s Plans For Human Exploration Beyond Low Earth Orbit,” Washington D.C, 2017.

[3] White House, “We’re Heading Back to the Moon and Then On to Mars,” Washington D.C, 2019.

[4] J. Norcross and K. Clowers, “Metabolic Costs and Biomechanics of Level Ambulation in a Planetary Suit,” 2010.

[5] L. R. Lee, J. K. De Witt, J. R. Vos, M. L. Gernhardt, and M. E. I. Technologies, “Feasibility of Performing a Suited 10-km Ambulation on the Moon - Final Report of the EVA Walkback Test (EWT),” 2009.

[6] R. S. Johnston, L. F. Dietlein, C. A. Berry, F. Parker, J. Vernon, and E. Larry, *Biomedical Results of Apollo*. Washington D.C: Scientific and Technical Information Office, 1975.

[7] Wikipedia, “List of spacewalks 1965-1999.” [Online]. Available: https://en.wikipedia.org/wiki/List_of_spacewalks_and_moonwalks_1965–1999.

[8] Wikipedia, “List of spacewalks 2000-2014.” [Online]. Available: https://en.wikipedia.org/wiki/List_of_spacewalks_2000–2014.

[9] Wikipedia, “List of spacewalks since 2015.” [Online]. Available: https://en.wikipedia.org/wiki/List_of_spacewalks_since_2015.

[10] NASA Kennedy Space Center, “STS 102 mission.” [Online]. Available: https://science.ksc.nasa.gov/shuttle/missions/sts-102/mission-sts-102.html.

[11] R. W. Orloff, *Apollo By The Numbers: A Statistical Reference*. NASA History Division, Office of Policy and Plans, 2000.

[12] “Definition of Metabolic Rate.” [Online]. Available: https://www.merriam-webster.com/medical/metabolic rate.

[13] J. R. Drain, B. Aisbett, M. Lewis, and D. C. Billing, “The Pandolf equation under-predicts the metabolic rate of contemporary military load carriage,” *J. Sci. Med. Sport*, vol. 20, pp. 104–108, 2017.

[14] S. Blair *et al.*, *ACSM’s Guidelines for Exercise Testing and Prescription*, 9th ed. 1991.

[15] W. T. Donahoo, J. Levine, and E. L. Melanson, “Variability in energy expenditure and its components.,” *Curr. Opin. Clin. Nutr. Metab. Care*, vol. 7, no. 6, pp. 599–605, 2004.

[16] A. Harris and F. Benedict, “A Biometric Study of Human Basal Metabolism,” *Proc. Natl. Acad. Sci.*, vol. 4, no. 12, pp. 370–373, 1918.

[17] A. M. Roza and H. M. Shizgal, “The Harris Benedict equation reevaluated: resting energy requirements and the body cell mass,” *Am. J. Clin. Nutr.*, vol. 40, no. 1, pp. 168–182, Jul. 1984.

[18] M. D. Mifflin, S. T. St Jeor, L. A. Hill, B. J. Scott, S. A. Daugherty, and Y. O. Koh, "A new predictive equation for resting energy expenditure in healthy individuals," *Am. J. Clin. Nutr.*, vol. 51, no. 2, pp. 241–247, Feb. 1990.

[19] J. E. Cotes and F. Meade, "The energy expenditure and mechanical energy demand in walking," *Ergonomics*, vol. 3, no. 2, pp. 97–119, 1960.

[20] Howard G. Knuttgen, "Oxygen Uptake and Pulse Rate while Running with Undetermined and Determined Stride Lengths at Different Speeds," *Acta Physiol.*, vol. 52, no. 3–4, pp. 366–371, 1961.

[21] C. R. Taylor, K. Schmidt-Nielsen, and J. Raab, "Scaling of energetic cost of running to body size in mammals.," *Am. J. Physiol.*, vol. 219, no. 4, pp. 1104–1107, 1970.

[22] G. Baruch and R. F. Goldman, "Predicting Metabolic Energy Cost," *J. Appl. Physiol.*, vol. 30, no. 3, pp. 429–433, 1971.

[23] R. G. Soule and R. F. Goldman, "Energy cost of loads carried on the head, hands, or feet.," *J. Appl. Physiol.*, vol. 27, no. 5, pp. 687–690, 1969.

[24] A. C. Bobbert, "Energy expenditure in level and grade walking," *J. Appl. Physiol.*, vol. 15, no. 6, pp. 1015–1021, 1960.

[25] R. F. Goldman and P. F. Lampietro, "Energy cost of load carriage," *J. Appl. Physiol.*, vol. 17, no. 4, pp. 675–676, 1962.

