UHASSELT
KNOWLEDGE IN ACTION

Maastricht University

Faculty of Sciences

School for Information Technology

Master of Statistics and Data Science

Master's thesis

Design and statistical analysis of experiments for determining the standardized performance of solar cooking appliances

Abdulaziz Mwandu

Thesis presented in fulfillment of the requirements for the degree of Master of Statistics and Data Science, specialization Biostatistics

SUPERVISOR :
Prof. dr. Steven ABRAMS
Prof. dr. Luc BIJNENS

2023
2024

Faculty of Sciences
School for Information Technology

Master of Statistics and Data Science

Master's thesis

Design and statistical analysis of experiments for determining the standardized performance of solar cooking appliances

Abdulaziz Mwandu

Thesis presented in fulfillment of the requirements for the degree of Master of Statistics and Data Science, specialization Biostatistics

SUPERVISOR :

Prof. dr. Steven ABRAMS

Prof. dr. Luc BIJNENS

Acknowledgments

First and foremost, I am profoundly grateful to my Almighty Allah (S.W) for His infinite blessings, guidance, and strength throughout this journey. His grace has been my anchor, His wisdom my compass, and His love my constant source of inspiration and perseverance. Without His divine intervention and unwavering support, this achievement would not have been possible. To Him be all the glory and honour.

I am deeply grateful to my supervisors, Prof. Dr. Luc Bijnens, Prof. Dr. Steven Abrams, and Prof. Dr. Didier Kumwimba, for their continuous support, guidance, and encouragement throughout my master thesis. Their insightful feedback and constructive suggestions, plus the contributions from the students who made the Solar Cooker for All (SC4all) team, were invaluable to the completion of this thesis.

I would like to thank all the professors who taught me at Hasselt University for expanding my knowledge, understanding, and working ability throughout this master's period. I am also thankful to the VLIR-UOS for granting me an opportunity to study at Hasselt University and providing me with the facilities and funding that made my studies possible.

Moreover, I would like to thank my family, especially my mother, Mrs. Mwajuma Rashid, and my father, Mr. Mengi Mwandu, for supporting and believing in me throughout my life. Further gratitude to all lectures at the University of Dodoma, especially Dr. Fransis Mange, Dr. Abdallah Hussein, and Dr. Abbas Ismail, for highly encouraging me to study for a master's degree immediately after finishing my bachelor's degree.

Lastly, I am immensely grateful to my friend, Ms. Felista Kauki and other classmates for their unwavering support and encouragement throughout my studies. Their patience and understanding were vital to my success.

Thank you all for your support and encouragement.

Abdulaziz Mwandu
June 18, 2024
Genk, Belgium.

Abstract

Background: In 2021, it was estimated that around 2.3 billion people globally do not have access to clean cooking. These individuals mostly live in low- and middle-income countries. The use of wasteful fuels around the home produces household air pollution. Each year, 3.2 million people die prematurely from illnesses attributable to household air pollution. Utilising available and renewable energy resources at the local level seems like a more sustainable solution. Solar energy is one of the sources and a potential replacement for wood in a large portion of developing countries. Solar cookers are devices that use solar energy to cook foods and are a viable option for clean cooking anywhere people have access to sunshine.

Objectives: The study aimed to use the standardised protocol (PEP) to evaluate and compare the current set of solar cooker prototypes within the Sc4all project.

Methods and Materials: The data used in this project was collected in Belgium between July 2022 and July 2023 from 10 different prototypes. The outcome of interest was the standardised performance, and the regressors were temperature difference, plastic bags, and measure openings. Simple linear regression was used to assess the single measure of performance of each cooker separately, while multiple linear (mixed) regression was used to assess the performance of each cooker, controlling for the above-mentioned regressors.

Results: The results revealed that Yamo Dudo had the highest performance compared to all the cookers used in the study. For the locally made prototypes, Prototype 5 was performing much better compared to other prototypes. Moreover, it was shown that the use of plastic bags and different measuring openings had a significant impact on the prototypes' performances.

Conclusion: The performances of the cookers are not only explained by the temperature differences but also by the use of plastic bags and measuring openings. These factors should be considered when designing and conducting future experiments. The linear mixed regression is seen as the most promising approach to evaluating the contribution of different factors to the prototypes' performances, including random effects.

Keywords: *Solar Energy, Solar Cooker Prototypes, Performance Evaluation Process, Standardised Performance, Linear (Mixed) Regression.*

Contents

1 Introduction

1.1 Background of the study

In 2021, it was estimated around 2.3 billion people globally do not have access to clean cooking, they still cook with solid fuels like wood, crop waste, charcoal, coal and dung, and kerosene in inefficient stoves and open fires [1]. These individuals mostly live in low- and middle-income countries [2]. The availability of cleaner cooking options varies greatly between urban and rural places. In 2021, about 14% of urban people relied on dirty fuels and technology, whereas 49% of people worldwide lived in rural areas [2].

Each year, 3.2 million people die prematurely from illnesses attributable to household air pollution, whereby around 32%, 23%, 21%, 19%, and 6% are from ischaemic heart disease, stroke, lower respiratory infection, chronic obstructive pulmonary disease (COPD) and lung cancer respectively [2]. Additionally, it is projected that in 2030, roughly 1.9 billion people would continue to rely on polluting cooking fuels. Nearly six out of ten individuals who lack access to clean cooking in 2030 will live in Sub-Saharan Africa if current trends continue [1].

The use of wasteful and harmful fuels and technologies within and around the home produces household air pollution, which includes a variety of harmful pollutants that can harm one's health, such as tiny particles that can enter the bloodstream and dilate the lungs, where the exposure is high among women and children, who spend most time near the domestic hearth [3]. In many developing countries, the extensive use of biomass for cooking raises the strain on local deforestation and associated soil degradation [4]. Utilising available and renewable energy resources at the local level through appropriate designs of energy technologies seems a more sustainable solution [5]. Solar energy is one of the sources and a potential replacement for wood in a large portion of developing countries; solar cookers are thus considered as one of the possible options for solar energy exploitation [6].

A solar cooker is a device that collects and absorbs direct sunlight into a cooking pot, raising the temperature and allowing the food within to cook. The potential energy source for solar cookers is solar radiation which varies from hour to hour due to the position of the sun [7]. Solar cookers are a viable option for clean cooking anywhere people have access to sunshine. Unlike traditional cooking methods that rely on finite and harmful energy sources, solar cookers emit zero emissions and have a low environmental impact, ensuring environmental sustainability. By harvesting renewable solar energy, solar cookers contribute to minimising climate change and reducing dependence on fossil fuels, fostering a cleaner and more sustainable energy future [3]. Solar cookers use has the potential to alleviate shortages of fuel available for household use and are able to lessen environmental problems by reducing dependence on wood as a cooking fuel and promoting affordable and clean energy (Sustainable Development Goal 7) [8]. With the aid of Solar Cooker International (SCI), varieties of commercial solar cookers such as Rudra-SK14, Yamo Dudo, Parvati, SUNplicity, and PRINCE-40 were developed [9]. The cost of materials and process of construction of these cookers are high hence they are less affordable to people living in developing countries. Therefore, to achieve acceptability and motivate use, a variety of locally made solar cooker designs must be created where every design must be linked to specific climates, customs, and economic factors [8].

There are numerous designs of household-level solar cookers which can be categorized as box-type cookers, concentrating-type cookers, and non-focusing type cookers which form other types such as solar box ovens, reflective-panel solar cookers, parabolic reflectors, evacuated-tube solar cookers, and solar cookers based on Fresnel lenses or Fresnel mirrors [10].

The box type is the most popular type of solar cooker since it is convenient to use [8]. Various box prototypes were designed, particularly in the 1990s and early 2000s [11]. A solar box cooker consists of an insulated box and a transparent glass lid to reduce heat loss from within the box to the outside environment. In the solar box cooker, each component has a considerable influence on cooking power [12]. The box is equipped with reflective surfaces (mirrors) that reflect sunlight into it, providing a high level of solar radiation intensity, increasing the effectiveness of the box solar cooker and reducing cooking time [11]. The interior of the box is painted black to enhance sunlight absorption. This sort of cooker can reach temperatures of around 100 °C, allowing the food to be cooked by boiling [11]. In addition, they can retain food at a biologically safe temperature for up to 3 hours after sunset [11]. Heat retention is crucial in box-style cookers. Further, they are slow to heat up because the sun rays are not concentrated on the pot [7]. They perform well in conditions such as diffuse radiation, low wind speed, intermittent cloud cover, and low ambient temperatures [13].

Other types of cookers are concentrating cookers which use multidimensional mirrors, fresnel lenses, or parabolic concentrates. They are characterized by multiple planes or curved reflective surfaces [14]. A parabolic cooker is made up of parabolic reflectors that are supported by wood or metals, with a cooking pot at the cooker's focal point. The solar parabolic cooker reaches very high temperatures faster than the solar box type so they do not need to use transparent covers [5]. Since the irradiance is concentrated on the focal point, solar parabolic cookers require frequent manual azimuthal tracking which is not the case for solar box type [14].

Parabolic cookers can be locally made by covering an old satellite dish with mirror fragments pasted to the surface. The parabola is supported by a wooden frame mounted on wheels, allowing the reflector to move with the sun [5]. A metal should be used as a support to hold the pot at the focus point of the parabola. The pot may be put inside a transparent container made of glass or plastic bag to enhance the greenhouse effect and decrease further thermal losses [15]. The parabolic cooker should be adjusted to face the sun every 5 to 10 minutes, to retain the focal point on the bottom of the pot and avoid reflection leakages; otherwise, the pot will not get any power and the food will not cook properly [5].

Rocco et al. (2023) [5] found that parabolic cookers are not commonly used due to difficulty in local resources availability, affordability, and safety of use though they can be self-made by using the required materials such as old parabolas and large quantities of mirrors which might be not locally affordable in the surroundings. Also, the amount of wood and metals needed is much larger compared to the cookers of box types. Furthermore, the use of parabolic solar cookers may impose a high risk of burning and blindness to the users since the sun rays are highly concentrated and improper tracking may dangerously reflect sunrays on people and damage their eyes. That is why we need frequent tracking on this type of solar cooker [5].

In this study, several solar cooker prototypes were developed under the project called Solar Cooker for All (Sc4all). This is a multidisciplinary research and development line at the University of Lubumbashi (UniLu, DR Congo), in collaboration with Hasselt University (UHasselt, Belgium) which is supported by the Flemish Government (VLIR-UOS SI project number CD2023SIN371A104). The analyses will include 10 cookers, 6 locally-made cookers named Oven_Prototype 1, Oven_Prototype 2, Prototype2, Prototype3, Prototype4 and Prototype5, 3 commercial cookers named Brother, Fornelia and Yamo Dudo. The last cooker was named OnlyPot displayed in Figure 1, the black cooking pot exposed to sunlight which receives direct sunrays and is not supported by any reflective panels (mirrors), this was also made with the purpose of comparison.

Figure 1: *OnlyPot cooker exposed to the sun without plastic bag.*

Beginning with cookers developed locally; the Oven_Prototype 1 is a box-type oven with a metal frame coated in aluminum foil for reflection purposes and plastic glass covering the upper portion of the cooker. The Oven_Prototype 2 is a box-type device consisting of a metal frame encased in a paper box, with plastic glass covering the upper portion of the cooker and a spiegel and aluminum foil acting as reflective panels. Prototype 5 is the box-type made of wooden boxes, and soda cans which served as reflection panels where the interior part of the cooker was black polished to enhance the sun absorption. These box-type cookers are displayed in Figure 2.

Figure 2: *Oven_Prototype 1 (Left), Oven_Prototype 2 (middle), and Prototype 5 (right); all covered with plastic glass on top.*

Prototype 2 is the parabolic-type cooker which was made with a wire frame fully covered by aluminum foil while the stand holding the pot was made of soda cans. Prototype 3 is the improved version of Prototype 2 with a longer improved holder for the pot. Prototype 4 is the parabolic-type cooker which was made with a wire frame, partially covered by aluminum foil while the stand holding the pot was much longer than that of Prototype 2 made of soda cans which were joined by aluminum foil.

Figure 3: *Prototype 2 with the pot not covered by a plastic bag (left), and Prototype 2/3 with the pot covered by a plastic bag (right).*

Finalising with the commercial solar cookers, Yamo Dudo which is the parabolic-type cooker was made with highly concentrated mirrors for reflection and increasing performance. Fornelia was made with the evacuated tube which helps to maintain the heat loss to the surrounding and high-concentrating mirrors for reflection purposes, whereas the Brother cooker was made with reflective mirrors. Another purpose of these concentrating mirrors is to help the proper reflection of the sun rays to the cooking pot.

Figure 4: *Brother (left), Fornelia (middle), and Yamo Dudo (right) exposed without pots.*

To evaluate the performance of novel solar cooker designs, the American Society of Agricultural and Biological Engineers (ASABE) developed a standardized protocol, i.e., the

Performance Evaluation Process (PEP), which is also used by Solar Cooker International (SCI) for evaluation, assessment and implementation of new devices. More specifically, this protocol highlights how to test the thermal performance of solar cookers [14]. The statistical analysis proposed in the PEP is a simple linear regression approach for the standardized performance of a specific cooker as the main outcome variable. In Section 2, more detailed information regarding the proposed statistical methodology will be highlighted.

1.2 Objective of the study

In this master thesis, the primary objective is to study the use of the PEP for the evaluation of the current set of solar cooker prototypes within the Sc4all project. Moreover, the secondary objective is to evaluate the proposed methods given potential improvements towards the standardised assessment and comparison of solar cookers. Finally, discuss how to design and conduct new experiments with devices that enhance performance, create sustainable designs adopted for local needs in the DRC and other developing countries, and increase acceptability among households in resource-limited settings.

1.3 Research questions

Primary research question

- What is the best solar cooker (locally made) compared to the commercial one in terms of standardised performance?

Secondary research question

- What is the effect of experimental setting on the performance of the prototypes, i.e., wind speed, plastic bags, and opening size of the lid (measure opening)?
- What are the crucial factors to consider when calculating the optimal sample size required for the improved prototypes?

The structure of the master thesis is as follows. Firstly, Section 2 is materials and methods; the details regarding the methods used to analyse the solar cooker data, and the standard testing procedure and performance evaluation process (PEP) are provided. In Section 3, the results of the data analysis are presented, and different models are compared to the extension of a sensitivity analysis. Section 4 discusses the main results, limitations and recommendations. Finally, Section 5 contains the conclusion, ethical consideration and stakeholder awareness.

2 Methods and Materials

2.1 Data Description

The data used in this project was gathered in Belgium between July 2022 and July 2023. A total of 19 different test dates were used to gather data from 10 cookers (see Section 1), resulting in a data set with 673 observations which contained 1 missing value. Further, the data set contained a total of 25 variables where the outcome variable (Standardized Performance) was calculated from several variables collected during the experiments i.e. Irradiation (W/m^2), water temperature (°C), mass (kg) and specific heat capacity of water (J/[kg·°C]), and time (*seconds*) [14]. Apart from those mentioned variables, other factors which might influence the performance of the cookers such as wind speed which was measured in the continuous scale of m/s, ambient temperature measured in the continuous scale of °C, testing date and location (latitude and longitude), the hole size on a lid of the pot (measure opening) measured in categories of ($2mm, 4mm$ and $10mm$), type of reflective materials, and the presence of plastic bags measured in categories of open or closed. An anemometer, pyranometer, and digital thermometer were among the several set instruments needed to collect data for the aforementioned variables. The digital thermometer was used to measure the temperature of the water inside the pot, the pyranometer was used for measuring the solar irradiance and an anemometer was used to measure the wind speed as well as ambient temperature. Figure 5 shows pictures of the anemometer, pyranometer, and digital thermometer from left to right.

