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Maastricht University

Faculty of Sciences

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Master of Statistics and Data Science

Master's thesis

The use of survival analysis for the determination of the performance of solar cookers in Africa

Felista Cosmas Kauki

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

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Transnational University Limburg is a unique collaboration of two universities in two countries: the University of Hasselt and Maastricht University.

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May the Almighty God bless you all
Felista Cosmas Kauki
June 18, 2024
Genk, Belgium.

Contents

Abstract

Background: About 2.4 billion people worldwide rely on solid fuels for cooking, heating, and other domestic needs because they lack sustainable fuel. The use of solid fuels leads to individuals inhaling smoke and soot that may cause health problems. In contrast, people who harness free solar energy breath clean air, obtain safe drinking water, and preserve the environment. Hence, there is increasing interest in renewable energy for cooking in the most vulnerable communities.

Objectives: The aim of this project is to evaluate the use of survival analysis methods to compare performance of various solar cooker designs developed within the Solar Cooker for All (Sc4all) Project. Specifically, the study examines the time taken by different prototypes of solar cookers to reach a temperature of 70°C, with the understanding that faster attainment of this temperature signifies better performance.

Methodology: To compare the performance of different prototypes, we used Kaplan-Meier estimators of the corresponding survival functions. Log-rank tests were used to compare the survival curves, and a Cox proportional-hazards model was applied to evaluate the impact of various covariates on the hazard of reaching a temperature of 70°C.

Results: Based on the findings in this master thesis, we conclude that survival analysis techniques provide a flexible alternative to compare different solar cooker devices, accounting for the complex nature of the data collected in these performance experiments, and offering additional insights as compared to standard analysis methods included in the existing protocol for evaluation of the performance of solar cookers. More specifically, our results clearly show that the YamoDudo device, one of the commercial cookers, has the best performance, and is superior to the devices that were locally produced within the Sc4all project. Among those locally produced devices, prototypes 3 and 4 (i.e., Proto3 and Proto4) showed the best performance.

Conclusions: In contrast to standard analysis techniques, including linear regression approaches to model the relation between standardized performance and the difference in temperature at the start and end of the experiment, the survival models used in this master thesis allow for the inclusion of relevant covariate information and provide an intuitive interpretation in terms of the (median) time to reaching a specific threshold in terms of the temperature in the cooking pot. Survival analysis are particularly useful for the data analysis of automated measuring station since measurements are taken every minute, allowing for a longitudinal perspective.

Key Words: Cox PH model, KM estimator, Sustainable energy, Survival analysis, Solar Cooker for All (Sc4all).

1 Introduction

1.1 Background

Among clean energy technologies, solar energy is recognized as one of the most promising options. It is considered advantageous as it is freely available and provides clean and environmentally friendly energy. Solar energy systems are particularly beneficial for communities in the developing world, aligning with the abundance of sunlight in these regions and the daily cooking activities of the local population (Sarangi et al., 2024). Most densely populated countries in the developing world are blessed with abundant solar irradiation, typically with a mean daily illumination intensity ranging from 5 to 7 kWh/m^2, and enjoy over 275 sunny days annually (Muthusivagami et al., 2010).

Recently more and more energy possibilities exists for food preparation. However, it is estimated that around 2.4 billion people globally depend on solid fuels (such as wood, animal dung, crop residues and charcoal) to meet their cooking, heating and other domestic needs (Idowu et al., 2023, Vanschoenwinkel et al., 2014). This results in increased time-investments in fuel collection as women and children in rural areas have to walk longer and further to collect the necessary wood to prepare their meals (Cuce and Cuce, 2013). Nevertheless, people in urban areas spend too much money on firewood which can be considered a major expenditure especially for poor families. This comes at the expense of economic, social and educational activities (Otte, 2013).

Risks associated with the use of solid fuels includes; serious ecological problems like deforestation and inhabitant loss in turn, disruption of ecosystems and threatening of wildlife populations, indoor air pollution, leading to serious health problems like burns, eye disorders and lung diseases. It is also emphasized by WHO that 1.6 million deaths per year are caused by indoor air pollution (Cuce and Cuce, 2013). Climate change, driven by greenhouse gas emissions, exacerbates global warming by increasing the release of carbon dioxide into the atmosphere. However people who harness free solar energy for cooking breathe clean air, drink safe water and preserve the environment (Mekonnen et al., 2020). Therefore, there is a rising attention regarding the renewable energy options to meet the cooking requirements of people in developing countries.

A solar cooker converts solar energy into heat, which is used to cook food kept in the cooking utensil. A solar cooker works in a simplified way since it collects light, absorbs the light and retains the heat which makes it easy, efficient and safe as well as sustainable. Solar cookers also enable some significant processes such as pasteurization and sterilization (Cuce and Cuce, 2013, Yettou et al., 2014). There are a number of factors that motivates the adoption of solar cookers which includes the price i.e., affordable solar cookers are assumed to be more acceptable to users and if price is too high will discourage many people from obtaining a solar cooker (Narayanaswamy, 2001). The successful adoption of solar cookers is more likely when users perceived additional economic benefits (Cuamba et al., 2006). The level of performance of a solar cooker plays a significant role for the adoption of cookers. Ease of use is another motivation for adoption of solar cookers. The more difficult a solar cooker is, the less interested someone will be in using the cooker. A solar cooker has to be user friend to avoid risks like burns or blindness caused by direct sun rays owing incorrect tracking (Murty et al., 2007). In order to be sustainable, the solar cookers should be built with local resources which has various advantages such as limited importation of raw materials in turn decrease in price, creates employment to local people that results in creation of income generating activities (Cuamba et al., 2006).

According to Solar Cooker International, solar cooking has been or is being introduced in 107 countries which is a way forward towards transformation of use of renewable energy (Saxena et al., 2011). There are several types of solar cookers since manufacturers are still developing new devices but they can actually be classified into three main categories: “solar panel cookers”, “solar box cooker”, and “solar parabolic cookers” (Cuce and Cuce, 2013). Other types include Evacuated tube and Institutional solar cooking systems, these systems can be mounted on rooftops to concentrate solar energy, heat water and create steam or heat a thermic fluid such as oil that is transferred to a kitchen inside the building (Eswara and Ramakrishnarao, 2013). Solar panel cookers may be considered the most common type available due to their ease of construction and low-cost material. In solar panel cookers, sunlight is concentrated from above (Mirdha and Dhariwal, 2008). Solar box cookers consists of an insulated box with a transparent glass cover and reflective surfaces to direct sunlight into the box (Saxena et al., 2011). The inner part of the box is painted black in order to maximize the sunlight absorption. It is worth to note that they are slow to heat up but work well even though there is diffuse radiation, convective heat loss caused by wind, intermittent cloud cover and low ambient temperatures (Funk, 2000, Cuce and Cuce, 2013). A solar parabolic cooker consists of a parabolic reflector with a cooking pot which is located on the focus point of the cooker and a stand to support the cooking system. This type of cookers can reach an extremely high temperature within a short period of time unlike the box and panel types (Ozturk, 2007). Parabolic cookers became more popular and attractive to the users around the world due to their outstanding performance (Cuce and Cuce, 2013).

In this research, we investigate the performance of various solar cooker designs developed within the Solar Cooker for All (Sc4all) Project, a collaborative effort between UHasselt and the University of Lubumbashi, the Democratic Republic of Congo (DRC), supported by the Flemish Government through a VLIR-UOS SI project (project number: CD2023SIN371A104). The prototypes encompass both oven and parabolic solar cooker variants. Specifically, our analysis encompasses a range of parabolic prototypes (referred to as prototype 2 - 4), oven prototypes (oven 1, 2 and 5) and commercially available solar cookers (referred to as Brother, Fornelia and YamoDudo). We evaluate the performance of these solar cookers in comparison to a black pot under direct sunlight. Figure 1 is a black pot labelled as OnlyPot in the remainder of this master thesis, which is positioned outdoors to receive direct sunlight. Water in the cooking pot is expected to heat up to approximately 70°C within 3 hours but struggles to maintain high temperatures.

Figure 1: *Picture showing a black port, labelled as OnlyPot which is positioned outdoors to receive direct sunlight without a plastic bag around the pot. The OnlyPot is not among the locally made prototypes was merely used for comparison purposes.*

Figure 2 shows parabolic prototypes (referred to as prototype 2-4). The prototypes are made with locally available materials. "Proto2" and "Proto3" consist of an iron frame covered with aluminum foil to reflect the sun. These prototypes lack a supporting stand, making it difficult to turn them towards the correct direction of the sun. "Proto4" is an improved version of "Proto3" with a supporting stand which can be easily turned to the right direction of the sun.

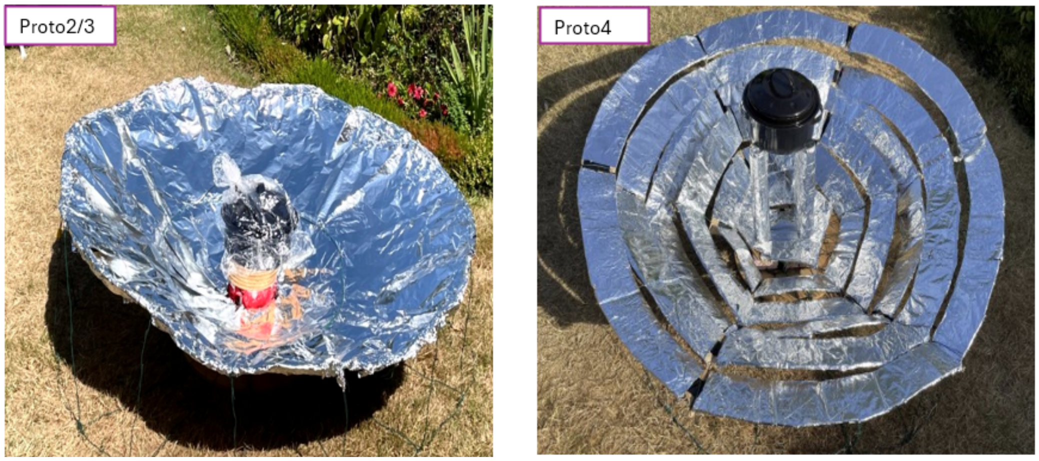

Figure 2: *Picture showing locally made parabolic prototypes i.e., Proto 2/3 (left) with a pot rapped with plastic bag and no supporting stand to allow easy tracking, and Proto4 (right) with a pot but no plastic bag around the pot with a supporting stand that allow easy tracking.*

Figure 3 shows the oven prototypes (referred to as prototype 1, 2 and 5). "OvenProto1" is made of a box with one reflective panel covered with aluminum foil. "OvenProto2" is an improved version of "OvenProto1" with four reflective panels covered with aluminum foil that can reflect sun from 4 angles. "Proto5" is made of wooden material with 4 reflective panels covered with recycled soda cans and cooking pot supported with bricks which also retain heat.

Figure 3: *Picture showing locally made oven prototypes (left) OvenProto1 contains one reflective panel covered with aluminum foil, (middle) OvenProto2 contains 4 reflective panels covered with aluminum foil and (right) Proto5 contain 4 reflective panels that are covered with soda cans. The prototypes are covered with plastic glass on top that accounts for the plastic bag effect.*

Figure 4 depicts the commercially available cookers (referred to as Brother, Fornelia and YamoDudo) respectively. These cookers are also used to evaluate their performance inline with the locally made prototypes.

Figure 4: *Picture showing the commercial available cookers included in the performance evaluation (left) Brother, (middle) Fornelia, and (right) YamoDudo*

1.2 Performance Evaluation According to Standard Protocol

Environmental factors influencing performance of solar cooker include “wind”, “ambient temperature” and “level of solar radiation”. If the area is characterized by many cloudy days this affects the performance of solar cookers (Otte, 2013). According to ASAE S580.1 protocol for testing and reporting solar cooker performance, in order to control the factors affecting the performance, testing is recommended under the following conditions: conduct solar cooker tests when wind is less than 1.0 m/s at the elevation of cooker being tested. If the wind is over 2.5m/s for more than 10 minutes the test data should be discarded due to the fact that heat loss is strongly influenced by wind velocity (Ebersviller and Jetter, 2020). Ambient temperature should be between 20°C-35°C since ambient temperature extremes experienced in one location may be difficult to replicate at another location (Eswara and Ramakrishnarao, 2013). Irradiation is to be measured in plane perpendicular to direct beam radiation. Variation in measured irradiation greater than $100W/m^2$ during a ten-minute interval, or readings below $450W/m^2$ or above 1100 W/m^2 during the test shall render the test invalid. It is strongly recommended to conduct the tests between 10:00 and 14:00 solar time, considering the solar altitude and azimuth angle. It is because zenith angle is somewhat constant at midday (Funk, 2000, Ebersviller and Jetter, 2020).

1.3 Objective of the Study

The aim of this project is to evaluate the use of survival analysis methods to compare performance of various solar cooker designs developed within the Solar Cooker for All (Sc4all) project. The survival endpoints were generated based on time to achieve temperature of 50°C, 70°C and 90°C. Accordingly, faster attainment of these temperatures indicates better device performance. Additionally, this study will investigate the external factors influencing performance of devices such as wind, irradiation, and ambient temperature.

1.4 Research Questions

Primary Research Question

- What is the most effective prototype in comparison to YamoDudo, which is a commercial cooker for use in resource-limited settings?

Secondary Research Question

- What insights can be derived from the analysis of the collected data to inform and enhance the design and implementation of future solar cooker experiments?

The report is divided into five consecutive sections. Compared with section 1 introduction, which states the goals of the study and provide a summary of the performance evaluation. The data being examined and the methodology employed in the study are described in detail in section 2. The results of the data analysis are presented in Section 3. A thorough analysis of the results, the study's limitations, and additional suggestions for further research are included in Section 4. Section 5 includes conclusion drawn, ethical thinking, stakeholder awareness, and societal relevance of the mater thesis.

2 Material and Methods

2.1 Data Description

The report utilizes data collected within the Sc4all project at UHasselt, Belgium, and pertain to various prototypes of solar cooking appliances designed and tested in the years 2022 and 2023. The dataset under investigation consists of 673 observations and 25 variables including categorical and continuous ones. Variables of interest includes water mass (kg), wind speed (m/s), ambient temperature (°C), irradiation (W/m^2), water temperature (°C), time (minutes), presence of plastic bag around the cooking pot and opening of the pot for the device used to measure the temperature of the water inside the pot. Several set of instruments were required to gather data for the aforementioned variable, including an electronic balance, digital thermometer, pyranometer, and anemometer. A pre-wetted container was used to measure the water load using an electronic balance; the water temperature inside the pot was measured using a digital thermometer; the solar irradiance was measured using a pyranometer; and the wind speed and ambient temperature were measured using an anemometer (ASABE, 2013). The description of the variables along with their abbreviations are presented in the Appendix (see Table A1).

2.2 Data Manipulation of the Raw Data

Time to event data were created with three different endpoints (i.e, time to reach 50°C, 70°C and 90°C) based on experimental window of 10 minutes and temperature at the beginning of experiment and temperature at the end of experiment. The main variables were also used to define new variables including censoring indicator (0 = censored and 1 = event of interest), and baseline temperature based on starting temperature for each experimental window and time to reach a specific temperature (50°C, 70°C and 90°C). In the final analysis time to reach 70°C was used. The time to reach 50°C was not a good candidate to approach the boiling temperature. The time to reach 90°C was only relevant for "YamoDudo". The data contains time-invariant and time-varying covariates they will be taken into account for the reminder of the master thesis.

