Estimation of Energy Expenditure Based on Divided Manual Material Handling Task: Waste Collection Example

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Received: 10th June 2016
Accepted: 26th December 2016
DOI: http://dx.doi.org/10.18466/cbujos.302640

Abstract

The objectives of this study were: i) to present an approach for potential areas of ergonomic analysis software usage and to get familiar with the usage of this kind of problem assessment by applying the software to a practical example in a problem area with significant ergonomic problems to be analyzed. ii) to estimate energy expenditure rates for waste collection task using the University of Michigan Energy Expenditure Prediction Program (EEPP) to comfort worker safety and health. iii) to compare with regression equations in literature to illustrate the performance of the EEPP software. The assessment will make use of a University of Michigan EEPP to predict energy expenditure of materials handling tasks to comfort worker safety and health. A manual waste collection task was selected as a job analysis and the results will be compared with NIOSH guidelines and regression equations in literature to illustrate the performance of the EEPP software. The results show that EEPP software and prediction equation estimated quite close average task energy rate (kcal/min). This predicted information can be useful for waste collection job design instead of using oxygen consumption measurement which takes long time and costly. Furthermore, these results can be used for recommendations to improve ergonomic factors of the waste collection tasks in form of a guideline.

Keywords — Energy expenditure, Ergonomic analysis tools, Job analysis, Prediction, Waste collection

1 Introduction

Municipal Solid Waste (MSW) is one of the waste type, mainly defined as "trash" or "garbage", including "durable goods, nondurable goods, containers and packaging, and other wastes" but excluding "industrial, hazardous, and construction wastes" [1]. MSW collection is the fundemantal stage of SW management including "generation", "collection", "transfer", "treatment", and "final disposal" [2].

Eliminating waste materials from households, especially in urban and suburban areas, to either the point of recycling or final disposal can be referred to waste collection [3]. According to the report in 1998, the U.S. Bureau of Labor Statistics declared that 49 fatalities per 100,000 waste collectors were experienced in 1996, and that task was the seventh dangerous job in the U.S [4]. Since waste is still collected manually, this manual part can be considered as an example of manual materials handling task which a person must be able to perform without excessive strain or fatigue.

Metabolic energy expenditure rate is the physiological measurement which has been suggested in the literature to determine the maximum task intensity that can be continuously performed without accumulating an excessive amount of physical fatigue [5]. Energy expenditure limits are often defined as a rate of oxygen consumption per min (VO2) in the domain of human factors and ergonomics and a limit of 1 liter of oxygen per min (approximately 5 kcal per min) is considered as a design criterion [6]. There are three approaches to measure energy expenditure [7]: i) oxygen consumption and/or carbon dioxide production is measured by using indirect calorimetry and converted to energy expenditure using formulae. ii) the rate of heat loss from the subject to the calorimeter is measured by using the direct calorimetry. iii) a number of non-calorimetric techniques have been applied to estimate the energy expenditure by extrapolation from physiological measurements and observations. There are several devices that can accommodate minute-by-minute information based on physical activity patterns. However, their validity to perform energy expenditure is not sufficient. For instance, several devices have performed better in a laboratory setting than nonlaboratory conditions.

A job can be categorized into tasks according to the assumption of the metabolic prediction model [5]. Each task requirement of the energy expenditure can be combined to calculate the energy expenditure of the entire job. The need for predictive models for energy expenditure has been pointed out by some researchers. A recent study by [8] examined the validity of predicting energy expenditure based on gender, heart rate, and physical activity in adults in Cameroon. Another study has been proposed by [9] and [10] such as new regression models using two-regression approach to improve estimated energy expenditure using accelerometry during physical activity. Zakeri et al. [11] have constructed Multivariate adaptive regression splines (MARS) models based on heart rate (HR) and accelerometer counts (AC) to accurately predict EE, and hence 24-h total energy expenditure in children and adolescents. Hay et al. [12] applied an artificial neural network technique to the problem of predicting energy expenditure with several dynamic input values including accelerometry, heart rate above resting (HRar), and electromyography (EMG).