Figure 5: *An anemometer (left), Pyranometer (middle), and Digital Thermometer (right) with readings of wind speed and ambient temperature, solar irradiance, and water temperature respectively.*

2.2 Testing Procedures

ASABE provided a clear description of evaluating the standardised performance of solar cooker devices by starting with the recording procedure, calculation of cooking (standardised) power, averages, temperature differences, and conditions to consider while testing.

Beginning with the recording part, it was proposed that the average water temperature (°C) of all cooking pots in a single cooker must be recorded every 10 minutes and should be in Celsius units to the nearest one-tenth of a degree. The record of solar insolation (W/m^2), ambient temperature (°C), and wind speed (m/s) at no more than ten-minute intervals have to be noted. Also, the test site's elevation, latitude, and testing dates should be reported [14].

The cooking power of the cooker should be calculated by using the change in water temperature for each non-overlapping ten-minute interval which was then multiplied by the mass and specific heat capacity of the water contained in the cooking vessels. This product should be divided by the 600 seconds contained in a ten-minute interval [14]. This results in the definition of the cooking power P_i for interval i measured in Watts, i.e.,

$$P_i = \frac{(T_2 - T_1)MC_v}{600} \tag{1}$$

where, T_1 is the initial water temperature (°C), T_2 is the final water temperature after 10 min (°C), M is the mass of water (kg), and C_v is the specific heat capacity of water which is constant (4186 J/[kg·°C]).

Further, a re-scaling of the cooking power for each interval should be corrected to a standard insolation of 700 W/m^2 by multiplying the interval observed cooking power (P_i) by 700 W/m^2 and dividing it by the interval average insolation recorded during the corresponding interval (I_i);

$$Ps = \frac{P_i * 700}{I_i} \tag{2}$$

where, Ps is the standardised cooking power measure in Watts, I_i is the interval average solar insolation (W/m^2) which is used as the normalization to scale the results to the amount of its power that is available during the day [14].

The calculation of interval averages of insolation, average ambient temperature, and average cooking vessel contents temperature were supposed to be calculated for each 10-minute interval. Additionally, the temperature difference which is the main regressor in PEP should be calculated by subtracting the ambient temperature for each interval from the average cooking vessel contents temperature for each corresponding interval:

$$Td = T_w - T_a \tag{3}$$

where, Td is the temperature difference (°C), T_w is the average water temperature (°C) and T_a is the ambient air temperature (°C) for every 10 minutes interval [14].

Furthermore, these variables were required to meet several conditions as described in the protocol such as the tests were supposed to be undertaken when the average wind speed was less than $1.0m/s$ at the cooker's elevation and within ten metres and if the wind speed exceeded $2.5m/s$ for more than ten minutes, the test data were supposed to be deleted. Ambient temperatures were supposed to be between 20°C and 35°C. The variation in measured insolation greater than $100W/m^2$ during a ten-minute interval or readings below $450W/m^2$ or above $1100W/m^2$ during the test was marked as invalid [14]. Conditions put in place in the protocol prevent the use of all data, hence, from a statistical efficiency point of view we would like to keep as much of the data as possible.

As a substitute for the PEP-provided conditions, a sensitivity analysis was also been carried out to measure the effect of deviating from the protocol specifications and to enable the utilisation of all data for the evaluation of the standardised performance of the various prototypes.

Regarding the guidance given by the PEP, the relationship between the outcome variable which is the standardized performance (Ps) and its main regressor which is the temperature difference (Td) should be assessed by using simple linear regression [14]. From the regression model, the single measure of the performance should be determined for a Td of 50°C [14]. It was hypothesised that the performance of the cookers is also affected by other factors such as wind speed, the greenhouse effect (use of plastic bags), and also the measure openings. Therefore, as an alternative to the simple linear regression approach, it was advocated that the aforementioned factors could be included in a multiple linear (mixed) model to study their impact on cooking performance.

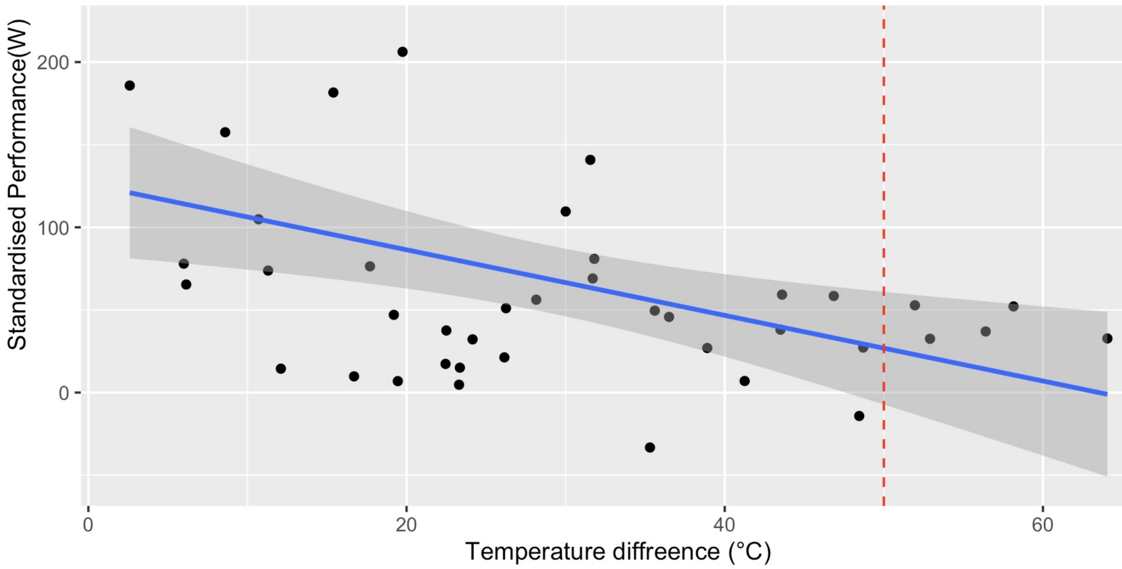

Figure 6: *Example of standardised cooking power plotted against temperature difference resulting to a regression line,* $P_s = 126.0976 - 1.9852Td$ *and the standardised performance = 26.84W [16]. The negative relationship is highly expected because a device takes more energy to heat up the cooking pot further when there is already a large temperature difference between the surroundings and the pot, this means that more energy is needed to achieve the same increase in temperature with larger differences in relation to outside temperature.*

2.3 Statistical Models

This section describes the statistical approaches used in performing data analysis in this study. The standardised performance is measured on a continuous scale, and so is the temperature difference. As described in section 2.2 on the use of simple linear regression to assess the relationship between the performance (Ps) and the temperature difference (Td), so this will be the first statistical model to be described. Since simple linear regression allows the presence of only one covariate (Td) as the predictor of the performance, to allow the correction of other factors that may contribute to the performance of the cookers, there is a need to use other extended statistical models, such as multiple linear regression. Additionally, due to the fact that the data were collected from 19 different days, there are potential unmeasured variables, i.e., clouds, that could differ between different test dates, thereby leading to association in the data. To take that into account, a more complex model, i.e., a linear mixed model, will be employed. This model will help to account for variability that may be brought by differences in those between different days on the same cooker as random effects [17].

2.3.1 Simple linear regression

Simple linear regression is a statistical method used to model a linear relationship between a single predictor variable and a continuous outcome [18]. It estimates the relationship between a continuous response variable, and a single explanatory variable, given a set of data that includes observations for both of these variables for a particular sample [19]. The equation for the regression line takes the form:

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \tag{4}$$

for $i = 1, \ldots, n$, with n number of observations. β_0 is the constant called the *intercept*, i.e., the intersection of the linear regression line with the y-axis. This is the point when the line crosses the $x - axis$ of the graph [18]. β_1 is the slope of the line, it expresses how much the value of the outcome variable (y) increases, for a one-unit increase in the independent variable (x) [19]. ϵ_i is the error term for the observation i, it quantifies the amount by which the predicted value is different to the actual value, i.e., ϵ_i $i.i.d.$ $N(0, \sigma^2)$ [19].

The method of least squares is commonly used to determine the estimates of β_0 and β_1 as $\hat{\beta_0}$ and $\hat{\beta_1}$, respectively [18]. Therefore, for given estimates $\hat{\beta_0}$ and $\hat{\beta_1}$, the estimated regression line is given by:

$$\hat{y_i} = \hat{\beta_0} + \hat{\beta_1} x_i \tag{5}$$

with i=1. . . ,n; where $\hat{\beta_0}$ and $\hat{\beta_1}$ is the estimated y-intercept and slope respectively. These parameters can be directly estimated by using the formula:

$$\hat{\beta_1} = \sum_{i=1}^{n} \frac{(y_i - \overline{y})(x_i - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \quad ; \quad \hat{\beta_0} = \overline{y} - \hat{\beta_1}\overline{x}. \tag{6}$$

As shown in equation 6, $\overline{x}$ and $\overline{y}$ are the sample means of predictor (x) and outcome (y) consecutively.

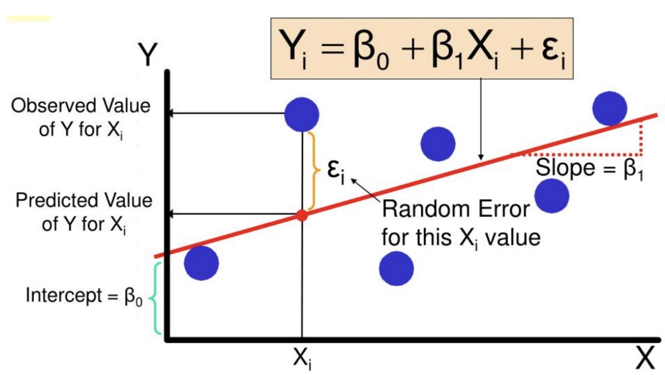

Figure 7: *Linear regression line visualising slope, y-intercept and error term.*

As mentioned in the previous sections, in this study the simple linear regression will be used to assess the performance of each cooker separately.

$$\hat{P}s = \hat{\beta}_0 + \hat{\beta}_1 Td \tag{7}$$

where $\hat{\beta}_0$ represents the performance of the cooker when the average water temperature is equal to the average ambient temperature ($Td = 0$). $\hat{\beta}_1$ represents how much the performance ($\hat{P}s$) increases by average, for a one-unit increase in the temperature difference (Td). Additionally, from the regression model in equation 7, the single measure of the performance for a given cooker $\hat{P}s$ will be determined at Td of 50°C (see Figure 6).

Finally, when fitting the linear regression model to all data, multiple linear regression with full interaction between Td and all cookers to allow for different starting points and slopes for the cooker-specific regression lines will be considered. Hence, although formulated as a simple linear regression model, in fact, the combined analysis (which corresponds to a stratified analysis by cooker anyway), refers to a multiple linear regression approach.

2.3.2 Multiple Linear regression

Multiple Linear regression (MLR) is a statistical technique used to model the relationship between a continuous outcome variable and two or more explanatory variables [20]. This is an extension of simple linear regression with more than one explanatory variable which is used to understand how the outcome variable changes when any one of the explanatory variables is varying while others are held fixed [21].

$$Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \epsilon_i \tag{8}$$

for $i \in \{1,\ldots,\text{n}\}$ and where x_{ik} is referring to the value of explanatory variable k for observation i, and ϵ_i $i.i.d.$ $N(0, \sigma^2)$. β_0, is the constant which will be the predicted value of the outcome variable when all explanatory variables are 0, and in this model with k explanatory variables, each explanatory variable has its own β coefficient [19]. The form of this model is seen only to contain the main effects (additive model), but it can also be modified to encompass the interaction effects of the variables [21]. The modified version of equation 7, which contains other variables, can be expressed below as follows:

$$\hat{P}s_i = \hat{\beta}_0 + \hat{\beta}_1 Td_i + \sum_{k=2}^{11} \hat{\beta}_k Cooker_i + \hat{\beta}_{12} Wind + \hat{\beta}_{13} Plasticbag_i + \hat{\beta}_{14} MeasureOpening_i \tag{9}$$

for $i = 1, \ldots, n$; where $\hat{\beta}_0$ and $\hat{\beta}_{1,\ldots,14}$ represent the intercept and parameter estimates of the model, respectively. $Wind$ represents the continuous value of wind speed. $Cooker$ represents the dummy variables for Cookers, i.e., i=0 for the Yamo Dudo cooker and i=1 for other types of cooker, $Plasticbag$ represents the dummy variable for the plastic bag presence, i.e., i=1 for the presence of a plastic bag and i=0 for no plastic bag. $MeasureOpening$ represents the dummy variable for the size of the hole size on the lid of the pot, i.e., i =1 for=10mm and $i = 0$ for 4mm. This model can be further extended to account for interaction effects.

2.3.3 Model Assumptions

The validity and reliability of the results of multiple linear regression analyses are guaranteed by several underlying assumptions. Comprehending and validating these presumptions is essential for precise model interpretation and prediction [22]. These assumptions are Linearity, normality of the error term, Constant error variance, Independence of the error term, and Multicollinearity [21].

The linearity assumption: This is a core premise of multiple linear regression which explains the existence of a linear relationship between the outcome variable and the explanatory variables [22]. This linearity can be visually inspected by using scatter plots of residuals against explanatory variables, and these plots should not show any systematic pattern to validate the assumption [21].

The normality of the error term: The MLR model implies that $\epsilon_i = Y_i - m(x_i;\beta) \mid x_i$ where $m(x_i;\beta)$ is the systematic part of the model, so to some extent residuals $e_i = y_i - m(x_i;\hat{\beta})$ can be considered as an estimate of ϵ_i, therefore the combination of residuals and normal QQ-plots will be used to assess the normality assumption [21]. The majority of the points in the QQ-plot should be close to the straight line with no systematic pattern; however, keep in mind that for large data sets, the central limit theorem tells us that the parameter estimators will be approximately normally distributed due to the relatively large sample size, so the normality assumption is not as relevant [21].

Constant error variance (Homoscedasticity); The MLR model implies that $Var(\epsilon_i) = Var(\epsilon_i \mid x_i) = Var(Y_i \mid x_i) = \sigma^2$, meaning that the variance of the outcome (and error term) is constant and does not depend on the values of the regressors [21]. The scatter plots of absolute or square residuals against regressors will be used to assess the homoskedasticity assumption, and to validate it, the plots should not show any systematic pattern [21].

Independence: This assumes that the residuals are independent. This assumption is mostly relevant when working with time series time data or data collected from different groups [23]. It requires that observations be non-informative about the next observation's error hence the observations of the outcome variables should be independent, and if they are not independent then more complex models such as linear mixed models should be employed to account for the correlation structure in the model [24]

Multicollinearity; The explanatory variables must not be too highly correlated with each other, and this can be checked using Variance Inflation Factors (VIF) [22]. The VIF value 1 means no multicollinearity; above 5 indicates that multicollinearity may be present; and above 10 indicates problematic multicollinearity [22]. The solutions may include centring the data (subtracting the mean score from each observation) or removing the variables causing multicollinearity [21].