Furthermore, the report includes sample data from experiments with two distinct electric devices. This experiment looks into how long it takes the device to get to 70°C. This sub-analysis aims to provide information about the use of electric appliances and solar cookers in relation to how well they perform in terms of how long it takes for the temperature to reach 70°C.

2.3 Notations and Terminology

The subsection addresses key notations and terminology used for the remainder of the master thesis. Time to event which is a random variable $T^* > 0$. Right-censored time to event $T = min(T^*, C)$ where C is censoring time and T is observation time. Indicator of censoring or event: $\delta = I(T \leq C)$ where the observed pairs are (T, δ). T^* has a distribution with density function $f(t)$, with survival function $S(t) = P(T^* \geq t)$. For continuous T^*, $S(t) = 1 - F(t)$, where $F(t)$ is a cumulative density function and $S(0) = 1$. The hazard function is given by

$$\lambda(t) = \lim_{h \to 0^+} \frac{P(t \leq T^* < t + h \mid T^* \geq t)}{h}.$$

The cumulative hazard function is defined by $\Lambda(t) = \int_0^t \lambda(u)du$.

The counting process formulation replaces the pair of variables (T_i, δ_i) with the pair of functions $(N_i(t), Y_i(t))$ where $N_i(t)$ is the event counting process equals to 0 initially as long as no event and 1 when their is an event; and $Y_i(t)$ defines the risk set. Therefore $Y_i(t) = 1$ when unit i is under observation and at risk at time t and 0 otherwise (Therneau et al., 2000).

2.4 Survival Analysis Methods

Survival analysis refers to the analysis of time-to-event data in which the non-negative time to a specific event is considered, typically in the presence of censoring (Burzykowski, 2024). In essence, a survival process describes a life span from a specified starting time to the occurrence of a particular event. The primary feature of survival data is the description of a change in status as the underlying outcome measure (Liu, 2012). For instance such changes in status includes; survival time where the event is death, time to progression where event is progression of disease or when an automobile breaks down. The second feature of survival data is a description of the time-to-event process. Time at the occurrence of a particular event is regarded as a random variable, referred to as event time, failure time or survival time. Therefore data used for the survival analysis consists of information about a discrete jump in status as well as about the time passed until the occurrence of such jump (Kartsonaki, 2016). The third feature of survival data is censoring. This is the main issue in the analysis of survival data and the reason why special methods are needed to analyze such data.

2.4.1 Censoring

Censoring means that we do not observe the exact event time denoted by T^*. Censoring is said to be present when information on the exact time to the event is not available for all study participants (Prinja et al., 2010). A description of different types of censoring are as follows; For right-censored observations, we only observe the censoring time C (i.e., in that case $T^* > C$) such that in general we solely observe T = min(T^*, C) for all subjects (Patti et al., 2007). Left-censored we only observe the upper bound for the time ($T^* < C$), that is lets say 70°C were reached before the first experiment. Interval-censored we only know the time interval ($C_L < T^* < C_U$) in which the event has happened, that is to say 70°C was achieved between the upper and lower bound of the time interval (Burzykowski, 2024, Williamson et al., 2018). In practice and for convenience purposes most often interval censored data are translated to right censored data, for this aspect we do assume that the event happened when 70°C was observed within the experimental window of consecutive 10 minutes interval (Liu, 2012). Within this master thesis project, we confine attention to the use of techniques accommodating the right censored nature of the data. The experiment took place in calendar time as presented in the Appendix (see Figure A1).

2.5 Kaplan-Meier Estimator for Survival Function

Kaplan-Meier is an estimator for survival function that makes proper allowance of censored observations as well as making use of information from those subjects up to the time when they are censored (Gijbels, 2010). The idea is to survive t time units, you need to survive the first $t-1$ units, and then the t^{th} one represented as

$$S(t) = S(t-1) \cdot P(\text{ surviving } t^{th} \text{ time unit}) \tag{1}$$

we need to assume that $S(0) = 1$ since at baseline no event of interest that took place. The KM estimator is also referred to as the product-limit estimator of $\hat{S}(t)$ which is given by

$$\hat{S}(t) = \prod_{t_{(j)} \leq t} \left(\frac{n_j - d_j}{n_j} \right) \tag{2}$$

where $t_1, t_2, \cdots, t_n$ are observed times, $t_{(1)}, t_{(2)}, \cdots, t_{(d)}$ are ordered event times for $d \leq n$ since some events can be censored, n_j is a risk-set size at $t_{(j)}$ which are the number of experiments which did not have any event or censoring before event time $t_{(j)}$. Consequently, $\frac{d_j}{n_j}$ is a non-parametric estimator of the hazard function, i.e., the instantaneous risk of experiencing the event of interest (Goel et al., 2010, Collett, 2023). Greenwood's formula used for the variance of the Kaplan-Meier estimator in combination with the delta method (to obtain the variance of the transformed S(t), i.e., log(-log(S(t)))) to obtain a point wise confidence intervals. A Kaplan-Meier estimator can be used for a uni-variable exploration of a effect of a single categorical covariate of the survival time distribution. The log-rank test is used to compare different survival curves. The log-rank test is a non-parametric procedure used to test whether the difference between survival times between two or more groups is statistically different or not (Etikan et al., 2017, Kleinbaum et al., 2012).

2.5.1 Estimating Quantiles of the Survival Time Distribution

Since the distribution of survival time is positively skewed the median time is used as the summary measure of the location of the distribution (Collett, 2023). Median time is the time beyond which 50% of the temperature of interest under the experiment is expected to be observed denoted by $t(50)$ which is equivalent to $S\left\{t(50)\right\} = 0.5$ (Lousdal et al., 2017). The estimated median survival time $\hat{t}(50)$ is the smallest observed survival time for which the value of estimated survival function is less than 0.5. Mathematically presented by $\hat{t}(50) = min\left\{t_i|\hat{S}(t_i) < 0.5\right\}$ where t_i is the observed survival time for the i^{th} subject, $i = 1, \cdots, n$.

Estimating other percentiles of the distribution of survival times will use similar procedure as for the median time. The p^{th} percentile of the distribution of survival times is defined to be the value $t(p)$ which is $F\left\{t(p)\right\} = \frac{p}{100}$, for any value of p from 0 to 100. In survival function expression, $t(p)$ is such that $S\left\{t(p)\right\} = 1 - \frac{p}{100}$ (Hosmer Jr et al., 2008). Thus the estimated p^{th} percentile is the smallest observed survival time $\hat{t}(p)$ for which $S\left\{\hat{t}(p)\right\} < 1 - \frac{p}{100}$. In the situation where the estimated survival function is greater than 0.5 for all values of t, then the median survival time can not be estimated (Collett, 2023). It is recommended to summarize the data in terms of other percentiles.

2.6 The Cox Proportional Hazards Model

The Cox PH model examines survival as a function of several different independent variables, and the statistical significance of each of these independent variable(s) is assessed for the outcome of interest i.e., occurrence of the event (Andrade, 2023). The Cox PH model has become mostly used procedure in modelling the relationship between covariates and an event time, potentially subject to censoring. The hazard of event of interest at time t for the i^{th} subject is in the form,

$$\lambda_i(t|X_i(t)) = \lambda_0(t)exp\left\{\sum_{j}^{p} \beta_j X_{ij}(t)\right\}. \tag{3}$$

Let $X_{ij}(t)$ be the j^{th} covariate of the i^{th} subject, where $i = 1, \cdots, n$, $j = 1, \cdots, p$, λ_0 is the baseline hazard, β is $p \times 1$ column vector of coefficients. For time-invariant covariate X_i is the covariate vector of subject i and $X_i(t)$ is the covariate vector of subject i in case of time-varying covariate (Therneau et al., 2000). The hazard ratio for two subjects with fixed covariate vectors X_i and X_j,

$$\frac{\lambda_i(t)}{\lambda_j(t)} = \frac{\lambda_0(t)e^{X_i\beta}}{\lambda_0(t)e^{X_j\beta}} \equiv \frac{e^{X_i\beta}}{e^{X_j\beta}}, \tag{4}$$

is constant over time, and therefore the model is known as proportional hazard model. The estimation of β is based on the partial likelihood function introduced by Cox (Grambsch and Therneau, 1994, Cox, 1972). The partial likelihood is of the form

$$P\mathcal{L}(\beta) = \prod_{i=1}^{n}\prod_{t\geq 0}\left\{\frac{Y_i(t)r_i(\beta,t)}{\sum_j Y_j(t)r_j(\beta,t)}\right\}^{dN_i(t)}, \tag{5}$$

where $r_i(\beta, t)$ is the risk score for subject i, and $r_i(\beta, t) = exp[X_i(t)\beta] \equiv r_i(t)$.

From Equation 3 the survival function is given by,

$$S(t|X) = exp(-\Lambda(t|X(t))),$$

however,

$$\Lambda(t|X(t)) = \int_0^t \lambda_0(t)exp(\beta X(u))du.$$

The cumulative hazard estimator is defined as,

$$\hat{\Lambda}\{t|X_i(t)\} = \sum_{i=1}^{n}\int_0^t \frac{exp(\hat{\beta}X_i(u))dN_i(u)}{\sum_j Y_j(u)exp(\hat{\beta}X_j(u))},$$

The corresponding estimated survival function $\hat{S}(t|X(t)) = exp(-\hat{\Lambda}(t|X(t)))$. For time varying covariates, $\hat{S}(t|X(t))$ does not simplify to $exp(-exp(\hat{\beta}X)\hat{\Lambda}_0(t))$ (Thomas and Reyes, 2014). Normally, a unique integration is required to estimate $\hat{\Lambda}(t|X(t))$ for every value of $X(t)$ rather than scalar multiplication of time-invariant covariate effects on an exponential scale with the baseline cumulative hazard function $\hat{\Lambda}_0(t)$. For prediction purpose, we are going to predict for a constant values of $X(t)$. Therefore

$$\hat{S}(t|X) = exp(-exp(\hat{\beta}X)\hat{\Lambda}_0(t)). \tag{6}$$

The final Cox PH model is given by the mathematical expression below adopted from general Cox PH model from Equation 3.

$$\lambda_i(t \mid X_i(t)) = \lambda_0(t) \exp \Bigg(\sum_{j=1}^{5} \beta_j \text{Cooker}_{ij} + \beta_6 \text{Baseline\_temp}_i + \beta_7 \text{Ambient}_i(t) + \beta_8 \text{Irradiation}_i(t) + \beta_9 \text{Wind}_i(t) + \beta_{10} \text{Pbag}_i + \beta_{11} \text{Opening}_i + \beta_{12} (\text{Pbag}_i * \text{Cooker}_i) \Bigg), \tag{7}$$

where $\beta_1, \beta_2, \cdots, \beta_{12}$ are the coefficients for each covariate. Cooker represents the dummy variables i.e., $i = 0$ for the YamoDudo and $i = 1$ other types of cookers, Pbag represents the dummy for the plastic bag use around the pot, i.e., $i = 1$ for the presence of a plastic bag and $i = 0$ absence of plastic bag. Opening represents the dummy variable for the size of the pot for device used to measure water inside the pot, i.e., $i = 1$ for 4 mm and $i = 0$ for 10mm. In the fitted model, clustering is handled internally by the *coxph* function using robust standard errors in the estimation process. To take into account time varying covariates (irradiation, wind, and ambient temperature) the data is structured into counting process (Thomas and Reyes, 2014).

2.7 Model Diagnostics

2.7.1 Martingale Residuals

Martingale residuals are based on counting process arguments, the counting process martingale for the i^{th} subject is defined as

$$M_i(t) = N_i(t) - E_i(t) = N_i(t) - \int_0^t Y_i(s) e^{X_i(s)\beta} \lambda_0(s) ds. \tag{8}$$

Martingale residuals are used to assess the functional form of continuous covariates. The model may be properly specified if a continuous covariate is put in a proper form, for instance as a logarithmic rather than linear. A smoothed plot of martingale residuals could indicate the functional form of the covariate which we will need to use in the model (Collett, 2023). The functional form is examined by plotting the martingale residuals from a null model, that is one with $\hat{\beta} = 0$, against each covariate separately and superimposing a scatter plot smooth.

In the context of representing a subject with one or more time-varying covariates using the counting process style, the martingale residual is still computed (Therneau et al., 2000). The experiment will be presented as one or more observations each consisting of time interval, the status, and fixed covariate values over that interval (Therneau et al., 2000). In the process of computing the residuals, the scatter plot will base on the collapsed data on the experimental window and not on each observation. The smoothed plot of martingale residuals for an empty model based on observation aspects will not work. This is because will be having cloud of points which will be dragging the smoothed plot towards itself. The use of these approach can be subject to bias if we opt to use the total martingale residual. Moreover, more than one approach is recommended to study the functional form to get more insight.

2.7.2 Poisson Regression Approach

The Poisson regression method is also recommended to check the functional form in the presence of time-varying covariates (Grambsch and Therneau, 1994). The Poisson regression method however controls for the bias by in-cooperating both the covariates and the estimated baseline hazard and can be used without modification of the data set (Therneau et al., 2000). The basic martingale method was extended to address both linear and non linear relationships using a Poisson regression approach. Let $f(x)$ denote the p-vector whose j^{th} component is $f_j(x_j)$, the true functional form of the covariate. The multivariate model with time-invariant is given by $\lambda_i(t) = exp(f(x)\beta)\lambda_0(t)$ where,

$$\varepsilon(N_i|x) = exp(f(x)\beta) \int_0 Y_i(s)\lambda_0(s)ds. \tag{9}$$

Since $\lambda_0(s)ds$ is unknown we can obtain a reasonable estimate by fitting a Cox model based on transformation of $f_j s$. The expected values are extracted from the fitted model object, the linear predictor values are also extracted from the fitted model, new time object and the counts are defined so as to fit the new model based on Poisson family. The Anova test provides per term test for non linearity, if the test does not indicate a significant curvature then the term has to be added in the Cox model as liner term (Therneau et al., 2000, Liu, 2012).

2.7.3 Scaled Schoenfeld Residuals

The scaled Schoenfeld residuals in practice are useful for assessing proportional hazards which is a key assumption of the Cox PH model. The Scaled Schoenfeld residual at the k^{th} event time is defined as

$$\hat{r}^*_{sk} = \hat{r}_{sk} I(\left(\hat{\beta}, t_{(k)}\right) = \hat{r}_{sk} var^{-1}\left(\hat{\beta}, t_{(k)}\right), \tag{10}$$

where $\hat{r}_{sk} = \int_{t_k-1}^{t_k} \sum_i (X_i(s) - \bar{X}(\hat{\beta}, s))dN_i(s)$, and $\hat{\beta}$ is the estimated coefficient. The plots of scaled Schoenfeld residuals are useful for detecting non-proportionality of predicted hazards of the fitted model across the covariate space. The smoothed plot indicate whether the proportional hazard assumption holds. A specific test based on scaled Schoenfeld residuals was also used to assess the proportionality of the hazard assumption. A significant p-value for any covariate indicates a violation of the proportional hazard assumption.

2.8 Model Building

Model building is a process to identify a set of explanatory variables that have the potential for being included in the linear component of Cox PH model (Collett, 2023). The selection criteria will base on the likelihood ratio test to select the most satisfactory model. However, the study suffers from study design with highly data imbalance. The analysis will base on subset of data set and not the full data set.

Multiple testing theory provides a framework for defining and controlling appropriate error rates to protect against wrong conclusions (Bender and Lange, 2001). Since the study is exploratory and not confirmatory, multiplicity correction not deemed necessary. However, we are working with a limited dataset.

