

# **Data Analysis of Heavy Haul Locomotive Wheel-sets' Running Surface Wear at Malmbanan**

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# Data Analysis of Heavy Haul Locomotive Wheel-sets' Running Surface Wear at Malmbanan

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# Summary

The research presented in this report was carried out at the Division of Operation and Maintenance Engineering at Luleå University of Technology between 2013 and 2014. It is a continuous study of “JVTC project 2012-2013: Using Integrated Reliability Analysis to Optimise Maintenance Strategies”.

In this research, both an integrated procedure for Bayesian reliability inference using Markov Chain Monte Carlo (MCMC) and other traditional statistics theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are applied to a number of case studies using heavy haul locomotive wheel-sets’ running surface wear data from Iron Ore Line (Malmbanan), Sweden. The research explores the impact of the locomotive wheel-sets’ installed position (incl. positions of the installed locomotive, bogie, axel.) on their service lifetime and attempts to predict the reliability related characteristics. Results from this research will support locomotive wheels’ maintenance strategies using data analysis of wheels’ running surface wear (Chapter 2).

Data used in this research span January 2010 to May 2013. Data analysis is carried out in two parts. In the first part (Chapter 3), corresponding to previous research, the data are collected from two specific locomotives at Malmbanan. The accompanying case study features reliability analysis using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel’s position on its service lifetime and to predict its other reliability characteristics. Results are used to illustrate how the wheel-sets’ running surface wear data can be modelled and analysed using classical and Bayesian approaches to flexibly determine their reliability. In the second part (Chapter 4), a holistic study is developed by analysing group data from 26 locomotives and 57 bogies at Malmbanan. In this part, data analysis is carried out from both the locomotives and bogies’ perspective. The results show that Malmbanan should consider the wheel-sets’ data not only from locomotives’ but also from bogies’ point of view. Next, wheel-sets’ running surface wear data from a group of 16 bogies are studied as a whole. More holistic results are drawn from both degradation analysis and wear rate analysis, including the following: for the studied group, a linear degradation path is more suitable; following the linear degradation, the best life distribution is a 3-parameter Weibull distribution, and the second is lognormal; comparing the wearing data of the wheel-sets’ running surfaces (including total wear rate, natural wear rate, re-profiling wear rate, the ratio of re-profiling and natural wear) is an effective way to optimise maintenance strategies; finally, more natural wear occurs for the wheels installed in axel 1 and axel 3, supportive evidence for other related studies at Malmbanan.

Finally, the report makes some recommendations for future research into locomotive wheel-sets’ running surface wear data analysis and suggests maintenance strategies for Malmbanan (Chapters 5 & 6).



# Preface

This research presented in this report was carried out at the Division of Operation and Maintenance Engineering at Luleå University of Technology between 2013 and 2014. It is a continuous study of “JVTC project 2012-2013: Using Integrated Reliability Analysis to Optimise Maintenance Strategies”.

I would like to thank Luleå Railway Research Centre (Järnvägstekniskt Centrum, Sweden) at Luleå University of Technology and Swedish Transport Administration (Trafikverket) for initiating the research study and providing financial support.

I would like to express my gratitude to all of my colleagues. In particular, I would like to thank Professor Uday Kumar for being the project’s supervisor and supporting me during my research at the Division of Operation and Maintenance Engineering.

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*To my family*

*Janet (Jing) Lin, 05/05/2014, Luleå*





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# 1 Introduction

This section presents the background, data description, and objectives and scope of this research.

## 1.1 Background

The service life of a train wheel can be significantly reduced due to failure or damage, leading to excessive cost and accelerated deterioration, a point which has received considerable attention in recent literature (Lin, 2013). In order to monitor the performance of wheel-sets and make replacements in a timely fashion, the railway industry uses both preventive and predictive maintenance (Palo, 2013). By predicting the wear (Johansson & Andersson, 2005; Braghin et al., 2006; Tassini et al., 2010), fatigue (Bernasconi et al., 2005; Liu, et al., 2008), tribological aspects (Clayton, 1996), and failures (Yang & Letourneau, 2005), the industry can design strategies for different types of preventive maintenance (re-profiling, lubrication, etc.) for various periods (days, months, seasons, running distance, etc.). Software dedicated to predicting wear rate has also been proposed (Pombo et al., 2010). Finally, condition monitoring data have been studied with a view to increasing the wheel-sets' lifetime (Skarlatos et al., 2004; Donato et al., 2006; Stratman et al., 2007; Palo, 2012).

One common preventive maintenance strategy (used in the case study) is re-profiling wheel-sets after they run a certain distance. Re-profiling affects the wheel-set's diameter; once the diameter is reduced to a pre-specified length, the wheel-set is replaced by a new one. Seeking to optimise this maintenance strategy, some researchers have examined wheel-sets' degradation data (i.e., the wheel-sets' running surface wear data used in this research) to determine wheel reliability and failure distribution. Furthermore, in previous studies, some researchers have noticed that the wheel-sets' different installed positions could influence the results. To avoid the potential influence of wheel location, Freitas et al. (2009, 2010) only consider those on the left side of a specified axle and on certain specified cars, arguing that "the degradation of a given wheel might be associated with its position on a given car". Yang and Letourneau (2005) suggest that certain attributes, including a wheel's installed position (right or left), might influence its wear rate. Palo et al. (2012) conclude that "different wheel positions in a bogie show significantly different force signatures," but they do not provide case studies.

To solve the combined problem of small data samples and incomplete datasets whilst simultaneously considering the influence of several covariates, Lin (2013) has explored the influence of locomotive wheel-sets' positioning on reliability using Bayesian parametric models. The results indicate that the particular bogie in which the wheel-set is mounted has more influence on its lifetime than does the axle or side it is on. Related studies were supported by Luleå Railway Research Centre (Järnvägstekniskt Centrum (JVTC), Sweden) and Swedish Transport Administration (Trafikverket) between 2012 and 2013 in the project titled "Using Integrated Reliability Analysis to Optimise Maintenance Strategies" (corresponding report and published paper appear in Appendix A). As a continuous study, in this research, both the integrated procedure for Bayesian reliability inference using Markov Chain Monte Carlo (MCMC, (Congdon, 2001 & 2003)) and other traditional statistical theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of

Experiments (DOE)) are applied to a number of case studies using heavy haul locomotive wheel-sets' running surface wear data from Iron Ore Line (Malmbanan), Sweden. The research continuously explores the impact of a locomotive wheel-set's installed position on its service lifetime and attempts to predict its reliability related characteristics. Results from this research aim to support maintenance strategies by analysing the data from the wheels' running surface wear.

The data analysis is carried out in two parts. In the first part, corresponding to previous research, data are collected from two specific locomotives at Malmbanan. The corresponding case study undertakes a reliability analysis using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel's position on its service lifetime and to predict its other reliability characteristics. Results are used to illustrate how the wheel-sets' running surface wear data can be modelled and analysed using classical and Bayesian approaches to flexibly determine their reliability. In the second part, a holistic study is developed by analysing group data from 26 locomotives and 57 bogies at Malmbanan. In this part, data analysis is carried out from both the locomotives and the bogies' perspective. The results suggest that Malmbanan should consider the wheel-sets' data from both the locomotives' and the bogies' point of view. Next, wheel-sets' running surface wear data from a group of 16 bogies' are studied as a whole. More holistic results are drawn from both degradation and wear rate analysis. The report concludes by proposing some recommendations for future research into locomotive wheel-sets' running surface wear data analysis and suggesting some maintenance strategies for Malmbanan.

## 1.2 Description of Data

In this project, all case studies come from Sweden's Iron Ore Line (Malmbanan). The data come from the heavy haul cargo trains' locomotive wheel-sets and were collected by LKAB\MTAB from January 2010 to May 2013. This section gives background information on the Iron Ore Line (Malmbanan). It also introduces the locomotive wheel-sets' running surface wear data (degradation data) and the re-profiling parameters for the wheel-sets being studied.

### 1.2.1 Iron Ore Line (Malmbanan)

The Iron Ore Line (Malmbanan) is the only existing heavy haul line in Europe; it stretches 473 kilometres and has been in operation since 1903. As Fig.1.1 shows, it is mainly used to transport iron ore and pellets from the mines in Kiruna (also Malmberget, close to Kiruna, in Sweden) to Narvik Harbour (Norway) in the northwest and Luleå Harbour (Sweden) in the southeast. The track section on the Swedish side is owned by the Swedish government and managed by Trafikverket (Swedish Transport Administration), while the iron ore freight trains are owned and managed by the freight operator (LKAB/MTAB). Each freight train consists of two IORE locomotives accompanied by 68 wagons with a maximum length of 750 metres and a total train weight of 8500 metric tonnes. The trains operate in harsh conditions, including snow in the winter and extreme temperatures ranging from - 40 °C to + 25 °C. Because carrying iron ore results in high axle loads and there is a high demand for a constant flow of ore/pellets, the track and wagons must be monitored and maintained on

a regular basis. The condition of the locomotive wheel profile is one of the most important aspects to consider.

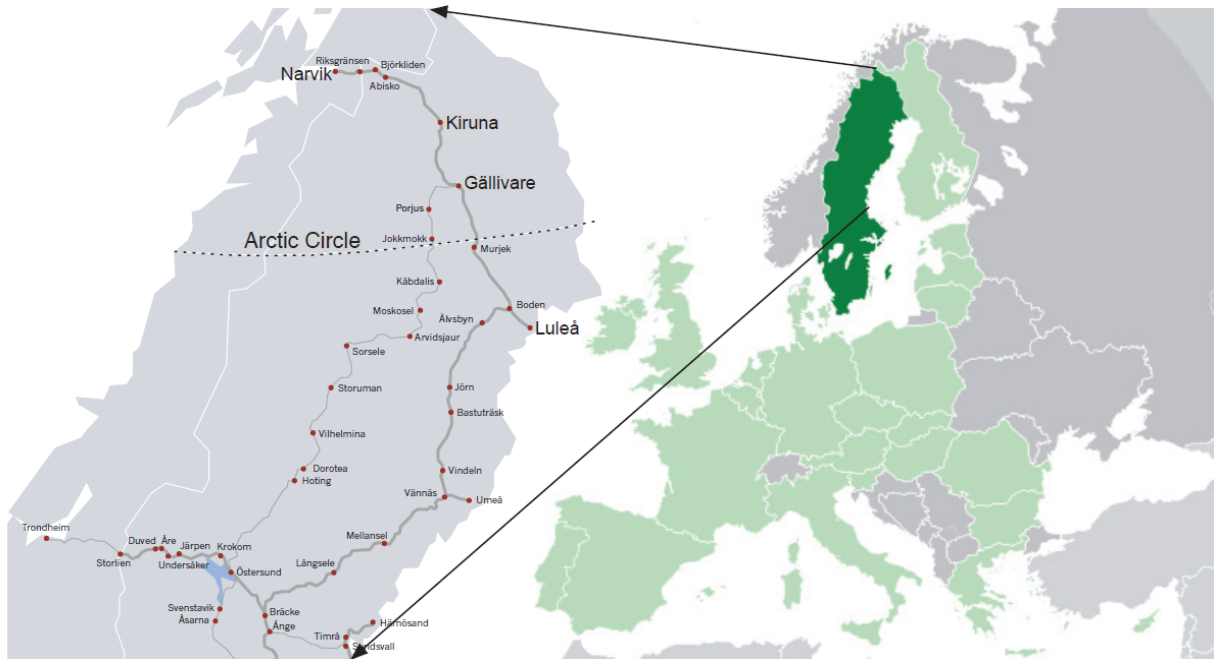


Fig.1.1 Geographical location of Iron Ore Line (Malmbanan) from Luleå to Narvik

### 1.2.2 Running Surface Wear Data and Re-profiling Parameters

This study uses running surface wear data on selected heavy haul cargo trains collected from January 2010 to May 2013.