[26] A. L. Hughes and R. F. Goldman, "Energy cost of 'hard work,'" *J. Appl. Physiol.*, vol. 29, no. 5, pp. 570–572, 1970.

[27] K. B. Pandolf, B. Givoni, and R. F. Goldman, "Predicting Energy Expenditure With Loads While Standing Or Walking Very Slowly," Natick, Massachusetts, 1976.

[28] B. M. Wood and Z. J. Wood, "Energetically optimal travel across terrain: Visualizations and a new metric of geographic distance with anthropological applications," *Vis. Data Anal. 2006*, vol. 6060, 2006.

[29] A. J. E. Bach, J. T. Costello, D. N. Borg, and I. B. Stewart, "The Pandolf load carriage equation is a poor predictor of metabolic rate while wearing explosive ordnance disposal protective clothing," *Ergonomics*, vol. 60, no. 3, pp. 430–438, 2017.

[30] R. Margaria, "Positive and Negative Work Performances and Their Efficiencies in Human Locomotion," *Int. Zeitschrift für Angew. Physiol. einschließlich Arbeitsphysiologie*, vol. 25, pp. 339–351, 1968.

[31] W. R. Santee, "A Proposed Model for Load Carriage on Sloped Terrain," *Aviat. Sp. Environ. Med.*, vol. 72, no. 6, pp. 562–566, 2001.

[32] R. Passmore and J. V. G. A. Durnin, "Human Energy Expenditure," *Physiol. Rev.*, vol. 35, no. 4, pp. 801–840, 1955.

[33] D. P. Looney, W. R. Santee, E. O. Hansen, P. J. Bonventre, C. R. Chalmers, and A. W. Potter, "Estimating Energy Expenditure during Level, Uphill, and Downhill Walking," *Med. Sci. Sport. Exerc.*, vol. 51, no. 4, pp. 1954–1960, 2019.

[34] K. S. Thomas and H. J. McMann, *US spacesuits*, 2nd ed. Springer, 2013.

[35] M. Scott-Pandorf and L. Kuznetz, "Apollo Extravehicular Activities Video and Data Archives: Stumbling, Locomotive Velocity, and Metabolic Rates," 2011.

[36] Technology Utilization Office, “Liquid Cooled Garments,” 1975.

[37] C. E. Carr, “The Bioenergetics of Walking and Running in Space Suits,” Massachusetts Institute of Technology, 2005.

[38] J. M. Wuligoru, R. Huwkins, and G. F. Humbert, “Apollo Experience Report - Assessment Of Metabolic Expenditures,” 1975.

[39] R. Kram, A. Domingo, and D. P. Ferris, “Effect of Reduced Gravity on the Preferred Walk-Run Transition,” *J. Exp. Biol.*, vol. 200, no. 4, pp. 821–826, 1997.

[40] C. E. Carr and D. J. Newman, “When is Running More Efficient Than Walking in a Space Suit?,” in *35th International Conference on Environmental Systems (ICES)*, 2005.

[41] L. Rodriggs, “xEMU Lite Development Plan,” in *EVA Technology Workshop 2017*, 2017.

[42] J. R. Norcross and K. G. Clow, “Metabolic Costs and Biomechanics of Inclined Ambulation and Exploration Tasks in a Planetary Suit,” Houston, 2010.

[43] NASA, “POGO: Partial Gravity Simulator.” [Online]. Available: https://www.hq.nasa.gov/alsj/pogo.htm.

[44] Y. Barr, G. Clément, and P. Norsk, “Human Health Countermeasures - Partial-Gravity Analogs Workshop,” Houston, 2015.

[45] NASA, “NASA active astronauts.” [Online]. Available: https://www.nasa.gov/astronauts/biographies/active.

[46] NASA, “NASA’s Newest Astronauts Ready for Space Station, Moon, and Mars Missions,” 2020. [Online]. Available: https://www.nasa.gov/press-release/nasa-s-newest-astronauts-ready-for-space-station-moon-and-mars-missions.

[47] A. W. Johnson, J. A. Hoffman, D. J. Newman, E. M. Mazarico, and M. T. Zuber, “An Integrated Traverse Planner and Analysis Tool for Planetary Exploration,” *Am. Inst. Aeronaut. Astronaut.*, vol. 9, no. September, pp. 1–28, 2010.

[48] J. Norheim *et al.*, “Architecture of a surface exploration traverse analysis and navigational tool,” in *IEEE Aerospace Conference Proceedings*, 2018, vol. March, pp. 1–11.

[49] S. Y. Lee *et al.*, “Acta Astronautica Reusable science tools for analog exploration missions: xGDS Web Tools, VERVE, and Gigapan Voyage,” *Acta Astronaut.*, vol. 90, no. 2, pp. 268–288, 2013.