Furthermore, when evaluating the assumptions of linearity, normality, and homoskedasticity, the residual plots will reveal any indications of outlying observations. For instance, the heavy tails in the QQ-plot indicate the presence of outlying observations, and the points with extremely high residual values in the other residual plots also support this indication. To be more confident with the detection of outlying and influential observations, several statistical approaches like Cook's distance, leverage, and standardised DFBeta will be used [21]. These approaches will be well explained in Section 2.4.

2.3.4 Linear Mixed regression

This is the extension of multiple linear regression with random effects (or factors) [17]. A random effect (or factor) is a quantitative (or qualitative) variable whose levels are randomly sampled from a population of levels being studied [25]. When continuous (normally distributed) hierarchical data are considered (clustered data), a general, and very flexible, class of parametric covariance models is obtained by introducing random effects $\boldsymbol{b_i}$ in the multivariate linear regression model [26]. Linear mixed models assume the outcome vector $\boldsymbol{Y_i}$ follows a multivariate normal distribution, with mean vector $X_i\boldsymbol{\beta} + Z_i\boldsymbol{b_i}$ and covariance matrix Σ_i, and assume that the random effects $\boldsymbol{b_i}$ also follow a (multivariate) normal distribution [26]. It is assumed that the n_i-dimensional random vector $\boldsymbol{Y_i}$ satisfies:

$$\boldsymbol{Y_i} \mid \boldsymbol{b_i} \sim N(X_i\boldsymbol{\beta} + Z_i\boldsymbol{b_i}, \Sigma_i) \quad ; \quad b_i \sim N(\mathbf{0}, D), \tag{10}$$

where X_i and Z_i are $(n_i \times p)$ and $(n_i \times q)$ dimensional matrices of known covariates, respectively, $\boldsymbol{\beta}$ is a p-dimensional vector of regression parameters known as fixed effects, D is a $(q \times q)$ covariance matrix, and Σ_i is a $(n_i \times n_i)$ covariance matrix that depends on i only through its dimension n_i, i.e., the set of unknown parameters in Σ_i will not depend upon i, and $\mathrm{E}(\boldsymbol{b_i} = \mathbf{0})$ implies that the mean of $\boldsymbol{Y_i}$ still equals $X_i\boldsymbol{\beta}$, such that the fixed effects in the random effects model in equation 13 can also be interpreted marginally [26].

Since the data were gathered over 19 distinct days, as detailed in Section 2.1, it is expected that these measurements may vary as a result of several unknown factors, such as different raters may have different learning curves, clouds etc. These factors will add additional sources of variability, which the regression model should account for by including a random factor called TestDate. Additionally, it will be presumed that measurements taken on the same day had less variability and that measurements done on separate days would have more variability because of the characteristics that are present on the same day. Therefore, the regression model contains the random factor TestDate can be described as follows:

$$
\begin{aligned}
Ps_{it} = \beta_0 + b_t + \beta_1 Td_i + \sum_{k=2}^{11} \beta_k Cooker_i + \beta_{12} Wind_i + \beta_{13} Plasticbag_i \\
+ \beta_{14} MeasureOpenning_i + \epsilon_{it}
\end{aligned}
\tag{11}
$$

for $i = 1, \ldots, n$; where b_t is the random factor for $TestDate \sim N(0, \sigma^2_{TestDate})$ expressing the variability between different TestDates while ϵ_{it} is the error term $i.i.d$ $N(0, \sigma^2_{res})$ expressing the variability within the same TestDate [27]. These b_t and ϵ_{it} are independent; therefore, the total variability of the mixed model is equal to the sum of between variability ($\sigma^2_{TestDate}$) and within variability (σ^2_{res}) [27]. Additionally, the measurements from different test days are assumed to be independent, while the observations from the same test days are correlated with the correlation coefficient given by:

$$
\text{Intraclass correlation } (\rho) = \frac{\sigma^2_{TestDate}}{\sigma^2_{TestDate} + \sigma^2_{res}} \tag{12}
$$

2.3.5 Model Building

This is the process of selecting a final set of regressors based on the sample data, and the resulting model can be used to answer the original research questions [21]. Since this study is highly focused on answering the research questions, i.e., the effects of wind, plastic bags, and measure-opening on the performance of the cookers, there will be no need to select the variables but to check for potential (significant) interactions that will help to answer the research questions and improve the model fit [21]. The Likelihood Ratio Test (LRT), Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC) will be used to lead this process of finding the best model among a set of candidate models.

Since this is an exploratory study, flexible approaches to design and analysis are often necessary for it. Multiple test adjustments are not technically necessary for exploratory studies because data were collected with the goals outlined in the study objectives [28]. Therefore, no multiplicity correction will be done throughout the analyses of this study.

When evaluating the interaction of plastic bags (or measure-opening) and cookers, it is possible that an imbalance in the data in the categorical variables will cause a problem in the estimation of the parameter estimates. To address this issue, the interactions will only be evaluated using the combination of cookers and other categorical variables with sufficient data.

2.4 Outliers and Sensitivity Analysis

Cook's distance: It quantifies the difference between all regression coefficient estimates obtained together while fitting the model with and without a given observation [29]. There is no objective cutoff value above which a Cook's distance is considered "large", instead look for observations with Cook's distances that are much larger than those of the other observations [30].

Leverage: It measures how far an observation's predictors, taken together, are from those of other observations [31]. Observations with large leverage have high leverage and are potentially (but not necessarily) influential. The leverage value is not objectively deemed "large" above a certain threshold; rather, one has to check for observations that have hat values significantly greater than those of the remaining observations [30].

Standardised DFBetas: Is the standardised difference in individual regression coefficient estimates when fitting the model with and without that observation, providing a measure of influence on each coefficient [30]. The standardised DFBetas can be compared to a threshold, and 0.2 is recommended as a suitable threshold [32].

Sensitivity analysis: The aim of performing the sensitivity analysis is to compare the conclusions between the analysis carried out and another analysis in which there were changes in some aspects of the methodology [30]. This method can be used to assess the sensitivity of the regression results (e.g., parameter estimates, 95% confidence intervals, p-values) to changes in the new approach. When presenting sensitivity analysis results, there may be quantitative or qualitative differences in the findings. A quantitative difference affects the strength of conclusions but may or may not affect the nature of the conclusions themselves [31]. Assume that a regression coefficient estimate is meaningfully large and points in the same direction in both cases, but its magnitude differs significantly between the approaches; this is an example of a quantitative difference [30]. A qualitative difference affects the nature of the conclusions, i.e., when comparing two approaches, the association might change in direction or change from meaningfully large to close to no association, or vice versa [31]. A change in statistical significance is also termed a qualitative difference, in that it affects conclusions based on a strict p-value cutoff [30].

As mentioned in Section 2.2, the observations that have to be used in the analysis should meet the conditions that were provided in PEP; therefore, the first approach of the regression analysis will be to follow the protocol conditions, test the assumptions, identify and report the influential (not necessarily) observations. The last approach will be to use all the observations that were collected in the regression analysis and compare these new results with the results that were obtained when following the protocol to see the impact of shifting away from the protocol guidance.

Software

The statistical software that has been used in the analyses of this study is R Version 4.3.2 [33].

3 Results

3.1 Exploratory data analysis

In this section, figures and tables were used to get a preliminary insight into the distribution of the variables collected in the dataset. Figure 8 presents the scatter plots that describe how the levels of irradiation and wind speed change over time. Regarding the condition of the variables explained in Section 2.2, it is seen that only three observations exceeded the recommended wind speed ($2.5m/s$), and other observations in the irradiation variable were below the recommended level ($<450W/m^2$). These observations that are outside of the recommended intervals (blue dots) will be removed and remain with those that meet the protocol conditions except for sensitivity analysis.

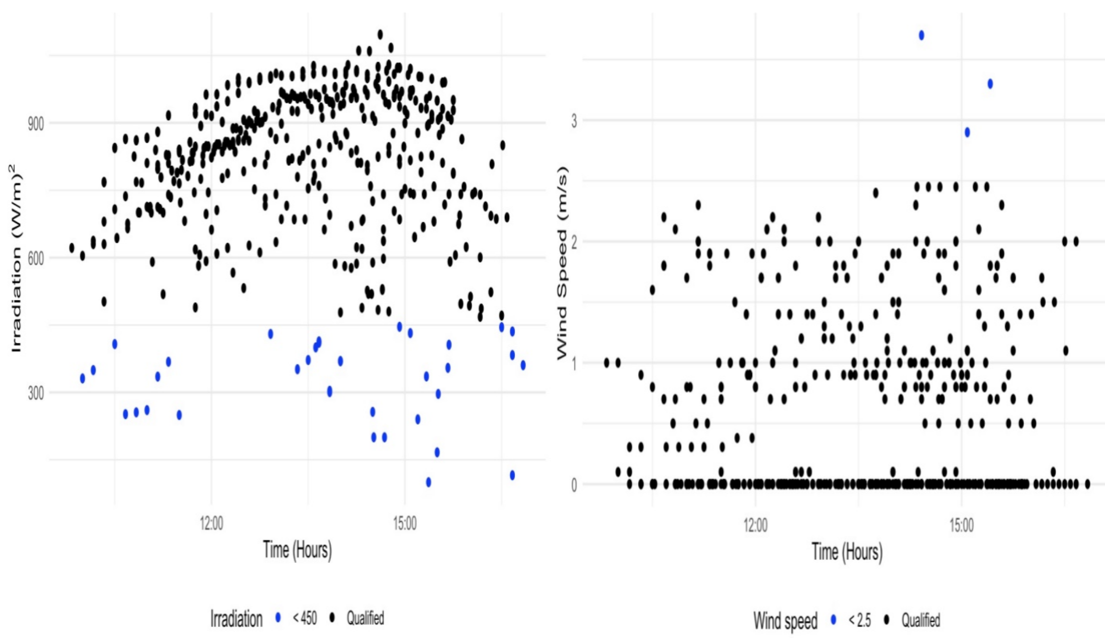

Figure 8: *Visualising the distribution of irradiation (left) and wind speed (right) on the data where some observations in both plots are seen to be out of the PEP-provided conditions (blue dots).*

Additionally, to explore how irradiation and ambient temperature influence the change of water temperature in the pots, the scatter plots in Figure 9 describe so. It is seen that there is a positive effect of irradiation and ambient temperature on increasing the water temperature, i.e., generally, the increase in irradiation and ambient temperature increases the temperature of the water inside the pots. The scatter plot of ambient temperature on the right indicates that several observations fall outside (red dots) of the recommended range, which is between 20°C and 35°C. As a result, these observations (red dots) will also be eliminated from the analysis except in sensitivity analysis.

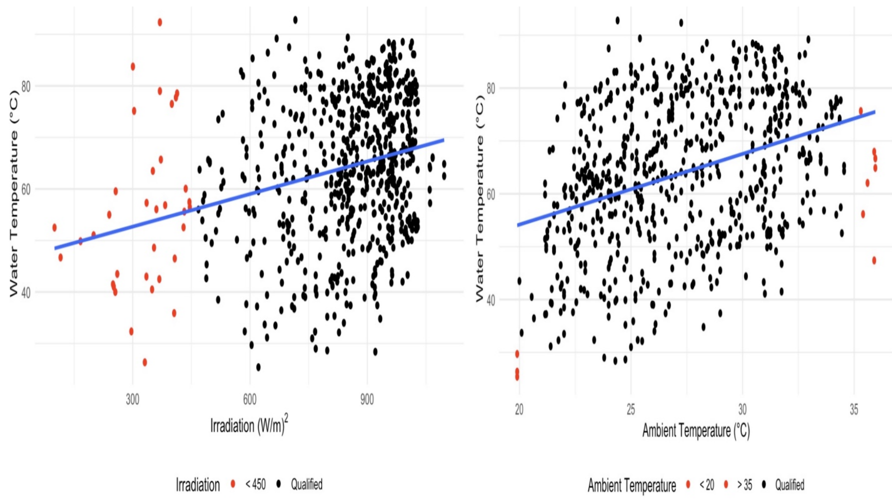

Figure 9: *Visualising the relationship between Water temperature and Irradiation/Ambient temperature on the whole data. The plots depict the positive relationship between these water temperatures and irradiation/ambient temperature. The red dots present the observations that did not meet the protocol conditions.*

Table 1 describes the distribution of the observations in the categorical variables cookers, plastic bags, and measure opening. It is revealed that there is a high data imbalance in these variables, i.e., all observations from prototypes 4, 3, and 5, Oven_prototype 1 and 2, and Fornelia were falling to only one level of the plastic bag and also of measure opening (Fornelia had its measure opening of $2mm$ which is not seen in the table). In general Prototype 5, Prototype 3 and Oven_Prototype 1 cookers had very low frequencies. As described in Section 2, the interactions of these variables will only be assessed at the levels with sufficient observations.

Table 1: *Distribution of the number of observations across cookers separately for the presence of plastic bag and different measure openings (i.e., 4mm and 10mm), where the last three prototypes show very low frequencies, and generally describe high data imbalance.*

Cookers	**Plastic bag**		**Measure opening**		**Total**
	Yes	**No**	**4mm**	**10mm**	
Brother	75	69	71	73	144
Prototype 4	89	0	46	43	89
Onlypot	43	41	75	9	86
Oven_Prototype 2	52	0	52	0	52
Prototype 2	45	0	4	41	45
Yamo Dudo	6	39	40	5	45
Fornelia	0	16	0	0	16
Prototype 5	7	0	0	7	7
Prototype 3	8	0	0	8	8
Oven_Prototype 1	0	9	0	9	9

3.2 Single Measure of Performance.

This section describes the results obtained after evaluating the standardised performance of the cookers as instructed in the PEP (see Section 2.3). Table 5 shows the results of point estimates and corresponding 95% confidence intervals for the model parameters of the standardised performance (at Td=50°C). The cookers are sorted from highest to lowest estimated standardised performance. The results reveal that Yamo Dudo was the best cooker with an average standardised performance of 152.67W with a 95% confidence interval ranging from 123.15W to 182.19W. Among the locally made cookers, Prototype 5 was performing much better compared to all others. It had an average standardised performance of 33.71 W with a 95% confidence interval ranging from 33.88 W and 49.35 W. The following locally made cookers were Prototype 3, Prototype 4, Oven_Prototype 2, Prototype 2, and Oven_Prototype 1 with average standardised performance values of 10.90 W [-0.45 W, 22.26 W], 10.33 W [6.21 W, 14.35 W], 2.99 W [-1.20 W, 7.18 W], 0.40 W [-6.88 W, 7.69 W], and -11.60 W [-28.16 W, 4.49 W], respectively. The average standardised performance of other commercial cookers such as Fornelia and Brother were 41.61 W [33.88 W, 49.35 W] and 3.49 W [-1.29 W, 8.26 W] respectively. The worst cooker was OnlyPot, with an average standardised performance of -13.84W with a 95% confidence interval ranging from -20.83W to -6.85W. Generally, a negative standardised performance seen in Oven_Prototype 1 and OnlyPot means that these cookers were performing so badly because they were losing larger amounts of heat than what was coming in the pot. They were cooling down instead of warming up the water inside the pot.