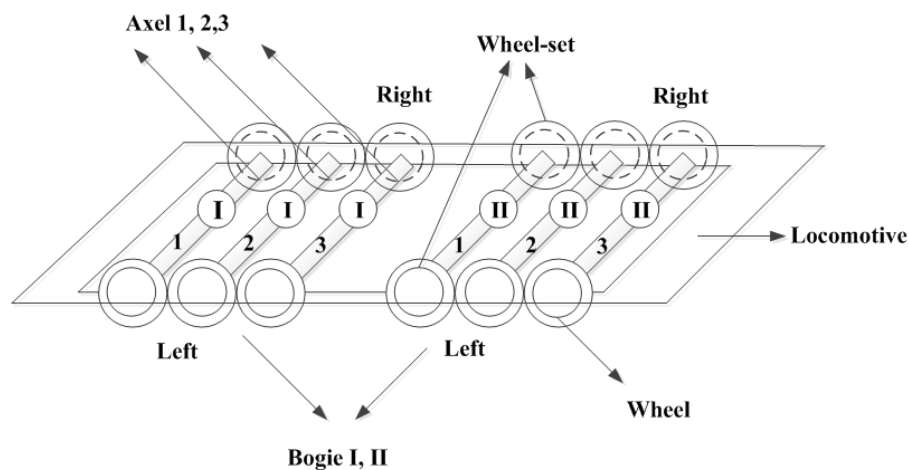


Fig.1.2 Wheel positions specified in this study

For each locomotive, see Fig.1.2, there are two bogies (incl., Bogie I, Bogie II); and each bogie contains three wheel sets. The installed position of a wheel on a particular locomotive is specified by the bogie number (I, II-number of bogies on the locomotive), an axle number (1, 2, 3-number of axles for each bogie) and the position of the axle (right or left) where each wheel is mounted.

The diameter of a new locomotive wheel in this study is around 1250 mm. Following the current maintenance strategy, a wheel's diameter is measured after it runs a certain distance. If it is reduced to 1150 mm, the wheel-set is replaced by a new one. Otherwise, it is re-profiled (see Fig.1.3). Therefore, in this study, a threshold level for failure, denoted as  $l_0$ , is defined as 100 mm ( $l_0 = 1250 \text{ mm} - 1150 \text{ mm}$ ). The wheel-set's failure condition is assumed to be reached if the diameter reaches  $l_0$ . The dataset includes the diameters of all locomotive wheels at a given inspection time, the total running distances corresponding to their “mean time between re-profiling”, and the wheels' bill of material (BOM) data, from which we can determine their positions.



Fig.1.3 Locomotive wheel-sets undergoing on-site re-profiling

The measurement tool is SIEMENS SINUMERIK (see Fig.1.4). During the re-profiling process, the re-profiling parameters include but are not limited to: 1) the diameters of the wheels; 2) the flange thickness; 3) the radial run-out; 4) the lateral run-out. As indicated by Lin (2013), the first parameter is the most important indicator for re-profiling decision making. Hence, the running surface wear data (recorded as diameters in the on-site re-profiling system) are the main parameters adopted for study.



Fig.1.4 Re-profiling equipment

### 1.3 Objectives and Scope of Work

As a continuous study of “JVTC project 2012-2013: Using Integrated Reliability Analysis to Optimise Maintenance Strategies”, this research explores the impact of a locomotive wheel-set's installed position (incl. positions of the installed locomotive, bogie, axel.) on its service lifetime and attempts to

predict its reliability related characteristics. Results from this project will support the locomotive wheel-sets' maintenance strategies through data analysis of wheel-sets' running surface wear.

In this research, data span January 2010 to May 2013. The approach and methodology are presented in Section 2. The integrated procedure for Bayesian reliability inference using MCMC and other traditional statistical theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are applied to a number of case studies using locomotive wheel-sets' running surface wear data from Iron Ore Line (Malmbanan), Sweden; these are presented in Section 3. Section 4 provides a holistic study, developed by analysing group data from 26 locomotives and 57 bogies at Malmbanan. Finally, conclusions and some recommendations appear in Chapter 5 and Chapter 6, respectively.





## 2 Approach and Methodology

This section discusses the research approach and methodology.

As shown in Fig. 2.1, the background of this research is the study of “JVTC project 2012-2013: Using Integrated Reliability Analysis to Optimise Maintenance Strategies”. Some updated publications appear in Appendix A, including an integrated procedure and analysis with Bayesian parametric models, Bayesian semi-parametric models, and Frailties models.

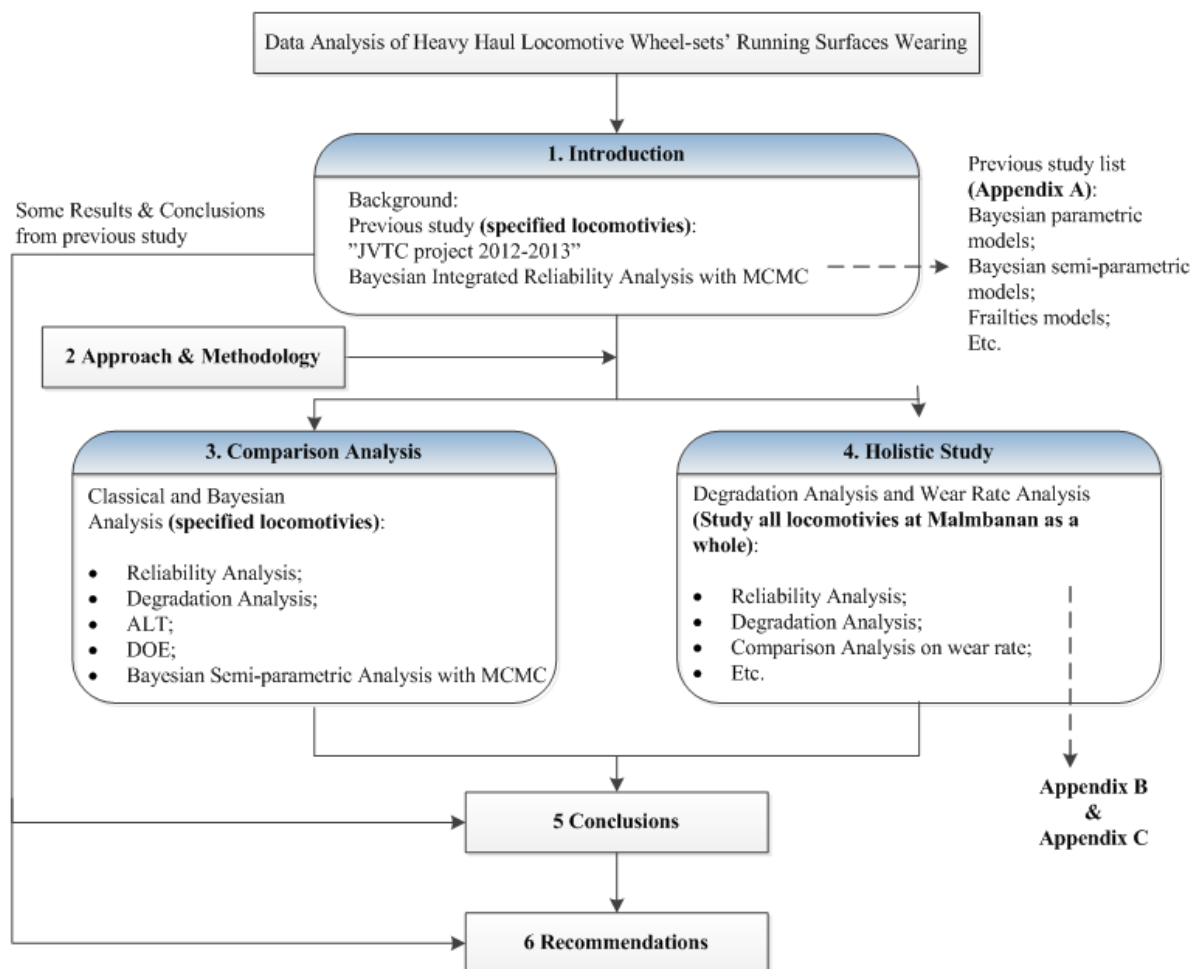


Fig.2.1. Research Approach and Methodology

As a continuous study, this research is carried out in two parts. In the first part (Section 3), the data are collected from two specific locomotives. The accompanying case study undertakes a reliability study using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel-set's position on its service lifetime and to predict its other reliability characteristics. Results are used to illustrate how a wheel-set's running surface wear data can be modelled and analysed using classical and Bayesian approaches to flexibly determine reliability. Both traditional statistical theories (reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments

(DOE), etc.) and Bayesian statistics using MCMC methodologies are used. The integrated Bayesian analysis framework adopted here is developed by Lin (2013); see Fig.2.2.

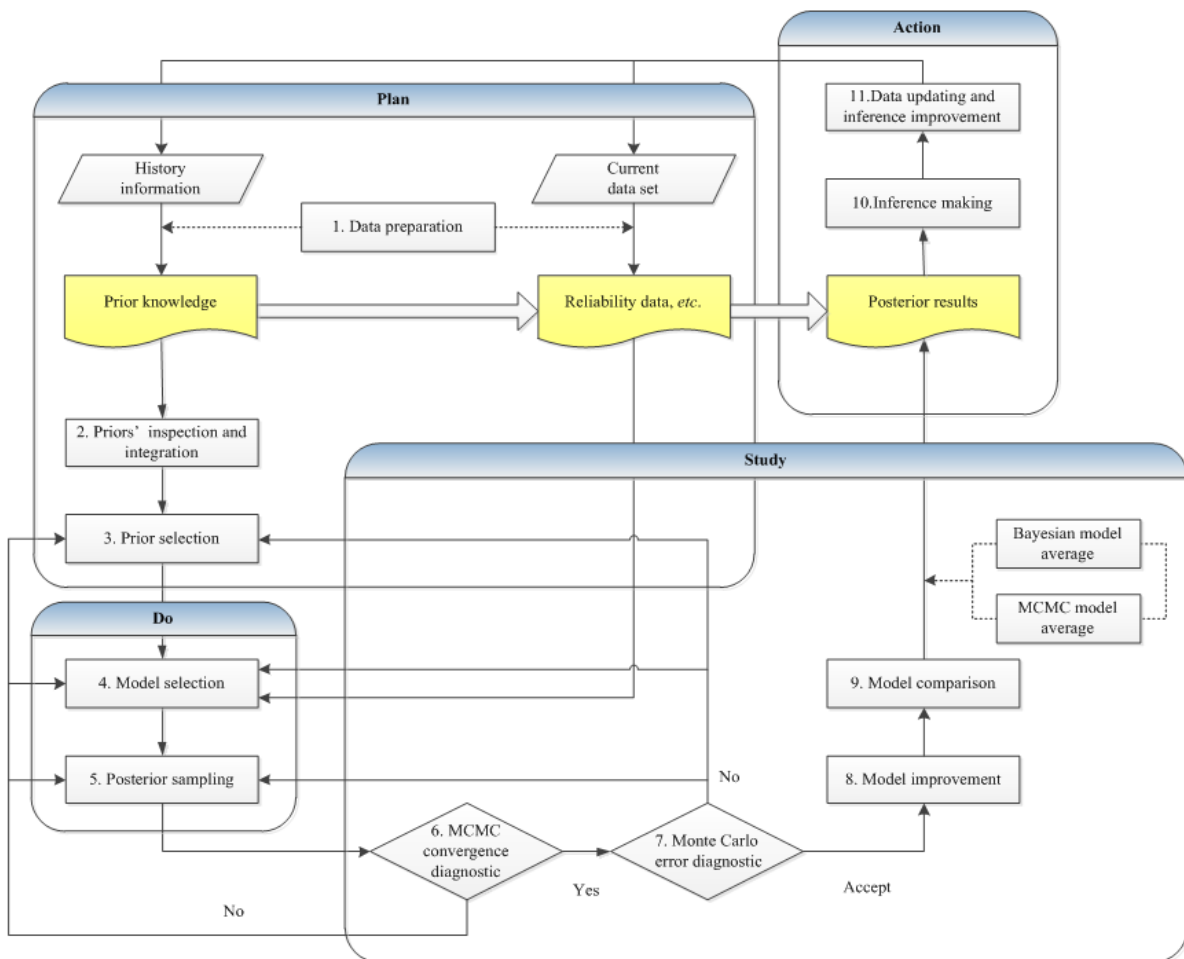


Fig.2.2 An Integrated Procedure for Bayesian Reliability Inference via MCMC

In the second part (Section 4), a holistic study is developed by analysing group data from 26 locomotives and 57 bogies at Malmaban. Data analysis is carried out from both the locomotives and the bogies' perspective. The results show that Malmaban should consider the wheel-sets' data from both points of view. Next, the wheel-sets' running surface wear data from a group of 16 bogies are analysed as a whole. The procedure is shown in Fig. 2.3; reliability analysis, degradation analysis, lifetime analysis, as well as a comparison study on wear rate are applied. Further details appear in Appendix B and Appendix C.