2.9 Influential Observations

In the assessment of model adequacy, it is important to determine whether any particular observation has an undue impact on the inferences made on the basis of a model fitted to an observed set of survival data (Collett, 2023). An influential observation is one if included in the dataset used to fit a model, alters the regression coefficients by a meaningful amount (Harrell, 2015). The impact of influential observations pull the regression fit towards themselves. The model results including parameter estimates, CI's and p-values can be quite different with and without these cases included in the analysis (Wilson, 2013). The standardized dfbetas were used which measures for each observation, the standardized difference in individual regression coefficient estimates when fitting the model with and without the observations providing a measure of influence on each coefficient (Collett, 2023). The standardized dfbeta with a cutoff point of 0.2 were used for comparison.

2.10 Software

Data management and all the analysis were done using R-software version 4.4.0 (R Core Team, 2024).

3 Results

3.1 Exploratory Data Analysis

In Figure 5, Kaplan-Meier estimates of survival probabilities are depicted with pointwise 95% confidence intervals shown as shaded areas. P-values mentioned in this figure refers to two-sided p-values corresponding to a log-rank test comparing the survival functions between different devices. The dashed line indicates the median survival time in minutes.

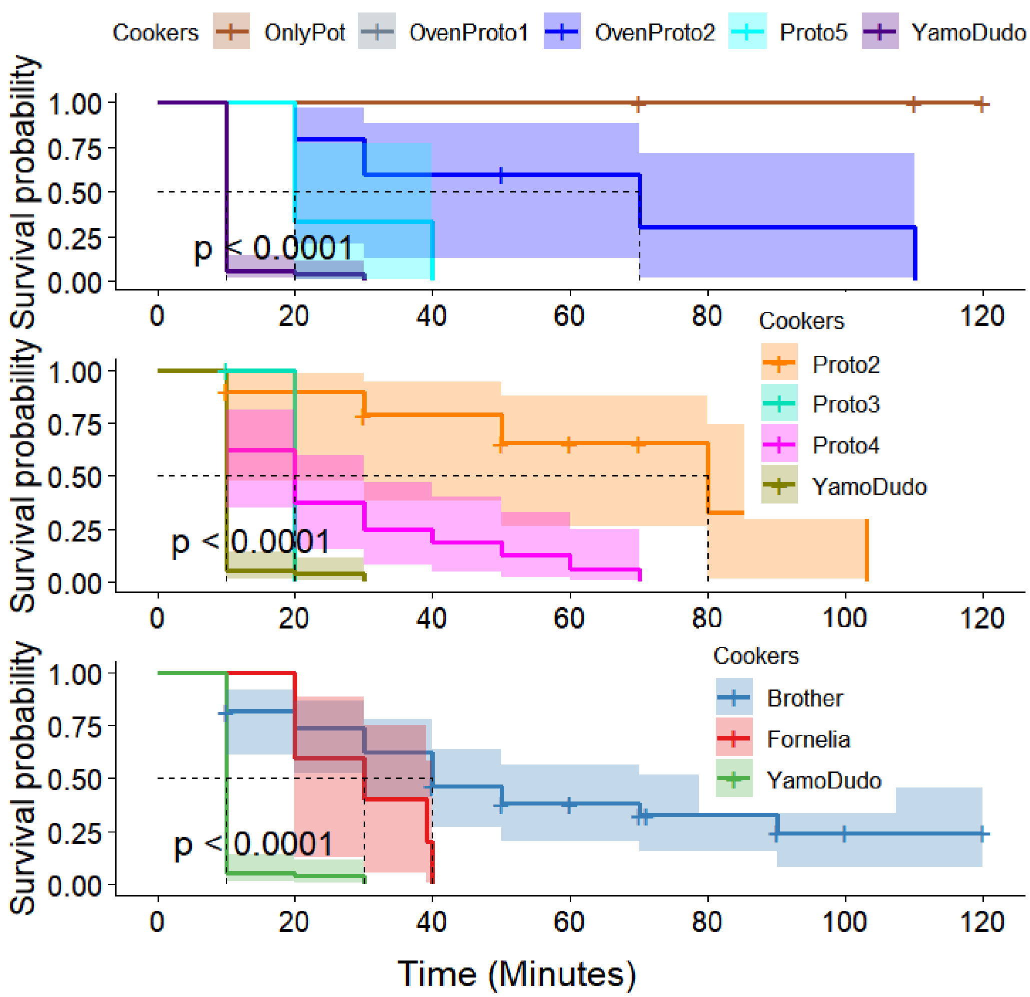

Figure 5: *Kaplan-Meier estimates of survival function for the type of devices. The two-sided p-values are based on a log-rank test comparing the survival functions for all devices considered in this study. The pointwise 95% confidence intervals are shown as shaded areas and the (median) time in minutes are shown as dashed lines. Each color corresponds to a different type of device.*

The results show that at a 5% significance level, there is a significant difference between the survival functions (p-value < 0.0001). The median survival time is 10 minutes for YamoDudo, 20 minutes for Proto3, Proto4, and Proto5, 30 minutes for Fornelia, 40 minutes for Brother, 70 minutes for OvenProto2, and 80 minutes for Proto2. However, the median survival time for OnlyPot and OvenProto1 could not be estimated due to the absence of events (Schober and Vetter, 2018). The plot with all cookers in a single panel is presented in the Appendix (see Figure A2).

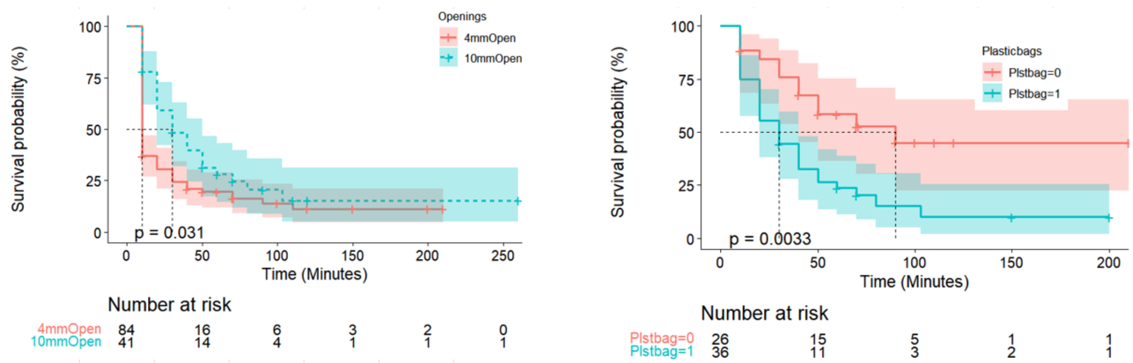

Figure 6: *Kaplan-Meier estimates of survival function for opening size of the pot for the device used to measure the temperature of water inside the pot (left), and the plastic bag around the cooking pot (right). The pointwise 95% confidence intervals are depicted as shaded areas and median time as dashed lines. The associated two-sided p-values are based on a log-rank test.*

In Figure 6, the Kaplan-Meier curves of opening size of pot (letf), shows a clear separation between the survival curves implying a significant difference in the survival probabilities (p-value $= 0.031$). The median survival time is approximated to be 10 minutes for the 4 mm opening size of pot and 30 minutes for the use of 10 mm opening size of the pot. Thus the use of 4 mm opening implies shorter time to reach temperature of 70 degrees Celsius compared to the use of 10 mm opening. However, presence of plastic bag around the pot (right), a significantly different survival curves is observed for experiments with and without plastic bags included (p-value $=$ 0.0033). This is inline with the findings and recommendations of Solar Cooker International as discussed later on (see Discussion section). The estimated median survival time is 30 minutes if plastic bag used and 90 minutes if plastic bag not used. The log-rank test results for levels of cookers, plastic bags and opening size are presented in Appendix (see Table A3).

In order to carry on the final analysis, the distribution of events across different covariates were investigated. Peduzzi et al., 1995) suggested that when the number of events per independent variable is "too small" in the multi-variable analysis, the results from the fitted regression model may not be accurate or precise. Also (Schober and Vetter, 2018) suggested that for multi-variable models like the Cox PH model, at least 10 events need to be observed per covariate to be included in the model. The power does not depend on the sample size alone but also the number of events. Table 1 depicts that with a sample size of 317 and a total of 86 events, six devices have a reasonable allocation of events. Due to the observed data imbalance, for the reminder of the study, we shall confine attention on devices with a reasonable number of events to evaluate this performance data.

Table 1: *Distribution of occurrence of events and censoring across levels of cookers involved in the experiment in relation to the presence and absence of plastic bags around the pot and opening size of the pot for the device used to measure temperature of water inside the pot. The coloured devices (blue) will be involved in the analysis for the reminder of the master thesis.*

	Censoring/Events		Distribution of PlasticBag		Distribution of MeasureOpening	
Devices	0	1	No	Yes	4mm	10mm
YamoDudo	3	39	36	6	37	5
Brother	57	14	39	32	29	42
Fornelia	8	5	13	0	0	0
OnlyPot	84	0	41	43	75	9
OvenProto1	9	0	9	0	0	9
OvenProto2	21	4	0	25	25	0
Proto2	22	5	7	20	4	23
Proto3	3	2	0	5	0	5
Proto4	22	16	1	37	17	21
Proto5	2	1	0	3	0	3

3.2 Model Building

The procedure begun by fitting models that contain each of the variable one at a time. The values of $-2\log\hat{L}$ are then compared to that of the null model to determine which variables of their own significantly reduce the value of the test statistic. The variable that seem to be important from step one are then fitted together in step 2. In step 3 variables that seem to be not important on their own are then investigated in the presence of other variables. The final check is made to verify that, no term in the model can be omitted without significantly increasing the value of $-2\log\hat{L}$ and no term not included significantly reduces the value of $-2\log\hat{L}$ (Collett, 2023, Fan and Li, 2002). The model selection results based on log-likelihood and the resulting p-values compared at 5% significance level are presented in the Appendix (see Table A2). We conclude that the most satisfactory model is that containing all the 9 explanatory variables. Although in the procedure mass seems to be important, in the remainder of the master thesis, won't be used due to observed data imbalance across the levels of cookers. However, for the cookers involved in the final analysis mass was the same except "Proto5" which was not further used for the remainder of the master thesis.

3.3 Model Diagnostic

3.3.1 Functional Form of Continuous Covariate

The smoothed plots of martingale residuals are presented in the Appendix (see Figure A3) for wind speed, ambient temperature, and irradiation. The results suggest wind, ambient temperature, and irradiation are reasonably linear i.e., no clear deviation from linearity. The continuous covariates will be included in the model as linear terms to study their effects.

3.3.2 Poisson Regression Approach

The approximated significance test of smooth term based on Anova to the Poisson model is shown in Table 2. At 5% significance level, all p-values are not statistically significant indicating insignificant curvature. Therefore the test suggests the covariates to be modelled as linear terms in the Cox PH model.

Table 2: *Approximate significance test of smooth terms for non-linearity for the continuous covariates included in the Poisson model. The (s) stands for the smoothing parameter.*

Variables	effective df	Reference df	Chisq	P-value
s(T1-Baseline)	1	1	3.225	0.073
s(Ambient)	1	1	0.183	0.669
s(Irradiation)	1	1	3.421	0.082
s(Wind)	1	1	0.408	0.523

Figure 7 shows the the results of extended basic martingale method to address both linear and nonlinear relationships using Poisson regression approach. The results suggests linear form for the continuous covariates. From the figure it is clear wind is based on only few data points as compared to other covariates as indicated by the tick marks along the bottom. The findings suggests the covariates to be added in the model as linear terms.

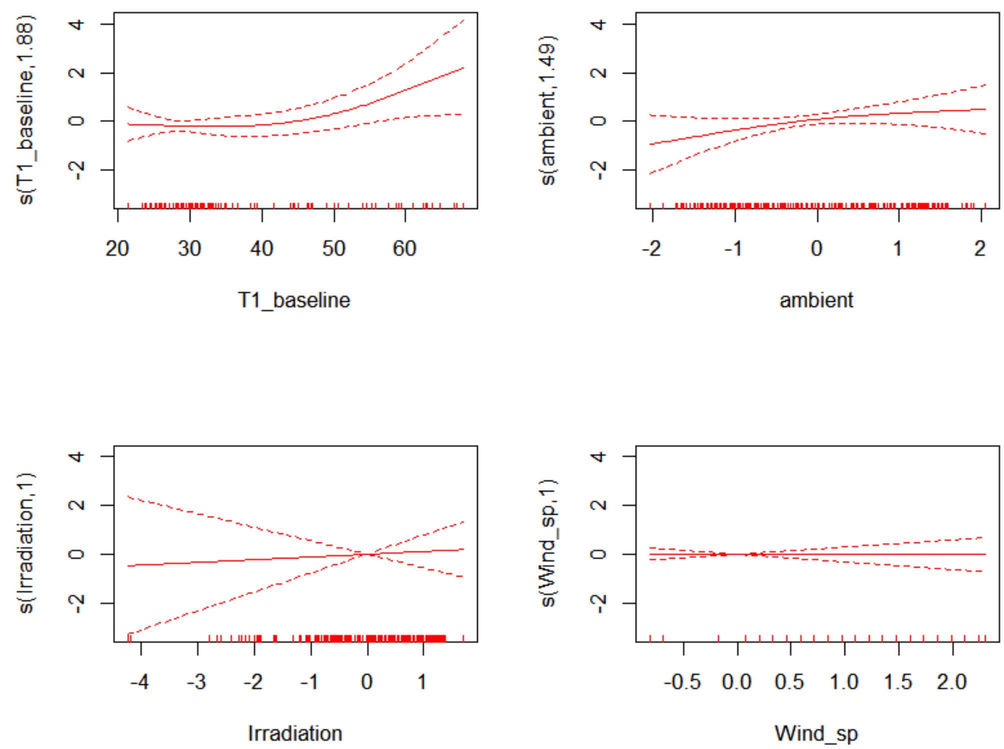

Figure 7: *Functional form based on Poisson regression approach for the continuous covariates, i.e., baseline temperature, ambient temperature, irradiation and wind speed. The smoothing spline is based on the default 4 degrees of freedom.*

3.3.3 Proportional Hazards Assumption

The Cox model was fitted with all the covariates in their correct functional form. The assumption was checked using scaled Schoenfeld residuals to test for independence between residuals and the transformed time. Additionally, the test performs a global test for the model as a whole. From Table 3 the test is not statistically significant for each of covariates, and the global test is also not statistically significant (p-value = 0.81). Therefore, at 5% significance level we can assume the proportional hazards.

Table 3: *Schoenfeld test results for covariates included in the model. The associated* χ^2*, p-values and degree of freedom for each variable are included in the table. The significant p-value for any of the covariate indicates PH assumption violation for that covariate. The significant global p-value is also an indication of violation of PH for the model as a whole.*

Variable	χ^2	df	P_value
Cooker	2.6314	5	0.76
Baseline_Temp	0.7046	1	0.40
Ambient_Temp	0.3991	1	0.53
Irradiation	0.0288	1	0.87
Wind	2.3614	1	0.12
PlasticBag	0.7909	1	0.37
MeasureOpeningmm	0.0060	1	0.94
PlasticBag:CookerBrother	0.6477	1	0.42
GLOBAL	7.7282	12	0.81

Figure 8 represents scaled Schoenfeld residuals plots for the covariates included in the model. It is necessary to note that, systematic departure from a horizontal line are indicatives of non-proportional hazards (Xue and Schifano, 2017). From the graphical inspection, their is no pattern with time. The proportional hazard assumption appears to be supported for each covariate.