There are various software tools in literature to predict energy expenditure. The University of Michigan's Energy Expenditure Prediction Program™ (EEPP) is one of them which predict metabolic energy expenditure rates by integrating the energy requirements of small, well-defined work tasks that comprise the entire job [13]. This tool can also identify specific work tasks that contribute heavily to an overall high job energy expenditure rate, which facilitates job redesign activities.

The objectives of this study were: i) to present an approach for potential areas of ergonomic analysis software usage and to get familiar with the usage of this kind of problem assessment by applying the software to a practical example in a problem area with significant ergonomic problems to be analyzed. ii) to estimate energy expenditure rates for waste collection task using The University of Michigan Energy Expenditure Prediction Program (EEPP) to help assure worker safety and health. iii) to compare with regression equations in literature to illustrate the performance of the EEPP software.

2 Methodology

This study aims to point out an approach to estimate energy expenditure rates for waste collection task using The University of Michigan EEPP. This software basically estimates the energy rate of the job by knowing the energy requirements of simple tasks that comprise the entire job. For this reason, waste collection task has been divided in 6 individual tasks is represented in Table 1.

Table 1. List of divided tasks

Task #	Task work	Activity list
1	Walk to the container	Walk
2	Pull the container	Push/Pull
3	Lift the container	Lift
4	Dump the container	Hold
5	Push the empty container	Push/Pull
6	Walk back to the vehicle	Walk

The information for each task required to calculate the energy requirements including force exerted, distance moved, frequency, task posture, lifting technique for lifting tasks, and time required to compute the tasks. Furthermore, gender and body weight are also needed. These information are separated as program inputs and outputs: inputs are subject's gender and weight, list of activity elements, and parameters specific to activity elements (e.g. frequency, weight of load, distance carried); outputs are: listing of activity elements with their corresponding energy expenditure, calculation of the total energy expenditure rate for the job in Kcal/minute.

Two survey forms were designed they include details on the waste collectors experience, physical comfort, safety practices and the injury history according to different types of waste collection practice. Based on these surveys, total task time, frequency, distance moved (walk to the container and walk back to the container) were entered into the software and predicted energy results were summarized. Finally, the results from the analysis section were compared with regression models in literature and interpreted in a wider context regarding their effect and meaning in terms of the ergonomic assessment.

3 Results and Discussion

3.1 Assumptions

There are some assumptions needed to do before data analysis. Since data was gathered from surveys, it was not possible to extract some of these variables. These approximate values are follows:

- Distance travelled for walking task is assumed 3.28 feet
- Average forces applied for pushing and pulling tasks are assumed 4 pounds and 1 pound respectively, and height of hands and horizontal displacement are assumed 35 and 40 inches respectively.

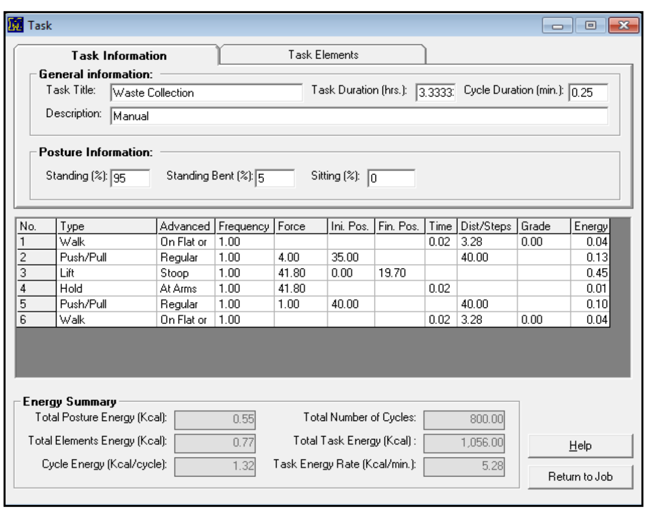

Figure 1. The screenshot after all data has been entered

3.2 University of Michigan Energy Expenditure Prediction Software

Based on the results illustrated in Figure 1, task energy rate has been calculated 5.28 kcal/min which is shown at the bottom of the screenshot. A physical work capacity limit of 5.2 Kcal/min is recommended for an eight-hour continuous and a young health male [14]. However, a limit guideline is exceeded significantly by the 3.5 kcal/min for an average 8 hour day set by the National Institute for Occupational Safety and Health (NIOSH) . This job is too fatiguing and it might be redesigned again to solve this problem.