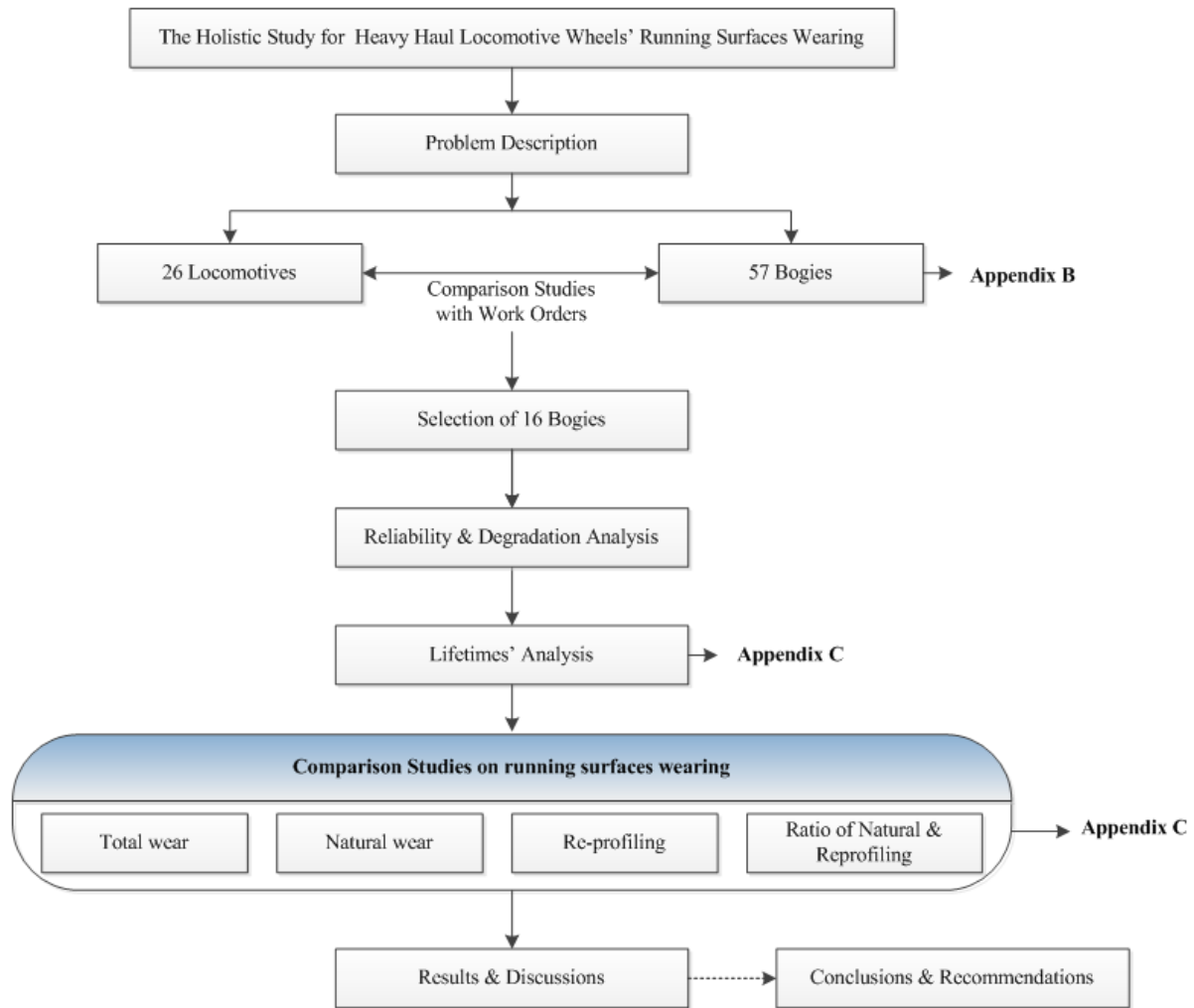


Fig.2.3. Procedure for holistic study

Section 3 and Section 4 provide the results and discussion, along with some results from previous study, with research conclusions and recommendations found in Section 5 and Section 6, respectively.



## 3 Comparison Analysis with Classical and Bayesian Approaches

As mentioned earlier, the data analysis is carried out in two parts. In this section, as in a previous study (Lin, 2013), the data are collected from two specific locomotives.

The section performs a reliability study using both classical and Bayesian semi-parametric frameworks to explore the impact of the locomotive wheel-set's position on its service lifetime and to predict its other reliability characteristics. The goal is to illustrate how a wheel-set's degradation data can be modelled and analysed using both classical and Bayesian approaches in order to flexibly determine reliability.

The remainder of the section is organised as follows. Section 3.1 describes the dataset for the case study of the wheel-sets on two locomotives in a heavy haul cargo train from Malmbanan, using both Exponential and Power degradation assumptions. Section 3.2 presents the models and results using a classical approach. In this approach, both Accelerated Life Tests (ALT) and Design of Experiments (DOE) technology are used to determine how each critical factor, i.e., locomotive or bogie, affects the prediction of performance. Section 3.3 presents the piecewise constant hazard regression model with gamma frailties. In the proposed model, a discrete-time martingale process is considered as a prior process for the baseline hazard rate. The section adopts a MCMC computational scheme and suggests maintenance strategies for optimisation. Finally, Section 3.4 compares Classical and Bayesian approaches.

### 3.1 Data for Comparison Analysis

This section presents the running surface wear data (degradation data), degradation path, and the lifetime data of the locomotive wheels. These data are used in Section 3.2 and Section 3.3.

#### 3.1.1 Degradation Data

The data were collected at Malmbanan from January 2010 to May 2012 (see Table 3.1, Table 3.2). We use the running surfaces wearing data (degradation data) from two heavy haul cargo trains' locomotives (denoted as Locomotive 1 and Locomotive 2). Correspondingly, there are two studied groups, and  $n = 2$ . For each locomotive, see Figure 1.2, there are two bogies (Bogie I, Bogie II), and each bogie has three wheel-sets, making a total of 12 wheels for each locomotive.

As noted above, the diameter of a new locomotive wheel is about 1250 mm and a wheel's diameter is measured after running a certain distance. If it is reduced to 1150 mm, the wheel is replaced by a new one. Otherwise, it is re-profiled or other maintenance strategies are implemented. Therefore, a threshold level for failure, denoted as  $l_0$ , is defined as 100 mm ( $l_0 = 1250 \text{ mm} - 1150 \text{ mm}$ ). The wheel's failure condition is assumed to be reached if the diameter reaches  $l_0$ . The complete dataset includes

the diameters of all locomotive wheel-sets at a given inspection time, the total running distances corresponding to their “time to be maintained (re-profiled or replaced)”, and the wheel-sets’ bill of material (BOM) data, from which we can determine their positions.

Table 3.1 and Table 3.2 present the degradation data for the wheel-sets of Locomotive 1 and Locomotive 2, respectively.

Table.3.1 Degradation Data of Locomotive 1

Distance (kilometres)	Degradation(mm)											
	Bogie I						Bogie II					
	1	2	3	4	5	6	7	8	9	10	11	12
106613	13.08	13.19	12.11	12.12	12.99	13.04	13.02	13.01	11.94	12.01	13.01	13.16
144207	27.11	27.07	23.01	22.86	25.03	25.09	24.09	24.12	23.95	24.06	26.56	26.55
191468	38.95	38.94	39.11	39.06	39.15	39.17	35.95	35.95	35.88	35.93	36.24	36.04
272697	70.6	70.53	69.94	69.87	69.9	69.9	79.7	79.73	79.73	79.74	79.59	79.76
309426	85.05	85.07	85.09	85.12	85.26	85.27	/	/	/	/	82.87	83.77

Table.3.2 Degradation Data of Locomotive 2

Distance (kilometres)	Degradation(mm)											
	Bogie I						Bogie II					
	1	2	3	4	5	6	7	8	9	10	11	12
33366	10.96	11.02	10.45	10.54	10.11	10.04	8.25	8.12	/	/	10.06	10.03
87721	24.59	24.56	25.11	25.3	26.68	26.65	28.02	27.99	27.92	28.36	28.05	28.07
161346	44.93	45.16	44.59	44.56	44.63	44.62	45.94	45.89	45.96	45.91	45.98	45.96
204349	75.35	75.12	74.94	75.02	74.7	74.68	80.66	80.76	80.52	80.68	80.87	80.91

### 3.1.2 Degradation Path and Lifetime Data

From the dataset (see Table 3.1, Table 3.2), we can obtain 3 to 5 measurements of the diameter of each wheel during its lifetime. By connecting these measurements, we can determine a degradation trend. The first step of the analysis is the selection of the degradation model. In their analyses of train wheel-sets, most studies (Freitas et al. 2009, 2010; Lin et al. 2013) assume a linear degradation path. In our study, we plot the degradation data for the locomotive wheel-sets using Exponential degradation, Power degradation, Logarithmic degradation, Gompertz degradation, and the linear degradation path in Weibull++.

The results (see Figure 3.1 – 3.4) show that the better choices are Gompertz degradation, Exponential degradation, and Power degradation, but the Gompertz model needs a total of more than 5 points to converge. The selection should be based on physics of failure (wear or fatigue). In our study, based on the type of physics of failures associated with wear and fatigue, we select Exponential and Power degradation models.

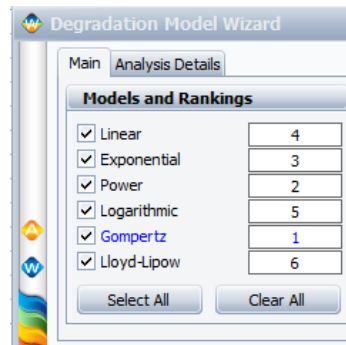


Figure 3.1 Degradation path analyses

An Exponential model is described by the following function (3.1) and the Power model by the function (3.2) from Nelson (1990):

Exponential:

$$y = b \cdot e^{a \cdot x} \quad (3.1)$$

Power:

$$y = b \cdot x^{a \cdot c} \quad (3.2)$$

where  $y$  represents the performance (here, the diameter of the wheels),  $x$  represents time (here, the running distance of the wheels), and  $a$ ,  $b$  and  $c$  are model parameters to be solved. Figures 3.2, 3.3, and 3.4 show the results of the analysis using a Power function, an Exponential function and the Gompertz degradation path, respectively, for a critical degradation level (threshold level  $l_0$ ) of 100mm.