Table 2: *Results of Single measure of performance (Watts) sorted from the highest to the lowest performed cookers.*

Cooker	**Standardised Performance**	**95%-CI**	
		Lower	**Upper**
Yamo Dudo	152.67	123.15	182.19
Fornelia	41.61	33.88	49.35
Prototype 5	33.71	-0.40	67.82
Prototype 3	10.90	-0.45	22.26
Prototype 4	10.33	6.21	14.45
Brother	3.49	-1.29	8.26
Oven_Prototype 2	2.99	-1.20	7.18
Prototype 2	0.40	-6.88	7.69
Oven_Prototype 1	-11.60	-28.16	4.94
Onlypot	-13.84	-20.83	-6.85

Figures 10, 11, and 12 provide a clear visual representation of the relationship between the standardised performance and the temperature difference of cookers based on their respective categories, and the red line depicts the temperature difference of 50°C. Figure 10 presents commercial cookers, and it is visualised that for Yamo Dudo and Brother cookers, there is a negative relationship between temperature difference and performance, which means the increase in temperature difference reduces the performance of these cookers, i.e., the higher the temperature difference, the more heat loss from the pot to the surrounding area since it takes more energy to heat up the cooking pot further when there is already a large temperature difference between the surroundings and the pot. Unlike Fornelia, which exhibits a very slight positive relationship, meaning that it can maintain the amount of heat loss from the pot to the surroundings even at higher temperatures. This is also explained by the physical structure of Fornelia that, food is cooked in the evacuated tube (see Figure 4).

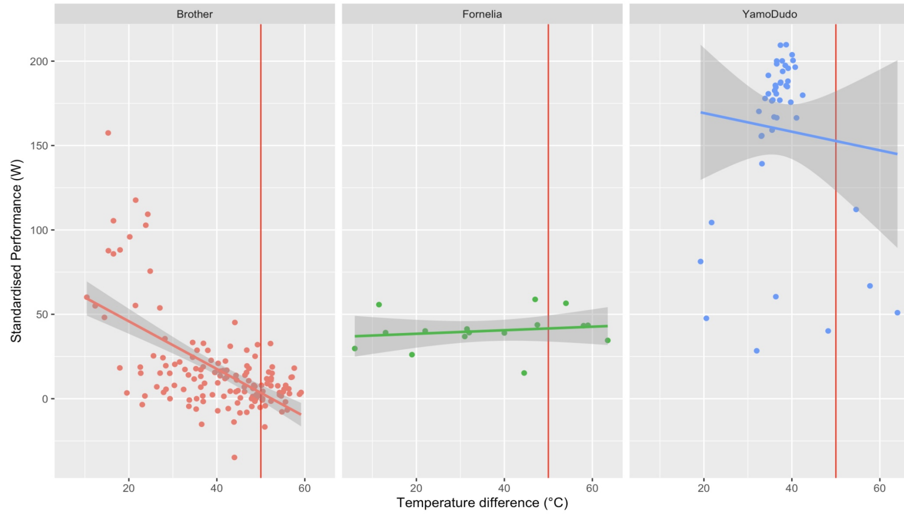

Figure 10: *Visualising the relationship between performance and temperature difference in commercial cookers, where Fornelia shows almost zero slope for temperature difference while other cookers show the negative relationship.*

Figure 11 presents box-type locally made cookers, and it is visualised that there is a negative relationship between these cookers' performance and the temperature difference, meaning that a higher temperature difference results in more heat loss from the pot to the surrounding area.

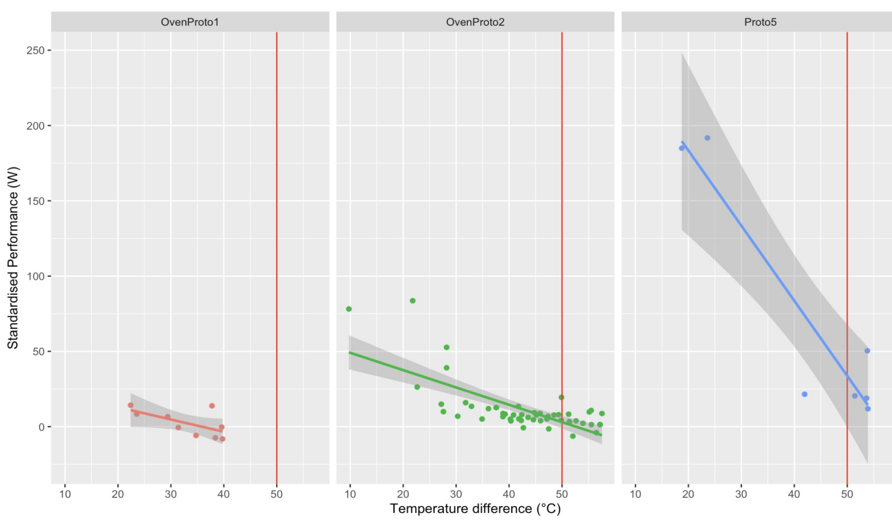

Figure 11: *Visualising the relationship between performance and temperature difference in box-type cookers, where it is seen that Oven_Prototype 1 and Prototype 5 had a very few frequencies.*

In parabolic locally-made cookers, the situation is the same as that in box-type locally-made cookers. A negative relationship is shown between the temperature difference and the performance of these locally made parabolic cookers (Figure 12), indicating that higher temperature differences lead to more heat escape from the pot to the surroundings.

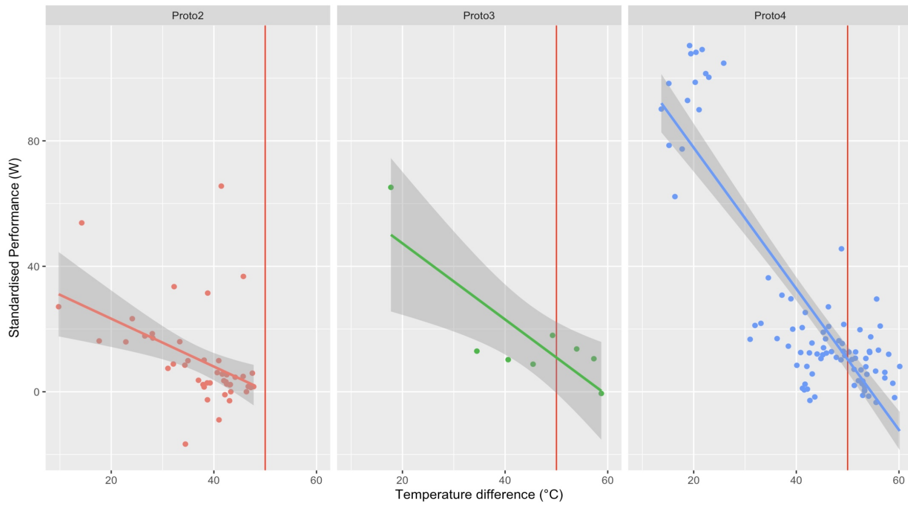

Figure 12: *Visualising the relationship between performance and temperature difference in parabolic-type cookers, where it is seen that Prototype 3 has a very low number of observations.*

3.3 Results of Multiple Linear regression

This section explains the assessment of the MLR model assumptions, the results obtained from the MLR, contrasts, and predictions (estimations) of the standardised performance of cookers.

3.3.1 Model Building Process

Table 3 shows the results of the model-building exercise. This was done to select appropriate interactions starting with the model which included all pairwise necessary for answering the research question, i.e., the interactions of plastic bags/Measure Opening/Temperature Difference and the Cookers. The first model showed no interaction effect of the plastic bag and cookers (OnlyPot and Brother) with the -2loglikelihood, AIC, and BIC of 4279.40, 4333.48, and 4446.34, respectively, so this interaction was removed. The 2^{nd} model resulted in the -2loglikelihood, AIC, and BIC values of 4280.40, 4332.51, and 4441.19, respectively. The results from the likelihood ratio test favoured the 2^{nd} model (p-value = 0.3101 >0.05), with the support of the smaller AIC and BIC values.

Table 3: *Results of Model Building showing steps taken to reach the final model which had the smallest AIC and BIC values, and insignificant p-value supporting its selection as the best among all candidate models.*

Model	**df**	**-2logL**	p-**value**	**AIC**	**BIC**
1	-	4279.40	-	4333.48	4446.34
2	2	4280.40	0.3101	4332.51	4441.19

3.3.2 Model Assumptions

The MLR assumptions were tested in the final model based on the model-building exercise. Figure A1 in the Appendix is a QQ plot showing theoretical quantiles under normality and sample quantiles for the residuals. It is visualised that the majority of the points in the QQ-plot were close to a straight line with no systematic pattern, although there is also an indication of outlying observations described by heavy tails.

Figure A2 in the Appendix presents the scatter plot and the box plot of residuals against regressors (temperature difference on the left and cookers on the right). Based on the visualisation of the pattern of the residuals from both plots, there was no suggestion of any systematic pattern of the residuals, hence the validation of the Linearity assumption. In addition, both plots also showed the presence of residuals with high values, which was an indication of outlying (not necessarily influential) observations.

Moreover, the constant error variance (homoscedasticity) assumption was assessed by using the scatter plot of absolute residuals against temperature difference and the box plot of absolute residuals against cookers as shown in the Appendix figure A3. There was no systematic pattern in the residuals that were observed from both plots, which validated the homoscedasticity assumption. Further, residuals with very large values were noticed from both plots, which was also an indication of outlying (not necessarily influential) observations.

Table A3 in the Appendix presents the results of the Variance Inflation Factors (VIF) which was used to assess the multicollinearity assumption. The maximum value of VIF was observed in the parameter temperature difference, 5.46, meaning that the variance of the temperature difference was 5.46 times larger than if there was no multicollinearity, indicating moderate multicollinearity. Since the maximum value observed did not indicate severe multicollinearity problems, no remedial measures were taken.

Finally, when assessing the normality, linearity, and homoscedasticity assumptions, there were indications of outlying observations. Essentially, what is observed is that these values are extreme, though that does not necessarily mean they are also influential. By using influence statistics like Cook's distance, leverage, and DFbeta, these observations will be studied to determine whether they exhibit a strong impact on the model results or not.

3.3.3 Model Results

Table A1 in the Appendix shows the results of the fitted model. Since the interaction effects were significant, the interpretation will focus on those interactions rather than the main effects [21]. The results reveal that there is a significant interaction effect of the presence of plastic bags and measure openings (p-value=0.0035 <0.05), and the positive value indicates that its combination has a positive effect on the cookers' performance. The interactions of the temperature difference and cookers revealed that the effect temperature differences are significantly different in Brother, Prototype 4, and Prototype 5 (values -1.15, -1.65W, and -4.37W, respectively; p-values < 0.05) compared to Yamo Dudo. Negative values indicated that, when compared to Yamo Dudo, there was a higher negative effect on these cookers' performance for every unit increase in temperature difference. Therefore, it can be inferred that the type of cooker being used affects the impact of temperature differences on average performance. Lastly, there were significant interaction effects of measure opening and certain cookers (Brother, OnlyPot, and Prototype 4, p-values<0.05). These interactions indicated that these cookers' performances are significantly affected by the size of the opening used on the lid of the pot.

In addition, the results of the contrast have been used to get more insight into how the plastic bags, temperature difference, and measure_opening affect the performance of individual cookers.

3.4 Contrast results

3.4.1 Effect of Measure Opening on the Performance of the Cookers

Table 4 presents the results of the contrast carried out to evaluate the effect of the measure_opening on the cookers' performance. The results reveal that there was a significant difference between different measure openings in the case of the Yamo Dudo device (p-value < 0.0001). Moreover, the average standardised performance was estimated to be 50.20W higher in the case of measure opening 4mm as compared to 10mm with a 95% confidence interval ranging from 30.96W to 73.36W. Notably, all estimated differences in mean standardized performance were positive, with significant differences in mean standardized performance between 4mm and 10mm measure opening at a significance level of 5% for all cookers, except for the case of OnlyPot (no significant difference, p-value $= 0.1153 > 0.05$).

Table 4: *Contrast Results of Measure Opening (4mm-10mm) and Cookers sorted from the highest to the lowest effects (Watts).*

Cooker	Estimate	SE	p-value	95%-CI	
				Lower	Upper
Yamo Dudo	50.20	10.60	<.0001	30.96	73.36
Prototype 2	33.80	11.76	0.0037	8.75	54.85
Brother	16.60	4.18	0.0001	9.12	26.48
Prototype 4	14.20	5.82	0.0470	0.27	24.27
OnlyPot	-12.90	8.18	0.1153	-7.76	27.36

3.4.2 Effect of Plastic Bags on the Performance of the Cookers

Table 5 shows the results of the use of plastic bags on the performance of cookers. It is seen that the use of plastic bags had a significant effect on the cookers' performances (Brother and OnlyPot, p-value < 0.0001). The positive value of $25.90W$ indicates an increase in performance in the presence of plastic bags by $25.90W$ compared to no plastic bags, with a 95% confidence interval ranging from $21.33W$ to $33.47W$.

Table 5: *Contrast results of Plastic Bags (Yes-No) and Cookers, showing the overall effect of plastic bags in Brother and OnlyPot prototypes (Watts).*

Cooker	Estimate	SE	p-value	95%-CI	
				Lower	Upper
All cookers	25.90	3.86	<.0001	21.33	33.47

3.4.3 Effect of Measure Opening plus levels of Plastic Bags on the Performance of the Cookers

Although it was noted that plastic bags and measure_opening had a significant interaction effect on the cookers' performance, it was not possible to evaluate the three-way interaction (Plastic bags:Measure_Opening:Cookers) directly by using the fitted model because of the high data imbalance in the levels of these categorical variables with the levels of cookers. By using the same model the contrast assisted in determining how the cookers' performances varied for the levels of plastic bags and measure_opening; that is, only those cookers that had data on these levels.

Table 6 shows the change in performance of Brother, Prototype 4 and Prototype 2 devices due to the change of the levels of measure opening where there was the use of plastic bags. It was observed that the use of plastic bags with either a 4mm or 10mm measure opening had a significant effect on the Prototype 2 device (p-value $= 0.0391 < 0.05$). The positive value of 22.65W indicates an increase in performance when using the measure opening 4mm as compared to 10mm, with the 95% confidence interval ranging from 1.19W to 44.11W. Moreover, this combination did not show any significant effecting Brother and Prototype 4 devices.

Table 6: *Contrast results of Measure Opening (4mm–10mm) + Plastic Bags (Yes) and Cookers, sorted by cooker with the highest to the lowest effects (Watts).*

Cooker	Estimate	SE	p-value	95%-CI	
				Lower	Upper
Prototype 2	22.65	10.95	0.0391	1.19	44.11
Brother	5.52	4.83	0.1350	-2.66	19.92
Prototype 4	3.09	4.43	0.4854	-5.59	11.77

Table 7 shows the change in performance of Yamo Dudo, Brother, and OnlyPot devices due to the change in the levels of measure opening where there was no use of plastic bags. It is observed that the absence of plastic bags with 4mm or 10mm measure openings had a significant effect on the performance of these devices except for OnlyPot (p-values $<$ 0.0001). The positive estimates in Yamo Dudo and Brother devices (61.27W and 27.72W, respectively) indicate the increasing performance of these devices when using a measure opening of 4mm as compared to 10mm. For the Yamo Dudo device, the 95% confidence interval was ranging from 41.85W to 80.69W, while for the Brother, it was ranging from 14.34W to 39.42W.