[50] M. Deans *et al.*, “Minerva: User-Centered Science Operations Software Capability for Future Human Exploration,” in *2017 IEEE Aerospace Conference*, 2017, pp. 1–13.

[51] J. J. Marquez and M. L. Cummings, “Design and Evaluation of Path Planning Decision Support for Planetary Surface Exploration,” *J. Aerosp. Comput. Information, Commun.*, vol. 5, no. 3, pp. 57–71, 2008.

[52] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. 2004.

[53] A. Y.-T. Ng, *Neural Networks Multi-class Classification*, vol. 3. 2012, pp. 1–12.

[54] K. Siu and V. Roychowdhury, “Optimal Depth Neural Networks for Multiplication and Related Problems,” in *Advances in Neural Information Processing Systems 5*, 1992, pp. 59–64.

[55] J. Duchi, E. Hazan, and Y. Singer, “Adaptive Subgradient Methods for Online Learning and Stochastic Optimization,” *J. Mach. Learn. Res.*, vol. 12, pp. 2121–2159, 2011.

[56] “Python Programming Language.” [Online]. Available: https://www.python.org/.

[57] V. Sainz, “Code Repository of this Thesis,” *GitHub*, 2020. [Online]. Available: https://github.com/visaub/metabolic-predictor.

[58] “Keras API.” [Online]. Available: https://keras.io/why-use-keras/.

[59] “PythonAnywhere.” [Online]. Available: https://www.pythonanywhere.com.

[60] “Amazon Web Services.” [Online]. Available: http://aws.amazon.com/.

[61] Pextant Contributors, “List of Commits on the Github repository of PEXTANT, the SEXTANT implementation in Python,” *GitHub*. [Online]. Available: https://github.com/nanastas-mit/pextant/commits/master.

[62] N. Seethapathi and M. Srinivasan, “The metabolic cost of changing walking speeds is significant, implies lower optimal speeds for shorter distances, and increases daily energy estimates,” *Biol. Lett.*, vol. 11, no. 9, pp. 1–4, 2015.

[63] Y. E. Tsekouras, K. D. Tambalis, and S. E. Sarras, “Validity and Reliability of the New Portable Metabolic Analyzer PNOE,” *Front. Sport. Act. Living*, vol. 1, no. 9, pp. 1–7, 2019.

[64] K. E. Friedl, “Military applications of soldier physiological monitoring,” *J. Sci. Med. Sport*, vol. 21, no. 11, pp. 1147–1153, 2018.

APPENDIX A: Documentation of the API

This appendix explains how to install the HTTP Application Programming Interface and how to use the methods currently available.

A.1 Installation

To run the api.py locally, it is necessary to download the source code first, which is located on a free Github repository[57].

The application is programed in Python, a version Python3.7 or superior is recommended. I also recommend creating a virtual environment to facilitate version control.

After installing Python, open a Command Console and type the following lines.

```
git clone https://github.com/visaub/metabolic-predictor
cd metabolic-predictor
pip install -r requirements.txt
```

The recommended backend for the Machine Learning operations is Theano because it is lighter, faster and multiplatform. If the API is only run locally, it is possible to make it work using Tensorflow, although in that case the library has to be downloaded individually.

However, Theano is a better option, especially if the application is intended to be run on the Internet.

To choose Theano as the ML backend, it is necessary to change the file keras.json, located on the parent directory, to something like the following:

```
{
    "floatx": "float32",
    "epsilon": 1e-07,
    "backend": "theano",
    "image_data_format": "channels_last"
}
```

Now the API should be ready to run

```
python api.py
```

A message should appear on the console:

```
Using Theano backend.
 * Serving Flask app "api" (lazy loading)
 * Environment: development
 * Debug mode: on
 * Restarting with stat
Using Theano backend.
 * Debugger is active!
 * Debugger PIN: XXX-XXX-XXX
 * Running on http://127.0.0.1:8800/ (Press CTRL+C to quit)
```

Now the API should be up and running on localhost (127.0.0.1), port 8800.

`http://127.0.0.1:8800/`

A.2 Endpoints

An endpoint is the access point of an application. In this case, the endpoint in the URL is what goes to the right of the domain, `http://127.0.0.1:8800`

/api/subjects, methods=['GET'], parameters=['type']

Returns a JSON object with all the existing traverses on the database.

If the parameter *type=list,* the JSON yielded is only the list of subjects.