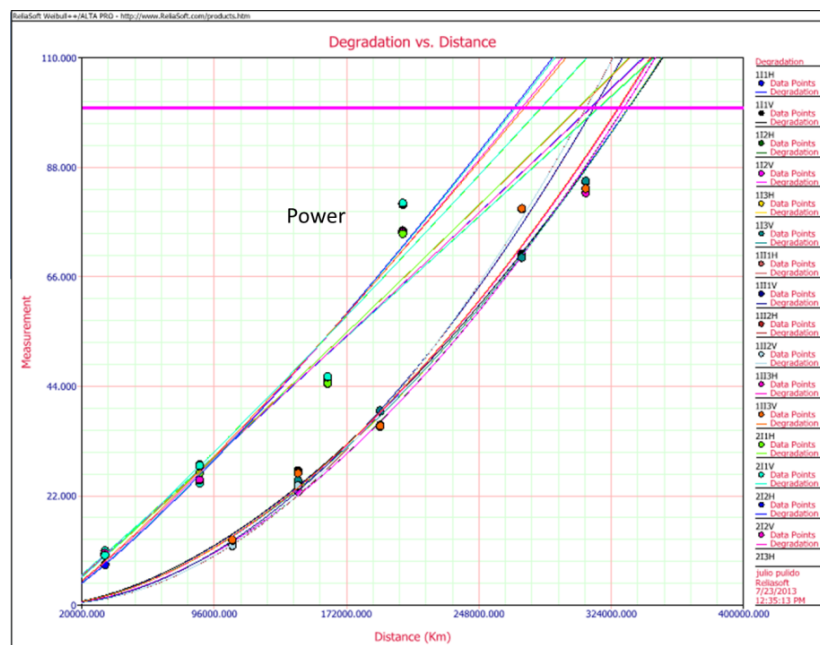


Figure 3.2 Degradation with Power function

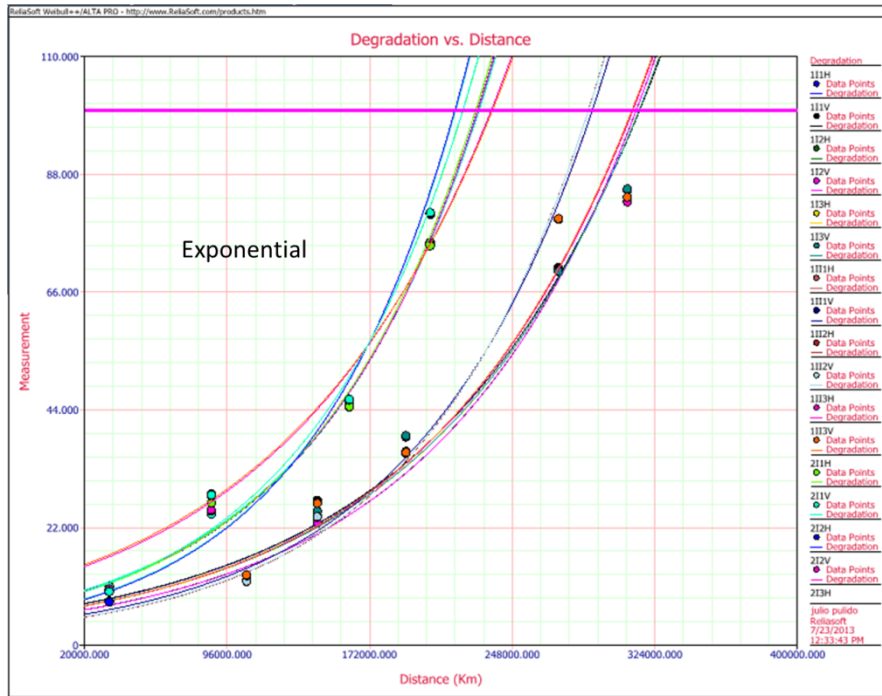


Figure 3.3 Degradation with Exponential function

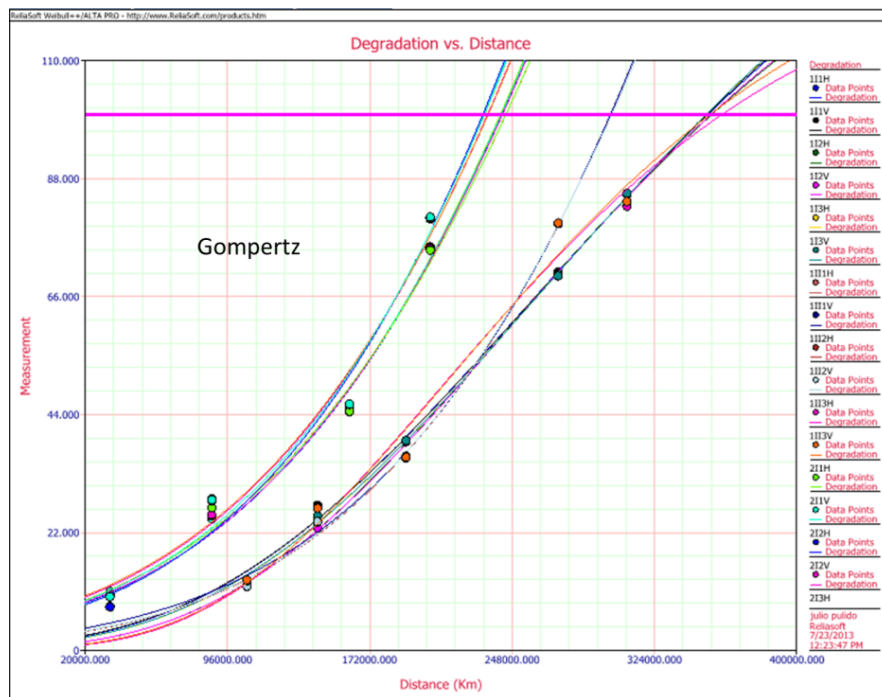


Figure 3.4 Degradation with Gompertz function

Following the above discussion, a wheel's failure condition is assumed to be reached if the diameter reaches  $l_0$ . We adopt the both the Exponential degradation path and Power degradation path for all wheel-sets and set  $l_0 = y$ . The lifetimes for these wheels are now easily determined and are shown in Table 3.3.



Note: As discussed by Lin et al. (2013), some lifetime data can be viewed as right-censored (denoted by asterisk in Table 2.3); Section 4 of this paper considers such data.

Table.3.3 Statistics on lifetime data

No.	Positions		Lifetime**		No.	Positions		Lifetime**	
	Loco.	Bogie	Exponential	Power		Loco.	Bogie	Exponential	Power
1	1	I	316	334	13	2	I	230	316
2	1	I	316	334	14	2	I	230	317
3	1	I	314	331	15	2	I	230	312
4	1	I	314	331	16	2	I	230	312
5	1	I	316	334	17	2	I	229	305
6	1	I	316	334	18	2	I	228	305
7	1	II	291*	314*	19	2	II	218	269
8	1	II	291*	314*	20	2	II	217	268
9	1	II	289*	310*	21	2	II	237	273
10	1	II	289*	310*	22	2	II	237	274
11	1	II	312	329	23	2	II	222	284
12	1	II	312	328	24	2	II	222	284

\* Right-censored data; \*\*  $\times 1000$  km.

## 3.2 Classical Approach

Estimating the failure-time distribution or long-term performance of components of high reliability products is particularly difficult. Many modern products are designed to operate without failure for years, tens of years, or more. Thus, few units will fail or significantly degrade in a test of practical length at normal use conditions. For this reason, Accelerated Life Tests (ALT) are widely used in manufacturing industries, particularly to obtain timely information on the reliability of product components and materials. Generally, information from tests at high stress levels of accelerating variables (e.g., use rate, temperature, voltage, or pressure) is extrapolated through a physically reasonable statistical model (e.g. Eiren, Arrhenius, Inverse Power Law), to obtain estimates of life or long-term performance at lower, normal use conditions. ALT results are used in design-for-reliability processes to assess or demonstrate component and subsystem reliability, certify components, detect failure modes, compare different manufacturers, and so forth. ALTs have become increasingly important because of rapidly changing technologies, more complicated products with more components, and higher customer expectations of better reliability.

In some reliability studies, it is possible to measure degradation directly over time, either continuously or at specific points in time. In most reliability testing applications, degradation data, if available, can have important practical advantages (Levin, 2003): particularly in applications where few or no failures are expected, they can provide considerably more reliability information than would be available from traditional censored failure-time data. Accelerated tests are commonly used to obtain reliability test information more quickly. Direct observation of the degradation process (e.g., tire wear)

may allow direct modelling of the failure-causing mechanism, providing more credible and precise reliability estimates and a valid basis for extrapolation. Modelling degradation of performance output of a component or subsystem (e.g., voltage or power) may be useful, but modelling could be more complicated or difficult because the output may be affected, albeit unknowingly, by more than one physical/chemical failure-causing process.

In this section, we analyse the degradation data with ALT, considering lifetime data from both the Exponential degradation path and the Power degradation path. The analysis uses a General Log Linear (GLL) life stress relationship. Then, using the Exponential degradation model, we perform a two factor full factorial Design of Experiments analysis. We conclude with a discussion of the findings.

### 3.2.1 Accelerated Life Testing (ALT)

Once we obtain the projected failures values for each degradation model, see Table 3.3, we carry out an accelerated life analysis using the locomotive and bogie as stress factors. The analysis is performed using a General Log Linear (GLL) life stress relationship (3.3) with a Weibull probability function (Meeker and Escobar, 1998).

$$L(X) = e^{\left( \alpha_0 + \sum_{i=1}^m \alpha_i X_i \right)} \quad (3.3)$$

This model can be expressed as an Exponential model, expressing life as a function of the stress vector  $X$ , where  $X$  is a vector of  $n$  stressors (Meeker and Escobar, 1998).

For this analysis, we consider stress applications of the model and a logarithmic transformation on  $X$ , such that  $X = \ln(V)$  where  $V$  is the specific stress. This transformation generates an inverse power model life stress relationship, as shown below for each stress factor (Meeker and Escobar, 1998):

$$L(V) = \frac{1}{KV^n} \quad (3.4)$$

The results of the life data analysis and reliability curves appear in Figure 3.1 and Figure 3.2.

As shown in Figures 3.5 and 3.6, the Exponential function for this set of data yields more conservative results and is in line with the field observation when life data are compared at different stress levels as previously defined. Figure 3.6 shows reliability values for Locomotive 2 and Bogie 2; both sides have 95% confidence level.

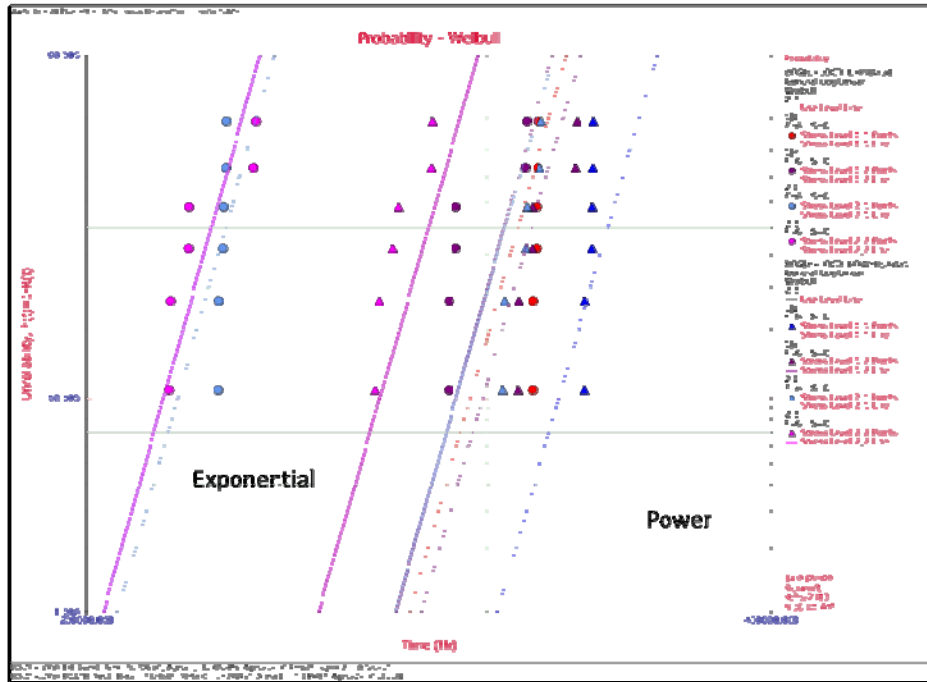


Figure 3.5 Life Data Analysis

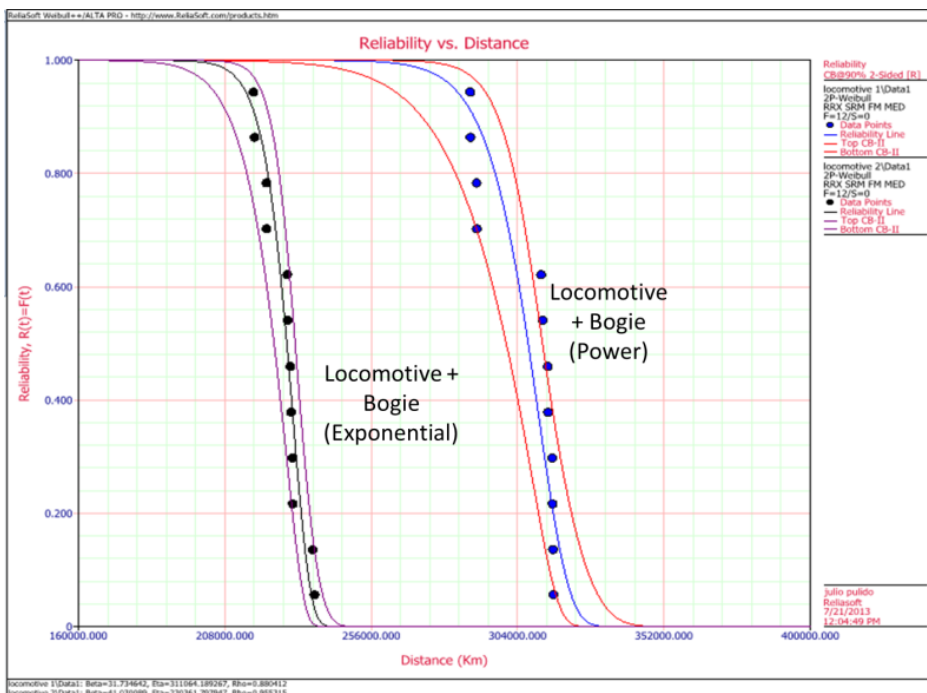


Figure 3.6 Reliability Curve for Degradation Type

### 3.2.2 Design of Experiments Analysis (DOE)

Using the exponential degradation model, we perform a two factor full factorial Design of Experiments analysis and find that the locomotive, bogie and interaction are critical factors (see Figure 3.7).