Table 7: *Contrast results of Measure Opening (4mm–10mm) + Plastic Bags (No) and Cookers, sorted by cooker with the highest to the lowest effects (Watts).*

Cooker	Estimate	SE	p-value	95%-CI	
				Lower	Upper
Yamo Dudo	61.27	9.91	$<$.0001	41.85	80.69
Brother	27.72	6.34	$<$.0001	14.34	39.42
OnlyPot	-1.81	7.70	0.8142	-15.62	15.26

3.4.4 Effect of Temperature Difference on the Performance of the Cookers

Table 8 shows the results of the effect of the temperature difference on the performance of each cooker separately. It is observed that a unit increase in the temperature difference had a significant effect of -4.99W on the average performance for Prototype 5, with a 95% confidence interval ranging from -6.57W to -3.41W. For Prototype 4, a unit increase in the temperature difference had a significant effect of -2.27W on the average performance, with a 95% confidence interval ranging from -3.45W to -1.09W. In line with the cookers discussed previously, Brother had a significant effect of -1.78W on the average performance for a unit increase in the temperature difference, with a 95% confidence interval ranging from -2.95W to -0.61W. The negative signs on the estimated effects indicate a decrease in performance due to the increase in temperature difference. In addition, OnlyPot, Prototype 3, Oven Prototype 2, Prototype 2, Oven Prototype 1, and Yamo Dudo devices showed non-significant effects of temperature differences on their performances (values -1.11W, -1.21W, -1.14W, -0.80W, -0.82W, and -0.61W, respectively) with two-sided confidence intervals that included zero.

Table 8: *Effect of Temperature Difference on Cookers sorted from the highest to the lowest negative estimates (Watts).*

Cooker	**Estimate**	**95%-CI**	
		Lower	**Upper**
Prototype 5	-4.99	-6.57	-3.41
Prototype 4	-2.27	-3.45	-1.09
Brother	-1.78	-2.95	-0.61
OnlyPot	-1.11	-2.43	0.21
Prototype 3	-1.21	-2.81	0.39
Oven_Prototype 2	-1.14	-2.39	0.112
Yamo Dudo	-0.61	-1.41	0.18
Prototype 2	-0.80	-2.13	0.525
Oven_Prototype 1	-0.82	-3.25	1.61

3.4.5 Estimation of the Cookers' Performance at 50°C Temperature Difference

Referring back to the concept of a single measure of a cooker's performance explained by ASABE, each cooker's performance was assessed at a 50°C temperature difference. The same idea was used here in terms of controlling for other factors that are affecting the cooker's performance [14]. Table 9 shows the results obtained after evaluating the performance of each cooker at a temperature difference of 50°C while accounting for the factors of the plastic bag and measure opening. The results reveal that when the Yamo Dudo cooker was used without plastic bags, its performance at a temperature difference of 50°C was 158.72W and 97.44W for measure openings of 4mm and 10mm, respectively. For Prototype 5, its performance at a temperature difference of 50°C with the use of a plastic bag and a 10mm measure opening was 33.71W. When the plastic bag was used in Prototype 4, the performance at a temperature difference of 50°C was 11.35W and 8.26W for measure openings of 4mm and 10mm respectively. For the Brother cooker, at a temperature difference of 50°C, the use of plastic bags resulted in a performance of about 15.35W and 6.72W for 4mm and 10mm measure openings, respectively, while no use of plastic bags resulted in -3.55W and -30.43W for 4mm and 10mm measure openings, respectively. For Prototype 3, its performance at a temperature difference of 50°C with the use of a plastic bag and a 10mm measure opening was 10.10W. When the plastic bag was used in Prototype 2, the performance at a temperature difference of 50°C was 11.35W and 8.26W for measure opening of 4mm and 10mm. For Oven_Prototype 1, its performance at a temperature difference of 50 °C with no use of a plastic bag with a 10mm measure opening was -11.60W. When the plastic bag was used in Oven_Prototype 2, the performance at a temperature difference of 50°C was 3.24W for the measure opening of 4mm. Lastly, for the OnlyPot cooker, at a temperature difference of 50°C the use of plastic bags resulted in a performance of about -19.08W and -0.66W for 4mm and 10mm measure openings, respectively, while no use of plastic bags resulted in -29.91W and -29.72W for 4mm and 10mm measure openings, respectively.

Table 9: *Results of Cookers' Performance (Watts) at 50°C Temperature Difference estimated at each combination of plastic bags and measure opening.*

Cooker	Plastic bag (Yes)		Plastic bag (No)	
	4 mm	10 mm	4 mm	10 mm
Yamo Dudo	-	-	158.72	97.44
Prototype 5	-	33.71	-	-
Prototype 4	11.35	8.26	-	-
Brother	15.35	6.72	-3.55	-30.43
Prototype 3	-	10.10	-	-
Prototype 2	20.60	-2.05	-	-
Oven_Prototype 1	-	-	-	-11.60
Oven_Prototype 2	3.24	-	-	-
OnlyPot	-19.08	-0.66	-29.91	-29.72

3.5 Outliers and Sensitivity Analysis

This section explains the analysis done to determine outlying (or influential) observations and the results of the sensitivity analysis. Figures A4, A5, A6 in the Appendix depict Cook's distance, the studentised residuals and leverage, and DFbeta plots. The combination of all four approaches and the analysis determined a total of 29 observations, which were termed influential observations. The sensitivity analysis was done by removing those 29 observations and refitting the model. The findings did not show any qualitative differences, meaning that the results obtained after performing the sensitivity analysis had the same conclusion as those in the main analysis. Moreover, after examining the behaviours of those observations and consulting with the scientists, it was decided to retain those observations in the main analysis because, initially, all of them complied with the protocol's requirements and they were impacted by regular variations such as the clouds or irradiation level at 10-minute intervals which could be extremely high or low and closer to the limits.

Another sensitivity analysis was performed by using the whole dataset to evaluate the robustness of the linear regression model predicting the cookers' performance based on the variables plastic bags, measure_opening and temperature difference. The objective was to assess the stability of the model's conclusion and the overall fit under different scenarios to see the effect of deviating from the protocol. Table A2 in the Appendix shows the results of the sensitivity analysis that was performed. In the first step of the model fitting, the interaction of plastic bags and Cookers did not show any significant effect, so it was removed and left with those results. The results did not reveal qualitative differences, meaning that there were some changes in the magnitude of the point estimates, but they did not change the nature of the conclusions from the main analysis (the significance of the variables). The sensitivity analysis confirmed the robustness of plastic bags, measure opening and temperature differences as potential predictors and highlighted the importance of interaction terms.

3.6 Results of Linear Mixed Regression

This analysis was performed by using the data from the Brother prototype only to show the applicability and importance of a linear mixed model, taking into account the variability brought by different test dates (refer Section 4). Table 10 shows the results of the fitted linear mixed model which contains two parts: Fixed and Randoms effects. The results reveal that conditioning on other factors, a unit increase in the temperature difference had a significant effect on the performance (p-value < 0.0001), and a negative estimate of -1.92 indicates a decrease in average performance by $1.92W$. Moreover, the use of plastic bags had a significant effect on the cooker's performance (p-value < 0.0001), and a positive estimate of 31.68 indicates an increase of $31.68W$ for the presence of plastic bags as compared to the absence of plastic bags. In addition, there was a significant effect of measure opening on the device's performance (p-value $= 0.0018 < 0.05$), and the negative mean performance of -23.71 indicates a decrease of $23.71W$ for measure opening 10mm as compared to 4mm. The intercept presents the average standardised performance of the cooker when the plastic bags were not used with 4mm of measure opening at the temperature difference of zero (average ambient and water temperatures are equal).

Table 10: *Results of the Linear Mixed model (Watts), partitioned in parts of fixed and random effects for the Brother prototype.*

Parameter	**Estimate**	**SE**	**p-value**
Fixed Effects			
Intercept	91.48	7.59	<.0001
Temperature Difference	-1.92	0.14	<.0001
Plastic bags (Yes)	31.68	6.07	<.0001
Measure Opening (10mm)	-23.71	6.77	0.0018
Random Effects			
Test Date	117.20	10.83	<.0001
Residual	331.90	18.22	

Furthermore, the estimates of random effects present the variances of the random factor Test Date and residuals. The results reveal the significant effect of the random factor Test Date (estimate = 117.20, p-value < 0.0001), presenting the additional variability explained by the random factor test dates, this is the variability explained by measurements that came from different test dates. The estimate of the residual was 331.90; this explains the variability accounted for by the measurements that came from the same test dates. The estimate of the intraclass correlation (ρ) was given by:

$$\text{Intraclass correlation } (\rho) = \frac{117.20}{117.20 + 331.90} = 0.26 \tag{13}$$

This means that the measurements from different test days were assumed to be independent, while the measurements from the same test days were correlated with a correlation coefficient of 0.26. Moreover, 26% ($\rho \times 100\%$) presents the percentage variability accounted by the random factor Test Date in the model.

3.6.1 Estimation of the Cooker's Performance at 50°C

Table 11 presents the results obtained after performing the prediction at the marginal level at a temperature difference of 50°C with the plastic bags and the measure openings. The results reveal that at a temperature difference of 50°C the use of plastic bags resulted in a performance of about 27.12W and 3.42W for 4mm and 10mm measure openings respectively, while no use of plastic bags resulted in -4.56W and -28.27W for 4mm and 10mm measure openings, respectively.

Table 11: *Results of the estimated Standardised Performance (at a temperature difference of 50°C) for the Brother prototype (Watts).*

		Measure Opening	
		4mm	**10mm**
Plastic bags	**Yes**	27.12	3.42
	No	-4.56	-28.27

Comparing the results of predicted standardised performance obtained from the main analysis (Table 9) and the results shown in Table 11 for the Brother device, some changes in the estimates of the standardised performance are observed. Both results show positive standardised performances when there was the use of plastic bags for all levels of measure opening and negative performances in the absence of plastic bags for all levels of measure opening. Also, the results of both analyses reveal that the highest performance was obtained in the presence of plastic bags and $4mm$ measure opening while, the least performance can be obtained in the absence of plastic bags and $10mm$ measure opening.

4 Discussion

The purpose of this study was to comprehend PEP and apply it to the assessment of the currently developed solar cooker prototypes within the Sc4all project, a collaboration between the UHasselt, Belgium, and the University of Lubumbashi, the Democratic Republic of Congo, and also to evaluate the proposed methods given potential improvements towards the standardised assessment and comparison of the solar cookers. Moreover, improving the design and conduct of new experiments with devices that exhibit improved performance, a sustainable design adapted to local needs in the DRC and other developing countries, and increased acceptability among households in resource-limited settings. This brought the discussion of first determining which one is the best prototype (locally made) compared to the commercial ones in terms of standardised performance, investigating the potential effects of the experimental setting, such as the use of plastic bags, wind speed, and measure opening on the performance of the prototypes, and lastly, making recommendations on the factors to consider during the sample size calculations for the improved prototypes.

Various analyses were performed to address the study's objective and answer research questions. Several linear regression-based approaches were used to analyse the data, including the Simple Linear Regression model for evaluation of the single measure of performance of the cookers, the Multiple Linear Regression (MLR) model for assessing the influence of other factors on the performance of the cookers and also for comparison between cookers in different settings, and Linear Mixed regression used as the extension of MLR to account for the variability explained by the measurements taken from different test dates.

Based on the Single Measure of Performance approach, Yamo Dudo was found to be the best cooker out of all the cookers tested in the study with a performance of $152W$, while Prototype 5 was deemed to be the best among the locally developed cookers with a performance of $33.71W$. In addition, Oven_Prototype 1 and OnlyPot revealed very bad performance, -11.60W and -13.84W. Kauki. F (2024) found that the Yamo Dudo Prototype 5 takes 10 minutes and 20 minutes, respectively, to reach a temperature of 70°C, whereas OnlyPot and Oven_Prototype 1 did not reach 70°C in any of the experiments [34].

The findings of Multiple linear regression suggested that not only temperature differences can be used to explain the cookers' performance but also other factors such as plastic bags and the size of the hole on the lid (measure opening). Table 8 presents further exploration that was done and revealed that each cooker has its rate of heat loss to the surroundings as a result of increasing the temperature difference, whereas Prototype 5 had the highest rate of losing heat, about $5W$ for every unit increase in the temperature difference. This means that it was so hard for it to maintain its performance at higher temperatures.

Moreover, it was investigated that the use of the lid with smaller holes increases the performance of cookers, and this effect is not the same in all cookers, whereas the effect was highest for Yamo Dudo ($50.20W$) as shown in Table 4. Furthermore, the results revealed that Plastic Bag is a very important factor in increasing the performance of cookers (refer to Table 5). The presence of plastic bags also prevents heat loss regardless of any level of measure opening (refer to Table 6). This means that plastic bags help to preserve the cookers' performance, which would otherwise be reduced by the larger hole in the lid. Table 7 provides more evidence of the significance of plastic bags; it showed that the cookers performed significantly better for measure opening of 4mm compared to 10mm when they were tested without plastic bags.

Additionally, the MLR was used to predict the performance of each cooker's performance conditioning to the levels of plastic bags and measure opening. Results from Table 9 revealed that in even the worst conditions (no plastic bag and a 10mm measure opening), the Yamo Dudo cooker had the highest performance compared to all other cookers. The comparison between the locally made cookers was made at the condition of plastic bags plus 10mm measure opening, whereas Prototype 5 was still the best, followed by Prototype 3, Prototype 4, and Prototype 2 cookers. On top of that, Table A4 in the appendix shows the approximated median time to reach the temperature difference of 50°C under the condition of plastic bags+10mm measure opening. Prototypes 4 and 3 were approximated to have the same median time of about 80 minutes to reach the temperature difference of 50°C [34]. This point proves that among all locally made cookers, Prototype 5 was the best, but comparing it with the best commercial cooker, Yamo Dudo, its performance was still so low (less than $\frac{1}{3}$ times the performance of Yamo Dudo).

Further analysis that was done using the Linear Mixed model by using only one cooker (Brother) showed the importance of taking into account the effect of the measurements which were taken from different test dates because they met different conditions, such as different raters who assessed the measurements. It was also seen in this cooker that about 26% of the variability was explained by the random factor, and this added variance was found to be significant. This approach was seen to be the best compared to Simple and Multiple Linear Regression but it was not fully employed in combined data (all cookers together) because of unequal cluster sizes being too small.

The temperature difference was the only predictor used in the simulation process to determine the sample size for the improved prototypes in the preceding studies. The results that have been obtained from this study have added other crucial factors to consider when calculating the sample size, i.e., plastic bags and measure openings. Therefore, it is recommended that temperature differences, plastic bags, and measure openings be taken into account when calculating the sample size for future improved prototypes to power the study to detect significant effects brought by these factors on the cookers' performances.