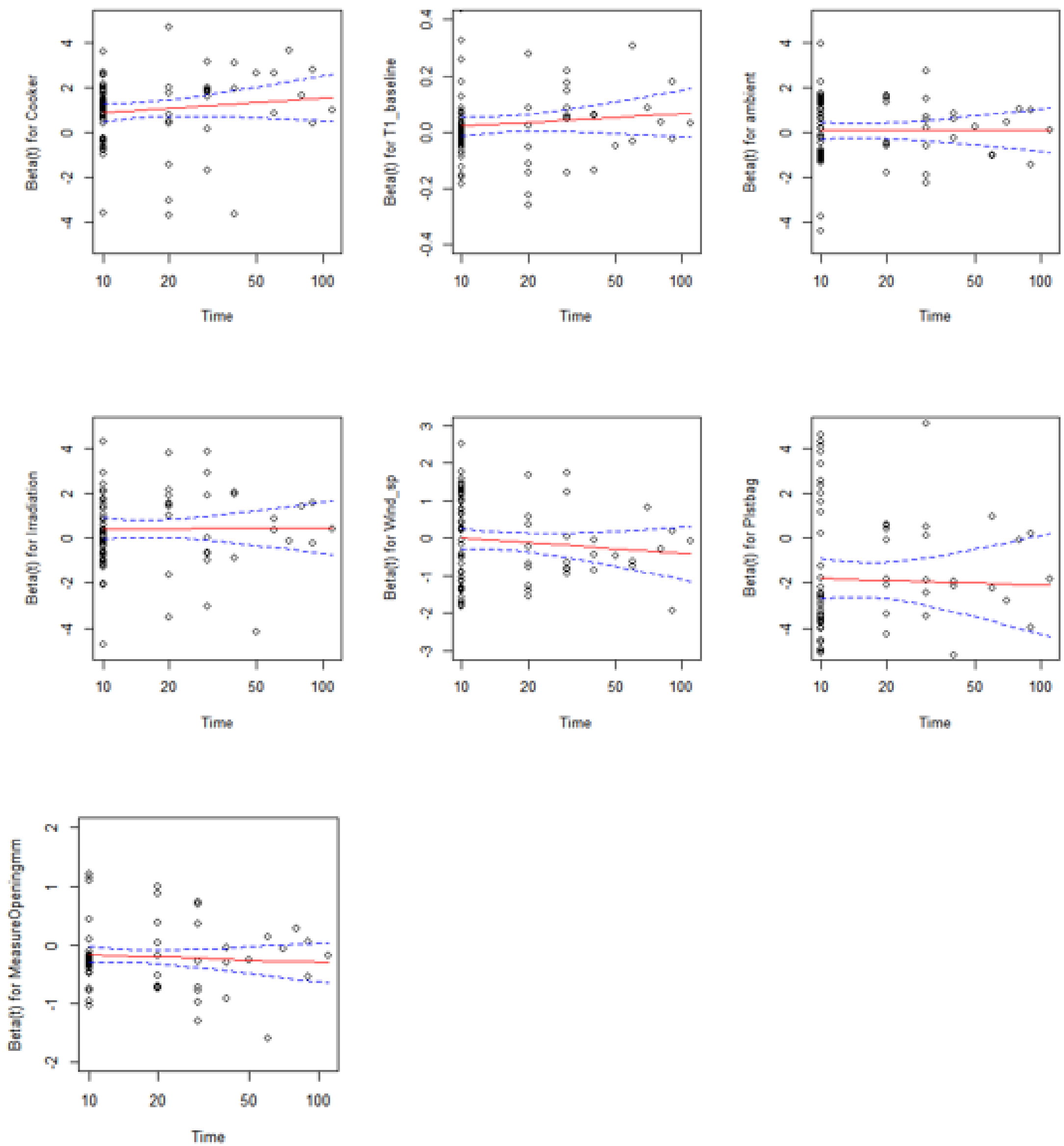

Figure 8: *The graphical diagnostics of the scaled Schoenfeld residuals for each covariate against the transformed time. The solid lines (red) are the smoothing spline fit to the plot, and the dashed lines (blue) representing a standard error band around the fit.*

3.4 Cox Proportional Hazards Model Results

Table 4 provides a summary of the parameter estimates of the fitted final Cox PH model as defined on Equation 7. The findings based on the model results is described below.

Table 4: *Summary of parameter estimates of the fitted final Cox PH model that incorporates the coefficients, hazards ratio, robust standard errors, corresponding two-sided p-values and 95% confidence intervals for the hazards.*

Variable	**Coef**	**Haz.Ratio**	**robust se**	**P-value**	**95% CI**
CookerBrother	-3.4007	0.0334	0.5799	< 0.0001**	[0.0107,0.1039]
CookerOvenProto2	-1.6708	0.1881	0.9541	0.0799	[0.0289,1.2204]
CookerProto2	-1.5761	0.2068	0.6136	0.0102*	[0.0621,0.6883]
CookerProto3	0.8765	2.4025	1.0079	0.3845	[0.3332,17.3237]
CookerProto4	0.4491	1.5669	0.7219	0.5338	[0.3807,6.4495]
Baseline-Temp	0.0301	1.0305	0.0145	0.0383*	[1.0016,1.0603]
Ambient Temp	0.0740	1.0768	0.1405	0.5983	[0.8176,1.4183]
Irradiation	0.4304	1.5378	0.1867	0.0211*	[1.0667,2.2172]
Wind	-0.0753	0.9274	0.0895	0.3998	[0.7781,1.1053]
PlasticBag(Ref:0)	1.8482	6.3484	0.7312	0.0115*	[1.5144,26.6128]
Openings(Ref:10mm)	1.1364	3.1156	0.3477	0.0011**	[1.5763,6.1585]
Brother*PlasticBag(Ref:0)	3.5680	35.4476	1.0482	0.0007***	[4.5436,276.55]

The interactions between plastic bags and levels of cookers are evaluated for the device with enough observations due to the data imbalance elaborated earlier (see Material and Methods section). Since the presence of interaction effects is significant, the interpretation will confine attention to interaction rather than the main effect for devices included in interaction.

For “Proto2”, the model reveals that the effects are significantly different from “YamoDudo” (p-values < 0.0001). The estimated coefficient (-1.5761) indicates an increase in time to reach 70°C as compared to “YamoDudo”. The Hazard ratio equals 0.2068, with a 95% confidence interval ranging from 0.0621 to 0.6883.

A unit increase in degrees Celsius of baseline temperature has a significant effect on the time to reach 70°C (p-value=0.0383). The estimated coefficient (0.0301) indicates a decrease in time to reach 70°C. The hazard ratio equals 1.0305, with 95% confidence interval ranging from 1.0016 to 1.0603. The irradiation effect is marginalized over the devices, and the effect is assumed to be the same across different levels of cookers. The unit increase in watt per square meter of irradiation has a significant effect (p-value = 0.0211) on the time to reach 70°C. The estimated coefficient of 0.4304 indicates a decrease in time to reach 70°C. The hazard ratio equals 1.5378, with 95% confidence interval ranging from 1.0667 to 2.2172. The results show that measure opening of the pot has a significant effect on the device's performance on the time to reach 70°C (p-value = 0.0011). Clearly, this effect is significant implying that the hazard is significantly different in the case of an opening of 4 mm as compared to an opening of 10 mm. The hazard ratio equals 3.1156, with 95% confidence interval ranging from 1.5763 to 6.1585.

However, wind speed showed no detectable effect on the performance of devices'. The insignificant results can be attributed to the wind range included in the study, i.e., 0 m/s to 2.5 m/s, as described in the protocol for evaluating and testing the performance of devices. Additionally, ambient temperature shows no detectable effect on the device's performance. The insignificant results can perhaps be due to the restrictive conditions of conducting a test with ambient temperature ranging between 20°C and 35°C as per protocol (ASABE, 2013).

3.5 Contrast Results

3.5.1 Estimating the Effect of Plastic bags on the Levels of Cookers

Table 5 depicts the contrast results for the cookers involved in the interaction. Essentially, this implies that the model assumes that the plastic bag effect is different for Brother as compared to other devices. Hence, the contrasts shown here merely show that the plastic bag effect is conditional on the cooker. Clearly, this effect is significant, implying that the hazard is significantly different in the case of a plastic bag as compared to no plastic bag. Since not all other cookers have sufficient replication in one of the two groups, their contribution in estimating the difference is primarily confined to estimating the effect of one of the two conditions (either with or without bag) this is evidenced from Table 1. The second contrast, the estimate is marginalized over all other cookers (including Proto2) which have either plastic bag yes or no. This effect is significant, implying that the hazard is significantly different in the case of plastic bag use. The findings demonstrate that for devices with marginal performance, the effect of using a plastic bag around the pot matters.

Table 5: *Contrast on the levels of cookers involved in the interaction in the case of plastic bag or no plastic bag. The contrast shows the plastic bag effect conditional on the cooker. Since not all the devices have a sufficient replication in the plastic bag or no plastic bag, the contribution in estimating their difference is primarily confined on estimating the effect of one of the condition (with plastic or without plastic bag).*

Contrast Description	Coef	HR	Standard Error	p-value
Cooker: Brother	-1.7200	0.1791	0.6380	0.0070
Other cookers (including Proto2)	-1.8500	0.1572	0.7310	0.0115

The sub-analysis to estimate the marginal effect of Fornelia device is presented in Appendix (see Table A4). In the main analysis, we were unable to estimate the effect of Fornelia due to data imbalance in the use of opening size of the pot for the device used to measure temperature of water inside the pot, and presence or absence of plastic bag around the pot as shown in Table 1. However, the model shows no detectable difference from YamoDudo (p-value = 0.1405). The estimated effect equals -0.9467, the hazard ratio 0.388 and 95% confidence intervals ranging from 0.1102 to 1.3663.

3.6 Predicting the Median Survival Time

To identify the best devices from the analysis, predictions were based on the median survival time. The objective was to find the device that reached a temperature of 70°C in the shortest median time. The prediction was based on fixing other covariates, including baseline temperature (20°C), wind speed (0 m/s), ambient temperature (22°C), presence or absence of plastic bags around the pot, opening size of the device used to measure the temperature of water inside the pot (4 mm or 10 mm), and the irradiation level at $700W/m^2$. The irradiation was evaluated at $700W/m^2$ because according to ASAE S580.1 protocol, cooking power should be corrected to a standard insolation of $700W/m^2$ (Funk, 2000).

Table 6 provide a summary of estimated median survival time for the devices as shown in Figure 9 which incorporates the uncertainty with regard to the estimation of median time. It is postulated that when a plastic bag was used with a 4 mm opening size of the pot, Proto4 had a median time of 30 minutes to reach 70°C, and 70 minutes without a plastic bag. Also, for the opening size of the pot being 10 mm (large opening), Proto4 took 80 minutes. However, for Proto3 with a 4 mm opening size of pot and the presence of a plastic bag around the pot, the median time was 30 minutes and 60 minutes without the plastic bag. However, the findings showed that

OvenProto2 was only efficient with small opening size (4 mm) and when a plastic bag was used with median time of 90 minutes. The findings depict that the higher the irradiation, the better the performance of the device, the shorter the time it takes to reach the threshold, and vice versa. The plots showing the estimated median survival time for 4 mm openings without a plastic bag and 10 mm opening with plastic bag are presented in Appendix (see Figures A6, and A7).

Table 6: *The predicted median survival time in (minutes) for hypothetical conditions on the devices involved in the analysis, the opening size of the pot for the device used to measure the temperature of water inside the pot and the presence or absence of plastic bag around the pot during the experiment. The conditions are based on irradiation of 700W/m^2, constant wind speed, ambient temperature and baseline temperature.*

Cooker	MeasureOpening 4mm		MeasureOpening 10mm	
	PlasticBag 1	PlasticBag 0	PlasticBag 1	PlasticBag 0
Brother	50	90	90	-
OvenProto2	90	-	-	-
Proto2	70	90	110	-
Proto3	30	60	80	-
Proto4	30	70	80	-

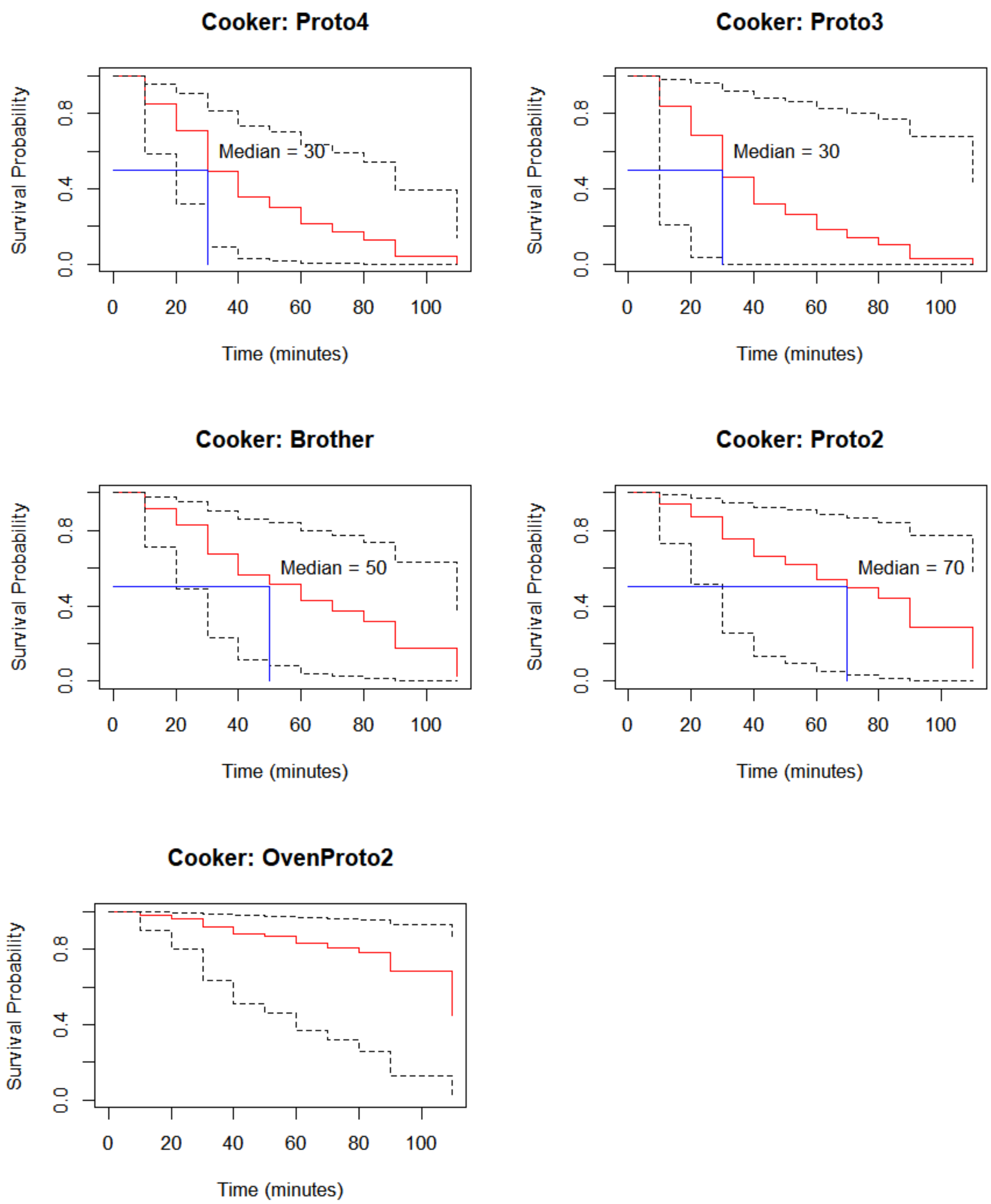

Figure 9: *The predicted median survival time in (minutes) for hypothetical conditions on the devices involved in the analysis, the opening size of the pot for the device used to measure the temperature of water inside the pot (4 mm) and the use of plastic bag around the pot during the experiment.*

4 Discussion

This project aimed to evaluate the use of survival analysis methods to compare the performance of various solar cooker designs developed within the Solar Cooker for All (Sc4all) project. The master thesis project examined the time taken by different prototypes of solar cookers to reach 70°C. The use of survival analysis techniques provided a flexible alternative to compare different solar devices, accounting for the complex nature of the data collected in these performance experiments, and offering additional insights as compared to standard analysis methods (single measure of performance by using simple linear regression) as described in the existing protocol (Funk, 2000). This "novel" method is suited to analyze performance data, due to the added value of being able to investigate the external factors i.e., irradiation, wind speed, ambient temperature, baseline temperature, water mass, etc) that influence performance unlike the single measure of performance method (Riva et al., 2017). However, the data coming from future experiments including the use of automated measuring stations with longitudinal readings, leads to a better resolution in terms of the event time process. The findings based on this technique are easier to communicate to end users due to the incorporated time aspect.