3.3 Prediction Model

Equations 2 to 5 for the net metabolic cost (ΔE) of each task as a function of personal and task variables were performed using least squared error regression analysis [5]. Some of these equations are considered for our model, these equations are:

(i)Maintenance of body posture:

(1) Standing $\dot{E} = 0.024*BW$

(ii)”Net metabolic cost of tasks:”

(2) “Stoop lift (Kcal/lift)”

“$\Delta E = 10\text{-}2 *[0.325*BW*(0.81-h1) + (1.41*L+0.76*S*L)(h2-h1)$ for $h1<h2\leq 0.81$”

(3) Walking (Kcal)

$\Delta E = 10\text{-}2 *(51+2.54*BW*V2 +0.379*BW*G*V)*t$

(4) “Holding at arms length, against thighs or at sides (both hands) (Kcal)”

$\Delta E = 0.037*L*t$

(5) “Pushing/pulling, at bench height (0.8 meter) (Kcal/push)”

$\Delta E = 102 * X*(0.112*BW +1.15*F+0.505*S*F)$

Where:

$\dot{E}$ = Metabolic rate (Kcal /min.)

ΔE = “Kcal for walking, carrying and holding. For all other tasks, units are Kcal/performance.”

BW = “Body weight(kg)”

F = “Average pushing/pulling force applied by hands (kg)”

G = “Grade of the walking surface (%)”

h1 = “Vertical height from floor (m); starting point for lift and end point for lower.”

h2 = “Vertical height from floor (m); starting point for lift and starting point for lower.”

L =”Weight of the load (kg)”

S =”Gender; 1 for males; 0 for females”

V =”Speed of walking(m/s)”

X =”Horizontal movement of work piece(m)”

t =”Time (minutes)”

After using required data for each equation, $\dot{E}$pos. (from equation 1) and ΔE (from equation 2 to 5) have been calculated. Then based on the equation, $\bar{\dot{E}}$ job is calculated using this equation:

$$\bar{\dot{E}}\,\text{job} = \frac{\sum_{i=1}^{ni} \dot{E}\text{pos}*\text{ti} + \sum_{i=1}^{n} \Delta E \text{ task i}}{T}$$

$\bar{\dot{E}}$ job = "Average energy expenditure rate of the job (Kcal/min)"

$\dot{E}$pos = "Metabolic energy expenditure rate due to maintenance of ith posture (kcal/min)"

Ti = "Time duration of ith posture(min)"

Ni = "Total number of body postures employed in the job"

ΔE task i = "Net metabolic energy expenditure of the ith task in steady state (Kcal)"

N = "Total number of tasks in the given job"

T = "Time duration of the job (min)"

Thus, the average metabolic rate of the job is calculated:

$$\bar{\dot{E}}\text{ job} = \frac{2.177*0.25+0.7304}{0.25}$$

$$= 5.098 \text{ Kcal/min.}$$

This value is quite close to previous value 5.28 Kcal/min that was calculated with software.

4 Conclusion

This study shows that the energy expenditure can be predicted for waste collection task by using software and prediction models. The results show that the difference between software output and prediction equation result is small and can be ignored. This predicted information can be useful for waste collection job design instead of using oxygen consumption measurement which takes long time and costly. Furthermore, these prediction approaches can be used for other practical applications. In this study, the demo version of the software has been used, that is why there are some limitations in entering gender and body weight to the software. Gender and body weight are set as male and 200 pounds respectively. Since all participants are male, only body weight might have had an effect on the results. Other assumptions based on limitations are also explained in result section. For future studies, these limitations and restriction should be considered and this study can be extended by using other software in literature to compare with each other, to get common result and to see advantages and disadvantages of individual software.

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