Since all tests carried out by Solar Cooker International adhere to the PEP provided by ASABE, it was necessary for this study to follow the protocol guidelines in the analyses to allow for international comparison of the results [3]. The PEP requires all tests to be conducted under several conditions (refer to Section 2.2). Throughout the analyses, the effect of wind speed was not assessed because, at a speed of 2.5 m/s, the wind does not affect the cookers' performance [14]. The data collected had only 3 observations above the restricted wind speed; therefore, to evaluate the wind speed effect, it is recommended that future research make every effort to gather more measurements at greater wind speeds. Furthermore, it was also advised in the protocol that at least 30 observations have to be collected for the cooker to get a good estimation of the regression line, and measure its performance. It has been observed in Table 1 that several cookers including Fornelia, Prototype 5, Prototype 3, and Oven_Prototype 1 had less than 30 observations. Therefore, it is recommended that for future experiments more observations be collected for a more accurate approximation of the results.

Moreover, it was observed that there was a high data imbalance in the categorical variables (see Table 1). This problem was led by the poor study design. It has resulted in incomplete results, i.e., it was not possible to evaluate the effect of the combination of several factors on the cooker's performance. On top of that, it was not possible to evaluate the effect of plastic bags and measure opening in the Fornelia cooker since it had used only 2mm of measure opening and was tested without plastic bags only. Several efforts were taken to tackle this problem, such as performing stratification in categorical variables, where the interactions were assessed at the levels that had only observations. Since this study was done to get more insights into improving the designs for future experiments, this aspect of data imbalance should be taken into account in the testing process.

Due to the best performance of the Yamo Dudo cooker reaching more than 100°C in a short time, this resulted in the burning of all plastic bags used on it during the testing; therefore, the six mentioned plastic bags were classified as being in the no plastic bags category, so making it impossible to evaluate the impact of plastic bags in the Yamo Dudo cooker. Prototype 2 also experienced variable collapsing; in this instance, the "no plastic bags" category contained plastic bags that were partially closed (folded), and the "plastic bags" category contained fully closed bags. Consequently, both categories had the same impact and hence collapsed.

Lastly, it is instructed in PEP that the measurements should be taken every 10 minutes; this can be termed as the obstacle to obtaining the true measurements that capture all the variations of wind speed and level of irradiation that might happen between those 10 minutes. This also contributes to the less accurate measurements, which do not explain how the cookers perform. This problem has also led to the discarding of many data points to make sure that the analyses follow the protocol. The solution to that is to use the "Test Station" as a way of collecting raw measurements that can capture the variations of these factors and also the changes in water temperature after every interval less than the proposed time of 10 minutes.

5 Conclusion

This study was developed from the project called Solar Cooker for All (Sc4all), supported by the Flemish Government (VLIR-UOS SI Project Nr. CD2023SIN371A104), done in collaboration between Hasselt University (UHasselt, Belgium) and the University of Lubumbashi (UniLu, DR Congo). The study has tested and evaluated the performance of commercial and locally made cookers that were developed under this project by following the Performance Evaluation Process (PEP) provided by the American Society of Agricultural and Biological Engineers (ASABE). It has examined the effects of the temperature difference, plastic bags, measure opening, and wind on the performance of the cookers. The study has added more insights on how to evaluate and compare the performance of the cookers under different combinations of these factors.

The study has shown that the performance of the cookers can be greatly increased by the use of plastic bags and smaller measure openings. Moreover, it has highlighted the crucial factors such as plastic bags and measure openings to be considered in the sample size calculations for the improved prototypes. Also, it has raised the issue of heat loss from the pot to the surroundings at higher temperatures being a potential factor to consider when developing new prototypes. In addition, the Linear Mixed Model was seen as a more promising approach to evaluating how these factors influence the performance of the cookers since measurements are also dependent on the assessments done on the same or different test dates. Furthermore, the findings of this study have shown the disadvantages of not preparing and following a good experimental or study design. Also, it has been proposed that the use of a Test Station is a better way of collecting the measurements than using the guidelines for recording the measurements every 10 minutes as provided in PEP.

The findings of this master thesis can be used for designing new studies, testing, evaluating, and comparing new prototypes. For the design of new studies aspect, it is recommended to collect data in a balanced way by which all levels of categorical variables should have enough data for better comparison. For testing procedures, it is recommended to collect more data as guided by the standard protocol and also to deviate from its conditions for investigating statistically the effects of those factors on the performance of the prototypes. In addition to that, for the case of ongoing data collection taken at continuous readings by using test stations. The data collected can be well transformed into interval format by averages in 10 minutes or using the alternative for partitioning them in minutes less than 10, also using that data in the longitudinal analyses. The other advantage of the data that are collected in the test station, they can not only be used to test the performance of the prototypes but also simplify the structure of applying other statistical approaches such as Survival Analysis by using the Cox PH models and give more clarification on the time it takes for the prototypes to reach a specific level of temperature [34]. Generally, the findings of this master thesis will help in development of the future prototypes that will be made in local settings with limited resources, not only in the DRC but also in all other developing countries. The use of local materials will increase the acceptability of these cookers since they will be much more affordable and will provide clean energy, which promotes good health and well-being. Moreover, they will reduce deforestation and environmental and air pollution with no negative impact on the climate [1].

The analyses performed in this master this had several statistical limitations. Beginning with the single measure of performance, this is the standard approach suggested by ASABE which evaluates the performance of prototypes due to the effect of the temperature differences. The improved statistical method which has been described in this master thesis, i.e., Multiple Linear Regression, this approach is better because it allows the evaluation of other factors on the performance of the prototypes but the problem of high data imbalance has made it impossible to assess the effect of all factors on the performance of all cookers. Therefore, in terms of well-balanced data and sufficient measurements, the study could investigate more about the performance of these prototypes. The more advanced approach, i.e., Linear Mixed Regression was the best approach to account for the variability that can be brought by unmeasured factors varying across days but it was also impossible to use this approach in all data because of the unequal cluster sizes were too small which would bring invalid results.

Ethical Consideration

The data that has been used in this study was collected in Belgium under the Solar Cooker for All (Sc4all) project and has been used for Master thesis and publication purposes. The work has been done under Accountability and Transparency conditions, and the findings of this study can be used for learning purposes.

Stakeholder Awareness

The Solar Cooker for All (Sc4all) project is supported by the Flemish Government (VLIR-UOS), done in collaboration between UHasselt and the ULubumbashi. The project involves technicians from Physics, Engineering, Statistics, and Social and Economic fields. It is also done under the supervision of Professors at the UHasselt and the ULubumbashi. To guarantee that the prototypes developed will fulfil the demands of the citizens of the DRC, the student-led Solar Cooker team will have the chance to visit ULubumbashi, engage in capacity building, and confer with another team in ULubumbashi about various aspects that will assist in the development of new prototypes that will satisfy the local citizens' requirements.

References

[1]World Bank, *Tracking SDG 7: the energy progress report*, 2022.

[2]World Health Organization, *Household air pollution*, Geneva, 2023.

[3]A. W. Bigelow, J. Tabatchnick, and C. Hughes, *Development and implementation of a performance evaluation process (pep) for solar thermal cooking devices*, California, USA, 2021.

[4]N. Hosonuma, M. Herold, V. D. Sy, et al., *An assessment of deforestation and forest degradation drivers in developing countries*, 2012.

[5]F. Riva, M. V. Rocco, F. Gardumi, G. Bonamini, and E. Colombo, *Design and performance evaluation of solar cookers for developing countries: the case of mutoyi, burundi*, 2023.

[6]M. Tucker, *Can solar cooking save the forests?*, 1999.

[7]H. D. Kambezidis, E. M. Katevatis, M. Petrakis, S. Lykoudis, and D. N. Asimakopoulos, *Estimation of the linke and unsworth–monteith turbidity factors in the visible spectrum: application for athens, greece*, 1997.

[8]P. A. Funk and D. L. Larson, *Parametric model of solar cooker performance*, 1997.

[9]*Solar cookers international*, `https://www.solarcookers.org`, 2023.

[10]A. W. Bigelow, J. Tabatchnick, and C. Hughes, *Testing solar cookers for cooking efficiency*, Solar Cookers International, 2400 22nd Street, Ste 210, Sacramento, CA, 95818, USA, 2024.

[11]F. Yettou, B. Azoui, A. Malek, A. Gama, and N. L. Panwar, *Solar cooker realizations in actual use: an overview*, `www.elsevier.com/locate/rser`, 2014.

[12]E. Cuce and P. M. Cuce, *A comprehensive review on solar cookers*, 2013.

[13]M. Telkes, *Solar cooking ovens*, 1999.

[14]American Society of Agricultural and Biological Engineers, *Testing and reporting solar cooker performance*, ASAE S580.1, Nov. 2013.

[15]C. Emanuela, J. Barbieri, and F. Riva, *Guidelines on sustainable energy technologies for food utilization*, Milan, 2015.

[16]E. DeVirgilio and L. Deleux, *Solar cooker for all: project experimental techniques*, University of Hasselt, 2024.

[17]G. Verbeke and G. Molenberghs, *Linear mixed models for longitudinal data*, 2000.

[18]K. Marill, *Advanced statistics: linear regression, part i: simple linear regression*, 2004.

[19]M. Tranmer, J. Murphy, M. Elliot, and M. Pampaka, *Multiple linear regression (2nd edition)*, Working Paper, 2020.

[20] D. C. Montgomery and G. C. Runger, *Applied statistics and probability for engineers*, 2003.

[21] O. Thas, *Linear models*, `https://othas.github.io/LIMO/`, 2022.

[22] Statistics Solutions, *Complete dissertation*, `https://www.statisticssolutions.com/complete-dissertation/`, Accessed: 2024-05-22.

[23] Z. Bobbitt, *Multiple r vs. r-squared: what's the difference?*, Accessed: February 12, 2021.

[24] R. J. Casson and L. D. Farmer, *Clinical and experimental ophthalmology*, Aug. 2014.

[25] B. T. West, K. E. Welch, and A. T. Galecki, *Linear mixed models: a practical guide using statistical software*, Boca Raton, 2007.

[26] M. Aerts, H. Geys, G. Molenberghs, and L. M. Ryan, *Topics in modelling of clustered data*, London, 2002.

[27] G. Verbeke, *Concepts of multilevel, longitudinal, and mixed models*, Lecture Notes, Master of Statistics, KU Leuven, Katholieke Universiteit Leuven & Universiteit Hasselt, Belgium, 2022.

[28] R. Bender and S. Lange, *Adjusting for multiple testing—when and how?*, 2001.

[29] R. D. Cook, *Detection of influential observation in linear regression*, 1997.

[30] R. W. Nahhas, *Introduction to regression methods for public health using r*, Accessed:2024-04-22, `https://bookdown.org/rwnahhas/RMPH/`.

[31] J. Fox, S. Weisberg, and B. Price, *Car: companion to applied regression*, `https://r-forge.r-project.org/projects/car/`, 2023.

[32] F. E. H. Jr., *Regression modeling strategies*, Switzerland, 2015.

[33] R Core Team, *R: a language and environment for statistical computing*, Vienna, Austria: R Foundation for Statistical Computing, 2024.

[34] F. C. Kauki, *The use of survival analysis for the determination of the performance of solar cookers in africa*, Belgium, 2024.

A Appendix

A.1 Appendix Figures

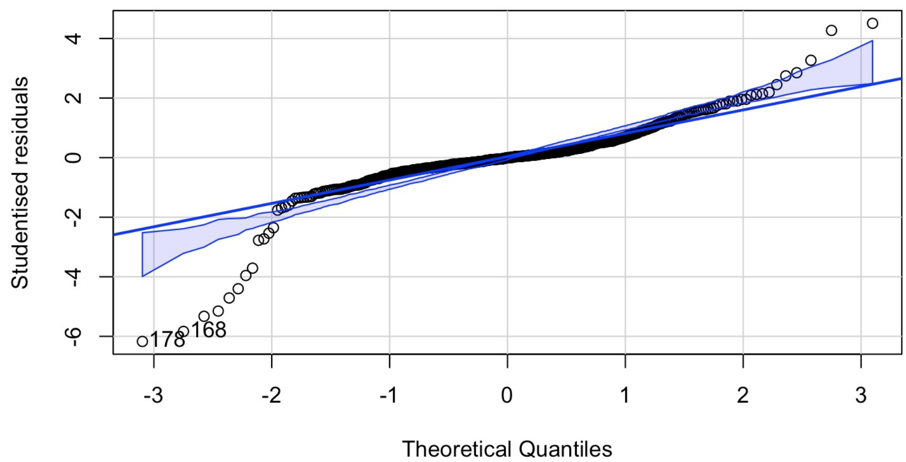

Figure A1: *Visualising normality assumption through QQ-plot with its 95% confidence interval, showing mostly of the points falling on the line but also depicts the presence of right and left heavy tails.*

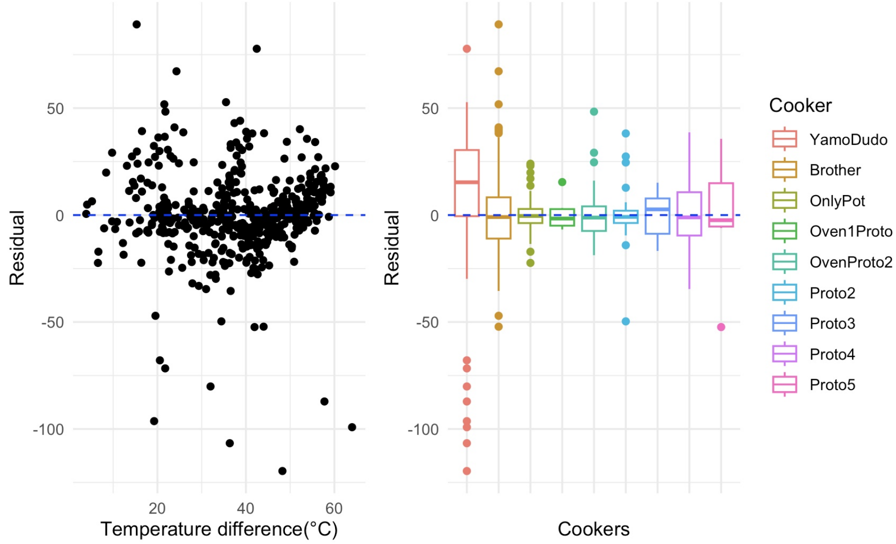

Figure A2: *Visualising linearity assumption through diagnosis plots of residuals against regressors, left is for temperature difference and right is for cookers, both plots show no systematic of residuals hence validating linearity assumption.*