Various analyses were performed to address the study's objective. Kaplan-Meier estimators of the corresponding survival function were used to compare the marginal effect of different prototypes. The log-rank test were used to compare the survival curves. Additionally, a Cox PH model was used for the final analysis to account for other factors affecting the performance of devices, as the other methods can be used for a uni-variable exploration of an effect of a single categorical covariate of the survival time distribution. However, the use of Cox PH model accommodated the time-invariant and time varying covariates.

The marginal effect of cookers using Kaplan-Meier estimates as presented in Figure 5 showed that different devices have different performance despite of not correcting for other factors. The findings clearly showed that the YamoDudo device, one of commercial cookers, had the best performance and is superior to the devices that were locally produced within the Sc4all project. Among the locally made devices Prototypes 3, 4, and 5 (i.e., Proto3, Proto4, and Proto5) showed the best performance in terms of median time. (Mwandu, 2024) found that by using single measure of performance as described in the standard protocol YamoDudo, Proto3, Proto4 and Proto5 had best standardized performance of 152.67W, 10.90W, 10.33W and 33.71W respectively. The finding confine that with best performance, implies the shortest time for that particular device to reach the temperature of 70°C. However as shown in Figure 6, the use of plastic bag around the pot marginally influence the performance of devices as compared without the plastic bag. This results confine attention on the use of plastic bags during the experiments as described by Solar Cooker International. The use of small opening of the pot for the device to measure the temperature of water inside the pot (4 mm) showed high performance in terms of time to reach 70°C as compared to the use of large opening of the pot (10 mm).

To investigate the effect of other factors influencing performance of devices, the Cox PH model was used. The results as shown in Table 4 depicted that baseline temperature, irradiation, presence of plastic bag around the pot and opening size of the pot for the device to measure temperature of water inside the pot influences the performance of devices.

The baseline-temperature indicated a significant different in performance of devices for a unit increase in degree Celsius. This indicated that the higher the starting temperature of water in the pot, the faster the attainment of the boiling point hence higher performance of devices. Based on the findings is an indication that with different starting temperature we expect differences in reaching time to 70°C. Therefore since baseline temperature influence the performance it was necessary to correct for it in the model to avoid chance finding results.

The ambient temperature results showed that, the higher the ambient temperature the higher the performance hence faster the attainment of event of interest. However, the results were not statistically significant. To further study the influence of ambient temperature towards performance of devices, it is recommended to include data points outside the range of 20°C and 35°C contrary to protocol conditions since the model can correct for such confounding factors. The findings showed that lower wind speed conditions indicating better performance of devices. The results were not statistically significant. This can be due to the fact that the wind range from 0 m/s -2.5 m/s as described in protocol may not have influence on the devices' performance (Funk, 2000). The study by (Riva et al., 2017) case study in Burundi revealed that, wind condition influence the performance of devices. However they suggested the use of wind resistant to enhance the greenhouse effect and reduce the convective heat losses. In their experiment they recommended to cover the pot with a transparent plastic bag to correct for wind effect which refers to a plastic bag in our case study. Another study showed that the minimal heat loss of examined parabolic device was due to the wind shield, which is an emphasize of influence of performance of device (Yettou et al., 2014).

The findings depicted a significant effect in performance of devices for a watt per square meter increase of irradiation marginalized over the devices. However, in this study the irradiation readings ranged from $450W/m^2$ to 1100 W/m^2, and within a 10 minute interval, the difference between irradiation at the beginning and irradiation at the end of experiment did not exceed $100W/m^2$ to abide by the protocol (ASABE, 2013). Several studies showed different type of devices have different performance with irradiation conditions. (Riva et al., 2017) showed that panel solar cookers are inefficient under cloudy conditions i.e., performance depends on the reflected irradiance and wind conditions. (Kimambo, 2007) a case study in Tanzania showed that with average insolation of about $1000W/m^2$ the reflector cooker with glass reflectors managed to reach maximum temperature of 96°C in 90 minutes. Therefore the different studies investigating the factors influencing performance of devices are inline with the findings observed in this master thesis.

To further study the effect of plastic bag on the level of cookers we performed contrast among levels of cookers and plastic bag that were involved in interaction. Not all cookers were included in the interaction since the design was not optimal to ensure balance with regard to, for example, the distribution of experiments with and without plastic bag, for the different devices considered. This, of course, complicates subsequent analysis of the data. However, the findings showed that, the plastic bag effect is different for different devices as compared to no plastic bag. (Riva et al., 2017) showed that, performance of oven types are less influenced by the use of plastic bag. This is due to the fact that they are made up of insulated box with reflective surface and black painted bottom, normally the green house effect is accounted for by the plastic glass on top of the oven. Nevertheless, performance of investigated parabolic devices were influenced by the use of plastic bags i.e., greenhouse effect decreases further thermal losses (Riva et al., 2017). Therefore, based on different studies and findings from this master thesis, it can be concluded that plastic bag effect is also influenced by the type of devices since their use increase the performance for particular devices.

To study the effect of plastic bag around the pot on different devices, for YamoDudo cooker, 6 observations with presence of plastic bags were collapsed with no plastic bags since during tests the bags were burnt and they are part of the tail of the other distribution (i.e., no plastic bags). The potential danger of collapsing if they were not really burnt, then we are diluting the performance of YamoDudo.

To be able to rank the devices to come up with best devices predictions were used. Therefore "Proto3" and "Proto4" are the best device with the smallest median time with the use of small opening size of the pot (4 mm), presence of plastic bags around the pot, irradiation readings at $700W/m^2$ as described in the protocol, constant wind speed, ambient temperature and baseline temperature. The findings further showed that when the irradiation readings are below $700W/m^2$ the median survival time is longer. Hence this justifies the importance of irradiation for the device to perform better which is the source of energy coming from the sun (Muthusivagami et al., 2010).

To justify the use of survival techniques since was not described in the protocol, collaboration with colleague working on the same dataset and mimicking the protocol was valuable. Table 7 shows the results based on the two techniques used to study the performance of solar cooker devices left (survival technique) and right (standardized performance). The best device with the smallest median time to reach the temperature of 70°C was "Proto4" and "Proto3". The device with the best standardized performance was "Proto5", "Proto4", and "Proto3" (Mwandu, 2024). Since "Proto5" was not evaluated with the survival technique, it can be concluded that the two methods identified the same devices as the best in performance. However, given the restrictive conditions specified in the protocol, hence, the loss of information collected under sub-optimal conditions, more complicated analysis techniques ensure the use of all available information and are therefore more efficient from a statistical point of view. Needless to say, application of survival techniques comes with an additional price of data complexity including for example interval-censored nature of data, conversion of traditional data in survival endpoints, and differences in interpretation (albeit that the latter is more natural in the survival case). Nevertheless, the advantage of survival technique over the linear regression approach i.e., it gives more insight into time-to-event and taking into account censoring nature of the data, the data coming from future experiments including the use of automated measuring stations with longitudinal readings, leads to a better resolution in terms of the event time process, and findings based on this approach are easier to communicate to the end user due to the time aspect incorporated using survival analysis.

Table 7: *Predicted median survival time (minutes) and standardized performance (watts) for devices included in the performance evaluation. The median time and standardized performance for Fornelia* is not corrected for other factors and had 2 mm opening size of pot and 0.33 (kg) water mass. The conditions for Fornelia* were not further evaluated in the final analysis since has no optimal conditions of plastic bags and opening size of pot.*

Cooker	**Median Survival Time (minutes)**				**Standardized Performance**			
	Plastic Bag (Yes)		**Plastic Bag (No)**		**Plastic Bag (Yes)**		**Plastic Bag (No)**	
	4mm	**10mm**	**4mm**	**10mm**	**4mm**	**10mm**	**4mm**	**10mm**
YamoDudo	-	-	-	-	169.54	126.52	158.72	97.44
Proto4	30	80	70	-	11.35	8.26	-	-
Proto3	30	80	60	-	-	10.10	-	-
Fornelia*	-	-	30*	-	-	-	41.6*	-
Brother	50	90	90	-	15.35	6.72	-3.55	-30.43
Proto2	70	110	90	-	20.60	-2.05	-	-
OvenProto2	90	-	-	-	3.24	-	-	-
Proto5	-	-	-	-	-	33.71	-	-
OvenProto1	-	-	-	-	-	-	-	-11.60
OnlyPot	-	-	-	-	-19.08	-0.66	-29.91	-29.72

Source: (Kauki, 2024 and Mwandu, 2024)

Nevertheless, during the analysis, influential observations were evaluated. The study of influential observation is of important since it can impact the conclusions based on the findings (Harrell, 2015). The total of 21 observations were observed and further verification was conducted. The data were revisited and found out that most of observations were from YamoDudo device which tend to reach the threshold faster as compared to other devices. However, the extreme values are due to fluctuations happening during the experiments for-instance, irradiation reading so high or low within the experimental window of 10 minutes. The observations were retained in the analysis since were correct observations. Also to take into account the limited power observed in these study, leaving out large amount of observations was not recommended. Moreover, no changes observed in the nature of conclusion with and without the extreme values i.e., no highly significant p-value, no changes of directions of estimates as compared to the main analysis that would impact the findings. The plots showing the distribution of influential observations per covariate is presented in the Appendix (see Figure A4).

In order to gain additional insight into the data collected, it was decided to evaluate an alternative endpoint that looked at the time to reach a specific temperature difference of 50°C, which is a standardized version, rather than correcting for baseline temperature in the model (i.e., first evaluated endpoint time to reach 70°C). From the analysis it reveals that devices included (Brother, Proto4, and Proto5) have a significant effect in the performance compared to YamoDudo. The opening size of pot (4 mm) showed a significant effect compared to when a opening size of pot was 10 mm. However the interaction between Proto4 and irradiation showed a significant difference in performance. The findings of the two endpoints (time to reach 70°C and time to reach temperature difference of 50°C) showed similar conclusions for the preliminary analysis conducted. The alternative endpoint can further be explored in future studies since it mimics the outcome of standard protocol. The table of results is presented in Appendix (see Table A5).

The performance of electric devices was also investigated during the course of implementing this study. The results revealed that, the median time to reach a temperature of 70°C with an electric device is 2 minutes, which is 5 times faster compared to YamoDudo, a well-known device with good performance. The Kaplan-Meier estimates of survival probabilities are presented in the Appendix (see Figure A5).

The study used various methods and some of the methods have limitations. The method such as log-rank is only used for crude, unadjusted comparisons does not study other factors (Schober and Vetter, 2018). Also the use of smoothed plots of martingale residuals to check the functional form with counting process is subject to bias. The findings based on this method should be interpreted with caution. The residuals per observation is subject to distortion and rarely works well in practice (Therneau et al., 2000). In the current analyses, the interval-censored nature of the data was not accommodated. This is pitty indeed though future work should include the use of techniques in which the interval-censored nature of data could be accounted for, or in case of longitudinal readings, leads to a better resolution in terms of the time-to-event. However, differences in handling or assessment of the devices over time (i.e., turning the device towards the sun after every 5 to 10 minutes) introduce variability in the measurements that can be caused by raters and steep learning curve during assessment. For these aspects, in future studies, it is recommended to take into account the random effect in the model to account for the heterogeneity that can be introduced. This can be achieved by extending the statistical analysis using frailty models to account for the introduced variability.

Despite the complexity of the techniques used, the study suffers from study design (i.e., the study design was not optimal). The analysis was not based on the full dataset due to imbalance observed as shown in Table 1. The use of survival analysis was not described in the study design. The experiment setup did not favour the use of survival technique thus was tiresome to come up with time to event data. The collected data was not structured in time to event and no any supporting document towards the use of survival analysis on this context. The final analysis evaluated performance of 6 devices out of 10 devices expected, could be more of interest to evaluate all devices to avoid chance finding results. The devices were left out since the design was not optimal to ensure balance with regard to, for example, the distribution of experiments with and without plastic bag, opening size of pot, for the different devices considered thus results may not be accurate and precise (Peduzzi et al., 1995).

Improvements for future designs: It is recommended to carry on experiments up to 90°C before starting a new experiment. The reason is that 90°C is close to the boiling temperature of water. At 100°C the phase shift of water from liquid form to steam (Chang, 2008). In the analysis high data imbalance was observed (see Table 1). This hindered full analysis of the data set and faliure to evaluate the perfomance of other devices like Fornelia, OnlyPot, Proto5 and OvenProto1. Indeed to improve future designs it is highly recommended to conduct tests with even allocation of the conditions. That is to say, for comparison purpose, to study the effect of plastic bags around the pot, its use should be balanced across the devices under a test. The data imbalance aspect should be taken into account through out the future experiments to avoid chance finding results.

The factors affecting the performance of devices like wind, is highly recommended not to throw away data that is outside the range of 2.5m/s as described on the protocol. To keep the data point outside range will help to have enough data point hence study the effect of having those factors since the Cox PH model can take into account those confounding factors. Therefore by study design, future experiments should also include the high wind speed to have a wide range to study its effect.

It is also advised that future experiments have an optimal sample size so as to power the study to detect differences on the performance of devices. The following considerations should be made in order to illustrate how the sample size estimates for this endpoint should be done in subsequent experiments: The sample size would be determined by taking into account important parameters that shown a major impact on the devices' performance, as determined by the results of this master's thesis. The important elements are the pot's opening size, plastic bag around the pot, baseline temperature, and radiation (energy coming from the sun). Estimation of event rate should be attained by using the proportional of cookers that reached target temperature of 70 degrees Celsius. Identification of the hypothesis and significance level to be used in the computation, the power that can detect the difference between devices, and sample size can further be computed using the available software like Power analysis and Sample Size Software (PASS).

Since the study of solar cookers progresses, it would be beneficial for the team to refine the study design to improve the quality of future investigations. Developing a study design that outlines forthcoming studies in accordance with the standard protocol holds promise for enhancing future studies.

5 Conclusion

The aim of this project was to evaluate the use survival analysis methods to compare performance of various solar cooker designs developed within the Sc4all Project, a collaborative effort between UHasselt and the University of Lubumbashi, the Democratic Republic of Congo (DRC), supported by the Flemish Government through a VLIR-UOS SI project (project number: CD2023SIN371A104). Specifically our analysis evaluated the performance of locally made parabolic prototypes, oven prototypes and commercially available cookers. The master thesis evaluated the performance of devices using the "novel" method that was able to investigate the external factors influencing devices' performance unlike the single measure of performance method as described in the protocol. The factors investigated including irradiation (i.e., energy coming from the sun), wind speed, ambient temperature, the plastic bags around the pot, and opening size of the pot for device used to measure the temperature of water inside the pot.