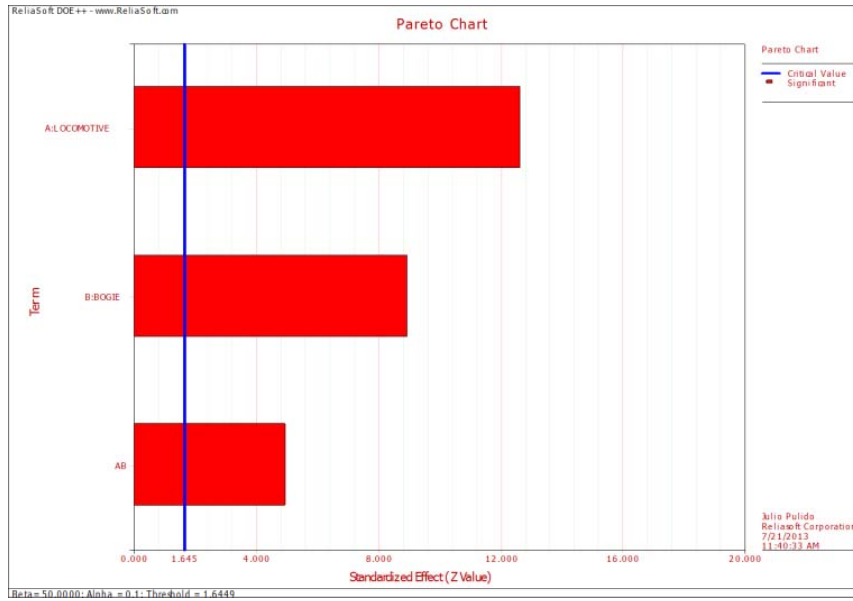


Figure 3.7 Factors Pareto Chart

A review of the life stress relationship between the factors indicates the locomotive is a higher contributor to the degradation of the system than the bogie (Figures 3.8 and 3.9).

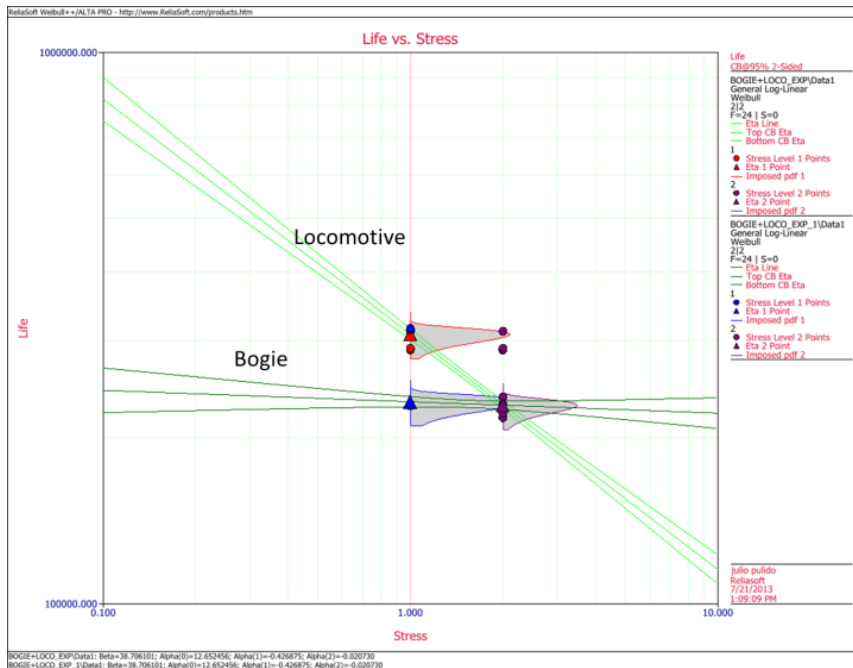


Figure 3.8 Life vs. Stress

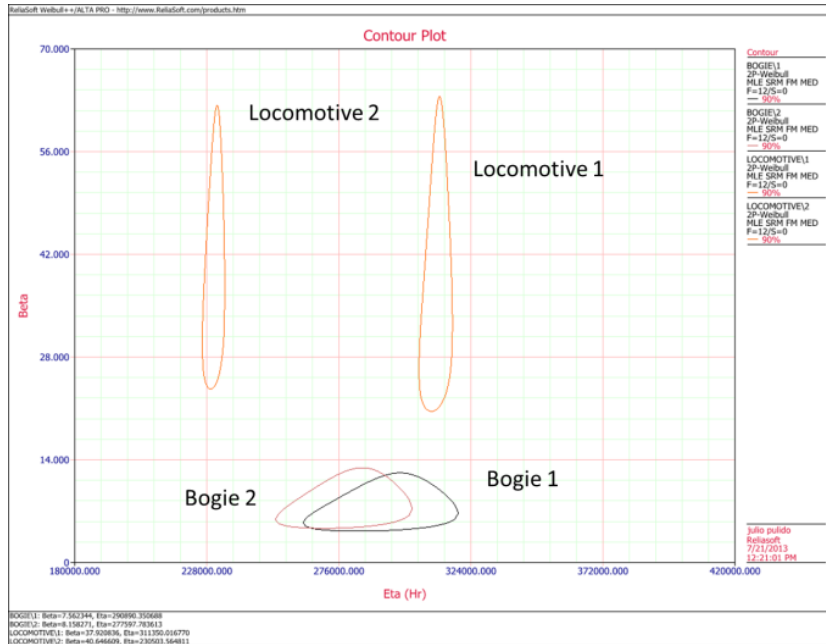


Figure 3.9 Contour Plot

### 3.2.3 Classical Approach: Results and Conclusions

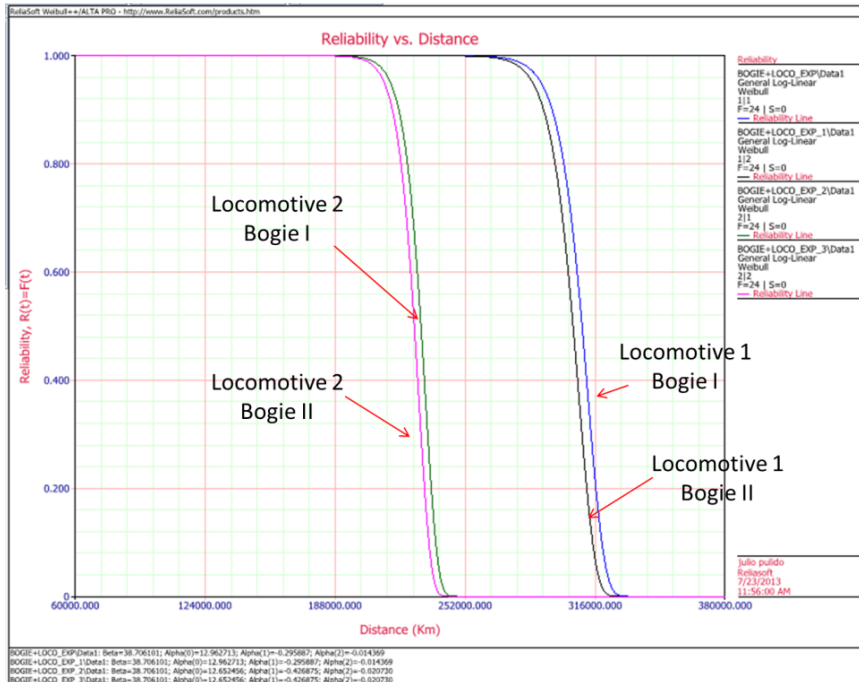


Figure 3.10 Reliability Curves at each condition

Based on the analysis, we reach the following conclusions. Independent of the Degradation model, the locomotive factor is the more critical stressor, as shown in the data above. Failure modes obtained

from the data are similar for the locomotive and for the bogies. Of the two stress conditions, level 2 is the highest for the locomotive and bogie, as shown in Figure 3.9.

Figures 3.9 and 3.10 show the reliability values at each operating distance. Figure 3.10 indicates that Locomotive2 has the highest degradation per distance travelled.

### 3.3 Bayesian Semi-parametric Approach

Most reliability studies are implemented under the assumption that individual lifetimes are independent identically distributed (i.i.d). At times, however, Cox proportional hazard (CPH) models cannot be used because of the dependence of data within a group. For instance, because they have the same operating conditions, the wheel-sets mounted on a particular locomotive may be dependent. In a different context, some data may come from multiple records which actually belong to the wheel-sets installed in the same position but on another locomotive. Modelling dependence in multivariate survival data has received considerable attention in cases where the datasets may come from subjects of the same group which are related to each other (Sahu et al., 1997; Aslanidou et al., 1998). A key development in modelling such data is to consider frailty models, in which the data are conditionally independent. When frailties are considered, the dependence within subgroups can be considered an unknown and unobservable risk factor (or explanatory variable) of the hazard function. In this section, we consider a gamma shared frailty, first discussed by Clayton (1978) and later developed by Sahu et al. (1997), to explore the unobserved covariates' influence on the wheel-sets on the same locomotive.

In addition, since semi-parametric Bayesian methods offer a more general modelling strategy that contains fewer assumptions (Ibrahim et al., 2001), we adopt the piecewise constant hazard model to establish the distribution of the locomotive wheel-sets' lifetime. The applied hazard function is sometimes referred to as a piecewise exponential model; it is convenient because it can accommodate various shapes of the baseline hazard over the intervals.

In this section, first, we propose a Bayesian semi-parametric framework, incorporating the piecewise constant hazard regression model, a gamma shared frailty model, the discrete-time martingale process for the baseline hazard rate, and a MCMC computation scheme. Second, we present the case study's results from the Bayesian semi-parametric model. We conclude with a discussion of the results.

Note that after considering the results from Section 3.1 and Section 3.2, we adopt the results found by using the Exponential degradation path.

#### 3.3.1 Piecewise Constant Hazard Regression Model

The piecewise constant hazard model is one of the most convenient and popular semi-parametric models in survival analysis. We begin by denoting the  $j^{\text{th}}$  individual in the  $i^{\text{th}}$  group as having lifetime  $t_{ij}$ , where  $i = 1, \dots, n$  and  $j = 1, \dots, m_i$ . Divide the time axis into intervals  $0 < s_1 < s_2 < \dots < s_k < \infty$ , where  $s_k > t_{ij}$ , thereby obtaining  $k$  intervals  $(0, s_1], (s_1, s_2], \dots, (s_{k-1}, s_k]$ . Suppose the  $j^{\text{th}}$  individual in the  $i^{\text{th}}$  group has a constant baseline hazard  $h_0(t_{ij}) = \lambda_k$  as in the  $k^{\text{th}}$  interval, where  $t_{ij} \in I_k = (s_{k-1}, s_k]$ . Then, the hazard rate function for the piecewise constant hazard model can be written as

$$h_0(t_{ij}) = \lambda_k, \quad t_{ij} \in I_k \quad (3.5)$$

Equation (3.5) is sometimes referred to as a piecewise exponential model; it can accommodate various shapes of the baseline hazard over the intervals.

Studies of how to divide the time axis into  $k$  intervals include the following. Kalbfleisch & Prentice (1973) suggest that the selection of intervals should be made independently of the data; this has been adopted in the construction of the traditional lifetime table. Breslow (1974) suggests using distinct failure times as end points of each interval. Sahu et al. (1997), Aslanidou et al. (1998), and Ibrahim et al. (2001) discuss the robustness of choosing different  $k$ . In this section, we discuss the choice of  $k$  in the case study.

Suppose  $\mathbf{x}_i = (x_{1i}, \dots, x_{pi})'$  denotes the covariate vector for the individuals in the  $i^{\text{th}}$  group, and  $\boldsymbol{\beta}$  is the regression parameter. Therefore, the regression model with the piecewise constant hazard rate can be written as

$$h(t_{ij}) = \begin{cases} \lambda_1 \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & 0 < t_{ij} \leq s_1 \\ \lambda_2 \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_1 < t_{ij} \leq s_2 \\ \vdots & \vdots \\ \lambda_k \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_{k-1} < t_{ij} \leq s_k \end{cases} \quad (3.6)$$

Its corresponding probability density function  $f(t_{ij})$ , cumulative distribution function  $F(t_{ij})$ , reliability function  $R(t_{ij})$ , together with the cumulative hazard rate  $\Lambda(t_{ij})$  can now be achieved (Ibrahim et al., 2001).