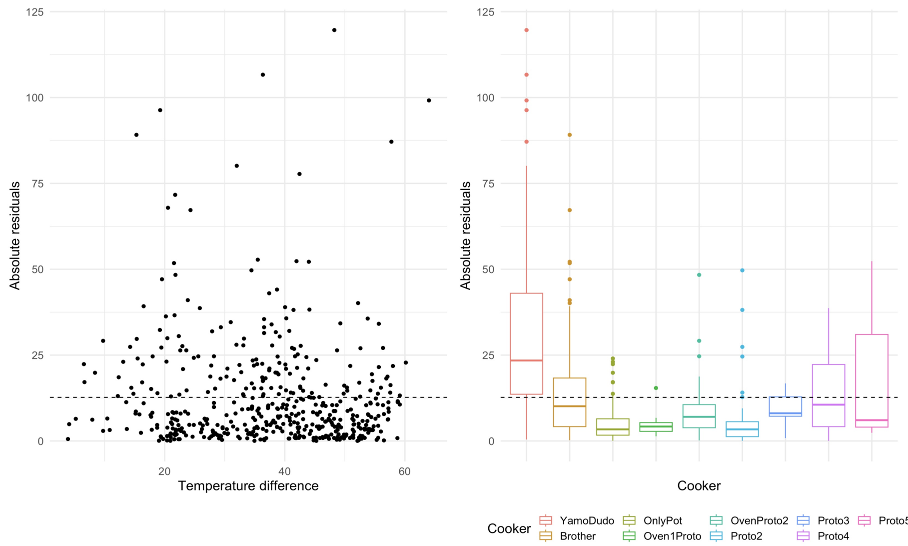

Figure A3: *Visualising homoskedasticity assumption through diagnosis plots of absolute residuals against regressors, left is for temperature difference and right is for cookers, both plots show no systematic of residuals hence validating homoscedasticity assumption.*

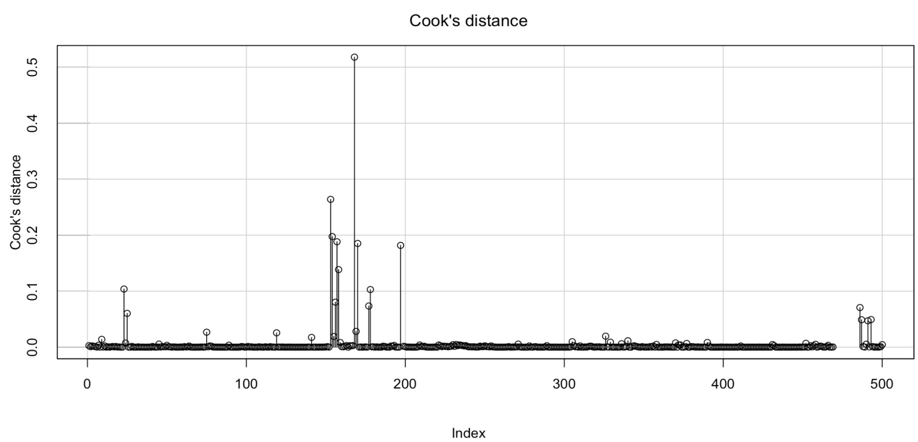

Figure A4: *Visualising Cook's distance of the observations, where x-axis presents observations as they appear in the data. The cut-off of 0.2 was used as the comparison for influential observations.*

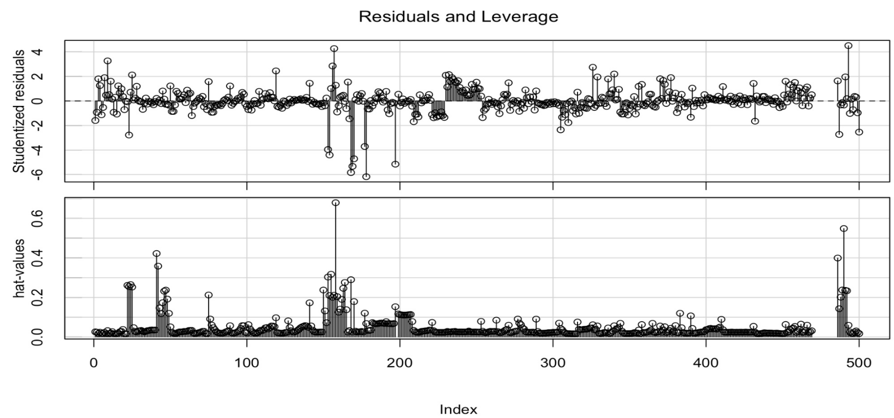

Figure A5: *Visualising Residuals and Leverage of the observations, where x-axis presents observations as they appear in the data. The cut-off of 0.4 for leverage plot (hat-values) and ±4 for residual plot were used as the comparison for influential observations.*

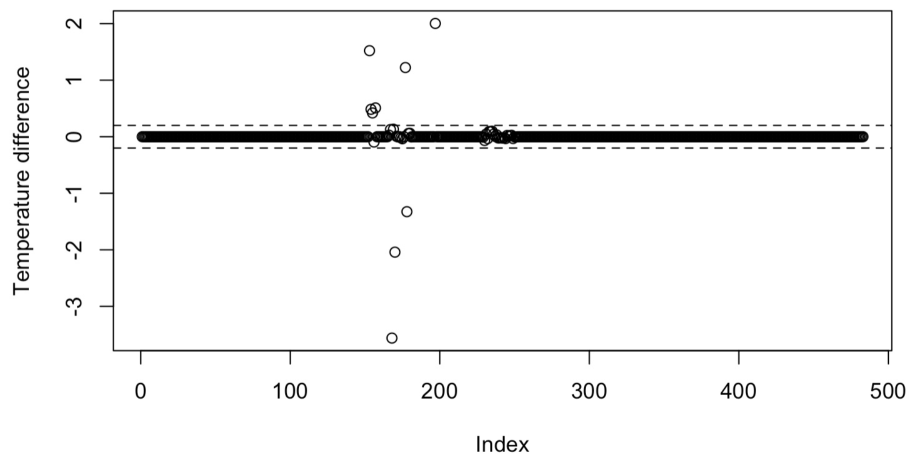

Figure A6: *Visualising outlying observations by using DFBetas, where x-axis presents observations as they appear in the data. The cut-off of 0.2 as the comparison for influential observations.*

A.2 Appendix Tables

Table A1: *Results of the Multiple linear regression showing the results of the main analysis.*

Parameter	**Estimate**	**SE**	**p-value**
Intercept	189.40	15.66	<.0001
Temperature difference	-0.61	0.40	0.1324
Plastic bag_Yes	14.79	4.09	0.0003
Cookers:			
Brother	-103.63	17.16	<.0001
OnlyPot	-163.26	17.33	<.0001
Oven_Prototype 1	-98.86	40.96	0.0162
Oven_Prototype 2	-144.13	20.28	<.0001
Prototype 2	-143.72	23.58	<.0001
Prototype 3	-93.55	32.79	0.0045
Prototype 4	-79.54	18.18	<.0001
Prototype 5	118.01	31.40	<.0001
Measure opening_10mm	-61.27	-6.184	<.0001
Plastic bag_Yes:Measure opening_10mm	22.20	7.56	0.0035
Temperature difference:Cookers			
Brother	-1.15	0.43	0.0087
OnlyPot	-0.62	0.52	0.2352
Oven_Prototype 1	-0.20	1.17	0.8620
Oven_Prototype 2	-0.52	0.49	0.2890
Prototype 2	-0.18	0.54	0.7333
Prototype 3	-0.60	0.71	0.3960
Prototype 4	-1.65	0.44	0.0002
Prototype 5	-4.37	0.69	<.0001
Measure opening_10mm:Cookers			
Brother	33.55	11.76	0.0045
OnlyPot	63.08	12.55	<.0001
Prototype 2	16.41	16.59	0.3230
Prototype 4	35.97	13.22	0.0068

Table A2: *Results of Sensitivity Analysis performed for all observations (even those deviating from the protocol). Comparing these results and those from the main analysis we observed no qualitative differences meaning that both results had the same conclusions.*

Parameter	**Estimate**	**Std. Error**	**t value**
Intercept	188.93951	15.94804	<.0001
Temperature Difference	-0.61231	0.41449	0.1403
Plastic Bags(Yes)	16.41922	3.11559	<.0001
Cookers:			
Brother	-110.64421	17.32737	<.0001
OnlyPot	-162.50962	17.64365	<.0001
OvenPrototype 1	-82.38780	41.82250	0.0494
OvenPrototype 2	-145.29597	20.45899	<.0001
Prototype 2	-137.45359	23.70519	<.0001
Prototype 3	-56.50296	32.73473	0.0850
Prototype 4	-81.62929	18.29583	<.0001
Prototype 5	155.05922	31.28823	<.0001
Measure Opening(10mm)	-77.27781	10.53538	<.0001
Cookers:Measure Opening(10mm)			
Brother	66.62325	10.76834	<.0001
OnlyPot	79.75832	13.37945	<.0001
Prototype 2	44.55458	15.07812	0.0033
Prototype 4	75.35358	11.46907	<.0001
Temperature Difference:Cookers			
Brother	-0.98152	0.44238	0.0270
OnlyPot	-0.67561	0.52493	0.1987
OvenPrototype 1	-0.20520	1.19317	0.8635
OvenPrototype 2	-0.52424	0.50159	0.2965
Prototype 2	0.04839	0.55084	0.9300
Prototype 3	-0.60114	0.71891	0.4035
Prototype 4	-1.63245	0.45190	0.0003
Prototype 5	-4.37625	0.70605	<.0001

Table A3: *Results of the Variance Inflation Factors (VIF) where all values of Generalised VIF of the variables show moderate multicollinearity.*

Parameter	df	$GVIF^{1/(2*df)}$
Temperature difference	1	5.46
Plastic bag	1	2.04
Measure Opening	1	4.44
Cookers	8	5.04
Temperature difference:Cookers	8	2.24
Plastic bag:Measure opening	1	3.69
Measure opening:Cookers	5	2.21

Table A4: *Predicted median survival time (minutes) for all combinations of plastic bags and measure openings.*

Cooker	Measure Opening 4mm		Measure Opening 10mm	
	Plastic Bags (Yes)	Plastic Bags (No)	Plastic Bags (Yes)	Plastic Bags (No)
Brother	50	90	90	-
Oven_Prototype 2	90	-	-	-
Prototype 2	70	90	110	-
Prototype 3	30	60	80	-
Prototype 4	30	70	80	-