The findings revealed different devices have different performance metrics in terms of time taken to reach the event of interest. However, the study showed that the use of plastic bags around the pot significantly influences the performance of devices. The study has also highlighted the effect of heat loss due to opening size of the pot. Irradiation showed an influence in the performance of devices with direct translation that the higher the irradiation the better the performance of device the shorter the time it takes to reach the boiling point. Nonetheless, the findings supported the central objective, affirming that survival techniques are indeed effective for evaluating device performance. The advantage of survival techniques is that they provide a direct translation of how much time it takes to cook. In terms of implementation, time is easier to convey than the mathematical computation of standardized performance. However, since the future experiments will use the automated measuring station with longitudinal readings, leads to a better resolution in terms of the event time process.

The master thesis findings can be used as a basis to conduct future experiments, develop new prototypes using locally available materials and optimize the currently prototypes under investigation. Generally, the findings will promote or foster the use of alternative energy, hence promote sustainable energy solutions, improve access to clean cooking technology and enhance livelihoods of people in resource-limited settings (Cuce and Cuce, 2013). Nevertheless, the study findings can be used to strengthen the current protocol that is used as a guide manual to conduct all the solar cooker test. Therefore since the "novel" method provided a flexible alternative to compare the solar devices' it is necessary to be adopted for future experiments and study designs.

Ethical Thinking

The study used data collected within the Sc4all Project at UHasselt, Belgium, and pertain to various prototypes of solar cooking appliances designed and tested in the years 2022 and 2023. The research work emphasized transparency and integrity, openly sharing of methods, findings, and data with the public and stakeholders. This ensures accountability, fosters trust and promotes collaborative efforts and awareness towards adoption of alternative renewable energy.

Stakeholder Awareness

The research was a joint effort involving multidisciplinary stakeholders including UHasselt, the University of Lubumbashi in the Democratic Republic of Congo (DRC), the Solar Cooker for All (Sc4All) Project supported by the Flemish Government, and the electro-mechanics and physics team. Through the collaboration, we aimed to implement a "novel" method of evaluating the performance of locally made solar cookers. Their knowledge and perspectives made the master thesis more relevant and useful. Through collaborative efforts, we were able to raise awareness, encourage discussion, and promote collaboration in solar energy and sustainable development. However, the Sc4all Project team will have an opportunity to visit the University of Lubumbashi to share the thesis findings, develop new prototypes, and engage in capacity building on sustainable energy.

Societal Relevance

The findings of this master thesis will be used as a basis for producing affordable devices for developing countries. The use of alternative renewable energy will promote sustainable energy solutions, improve access to clean cooking technology and enhance livelihoods. Promoting adoption of solar cookers can significantly reduce reliance on traditional cooking fuels. Educating communities about solar cookers will raise awareness about sustainable practices, empower local craftspeople and producers to enable them to design, create and distribute solar cookers, and contribute to environmental conservation efforts. However, the thesis work supports the transition to renewable energy sources, fostering energy independence and resilience in resource-limited settings. Finally, promoting adoption of solar cooking technology will mitigate climate change, reduce greenhouse gas emissions and protect natural resources, while providing a reliable and cost-effective cooking solution for communities in need.

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6 Appendix

6.1 Appendix Tables

Table A1: *Description of variables that were involved in the data set used in the context of master thesis. The table contains both categorical and continuous variable as well as the abbreviations used in the original data. The table contains the additional variables like status (indicator) that was not in the original data set.*

Variable	Description	Details
Cooker Type	10 categories of prototypes used	4 oven types, 5 parabolic types, 1 OnlyPot
M	Water mass used in the experiment	Measured in kg
Wind	Wind speed	Measured in m/s
Ta1	Ambient temperature at the beginning	Degree Celsius (°C)
Ta2	Ambient temperature at the end of experiment	Degree Celsius (°C)
T1	Temperature of the pot at the beginning	Degree Celsius (°C)
T2	Temperature of the pot after the experiment	Degree Celsius (°C)
I1	Irradiation at the beginning	Watts per square meters
I2	Irradiation at the end of experiment	Watts per square meters
H1	Time at the beginning	Minutes
H2	Time at the end of experiment	Minutes
MeasureOpeningmm	Indicates the mm of openings of the pot	2-mm & 4-mm & 10-mm
Time	Time to reach a defined temp	Minutes
status	Event indicator to reach a certain temp threshold	0= No event, 1= event of interest
PlasticBag	Used to capture the greenhouse effect	0-No bag or open bag, 1-Bag present closed

Table A2: *Model building procedure for an appropriate model to be used in the final analysis. The selection criteria was based on the likelihood ratio test.*

Variables in model	$-2\log\hat{L}$	χ^2	**P value**
Model1(Null)	636.22	-	-
Model2(Cooker)	536.54	99.682	< 0.0001
Model3(T1-base)	632.68	3.5289	0.0603
Model4(Mass)	630.50	5.7135	0.0168
Model5(Ambient temp)	634.68	1.5304	0.2161
Model6(Wind)	630.84	5.3681	0.0205
Model7(Irradiation)	609.96	26.250	< 0.0001
Model8(PlasticBag)	633.46	2.7625	0.0965
Model9(Measure)	625.52	10.688	< 0.0001
Model10(Cooker+Mass+Wind+Irradiation+Measure)	516.84	119.39	< 0.0001
Model11(Model10+T1-base)	511.96	4.8726	0.0273
Model12(Model10+Ambient temp)	516.58	0.2506	< 0.0001
Model13(Model10+PlasticBag)	515.76	1.0768	< 0.0001

Table A3: *The log-rank test with respective χ^2 for the comparison of survival curves for two levels of opening of the pot, presence of plastic bags around the pot, and levels of cookers involved in the study.*

Variables	**degrees of freedom**	**Chi-square test**	**P-value**
MeasureOpening	1	4.6	0.031
PlasticBags	1	8.6	0.003
Cookers	8	105	< 0.0001

Table A4: *Summary results for marginal estimates based on sub-analysis to estimate the effect of Fornelia. The table incorporates the coefficients, hazard ratio, robust standard errors, two-sided p-value and 95% confidence intervals, and the coloured device is Fornelia.*

Variable	Coef	Haz.Ratio	robust se	P-value	95% CI
CookerBrother	-2.7628	0.0631	0.4321	< 0.0001***	[0.0271,0.1472]
CookerFornelia	-0.9467	0.3880	0.6423	0.1405	[0.1102,1.3663]
CookerOvenProto2	-2.9209	0.0539	0.5314	< 0.0001***	[0.0190,0.1527]
CookerProto2	-2.9582	0.0519	0.6448	< 0.0001***	[0.0147,0.1837]
CookerProto3	-1.8308	0.1603	0.6055	0.0025**	[0.0489,0.5252]
CookerProto4	-1.5887	0.2041	0.3614	< 0.0001***	[0.1006,0.4146]
Baseline-Temp	0.0259	1.0262	0.0152	0.0890	[0.9961,1.0573]
Ambient Temp	0.1179	1.1252	0.1716	0.4919	[0.8038,1.5751]
Irradiation	0.3848	1.4693	0.2426	0.1127	[0.9133,2.3637]
Wind	-0.0529	0.9484	0.0852	0.5337	[0.8026,1.1207]

Table A5: *Summary of parameter estimates of the fitted Cox PH model for the alternative endpoint time to reach temperature difference of 50. The table of results incorporates the coefficients, hazards ratio, robust standard errors, corresponding two-sided p-values and 95% confidence intervals for the hazards.*

Variable	**Coef**	**Haz.Ratio**	**robust se**	**P-value**	**95% CI**
CookerBrother	-4.3916	0.0124	0.8524	< 0.0001***	[0.0023,0.0658]
CookerProto4	-5.8180	0.0029	1.3797	< 0.0001***	[0.0002,0.0444]
CookerProto5	-2.3728	0.0932	0.8874	0.0075**	[0.0164,0.5307]
Irradiation	0.3941	1.4830	0.1919	0.0400*	[1.0181,2.1602]
Wind	0.0059	1.0059	0.1059	0.9554	[0.8173,1.2381]
Ambient	-0.1125	0.8936	0.1340	0.4014	[0.6872,1.1621]
PlasticBag(Ref:0)	-0.2844	0.7524	0.6974	0.6834	[0.1918,2.9516]
Openings(Ref:10mm)	0.9135	2.4931	0.3389	0.0070**	[1.2831,4.8438]
Brother*PlasticBag(Ref:0)	-2.2245	0.1081	0.9904	0.0247*	[0.0155,0.7533]
Proto4*PlasticBag(Ref:0)	0.3653	1.4410	0.9682	0.7059	[0.2161,9.6112]
Brother*Irradiation	0.2098	1.2335	0.4007	0.6004	[0.5624,2.7053]
Proto4*Irradiation	3.5123	33.5242	1.4284	0.0139*	[2.0394,551.0876]
Proto5*Irradiation	0.1535	1.1659	0.9215	0.8677	[0.1916,7.0955]

6.2 Appendix Figures

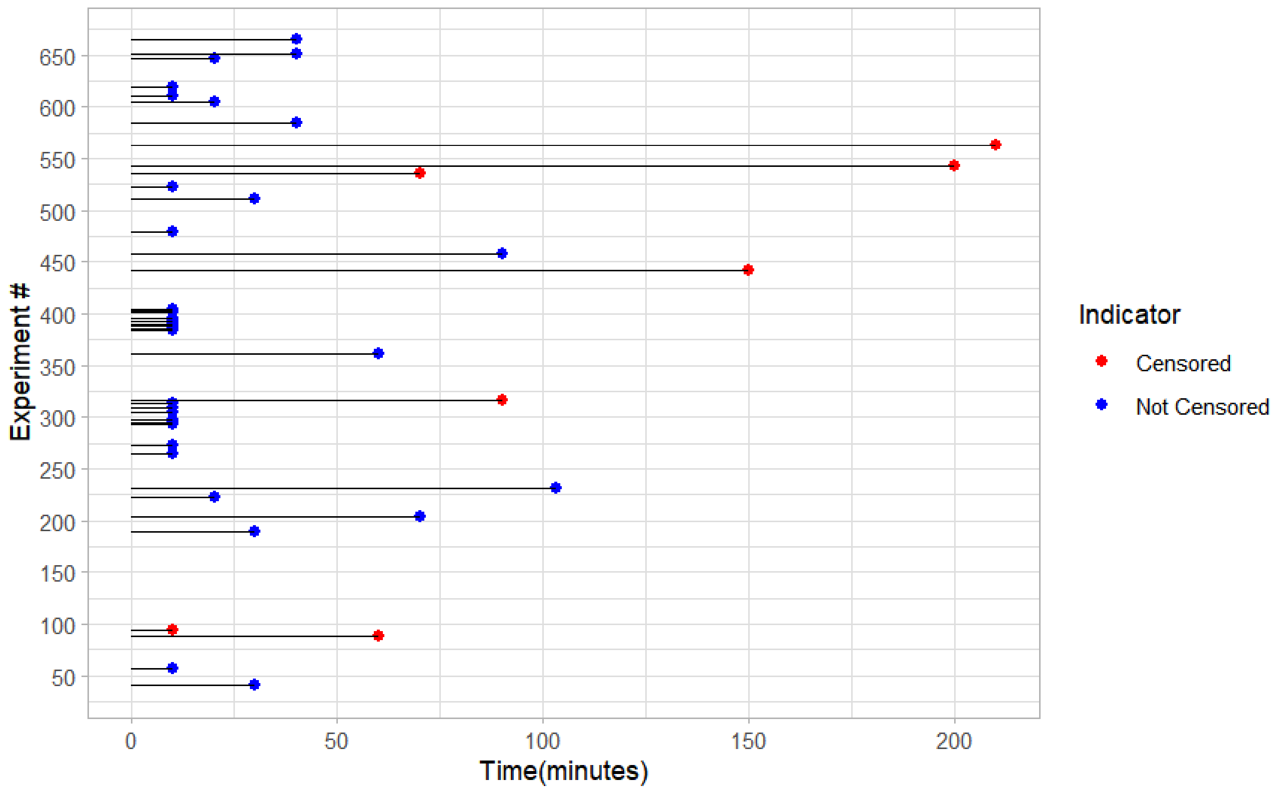

Figure A1: *Distribution of right censored for the sampled data (red) indicates censored experiments and (blue) indicates event of interest i.e., the experiment reached temperature of 70 degrees during the test.*

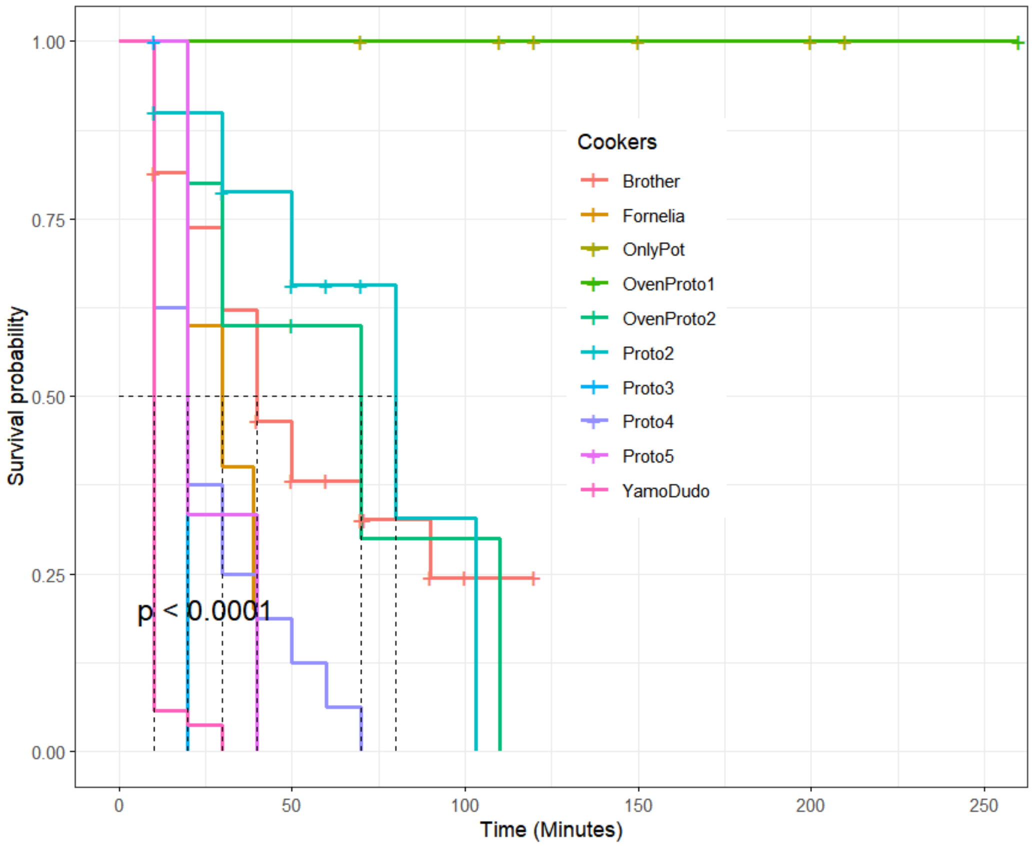

Figure A2: *Kaplan-Meier estimates of survival function for the prototypes in a single panel. The median time as dashed lines and associated two-sided p-value is based on a log-rank test.*