Example:


```
{
 "subjects": [
   "subject_test_0",
   "subject_test_1",
   "subject_test_10",
   "subject_test_11",
   "subject_test_12",
   "subject_test_13",
   "subject_test_14",
   "subject_test_15",
   "subject_test_16",
   "subject_test_17",
   "subject_test_18",
   "subject_test_19",
   "subject_test_2",
   "subject_test_3",
   "subject_test_4",
   "subject_test_5",
   "subject_test_6",
   "subject_test_7",
   "subject_test_8",
   "subject_test_9",
   "test_GG",
   "test_PL",
   "train_GG",
   "train_PL",
   "user1"
```

 ]
}

/api/route/<ID>/<traverse>, methods=['GET']

Returns a JSON object of *traverse* of subject *ID*

JSON example of a traverse


```
{
 "ID": "user1",
{
 "data": {
  "0": {
   "Eta": 1.0,
   "Fatigue": 0.0,
   "Load": 22.69777546220526,
   "Rate": 403.33062831258127,
   "Slope": -7.072679833003135,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  },
  "60": {
   "Eta": 1.0,
   "Fatigue": 24199.837698754876,
   "Load": 22.69777546220526,
   "Rate": 382.43874490630907,
   "Slope": -7.050021549629794,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  },

....

  " "7140": {
   "Eta": 1.0,
   "Fatigue": 3837140.765185034,
   "Load": 22.69777546220526,
   "Rate": 594.5620916070777,
   "Slope": 2.3592928096460932,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  }
 },
 "elements": [
  "TIME",
  "Weight",
  "Load",
  "Velocity",
  "Slope",
  "Eta",
  "Rate",
  "Fatigue"
 ],
 "traverse type": "energy"
}
```


/api/route, methods=['POST']

Adds a new traverse to the database. The request body must include a json of the traverse, with the same format as the traverse above, including the user ID and the traverse name. If the user did not exist when the request is made, a new user with that ID is initiated.

/api/prepare/<ID>, parameters=input_names, methods=['GET']

A model for subject *ID* is trained using the existing data. It is possible to specify the input_names of the model. If input_names is declared the default is: input_names = ['Weight', 'Load', 'Velocity', 'Slope']

The variables in input_names have to be products of ['Weight', 'Load', 'Velocity', 'Slope']

Example: input_names = ['Weight', 'Load*Slope', 'Velocity*Slope', 'Slope', 'Weight*Velocity*']

/api/predictions_ready, methods=['GET']

Returns a JSON object with all the subjects. For each subject it indicates if a trained model is stored or not.

Example:


```
{
 "1": false,
 "EE_1": true,
 "EE_2": true,
 "EE_3": true,
 "Moon": false,
 "proba": true,
 "subject_test_0": false,
 "subject_test_1": false,
 "subject_test_10": false,
 "subject_test_11": true,
 "subject_test_12": false,
 "subject_test_13": true,
 "subject_test_14": true,
 "subject_test_15": false,
 "subject_test_16": false,
 "subject_test_17": false,
 "subject_test_18": false,
 "subject_test_19": false,
 "subject_test_2": true,
 "subject_test_3": false,
 "subject_test_4": true,
 "subject_test_5": false,
 "subject_test_6": true,
 "subject_test_7": false,
 "subject_test_8": true,
 "subject_test_9": true,
 "test_GG": false,
 "test_PL": false,
 "train_GG": false,
 "train_PL": false,
 "user1": true
}
```


/api/predict, methods=['POST']

Returns a JSON of a traverse with a predicted MR. The request body must include a json of with the traverse data.

Example of response:


```
{
 "ID": "user1",
 "Rate Predicted": [
  390.08819580078125,
  390.5118713378906,
  391.525146484375,
  …
  689.4677124023438,
  640.1978149414062,
  610.2174682617188
 ],
 "Traverse": "3",
 "data": {
  "0": {
   "Eta": 1.0,
   "Fatigue": 0.0,
   "Load": 22.69777546220526,
   "Rate Predicted": 390.08819580078125,
   "Slope": -7.072679833003135,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  },
  "60": {
   "Eta": 1.0,
   "Fatigue": 24199.837698754876,
   "Load": 22.69777546220526,
   "Rate Predicted": 390.5118713378906,
   "Slope": -7.050021549629794,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
   },
  "120": {
   "Eta": 1.0,
   "Fatigue": 47146.16239313342,
   "Load": 22.69777546220526,
   "Rate Predicted": 391.525146484375,
   "Slope": -6.995933907793742,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  },

          …..

  "7140": {
   "Eta": 1.0,
   "Fatigue": 3837140.765185034,
   "Load": 22.69777546220526,
   "Rate Predicted": 610.2174682617188,
   "Slope": 2.3592928096460932,
   "Velocity": 1.5470436853108909,
   "Weight": 74.21907655653825
  },
 }
 "elements": [
  "TIME",
  "Weight",
  "Load",
  "Velocity",
  "Slope",
  "Eta",
  "Rate",
  "Fatigue"
 ],
 "traverse type": "energy"
}
```