### 3.3.2 Gamma Shared Frailty Model

Frailty models were first considered by Clayton (1978) to handle multivariate survival data. In these models, the event times are conditionally independent according to a given frailty factor, which is an individual random effect. As discussed by Sahu et al. (1997), the models formulate different variabilities and come from two distinct sources. The first source is natural variability, explained by the hazard function; the second is variability common to individuals of the same group or variability common to several events of an individual, explained by the frailty.

Assume the hazard function for the  $j^{\text{th}}$  individual in the  $i^{\text{th}}$  group is

$$h_{ij}(t) = h_0(t) \exp(\mu_i + \mathbf{x}_{ij}'\boldsymbol{\beta}) \quad (3.7)$$

In equation (3.7),  $\mu_i$  represents the frailty parameter for the  $i^{\text{th}}$  group. By denoting  $\omega_i = \exp(\mu_i)$ , the equation can be written as

$$h_{ij}(t) = h_0(t) \omega_i \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) \quad (3.8)$$

Equation (3.7) is an additive frailty model, and equation (3.8) is a multiplicative frailty model. In both equations,  $\mu_i$  and  $\omega_i$  are shared by the individuals in the same group; they are thus referred to as shared-frailty models and are actually extensions of the CPH model.

To this point, discussions of frailty models have focused on the choices of: 1) the form of the baseline hazard function; 2) the form of the frailty's distribution. Representative studies related to the former

include the gamma process for the accumulated hazard function (Clayton, 1991; Sinha, 1993), the Weibull baseline hazard rate (Sahu et al., 1997), and the piecewise constant hazard rate (Aslanidou et al., 1998) which is adopted in this report due to its flexibility. Some researchers have examined finite mean frailty distributions, including gamma distribution (Clayton et al., 1978; Clayton & Cuzick, 1985), lognormal distribution (McGilchrist, 1991), and the like; others have studied non-parameter methods, including the inverse Gaussian frailty distribution (Hougaard, 1986), the power variance function for frailty (Crowder, 1989), the positive stable frailty distribution (Hougaard, 1995; Qiou et al., 1999), the Dirichlet process frailty model (Pennell & Dunson, 2006) and the Levy process frailty model (Hakon et al., 2003). In this report, we consider the gamma shared frailty model, the most popular model for frailty.

From equation (3.8), suppose the frailty parameters  $\omega_i$  are independent and identically distributed (i.i.d) for each group, and follow a gamma distribution, denoted by  $Ga(\kappa^{-1}, \kappa^{-1})$ . In this case, the probability density function can be written as

$$f(\omega_i) = \frac{(\kappa^{-1})^{\kappa^{-1}}}{\Gamma(\kappa^{-1})} \cdot \omega_i^{\kappa^{-1}-1} \exp(-\kappa^{-1}\omega_i) \quad (3.9)$$

In equation (3.9), the mean value of  $\omega_i$  is 1, where  $\kappa$  is the unknown variance of  $\omega_i$ s. Greater values of  $\kappa$  signify a closer positive relationship between the subjects of the same group as well as greater heterogeneity among groups. Furthermore, as  $\omega_i > 1$ , the failures for the individuals in the corresponding group will appear earlier than if  $\omega_i = 1$ ; in other words, as  $\omega_i < 1$ , their predicted lifetimes will be greater than those found in the independent models.

Suppose  $\boldsymbol{\omega} = (\omega_1, \omega_2, \dots, \omega_n)'$ ; then

$$\pi(\boldsymbol{\omega}|\kappa) \propto \prod_{i=1}^n \omega_i^{\kappa^{-1}-1} \exp(-\kappa^{-1}\omega_i) \quad (3.10)$$

### 3.3.3 Discrete-time Martingale Process for Baseline Hazard Rate

Based on the above discussion (equations (3.6), (3.8), and (3.9)), the piecewise constant hazard model with gamma shared frailties can be written as:

$$h(t_{ij}) = \begin{cases} \lambda_1 \omega_i \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & 0 < t_{ij} \leq s_1 \\ \lambda_2 \omega_i \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_1 < t_{ij} \leq s_2 \\ \vdots & \vdots \\ \lambda_k \omega_i \exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) & s_{k-1} < t_{ij} \leq s_k \end{cases} \quad (3.11)$$

In equation (3.11),  $\omega_i \sim Ga(\kappa^{-1}, \kappa^{-1})$ .

To analyse the baseline hazard rate  $\lambda_k$ , a common choice is to construct an independent incremental process, e.g., the Gamma process, the Beta process, or the Dirichlet process. However, as pointed out by Ibrahim et al. (2001), in many applications, prior information is often available on the smoothness of the hazard rather than the actual baseline hazard itself. In addition, given the same covariates, the ratio of marginal hazards at the nearby time-points is approximately equal to the ratio of the baseline hazards at these points. In such situations, correlated prior processes for the baseline hazard can be



more suitable. Such models, for instance, the discrete-time martingale process for the baseline hazard rate  $\lambda_k$ , are discussed by Sahu et al. (1997) and Aslanidou et al. (1998).

Given  $(\lambda_1, \lambda_2, \dots, \lambda_{k-1})$ , we specify that

$$\lambda_k | \lambda_1, \lambda_2, \dots, \lambda_{k-1} \sim Ga(\alpha_k, \frac{\alpha_k}{\lambda_{k-1}}) \quad (3.12)$$

Let  $\lambda_0 = 1$ . In equation (3.12), the parameter  $\alpha_k$  represents the smoothness for the prior information. If  $\alpha_k = 0$ , then  $\lambda_k$  and  $\lambda_{k-1}$  are independent. As  $\alpha_k \rightarrow \infty$ , the baseline hazard is the same in the nearby intervals. In addition, the Martingale  $\lambda_k$ 's expected value at any time point is the same, and

$$E(\lambda_k | \lambda_1, \lambda_2, \dots, \lambda_{k-1}) = \lambda_{k-1} \quad (3.13)$$

Equation (3.13) shows that given specified historical information  $(\lambda_1, \lambda_2, \dots, \lambda_{k-1})$ , the expected value of  $\lambda_k$  is fixed.

### 3.3.4 Bayesian Semi-parametric Model using MCMC

In reliability analysis, the lifetime data are usually incomplete, and only a portion of the individual lifetimes are known. Right-censored data are often called Type I censoring, and the corresponding likelihood construction problem has been extensively studied in the literature (Lawless, 1982; Klein & Moeschberger, 1997). Suppose the  $j^{\text{th}}$  individual in the  $i^{\text{th}}$  group has lifetime  $T_{ij}$  and censoring time  $L_{ij}$ . The observed lifetime  $t_{ij} = \min(T_{ij}, L_{ij})$ ; therefore, the exact lifetime  $T_{ij}$  will be observed only if  $T_{ij} \leq L_{ij}$ . In addition, the lifetime data involving right censoring can be represented by  $n$  pairs of random variables  $(t_{ij}, \nu_{ij})$ , where  $\nu_{ij} = 1$  if  $T_{ij} \leq L_{ij}$  and  $\nu_{ij} = 0$  if  $T_{ij} > L_{ij}$ . This means that  $\nu_{ij}$  indicates whether lifetime  $T_{ij}$  is censored or not. The likelihood function is deduced as

$$L(t) = \prod_{i=1}^n \prod_{j=1}^{m_i} [f(t_{ij})]^{\nu_{ij}} R(t_{ij})^{1-\nu_{ij}} \quad (3.14)$$

In the above piecewise constant hazard model, we denote  $g_{ij}$  as  $t_{ij} \in (s_{g_{ij}}, s_{g_{ij}+1}) = I_{g_{ij}+1}$  and the model's dataset as  $D = (\omega, \mathbf{t}, \mathbf{X}, \mathbf{v})$ . Following equations (3.11) ~ (3.14), the complete likelihood function  $L(\boldsymbol{\beta}, \boldsymbol{\lambda} | D)$  for the individuals for the  $i^{\text{th}}$  group in  $k$  intervals can be written as

$$\prod_{i=1}^n \prod_{j=1}^{m_i} \left\{ \left[ \prod_{k=1}^{g_{ij}} \exp(-\lambda_k \omega_i \exp(\mathbf{x}'_{ij} \boldsymbol{\beta})) (s_k - s_{k-1}) \right] \times (\lambda_{g_{ij}+1} \omega_i \exp(\mathbf{x}'_{ij} \boldsymbol{\beta}))^{\nu_{ij}} \times \exp[-\lambda_{g_{ij}+1} \omega_i \exp(\mathbf{x}'_{ij} \boldsymbol{\beta}) (t_{ij} - s_{g_{ij}})] \right\} \quad (3.15)$$

Let  $\pi(\cdot)$  denote the prior or posterior distributions for the parameters. Following equations (3.10) and (3.15), the joint posterior distribution  $\pi(\omega_i | \boldsymbol{\beta}, \boldsymbol{\lambda}, D)$  for gamma frailties  $\omega_i$  can be written as

$$\begin{aligned} \pi(\omega_i | \boldsymbol{\beta}, \boldsymbol{\lambda}, D) &\propto L(\boldsymbol{\beta}, \boldsymbol{\lambda} | D) \times \pi(\omega_i | \kappa) \\ &\propto \omega_i^{\kappa^{-1} + \sum_{j=1}^{m_i} \nu_{ij} - 1} \exp \left\{ -(\kappa^{-1} + [\sum_{j=1}^{m_i} \exp(\mathbf{x}'_{ij} \boldsymbol{\beta})]) \times (\sum_{k=1}^{g_{ij}} \lambda_k (s_k - s_{k-1}) + \lambda_{g_{ij}+1} (t_{ij} - s_{g_{ij}})) \right\} \\ &\sim Ga \left\{ \kappa^{-1} + \sum_{j=1}^{m_i} \nu_{ij}, \kappa^{-1} + [\sum_{j=1}^{m_i} \exp(\mathbf{x}'_{ij} \boldsymbol{\beta})] (\sum_{k=1}^{g_{ij}} \lambda_k (s_k - s_{k-1}) + \lambda_{g_{ij}+1} (t_{ij} - s_{g_{ij}})) \right\} \end{aligned} \quad (3.16)$$

Equation (3.16) shows that the full conditional density of each  $\omega_i$  is a gamma distribution. Similarly, the full conditional density of  $\kappa^{-1}$  and  $\boldsymbol{\beta}$  can be given by

$$\pi(\kappa^{-1}|\boldsymbol{\beta}, \boldsymbol{\omega}, \boldsymbol{\lambda}, D) \propto \prod_{i=1}^n \omega_i^{\kappa^{-1}-1} (\kappa^{-1})^{-n\kappa^{-1}} \times \frac{\exp\left(-\kappa^{-1} \sum_{i=1}^n \omega_i\right)}{[\Gamma(\kappa^{-1})]^n} \cdot \pi(\kappa^{-1}) \quad (3.17)$$

$$\pi(\boldsymbol{\beta}|\kappa^{-1}, \boldsymbol{\omega}, \boldsymbol{\lambda}, D) \propto \exp\left\{ \sum_{i=1}^n \sum_{j=1}^{m_i} \nu_{ij} \mathbf{x}'_{ij} \boldsymbol{\beta} - \sum_{i=1}^n \sum_{m=1}^{n_i} \exp(\mathbf{x}'_{ij} \boldsymbol{\beta}) \omega_i \times \left[ \sum_{k=1}^{g_{ij}} \lambda_k (s_k - s_{k-1}) + \lambda_{g_{ij}+1} (t_{ij} - s_{g_{ij}}) \right] \right\} \times \pi(\boldsymbol{\beta}) \quad (3.18)$$

Let  $R_k = \{(i, j); t_{ij} > s_k\}$  denote the risk set at  $s_k$  and  $D_k = R_{k-1} - R_k$ ; let  $d_k$  denote the failure individuals in the interval  $I^k$ . Let  $\pi(\lambda_k | \boldsymbol{\lambda}^{(-k)})$  denote the conditional prior distribution for  $(\lambda_1, \lambda_2, \dots, \lambda_j)$  without  $\lambda_k$ . We therefore derive  $\pi(\lambda_k | \boldsymbol{\beta}, \boldsymbol{\omega}, \kappa^{-1}, D)$  as

$$\lambda_k^{d_k} \exp\left\{ -\lambda_k \omega_i \exp(\mathbf{x}'_{ij} \boldsymbol{\beta}) \times \left[ \sum_{(i,j) \in R_k} (s_k - s_{k-1}) + \sum_{(i,j) \in D_k} (t_{ij} - s_{k-1}) \right] \right\} \times \pi(\lambda_k | \boldsymbol{\lambda}^{(-k)}) \quad (3.19)$$

### 3.3.5 Parameter Configuration

In this model, the installed positions of the wheel-sets on a particular locomotive are specified by the bogie number and are defined as covariates  $\mathbf{x}$ . The covariates' coefficients are represented by  $\boldsymbol{\beta}$ . More specifically,  $x = 1$  represents the wheel-sets mounted in Bogie I, while  $x = 2$  represents the wheel-sets mounted in Bogie II.  $\beta_1$  is the coefficient, and  $\beta_0$  is defined as natural variability.