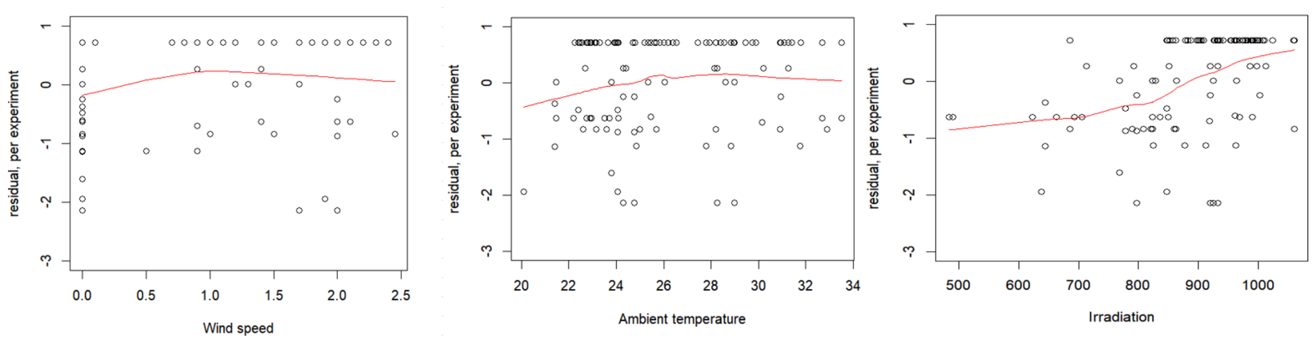

Figure A3: *Martingale residual vs the continuous covariate i.e., wind speed, ambient temperature, and irradiation. The red line is the lowess smooth imposed on the scatter plot that is used to evaluate the true functional form of a specific continuous covariate.*

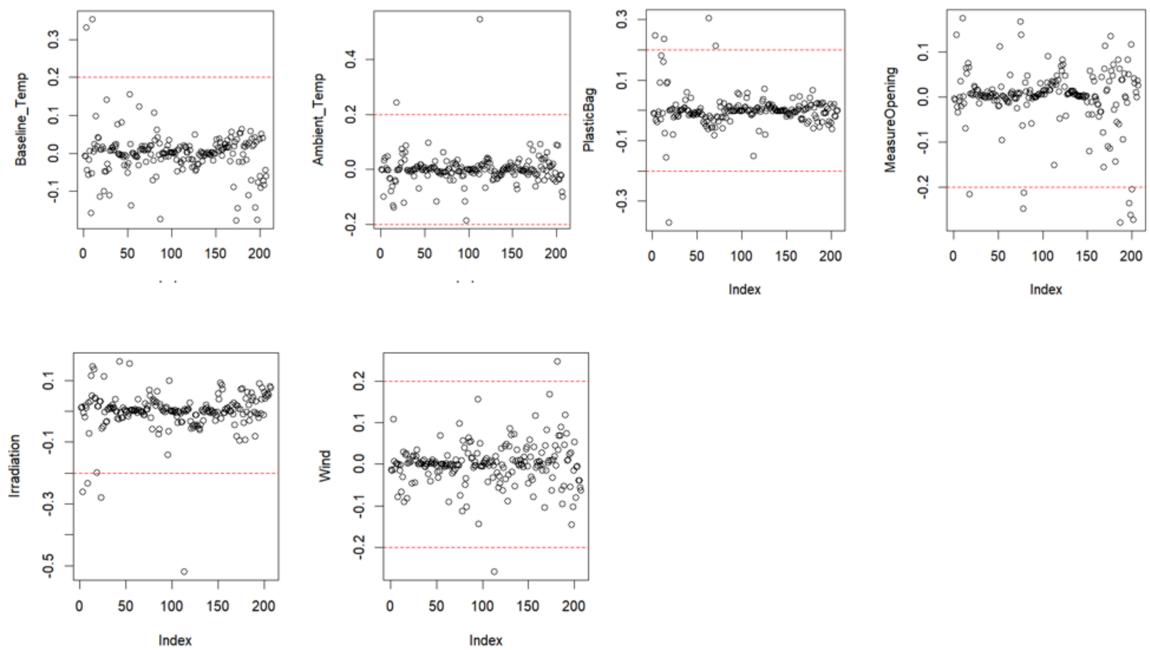

Figure A4: *Distribution of influential observations on parameter estimates for covariates included in the model. The red line showing the cut off point of +-2 indicating the point above or below the line are considered as influential.*

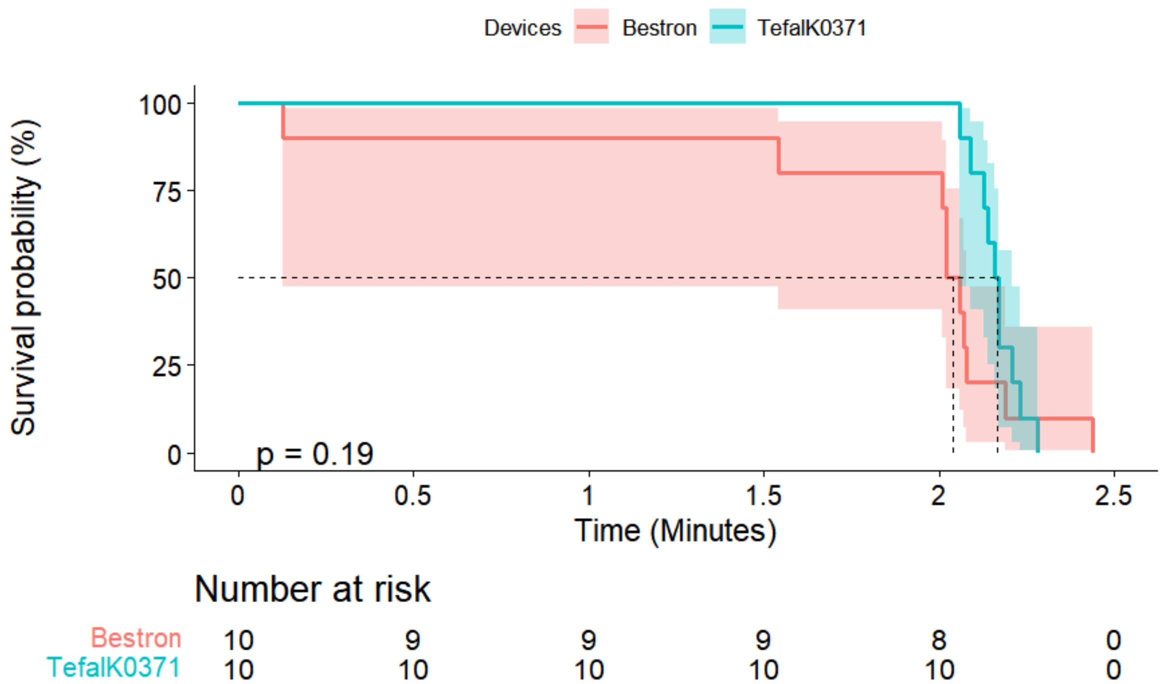

Figure A5: *Kaplan-Meier estimates of survival function for two electric devices (Bestron and TefalK0371). The pointwise 95% confidence intervals are depicted as shaded areas and median time as dashed lines. The associated two-sided p-values are based on a log-rank test, the dotted.*

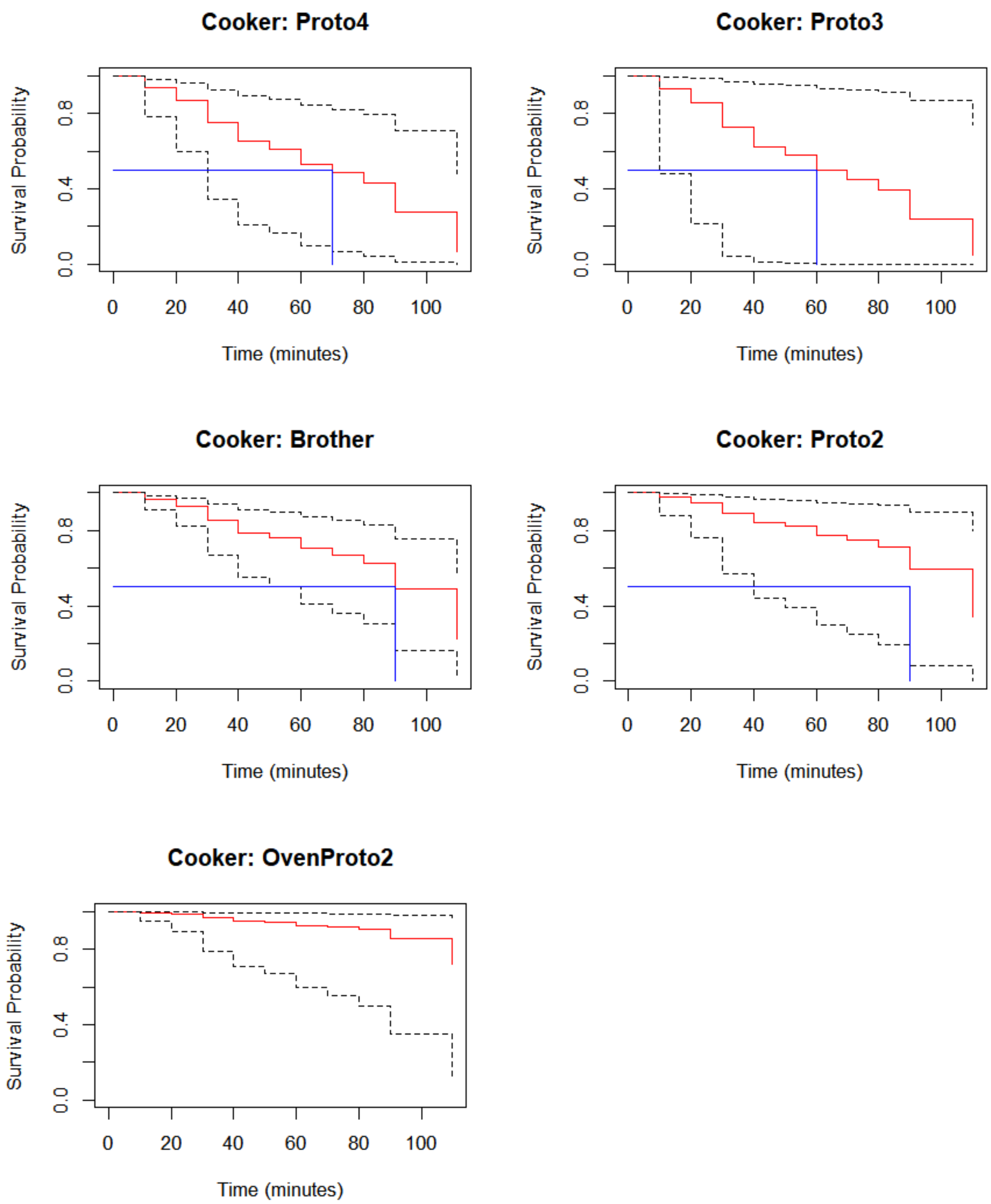

Figure A6: *The predicted median survival time in (minutes) for hypothetical conditions on the devices involved in the analysis, the opening size of the pot for the device used to measure the temperature of water inside the pot (4 mm) and no plastic bag around the pot during the experiment. The conditions are based on irradiation of 700W/m2, constant wind speed, ambient temperature and baseline temperature. The dashed lines are the confidence bands, and the blue line is the median time in minutes.*

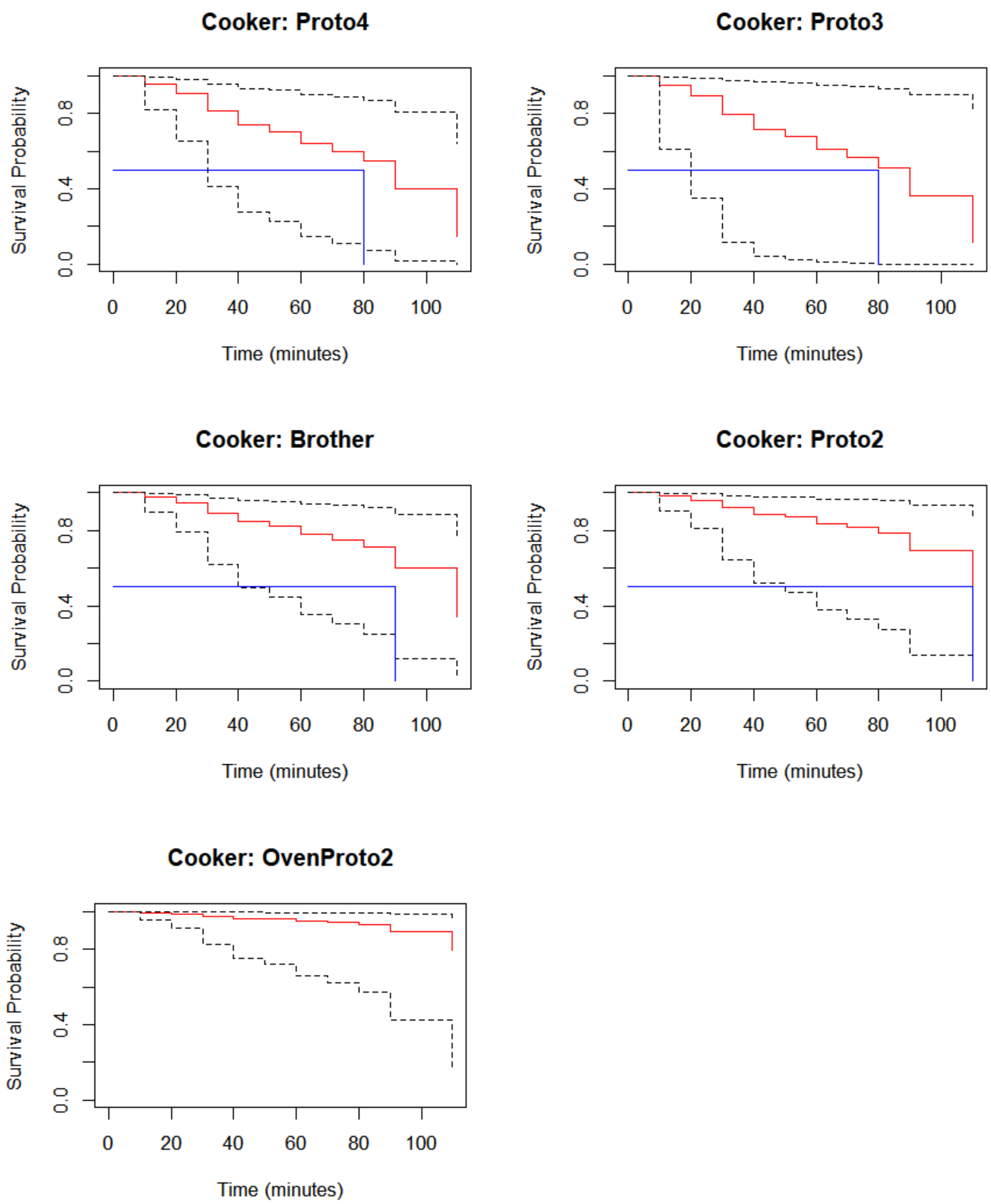

Figure A7: *The predicted median survival time in (minutes) for hypothetical conditions on the devices involved in the analysis, the opening size of the pot for the device used to measure the temperature of water inside the pot (10 mm) and the use of plastic bag around the pot during the experiment. The conditions are based on irradiation of 700W/m2, constant wind speed, ambient temperature and baseline temperature. The dashed lines are the confidence bands, and the blue line is the median time in minutes.*