A.3 R Codes

```
library(RLRsim)
library(pbkrtest)
library(gridExtra)
library(patchwork)
library(dplyr)
library(lme4)
library(merTools)
library(emmeans)
library(readxl)
library(ggplot2)
library(tidyverse)
library(lmtest)
library(car)
#######################################
Data exploration.
######################################

#####Time vs Irradiation
newsolar2$color <- with(newsolar2, ifelse(avg_amb_temp < 20, "< 20",
                        ifelse(avg_amb_temp > 35, "> 35", "Qualified")))
ggplot(newsolar2, aes(x = H1, y = avg_radiation)) +geom_point(aes(color = color)) +
scale_color_manual(values = c("< 450" = "blue", "> 1100" = "red", "Qualified" = "black"))+
labs(title = "Scatter Plot with Conditional Coloring", x = "Time (Hours)",
y = expression("Irradiation (W/m)"^2), color = "Irradiation") +theme_minimal()+
theme(legend.position = "bottom")

#####Irradiation vs Water temperature
newsolar2$color <- with(newsolar2 , ifelse(avg_radiation< 450, "< 450",
                        ifelse(avg_radiation > 1100, "> 1100", "Qualified")))
ggplot(newsolar2, aes(x = avg_radiation, y = avg_water_temp)) +
geom_point(aes(color = color))+scale_color_manual(values =
c("< 450" = "red", "> 1100" ="blue", "Qualified" = "black")) +
labs(title = "Scatter Plot with Conditional Coloring",
x = expression("Irradiation (W/m)"^2),
y = "Water Temperature (°C)",
color = "Irradiation") +theme_minimal() +
  geom_smooth(method = "lm", se = FALSE)+
  theme(legend.position = "bottom")
```

```
#####Water temperature vs Ambient temperature
newsolar2$color <- with(newsolar2, ifelse(avg_amb_temp < 20, "< 20",
                        ifelse(avg_amb_temp > 35, "> 35", "Qualified")))
ggplot(newsolar2, aes(x = avg_amb_temp, y = avg_water_temp)) +
geom_point(aes(color = color)) + scale_color_manual(values = c("< 20" = "red",
"> 35" = "red", "Qualified" = "black")) +
labs(title = "Scatter Plot with Conditional Coloring",
x = "Ambient Temperature (°C)", y = "Water Temperature (°C)",
color = "Ambient Temperature") +
geom_smooth(method = "lm", se = FALSE)+theme_minimal()+
theme(legend.position = "bottom")

newsolar2$color <- with(newsolar2 , ifelse(Wind >2.5 ,"< 2.5","Qualified"))

#####Time vs Wind
ggplot(newsolar2, aes(x = H1, y = Wind)) +geom_point(aes(color = color)) +
scale_color_manual(values = c("< 2.5" = "blue", "Qualified" ="black")) + labs(title =
"Scatter Plot with Conditional Coloring",x = "Time (Hours)", y = "Wind Speed (m/s) ",
color = "Wind speed") +theme_minimal()+ theme(legend.position = "bottom")

###########################
Preparing data that follows the protocol
###########################

##Subset the data to keep rows where the Ambient temperature is between 20 and 35 °C,
##Wind speed is at most 2.5 m/sec, and Irradiation is between 450 and 1100 units
SolarCooker_B <- subset(newsolar2, Ta1 >= 20 & Ta1<= 35 &  Ta2 >= 20 & Ta2<= 35 &
Wind <= 2.5 &I1 >= 450 & I1 <= 1100 & I2 >= 450 & I2 <= 1100)

#Difference if I's in 10 minutes intervals
#It should not be greater than absolute 100W/m2
SolarCooker_B$dI<-SolarCooker_B$I2-SolarCooker_B$I1
SolarCooker_C<-SolarCooker_B%>%mutate(INDdI=ifelse(abs(dI)>100,0,1))
#table(protocol_data0$INDdI) 69 didn't meet the condition
protoc_data2_1 <- subset(SolarCooker_C, (INDdI %in% c("1")))

###########################
A single measure of performance
###########################
```

```
Brother<-protoc_data2_1 %>%filter(Cooker=="Brother")
Brother_Model <- lm(Ps ~ Td, data=Brother)
summary(Brother_Model); confint(Brother_Model)
ggplot(data = Brother, aes(x = Td, y = Ps))+geom_point() + geom_smooth(method = "lm",
se = TRUE) +geom_vline(xintercept = 50, linetype = "dashed", color = "red")


fornelia<-protoc_data2_1 %>%select(Cooker,Td,Ps)%>%filter(Cooker=="Fornelia")
fornelia_Model <- lm(Ps ~ Td, data=fornelia)
summary(fornelia_Model); confint(fornelia_Model)
ggplot(data = fornelia, aes(x = Td, y = Ps)) + geom_point() + geom_smooth(method = "lm",
se = TRUE) +geom_vline(xintercept = 50, linetype = "dashed", color = "red")


Onlypot<-protoc_data2_1 %>% select(Cooker,Td,Ps)%>%filter(Cooker=="OnlyPot")
Onlypot_Model <- lm(Ps ~ Td, data=Onlypot)
summary(Onlypot_Model); confint(Onlypot_Model)
ggplot(data = Onlypot, aes(x = Td, y = Ps)) +
geom_point() + geom_smooth(method = "lm", se = TRUE) +
geom_vline(xintercept = 50, linetype = "dashed", color = "red") +labs(y = expression("Stand


OvenProto1<-protoc_data2_1 %>% select(Cooker,Tdd,Ps)%>%filter(Cooker=="OvenProto1")
OvenProto1_Model <- lm(Ps ~ Tdd, data=OvenProto1)
summary(OvenProto1_Model); confint(OvenProto1_Model)
ggplot(data = OvenProto1, aes(x = Tdd, y = Ps)) + geom_point() +geom_smooth(method = "lm",
se = TRUE) +
geom_vline(xintercept = 0, linetype = "dashed", color = "red")


OvenProto2<-protoc_data2_1 %>% select(Cooker,Td,Ps)%>%filter(Cooker=="OvenProto2")
OvenProto2_Model <- lm(Ps ~ Td, data=OvenProto2)
summary(OvenProto2_Model); confint(OvenProto2_Model)
ggplot(data = OvenProto2, aes(x = Td, y = Ps)) + geom_point() +
geom_smooth(method = "lm", se = TRUE)+
geom_vline(xintercept = 50, linetype = "dashed",color = "red")

Proto2<-protoc_data2_1 %>%filter(Cooker=="Proto2")
Proto2_Model <- lm(Ps ~ Td, data=Proto2)
summary(Proto2_Model); confint(Proto2_Model)
```

```
ggplot(data = Proto2, aes(x = Td, y = Ps)) + geom_point() + geom_smooth(method = "lm",
se = TRUE) + geom_vline(xintercept = 50, linetype = "dashed", color = "red")

Proto3<-protoc_data2_1 %>% select(Cooker,Td,Ps)%>%filter(Cooker=="Proto3")
Proto3_Model <- lm(Ps ~ Td, data=Proto3)
summary(Proto3_Model); confint(Proto3_Model)
ggplot(data = Proto3, aes(x = Td, y = Ps)) + geom_point() +
geom_smooth(method = "lm", se = TRUE) +
geom_vline(xintercept = 50, linetype = "dashed", color = "red")

Proto4<-protoc_data2_1 %>% filter(Cooker=="Proto4")
Proto4_Model <- lm(Ps ~ Td, data=Proto4)
summary(Proto4_Model);confint(Proto4_Model)
ggplot(data = Proto4, aes(x = Td, y = Ps)) + geom_point() +
geom_smooth(method = "lm", se = TRUE) +
geom_vline(xintercept = 50, linetype = "dashed", color = "red") +
labs(x = "Temperature diffreence (°C)", y = "Standardised Performance(W)")


Proto5<-protoc_data2_1 %>% filter(Cooker=="Proto5")
Proto5_Model <- lm(Ps ~ Tdd, data=Proto5)
summary(Proto5_Model);confint(Proto5_Model)
ggplot(data = Proto5, aes(x = Tdd, y = Ps)) +
geom_point() + geom_smooth(method = "lm", se = TRUE)
+geom_vline(xintercept = 50, linetype = "dashed", color = "red")


YamoDudo<-protoc_data2_1 %>% filter(Cooker=="YamoDudo")
YamoDudo_Model <- lm(Ps ~ Td, data=YamoDudo)
summary(YamoDudo_Model);confint(YamoDudo_Model)
ggplot(data = YamoDudo, aes(x = Td, y = Ps)) + geom_point() +
geom_smooth(method = "lm", se = TRUE) +
geom_vline(xintercept = 50, linetype = "dashed", color = "red") +
labs(x = "Temperature diffreence (°C)", y = "Standardised Performance(W)")

##############################
Single measure plots
##############################
SOLAR_data1 <- subset(protoc_data2_1, (Cooker %in% c("YamoDudo","Brother","Fornelia")))
ggplot(data = SOLAR_data1, aes(x = Td, y = Ps, colour = Cooker)) +
```

```
geom_point() +facet_wrap(~ Cooker, nrow = 2, ncol = 5)+
labs(y = expression("Standardised Performance (W)"), x = "Temperature difference (°C)") +
geom_vline(xintercept = 50, color = "red")+geom_smooth(method = "lm", se = TRUE)

SOLAR_data2 <- subset(protoc_data2_1, (Cooker %in% c("OvenProto1","OvenProto2","Proto5")))
ggplot(data = SOLAR_data2, aes(x = Td, y = Ps, colour = Cooker)) +
geom_point() +facet_wrap(~ Cooker, nrow = 2, ncol = 5)+
labs(y = expression("Standardised Performance (W)"), x = "Temperature difference (°C)")
+geom_vline(xintercept = 50, color = "red")+geom_smooth(method = "lm", se = TRUE)

SOLAR_data3 <- subset(protoc_data2_1, (Cooker %in% c("Proto2","Proto3","Proto4")))
ggplot(data = SOLAR_data3, aes(x = Td, y = Ps, colour = Cooker)) +
geom_point() + facet_wrap(~ Cooker, nrow = 2, ncol = 5)+
labs(y = expression("Standardised Performance (W)"), x = "Temperature difference (°C)")
+geom_vline(xintercept = 50, color = "red")+geom_smooth(method = "lm", se = TRUE)

########################################
Multiple Linear regression
########################################
protoc_data2_1$Cooker <- relevel(as.factor(protoc_data2_1$Cooker), ref = "YamoDudo")
protoc_data2_1$plstbgs_nw1 <- relevel(as.factor(protoc_data2_1$plstbgs_nw1), ref = "0")

protoc3_15<-lm(Ps ~Td+Wind+Wind:as.factor(CookerBrother)+Wind:as.factor(CookerOnlyPot)+
as.factor(plstbgs_nw1)+as.factor(Cooker)+
as.factor(plstbgs_nw1):as.factor(Cooker)+ as.factor(MeasureOpeningmm)+
as.factor(plstbgs_nw1):as.factor(MeasureOpeningmm)+
as.factor(MeasureOpeningmm):as.factor(Cooker)+Td:as.factor(Cooker), data = protoc_data2_1 )
AIC(protoc3_15);BIC(protoc3_15)

protoc3_16 <- lm(Ps ~  Td +Wind+ as.factor(plstbgs_nw1)+as.factor(Cooker)+
as.factor(plstbgs_nw1):as.factor(Cooker)+as.factor(MeasureOpeningmm)
+as.factor(plstbgs_nw1):as.factor(MeasureOpeningmm)
+as.factor(MeasureOpeningmm):as.factor(Cooker)
+Td:as.factor(Cooker), data = protoc_data2_1 )
AIC(protoc3_16);BIC(protoc3_16)
# Perform the likelihood ratio test
lr_test56 <- lrtest(protoc3_16,protoc3_5); print(lr_test56)

protoc3_17 <- lm(Ps ~  Td + as.factor(plstbgs_nw1)+as.factor(Cooker)+as.factor
(plstbgs_nw1):as.factor(Cooker)+ as.factor(MeasureOpeningmm)+
```

```
as.factor(plstbgs_nw1):as.factor(MeasureOpeningmm)+as.factor(MeasureOpeningmm)
:as.factor(Cooker)+Td:as.factor(Cooker), data = protoc_data2_1 )
AIC(protoc3_17);BIC(protoc3_17)
# Perform the likelihood ratio test
lr_test67 <- lrtest(protoc3_17,protoc3_16); print(lr_test67)

protoc3_1 <- lm(Ps ~  Td + as.factor(plstbgs_nw1)+as.factor(Cooker)+
as.factor(MeasureOpeningmm)+as.factor(plstbgs_nw1):as.factor(MeasureOpeningmm)+
as.factor(MeasureOpeningmm):as.factor(Cooker)+
Td:as.factor(Cooker), data = protoc_data2_1 )
AIC(protoc3_1);BIC(protoc3_1)
# Perform the likelihood ratio test
lr_test17 <- lrtest(protoc3_1,protoc3_17); print(lr_test17)
Anova(protoc3_1, type="III"); summary(protoc3_1)


####################
Contrast results
########################
library(emmeans)
#####Plastic bags vs Cookers
# Compute the estimated marginal means
emmsPL <- emmeans(protoc3_1, ~ plstbgs_nw1 | Cooker)
# Look at the results
summary(emmsPL)
# Perform pairwise comparisons.
contrast(emmsPL, method = "pairwise")

#####Measure Opening vs Cookers
# Compute the estimated marginal means
emmsMO <- emmeans(protoc3_1, ~  MeasureOpeningmm  | Cooker )
# Look at the results
summary(emmsMO)
# Perform pairwise comparisons
contrast(emmsMO, method = "pairwise")

#####Measure Opening&Plastic bags vs Cookers
# Compute the estimated marginal means
emmsMOP <- emmeans(protoc3_1, ~  MeasureOpeningmm  | Cooker | plstbgs_nw1)
# Look at the results
```

```
summary(emmsMOP)
# Perform pairwise comparisons
contrast(emmsMOP, method = "pairwise")


##################################
Estimation of performance  at 50°C
##################################
library(lme4)
library(merTools)
# Get unique levels for categorical variables
plstbgs_nw1_levels <- unique(protoc_data2_1$plstbgs_nw1)
MeasureOpeningmm_levels <- unique(protoc_data2_1$MeasureOpeningmm)
Cooker_levels <- unique(protoc_data2_1$Cooker)
# Create a new data frame for prediction
new_data <- expand.grid(
Td = 50,
plstbgs_nw1 = plstbgs_nw1_levels,
MeasureOpeningmm = MeasureOpeningmm_levels,
Cooker = Cooker_levels
)
# Make predictions
predictions <- predict(protoc3_1, newdata = new_data, re.form = NA)
# Combine the new data with predictions
results <- cbind(new_data, Predicted_Ps = predictions)
# View results
View(results)

library(car)
########Normality
eprotoc3_1<-residuals(protoc3_1)
# Generate Q-Q plot with a custom confidence level 95%
qqPlot(protoc3_1, main="Q-Q Plot with 95% Confidence Band", envelope=0.95,
ylab="Studentised residuals", xlab="Theoretical Quantiles")


#######Linearity
# Create a data frame with the necessary data
data <- data.frame(
  Cooker = protoc_data2_1$Cooker,
```

```
  Residual = eprotoc3_1,
  Td = protoc_data2_1$Td,
  Wind = protoc_data2_1$Wind
)
# Plot 1: Residuals vs Temperature Difference
plot1 <- ggplot(data, aes(x = Td, y = Residual)) +
geom_point() +
geom_hline(yintercept = 0, color = "blue", linetype = "dashed") +
labs(x = "Temperature difference(°C)", y = "Residual") +
theme_minimal()
# Plot 3: Residuals vs Cookers
plot3 <- ggplot(data, aes(x = Cooker, y = Residual, color = Cooker)) +
geom_boxplot() +
geom_hline(yintercept = 0, color = "blue", linetype = "dashed") +
labs(x = "Cookers", y = "Residual") +
scale_x_discrete(labels = NULL) +
theme_minimal()
# Combine the plots using patchwork
combined_plot <- (plot1 | plot3)
# Display the combined plot
combined_plot


##########Multicollinearity
vif(protoc3_1)

######Homoscedasticity
library(ggplot2)
library(gridExtra)
# Create the first plot for Temperature difference
plot1 <- ggplot(protoc_data2_1, aes(x = Td, y = abs(eprotoc3_1))) +
geom_point() +
geom_hline(yintercept = sum(abs(eprotoc3_1)) / nrow(protoc_data2_1), linetype = "dashed")
+labs(x = "Temperature difference", y = "Absolute residuals") +
theme_minimal(base_size = 15)
# Create the second plot for Cookers
plot2 <- ggplot(protoc_data2_1, aes(x = as.factor(Cooker), y = abs(eprotoc3_1),
color = Cooker)) +geom_boxplot() +
geom_hline(yintercept = sum(abs(eprotoc3_1)) / nrow(protoc_data2_1), linetype = "dashed")
+labs(x = "Cooker", y = "Absolute residuals") +
```

```
theme_minimal(base_size = 15)+
scale_x_discrete(labels = NULL) +theme(legend.position = "bottom")
# Combine the plots using patchwork
combined_plot <- (plot1 | plot2)
# Display the combined plot
combined_plot

################################
Outliers detection
###############################
car::influenceIndexPlot(protoc3_1,
                        vars = c("Studentized", "hat"),
                        id=F,
                        main = "Residuals and Leverage")

# Compute DFBETAS
DFBETAS <- dfbetas(protoc3_1)
# Check the spelling of the terms and enter them accordingly
# in each plot() call below
# colnames(DFBETAS)
par(mfrow=c(1,2))
plot(DFBETAS[, "Td"], ylab="Temperature difference")
abline(h = c(-0.2, 0.2), lty = 2)
SUB.DFBETAS <- apply(abs(DFBETAS) > 0.2, 1, any)
Influencial_obs<-DFBETAS[SUB.DFBETAS, ]
DFBETASs<-as.data.frame(DFBETAS)


# Compute Studentized residuals
RSTUDENT <- rstudent(protoc3_1)
#RSTUDENT
# Use numeric cutoff from outlier test to identify outliers
SUB.OUTLIERS1 = RSTUDENT > (4)
RSTUDENT[SUB.OUTLIERS1]
SUB.OUTLIERS2 = RSTUDENT < (-4)
RSTUDENT[SUB.OUTLIERS2]

COOK <- cooks.distance(protoc3_1)
DFBETAS <- dfbetas(protoc3_1)
# Subjective cutoff from figure
```

```
SUB.COOK <- COOK > 0.2
# Standard cutoff for DFBeta
SUB.DFBETAS <- apply(abs(DFBETAS) > 0.2, 1, any)
# View the extreme Cook's distance values and compare
# to plot to make sure you captured all you wanted to capture
COOK[SUB.COOK]
SUB <- SUB.DFBETAS
sum(SUB)

######Sensitivity
subdat <- subset(protoc_data2_1, !SUB)
# Fit the linear model
protoc3_1Se <- lm(Ps ~ Td + as.factor(plstbgs_nw1) + as.factor(Cooker) +
as.factor(MeasureOpeningmm) +Td:as.factor(Cooker) +
as.factor(plstbgs_nw1):as.factor(MeasureOpeningmm) +
as.factor(plstbgs_nw1):as.factor(Cooker) +
as.factor(MeasureOpeningmm):as.factor(Cooker),
data = subdat)
summary(protoc3_1Se)


##########################
Linear Mixed Model
#########################

protocLMM<-lmer(Ps ~  Td + as.factor(plstbgs_nw1)  +
                    as.factor(MeasureOpeningmm)
                  +as.factor(MeasureOpeningmm):as.factor(plstbgs_nw1)+(1 | TestDate),
                  data = BrotherLMM)

# Get the summary of the model
summary(protocLMM)

protocLMM1 <- lmer(Ps ~  Td + as.factor(plstbgs_nw1)+
                  as.factor(MeasureOpeningmm)+(1 | TestDate),
                  data = BrotherLMM)
# Get the summary of the model
summary(protocLMM1)

##########Estimation at 50°C
```

```
plstbgs_nw1_levels <- unique(BrotherLMM$plstbgs_nw1)
MeasureOpeningmm_levels <- unique(BrotherLMM$MeasureOpeningmm)
Cooker_levels <- unique(BrotherLMM$Cooker)
# Create a new data frame for prediction
new_data <- expand.grid(
  Td = 50,
  plstbgs_nw1 = plstbgs_nw1_levels,
  MeasureOpeningmm = MeasureOpeningmm_levels,
  Cooker = Cooker_levels
)
# Make predictions
predictions <- predict(protocLMM1, newdata = new_data, re.form = NA)
# Combine the new data with predictions
results <- cbind(new_data, Predicted_Ps = predictions)
# View results
View(results)
```