It is clear that a very small  $k$  will make the model nonparametric. However, if  $k$  is too small, estimates of the baseline hazard rate will be unstable, and if  $k$  is too large, a poor model fit could result (Ibrahim et al., 2001). In our study, determining the degradation path requires us to make 3 to 5 measurements for each locomotive wheel; in other words, the lifetime data are based on the data acquired at 3 to 5 different inspections. Following the reasoning above, we divide the time axis into 6 sections piecewise. In our case study, no predicted lifetime exceeds 360,000 kilometres. Therefore,  $k = 6$ , and each interval is equal to 60,000km. We get 6 intervals (0, 60 000], (60 000, 120 000]... (300 000, 360 000].

For convenience, we let  $\lambda_k = \exp(b_k)$ , and vague prior distributions are adopted here as the following:

- Gamma frailty prior:  $\omega_i \sim Ga(\kappa^{-1}, \kappa^{-1})$
- Normal prior distribution:  $b_k \sim N(b_{k-1}, \kappa)$
- Normal prior distribution:  $b_1 \sim N(0, \kappa)$
- Gamma prior distribution:  $\kappa \sim Ga(0.0001, 0.0001)$
- Normal prior distribution:  $\beta_0 \sim N(0.0, 0.001)$
- Normal prior distribution:  $\beta_1 \sim N(0.0, 0.001)$

At this point, the MCMC calculations are implemented with the software WinBUGS (Spiegelhalter et al., 2003). A burn-in of 10,001 samples is used, with an additional 10,000 Gibbs samples.

### 3.3.6 Bayesian Approach: Results and Conclusions

Following the convergence diagnostics (incl., checking dynamic traces in Markov chains, time series, and comparing the Monte Carlo (MC) error with Standard Deviation (SD); see Spiegelhalter et al., 2003), we consider the following posterior distribution summaries (Table.3.4): the parameters' posterior distribution mean, SD, MC error, and the 95% highest posterior distribution density (HPD) interval.

Table.3.4 Posterior Distribution Summaries

Parameter	mean	SD	MC error	95% HPD Interval
$\beta_0$	-12.08	4.184	0.4019	(-22.17,-4.802)
$\beta_1$	0.04517	0.4889	0.02025	(-0.948,0.9669)
$\kappa$	0.1857	0.1667	0.008398	(0.008616,0.6128)
$\omega_1$	0.5246	0.2878	0.01401	(0.06489,1.064)
$\omega_2$	1.473	0.5807	0.01596	(0.6917,2.948)
$b_1$	-0.3764	4.113	0.1619	(-8.316,5.933)
$b_2$	0.3571	4.95	0.2429	(-8.836,8.181)
$b_3$	2.272	4.61	0.3029	(-6.4,10.81)
$b_4$	7.301	4.106	0.3938	(0.2106,17.13)
$b_5$	5.223	4.225	0.3281	(-3.166,13.41)
$b_6$	10.03	3.993	0.3802	(2.72,19.3)

In Table.3.4,  $\beta_1 > 0$  means that wheels mounted in the first bogie (as  $x=1$ ) have a shorter lifetime than those in the second (as  $x=2$ ). However, the influence could possibly be reduced as more data are obtained in the future, because the 95% HPD interval includes 0 point. In addition, the small value of  $\beta_1$  ( $\approx 0.045$ ) indicates that, in this case, heterogeneity among wheels installed in different bogies exists but is not significant. Because  $\kappa < 0.5$ , heterogeneity among the locomotives does exist but is not significant either. However, the frailty factors obviously exist. For instance,  $\omega_1 < 1$  suggests the predicted lifetimes for those wheels mounted on the first locomotive are longer than if the frailties are not considered; meanwhile,  $\omega_2 > 1$  indicates the wheels mounted on the second locomotive have a shorter lifetime than if the frailties are not considered.

Baseline hazard rate statistics based on the above results ( $b_1, \dots, b_6$ ) are shown in Table 3.5 and Figure 3.11. At the fourth piecewise interval, the wheels' baseline hazard rate increases dramatically (1481.78). It is interesting that at the fifth piecewise interval, it decreases (185.49) but increases again after the sixth piecewise (22697.27).

Table.3.5 Baseline Hazard Rate Statistics

Piecewise Intervals( $\times 1000\text{km}$ )	1	2	3	4	5	6
	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
$\lambda_k$	0.069	1.43	9.7	1481.78	185.49	22697.27

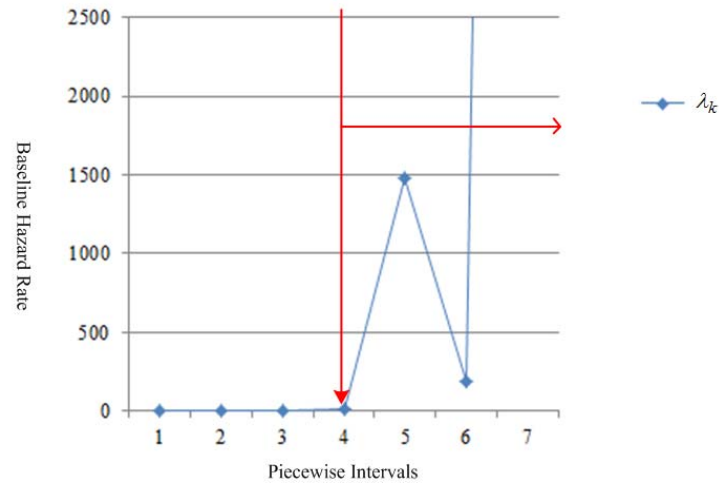


Fig.3.11 Plot of Baseline Hazard Rate

By considering the random effects resulting from the natural variability (explained by covariates) and from the unobserved random effects within the same group (explained by frailties), we can determine other reliability characteristics of the lifetime distribution. The statistics on reliability  $R(t)$  and cumulative hazard rate  $\Lambda(t)$  for the two wheels mounted in different bogies are listed in Table 3.6, Figure 3.12 and Figure 3.13.

Table.3.6 Reliability and Cumulative hazard statistics

Distance (1000 km)	Reliability $R(t)$				Cumulative hazard $\Lambda(t)$			
	Locomotive 1		Locomotive 2		Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II
60	0.999872	0.999866	0.99964	0.999624	5.57E-05	5.82E-05	0.000156	0.000164
120	0.999466	0.999442	0.998502	0.998433	0.000232	0.000243	0.000651	0.000681
180	0.99458	0.994331	0.984857	0.984162	0.00236	0.002469	0.006627	0.006933
240	0.330536	0.314054	0.044672	0.038695	0.480781	0.502996	1.349964	1.41234
300	0.840949	0.834245	0.614843	0.601179	0.07523	0.078707	0.211236	0.220996
360	8.98E-12	2.77E-12	9.61E-32	3.54E-33	11.0466	11.55701	31.01723	32.4504

For Locomotive 1 and Locomotive 2, Figure 3.12 and Figure 3.13 show the plots of reliability and cumulative hazard, respectively.

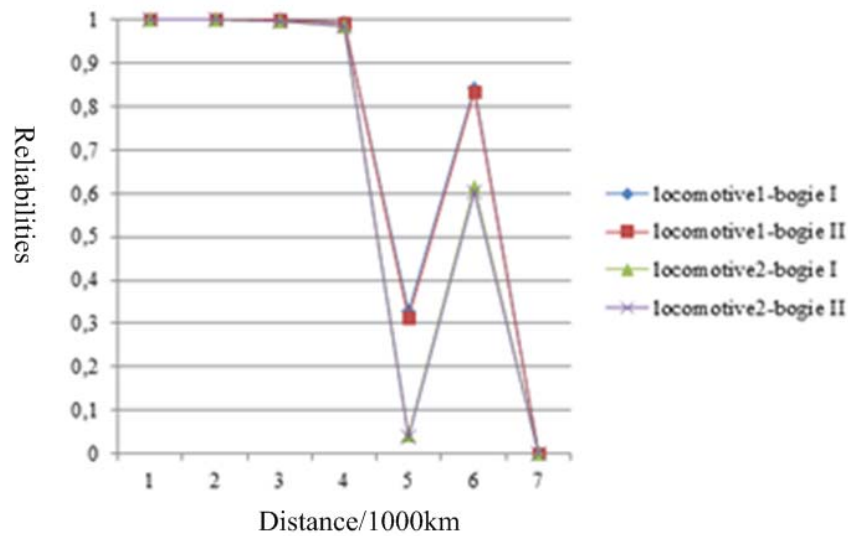


Fig.3.12 Plot of the Reliabilities for Locomotive 1 and Locomotive 2

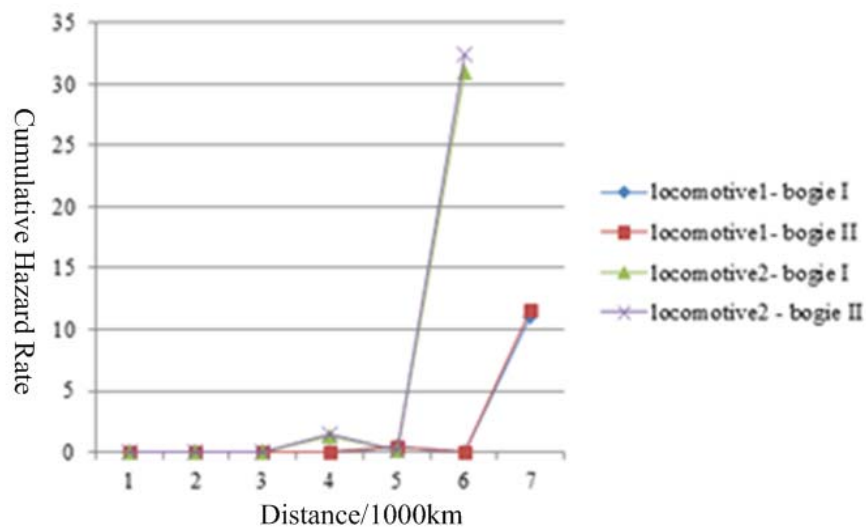


Fig.3.13 Plot of the Cumulative hazard for Locomotive 1 and Locomotive 2

It should be pointed that both Figure 3.12 and Figure 3.13 show change points in the wheels. For example, the reliability declines sharply at the fourth and the sixth piecewise interval. Meanwhile, after the fifth and the sixth piecewise interval, the cumulative hazard increases dramatically.

Table.3.7 Re-profiling Statistics

No.	Piecewise Intervals*	1	2	3	4	5	6
	Re-profiling	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
1	Locomotive 1	0	106	144	191	272	309
2	$\Delta D_1$	106	38	47	81	37	51
3	Locomotive 2	33	87	161	204	0	0
4	$\Delta D_2$	54	74	43	189	/	/

\*  $\times 1000\text{km}$

The above results can be applied to maintenance optimisation, including wheel-sets' re-profiling optimisation, lifetime prediction and replacement optimisation, and preventive maintenance optimisation.

Before continuing, in Table 3.7, we list the re-profiling times (running distance/kilometres) for Locomotive 1 and Locomotive 2, in row 1 and 3, respectively. We can see the difference of the re-profiling polices: for Locomotive 1, re-profiling is done, at most, 5 times; the wheel-sets on Locomotive 2 are re-profiled, at most, 4 times. For greater clarification, we list them under the  $k$  intervals. For instance, for Locomotive 1, the first re-profiling was performed at 106 000 kilometres, which belongs to the second piecewise interval. We can denote  $\Delta D$  as the gap from the "current re-profiling" to the next one in each piecewise interval (rows 2 and 4). For instance, for Locomotive 1, the first re-profiling is at 106 000 kilometres, and the next at 144 000 kilometres, creating a gap of 38 000 kilometres ( $=144\ 000 - 106\ 000$ ). For the last re-profiling, we use the boundary of 360 000 kilometres as the "next re-profiling". By comparing  $\Delta D$ , we can see the running distances of the wheels between profiling. If we do not consider the first interval's statistics (normally, the new wheel is treated as running in a good condition), the largest values appear at the fourth interval for each locomotive, consistent with the findings from Figures 3.11 and 3.12. Therefore, the re-profiling time will influence the wheel-sets' degradation rate. If the re-profiling was performed earlier than 272 000 kilometres for Locomotive 1, the degradation rate could be reduced, as could the baseline hazard rate. Meanwhile, the reliability in piecewise interval 4 could be increased. This conclusion could also explain why at the fifth interval, the baseline hazard rate decreased while the reliability increased. As discussed above, we recommend improving the re-profiling polices by considering the re-profiling intervals.