6.3 Appendix Software Code

Required Packages

```
# Loading the packages
library(nph)
library(survival)
library(survminer)
library(tidyverse)
library(readxl)
library(ggplot2)
library(writexl)
library(lubridate)
library(ggsurvfit)
library(gtsummary)
library(dplyr)
library(emmeans)
library(gamlss)
library(data.table)
```

Data Management

```
# Read in the data
solarp_count1<-read_excel("F:\\2nd year\\Year 2\\Semister 2\\Thesis\\Kauki's\\Datasets\\
Hasselt\\SolarCookerV20230711.xlsx")
# Define dummy variables for cookers
solarp_count1$Cooker <- relevel(as.factor(solarp_count1$Cooker), ref = "YamoDudo")
dummy_Cook <- model.matrix(~ Cooker - 1, data =solarp_count1)
dummy_Cook <- as.data.frame(dummy_Cook)
solarp_count1 <- cbind(solarp_count1, dummy_Cook)
# Filtering Wind, I1,I2, Ta1, & Ta2 as per protocol
solarp_count2 <- subset(solarp_count1, I1 >= 450 & I1 <= 1100 &
I2 >= 450 & I2 <= 1100 & Wind <= 2.5 &Ta1 >= 20 & Ta1 <=35 &Ta2 >= 20 & Ta2 <=35)
solarp_count2 <-solarp_count2%>%mutate(dI=I1-I2)%>%mutate(New_dI=ifelse(abs(dI)>100,0,1))
solarp_count2 <- subset(solarp_count2, (New_dI %in%c("1")))
# Average out I1 v sI2 & Ta1 vs Ta2
solarp_count2 <- solarp_count2 %>% mutate(ambient_temp = (Ta1 + Ta2)/2)
%>%mutate(Iradiation = (I1 + I2)/2)
# Define experiment window to be in longitudinal structure.
exp_window <- c(1) # Initialize with 1
for (i in 2:nrow(solarp_count2)){
  if (abs(solarp_count2$T2[i-1]-solarp_count2$T1[i])<=0) {
    exp_window <- c(exp_window, exp_window[length(exp_window)])
```

```
  } else {exp_window <- c(exp_window,exp_window[length(exp_window)] + 1)}}
solarp_count2$exp_window <- exp_window
# compress PlasticBag due to few observations
solarp_count2$PlasticBag<-ifelse(solarp_count2$PlasticBag==0,0,1)
# Collapse plastic bag (0= no bag or bag open and 1 bag present and closed)
solarp_count2 <- solarp_count2 %>%
mutate(Plstbag = ifelse(PlasticBag == 0, 0,ifelse(PlasticBag == 1 & BagClosed == 0, 0, 1)))
# Delete 13 observations above 70 before the start of the experiment
solarp_count2 <- solarp_count2%>%group_by(exp_window) %>%filter(first(T1) < 70)
# Filter out rows with 2mm and keep only 4mm and 10mm
solarp_count2 <-solarp_count2[solarp_count2$MeasureOpeningmm %in% c(4, 10), ]
# Add time in minutes
solarp_count2$time <- as.numeric(solarp_count2$H2-solarp_count2$H1)
# Add baseline temperature for each experiment window
solarp_count2 <-solarp_count2 %>%
  group_by(exp_window)%>% mutate(T1_baseline = first(T1))
# Calculate total time within each experiment group and add column T2.70
solarp_count3<-solarp_count2 %>%group_by(exp_window)%>%
mutate(cumtime = cumsum(time))%>%mutate(T2.70= ifelse(T2 >= 70, 1, 0))
```

```
# Define the true event
solarp_count3 <-solarp_count3 %>%group_by(exp_window) %>%filter(if (any(T2.70 == 1))
{row_number() == min(which(T2.70 == 1)) | (T2.70 == 0 & cumsum(T2.70) < 1)}else{TRUE})
# Discard some devices due to data imbalance
solarp_count4 <- subset(solarp_count4, (Cooker %in% c("YamoDudo","Brother","OvenProto2",
"Proto2","Proto3", "Proto4")))
# Reformat data into start, stop, status
solarp_count5 <- solarp_count4 %>%
group_by(exp_window) %>%mutate(
interval_start = lag(cumsum(time), default = 0),
interval_end = cumsum(time),
start = interval_start,
stop = interval_end,
interval = paste0(interval_start, "-", interval_end))
```

Data Explorations

```
# K-M: Curve Cookers
survfit(Surv(time = time70max,event = status) ~ Cooker,
data = uhasselt1, conf.type = "log-log")
ggsurvplot(KM_11,data = uhasselt1,legend.title = "Cookers", xlab = "Time (Minutes)",
pval = TRUE,surv.median.line = "hv",linetype = "solid",   palette = "terrain",
```

```
legend.labs = c("Brother", "Fornelia", "OnlyPot", "OvenProto1", "OvenProto2", "Proto2",
"Proto3", "Proto4", "Proto5", "YamoDudo"),legend = c(0.6, 0.6),conf.int = FALSE,
tables.theme = theme_cleantable(),ggtheme = theme_bw())
# K-M Curve MeasureOpening
survfit(Surv(time = time70max,event = status) ~ MeasureOpeningmm,
data = uhasselt2, conf.type = "log-log")
ggsurvplot(KM_p70,data = uhasselt1,risk.table = TRUE, conf.int = T,pval = TRUE,
legend.labs = c("4mm Opening", "10mm Opening"))
# K-M Curve PlasticBag
KM_p71 <- survfit(Surv(time = time70max,event = status) ~ PlasticBag,data = uhasselt1,
conf.type = "log-log")
ggsurvplot(KM_p71,data = uhasselt1,risk.table = TRUE,
conf.int = FALSE,tables.height = 0.3,pval = TRUE)
```

Functional Form

```
fit.0<-coxph(Surv(start,stop,T2.70)~1,data=solarp_count5)
rseq<-resid(fit.0)#per observation
# Collapsing residuals per experiment window after having
#the residuals from the null model per overlal observations
rid<-resid(fit.0,collapse = solarp_count5$exp_window)# per experiment
length(rseq),length(rid)
# Duplicate the code for ambient, wind and baseline temperature
plot(solarp_baseline$Iradiation[1:111],rid,ylim = c(-5,5),xlab="Irradiation",
ylab="residual, per experiment")
lines(lowess(solarp_baseline$Iradiation[1:111],rid,iter = 0), col = "red")
# Poisson regression approach
library(mgcv)
exp.fit<-predict(fit.11poi,type = "expected")
x.beta<-predict(fit.11poi,type = "lp")
newtime<-exp(-x.beta)*exp.fit
Count<-1*(solarp_count5$T2.70==1)
gfit<-gam(Count~ CookerBrother+CookerOvenProto2+
CookerProto2+CookerProto3+CookerProto4+s(T1_baseline)+s(ambient)+s(Irradiation)
+s(Wind_sp)+Plstbag+MeasureOpeningmm+CookerBrother:Plstbag+offset(log(newtime + 1e-10)),
data=solarp_count5,family=poisson)
anova(gfit)
# The diagnostic plots
plot(gfit, se = TRUE, rug = TRUE, col = "red")
```

Model building Procedure

```r
# null model:basis for comparison for all indivisual variable
m1<- coxph(Surv(start,stop,T2.70)~1,data=varselect, method = "efron")
# Cookers
varselect$Cooker <- relevel(as.factor(varselect$Cooker), ref = "YamoDudo")
m2<-coxph(Surv(start,stop,T2.70)~Cooker+cluster(exp_window),data=varselect,method="efron")
# null model vs cooker
lrtest(m1,m2)# <0.0001
m3<- coxph(Surv(start,stop,T2.70)~T1_baseline+cluster(exp_window),data=varselect,
method="efron")
# Null vs baseline temperature
lrtest(m1,m3) #0.06031
m4<- coxph(Surv(start,stop,T2.70)~M+cluster(exp_window),data=varselect, method = "efron")
# Null vs mass
lrtest(m1,m4) #0.01684
m5<- coxph(Surv(start,stop,T2.70)~ambient_temp+cluster(exp_window),data=varselect,
method = "efron")
# Null vs ambient
lrtest(m1,m5) #0.2161
m6<- coxph(Surv(start,stop,T2.70)~Wind+cluster(exp_window),data=varselect, method = "efron")
# Null vs wind
lrtest(m1,m6) # 0.02051
m7<- coxph(Surv(start,stop,T2.70)~Iradiation+cluster(exp_window),data=varselect,
method = "efron")
# Null vs irradiation
lrtest(m1,m7)# <0.0001
m8<- coxph(Surv(start,stop,T2.70)~Plstbag+cluster(exp_window),data=varselect,method="efron")
# Null vs plastic bag
lrtest(m1,m8)# 0.0965
m9<- coxph(Surv(start,stop,T2.70)~MeasureOpeningmm+cluster(exp_window),data=varselect,
method = "efron")
# Null vs measure opening
lrtest(m1,m9)# 0.001078
# Keep all variables found significant from the individual level
m10<- coxph(Surv(start,stop,T2.70)~Cooker+M+Wind+Iradiation+MeasureOpeningmm+
cluster(exp_window),data=varselect,method = "efron")
lrtest(m1,m10) # 0.001078
m11<- coxph(Surv(start,stop,T2.70)~Cooker+M+Wind+Iradiation+MeasureOpeningmm+T1_baseline+
cluster(exp_window),data=varselect, method = "efron")
# Null vs all sign plus T1_baseline
lrtest(m1,m11) #<0.0001
m12<- coxph(Surv(start,stop,T2.70)~Cooker+M+Wind+Iradiation+MeasureOpeningmm+ambient_temp
+cluster(exp_window),data=varselect, method = "efron")
```

```
# Null vs ambient plus all sign
lrtest(m1,m12) #<0.0001
m13<- coxph(Surv(start,stop,T2.70)~Cooker+M+Wind+Iradiation+MeasureOpeningmm+Plstbag
+cluster(exp_window),data=varselect, method = "efron")
# Null vs all significant plus plstic bag
lrtest(m1,m13) #<0.0001
```

PH Assumptions

```
solarp_comb<-read_excel("F:/2nd year/Year 2/Semister 2/Thesis/Kauki's/Datasets/Hasselt/
Thesis/solarp_fogood.xlsx")
solarp_comb$Cooker <- relevel(as.factor(solarp_comb$Cooker), ref = "YamoDudo")
fit.4a<-coxph(Surv(start,stop,T2.70)~Cooker+T1_baseline+ambient+Irradiation+Wind_sp+
Plstbag+MeasureOpeningmm+Plstbag:CookerBrother+cluster(exp_window),
data=solarp_comb,method = "efron")

zph.fit.n <- cox.zph(fit.4a,transform="log")
print( zph.fit.n)
par(mfrow=c(2,3))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=1,col = c("red","blue"),ylim=c(-5,5))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=2,col = c("red","blue"),ylim=c(-0.4,0.4))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=3,col = c("red","blue"),ylim=c(-5,5))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=4,col = c("red","blue"),ylim=c(-5,5))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=5,col = c("red","blue"),ylim=c(-3,3))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=6,col = c("red","blue"),ylim=c(-5,5))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=7,col = c("red","blue"),ylim=c(-2,2))
plot(zph.fit.n, df=2, nsmo=10, se=TRUE, var=8,col = c("red","blue"))
```

The final model

```
 # Standardized variables wind, ambient, irradiation and Mass
solarp_count5$Wind_sp<- (solarp_count5$Wind - mean(solarp_count5$Wind)) /
sd(solarp_count5$Wind)
solarp_count5$ambient<- (solarp_count5$ambient_temp- mean(solarp_count5$ambient_temp))/
sd(solarp_count5$ambient_temp)
solarp_count5$Irradiation <- (solarp_count5$Iradiation - mean(solarp_count5$Iradiation))/
sd(solarp_count5$Iradiation)
# Collapsing PlasticBag for "YamoDudo"
 solarp_count5<- solarp_count5 %>%mutate(Plstbag = ifelse(Cooker == "YamoDudo" &
 Plstbag == 1, 0, Plstbag))
# Deleting one observation for "Proto4" in the no PlasticBag
solarp_count5<-solarp_count5%>%filter(!(Cooker=="Proto4" & Plstbag==0))
# Fitted model
```

```
solarp_count5$Cooker <- relevel(as.factor(solarp_count5$Cooker), ref = "YamoDudo")
 fit.1<- coxph(Surv(start,stop,T2.70)~as.factor(Cooker)*Plstbag+T1_baseline+ambient
 +Irradiation+Wind_sp+as.factor(MeasureOpeningmm)+cluster(exp_window), data=solarp_count5,
 method = "efron")
```

Predicting the median survival time

```
par(mfrow = c(2, 2))
# Create the survival object
s <- with(solarp_count5, Surv(start, stop, T2.70))
# The fitted model
modelA <- coxph(s ~ as.factor(Cooker) + T1_baseline + ambient_temp+Iradiation+Wind+
as.factor(Plstbag) + as.factor(MeasureOpeningmm)+CookerBrother:Plstbag,
data = solarp_count5, model = TRUE)
# New data for prediction
new_data <- data.frame(
  Cooker = "Proto4",
  T1_baseline = 20,
  ambient_temp = 22,
  Iradiation = 700,
  Wind = 0,
  Plstbag = 1,
  MeasureOpeningmm = 4
)
# The linear predictor
pred <- predict(modelA, newdata = new_data, type = "lp", se.fit = TRUE)
linear_pred <- pred$fit
se_linear_pred <- pred$se.fit
# Extract the baseline survival function
base_surv <- survfit(modelA)
# Calculate the predicted survival probabilities
psp <- exp(-base_surv$cumhaz * exp(linear_pred))
# Calculate the pointwise confidence intervals
upper_CI <- exp(-base_surv$cumhaz * exp(linear_pred + 1.96 * se_linear_pred))
lower_CI <- exp(-base_surv$cumhaz * exp(linear_pred - 1.96 * se_linear_pred))
# Plot the survival probabilities with confidence intervals
plot(base_surv$time, psp, type = 's', col = 'red', ylim = c(0, 1),
     ylab = "Survival Probability", xlab = "Time(minutes)",
     main = "Cooker:Proto4")
lines(base_surv$time, upper_CI, type = 's', col = 'black', lty = 2)
lines(base_surv$time, lower_CI, type = 's', col = 'black', lty = 2)
# Calculate the median survival time
```

```
median_t <- base_surv$time[which.min(abs(psp- 0.5))]
# Add vertical and horizontal lines at the median survival time
segments(x0 = median_t, y0 = 0, x1 = median_t, y1 = 0.5, col = "blue")
segments(x0 = 0, y0 = 0.5, x1 = median_t, y1 = 0.5, col = "blue")
# Add text annotation for median time
text(median_t, 0.6, labels = paste("Median=", round(median_t, 2)), pos = 4)
```

Influential observations

```
# Compute DFBETAS
DFBETAS <- resid(fit.11, type = "dfbetas")
# Plots based on dfbetas to check the outlying observations
par(mfrow=c(1,2))
plot(DFBETAS[, 6], ylab="Baseline_Temp")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
plot(DFBETAS[, 7], ylab="Ambient_Temp")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
plot(DFBETAS[, 8], ylab="Irradiation")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
plot(DFBETAS[, 9], ylab="Wind")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
plot(DFBETAS[, 10], ylab="PlasticBag")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
plot(DFBETAS[, 11], ylab="MeasureOpening")
abline(h = c(-0.2, 0.2), lty = 2, col = "red")
head(DFBETAS)
# Approximately 21 outlying observations
SUB.DFBETAS <- apply(abs(DFBETAS)>0.2,1,any)
SUB <- SUB.DFBETAS
sum(SUB)
```