Now consider the seasonal influence (temperature). In this case, the re-profiling at the fourth piecewise was done between March 2010 and September 2010. Although the degradation rate should be lower than if it were winter, if the time between re-profiling is too long, the baseline hazard rate could increase dramatically and the reliability could decrease. Again, we recommend improving the re-profiling polices by considering the re-profiling intervals, although the seasonal influence should also be included.

It is interesting to see that in Figures 3.11, 3.12, and 3.13, the change points appearing in the fourth piecewise interval (from 180 000 to 360 000 kilometres) indicate that after running about 180 000 kilometres, the locomotive wheel has a high risk of failure. Although the  $\Delta D$  is sometimes larger (for instance,  $\Delta D_1$  equals 106 at the first interval), it is more stable before the fourth piecewise interval. Rolling contact fatigue (RCF) problems could start at the fourth interval (after 180 000 kilometres). Therefore, we recognize the whole period as two stages: one is stable (before 180 000 kilometres), and the second is unstable. Special attention should be paid if the wheel-sets have run longer than these change points (reaching an unstable stage). In addition, because re-profiling may leave cracks over time and reduce the wheel-set's lifetime, we recommend cracks be checked after re-profiling to improve the lifetime.

Although the difference is not that obvious, the wheel-sets installed in the first bogie should be given more attention during maintenance. Especially when the wheels are re-profiled, they should be checked, starting with the first bogie to avoid duplication of effort. Note that in the case study, the wheel-sets' inspecting sequences are random; this means that the first checked wheel-set could belong

in the second bogie. After the second checked wheel-set is lathed or re-profiled, if the diameter is less than predicted, the first checked wheel-set might need to be lathed or re-profiled again. Therefore, starting with the wheel-set installed in the first bogie could improve maintenance effectiveness.

Determining reliability characteristics distributed over the wheel-sets' lifetime (see Table 4.3) could be used to optimise replacement strategies. The results could also support related predictions for spares inventory.

Last but not least, the different frailties between locomotives could be caused by the different operating environments (e.g., climate, topography, and track geometry), configuration of the suspension, status of the bogies or spring systems, operating speeds, the applied loads and human influences (such as drivers' operations, maintenance policies and lathe operators). Specific operating conditions should be considered when designing maintenance strategies because even if the locomotives and wheel-set types are the same, the lifetimes and operating performance could differ.

### 3.4 Comparison of Classical and Bayesian Approaches

For the sake of comparison, Figure 3.8 presents the reliability statistics using the classical model and an Exponential degradation path, as discussed in Section 3.

Table.3.8 Reliability statistics using classical model

Distance (1000 km)	Reliability $R(t)$			
	Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II
60	1.000000000000	1.000000000000	1.000000000000	1.000000000000
120	1.000000000000	1.000000000000	1.000000000000	1.000000000000
180	0.999999999500	0.999999999100	0.999949988500	0.999912782200
240	0.999963596200	0.999936513100	0.032469287900	0.002535299700
300	0.814489640600	0.699174645800	0.000000000000	0.000000000000
360	0.000000000000	0.000000000000	0.000000000000	0.000000000000

The results of the two approaches show that Locomotive 2 has lower reliability than Locomotive 1. In addition, for both Locomotive 1 and Locomotive 2, before the fourth piecewise interval, the reliability statistics from the classical approach have a higher value; after the fifth piecewise interval, the reliability statistics from the Bayesian approach have a higher value.





## 4 Holistic Study of Running Surface Wear Data

This section presents a holistic study of heavy haul locomotive wheel-sets' running surface wear at Malmbanan. Data on the wheel-sets come from 26 locomotives and 57 bogies and were compiled between January 2010 and May 2013.

By analysing the wheel-sets' maintenance and re-profiling data, and comparing both from the locomotives' and bogies' perspectives, this section will determine the context based reliability characteristics of the wheel-sets. The goal is to find the best way to perform a reliability analysis using running surface wear data.

First, as shown in Fig. 2.2, an important background of the problem – Mean Time Between Re-profiling - is described in Section 4.1. Second, data analysis is carried out in Section 4.2 from both locomotives and bogies' perspective by comparing the work orders' history. The results show Malmbanan should to consider the wheel-sets' data not only from the locomotives' but also from the bogies' point of view. In Section 4.3, the wheel-sets' running surface wear data from a group of 16 bogies' are studied as a whole, applying reliability analysis, degradation analysis, lifetime analysis, as well as comparison studies of wear rates. Finally, Section 4.4. offers results and discussions deriving from this holistic study.

### 4.1 Mean Time Between Re-profiling

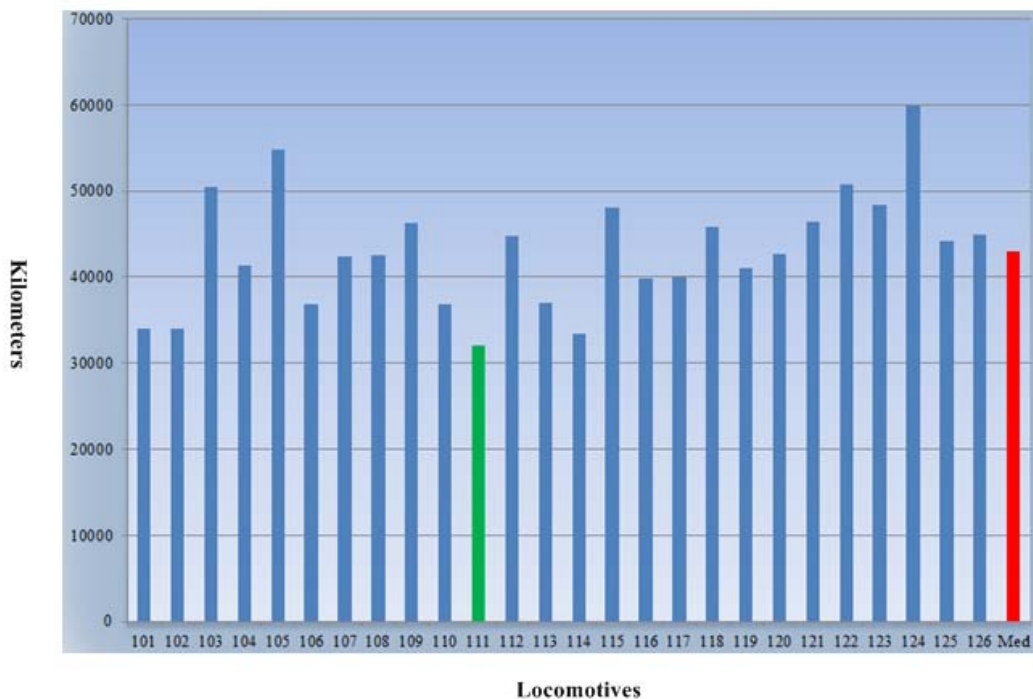


Fig.4.1 Statistics on mean time between re-profiling for 26 locomotives' wheel-sets at Malmbanan (Data Source: this figure is supplied by LKAB/MTAB)

In the current research, 26 locomotives at Malmbanan are numbered consecutively, starting at 101 and ending at 126 (see Fig.4.1). As mentioned earlier, re-profiling wheel-sets after they run a certain distance is a common preventive maintenance strategy. Re-profiling affects the wheel's diameter; once the diameter is reduced to a pre-specified length (a threshold level for failure, denoted as  $l_0$ , is defined as 100 mm ( $l_0 = 1250 \text{ mm} - 1150 \text{ mm}$ ) in this study), the wheel is replaced by a new one.

Fig.4.1, supplied by LKAB/MTAB, contains statistics taken from data on re-profiling (see Fig.1.4). For the wheel-sets of the 26 locomotives, statistics show that, from October 2010 to May 2013, the longest mean time between the wheels' two re-profileings (named Mean Time Between Re-profiling here) was around 60 000 kilometres (locomotive 124). Meanwhile, the shortest was about 31 000 kilometres (locomotive 111). Fig. 4.1 also presents the mean value in the red column (marked as "Med" in Swedish).

To determine the main factors influencing these differences and, thus, to facilitate maintenance strategy decision making, LKAB/ MTAB has organized regular on-site workshops, inviting experts from academia and industry, from Norway, Sweden, Germany, etc. This research presented in this report is also intended to help determine the root causes since 2011. Results of the previous study (Lin, 2013) show that the large difference can be attributed to the non-heterogeneous nature of the wheel-sets; each differs according to its installed position, operating conditions, re-profiling characteristics, etc. However, this and the former study are based on specific locomotives' wheel-sets.

Given the above, a better understanding of the re-profiling data based on a group of wheel-sets by bogies (not only by locomotives as in the previous study) could be necessary to better explain the behaviour of the difference in wheel-sets' Mean Time Between Re-profiling.

## 4.2 Comparison of Locomotives and Bogies using Work Orders

This section explains why the bogie-grouped strategy is selected for further study (why the wheel-sets are recommended to be studied not only from locomotive's perspective, but also from the bogies'.) in this research. As mentioned above, the data adopted by this research is from work orders history, including both the maintenance and re-profiling system, from January 2010 to May 2013.

### 4.2.1 Comparison of Total Re-profiling Statistics

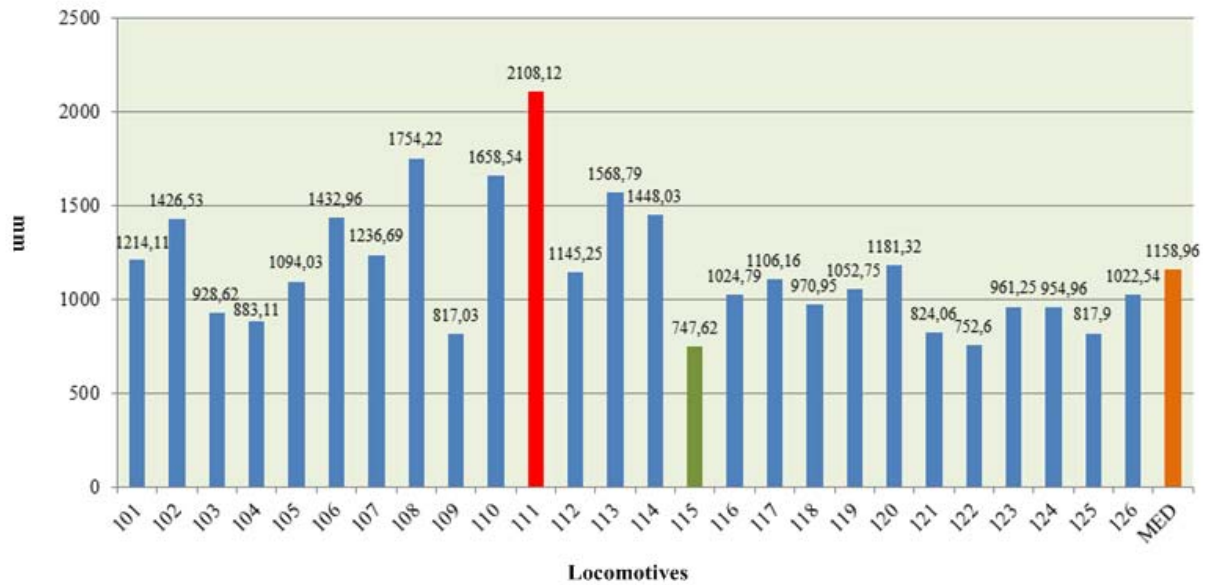


Fig.4.2 Statistics on amount of re-profiling for 26 locomotives' wheel-sets

In Fig.4.2, the horizontal axle represents the 26 locomotives (from 101 to 126) operating on the Iron Ore Line (Malmbanan). The longitudinal axle of Fig. 4.2 represents the total amount of re-profiling (mm) of the 6 installed wheel-sets on each locomotive. For instance, as seen in Fig.4.2, during the period in question (January 2010 to May 2013), the wheel-sets installed in locomotive 111 have the most re-profiling, a total of 2108.12 mm (red column); the wheel-sets installed in locomotive 115 have the lowest amount of re-profiling, a total of 747.62 mm (green column); the average for the 26 locomotives' wheels is 1158.96 mm (last column, orange).

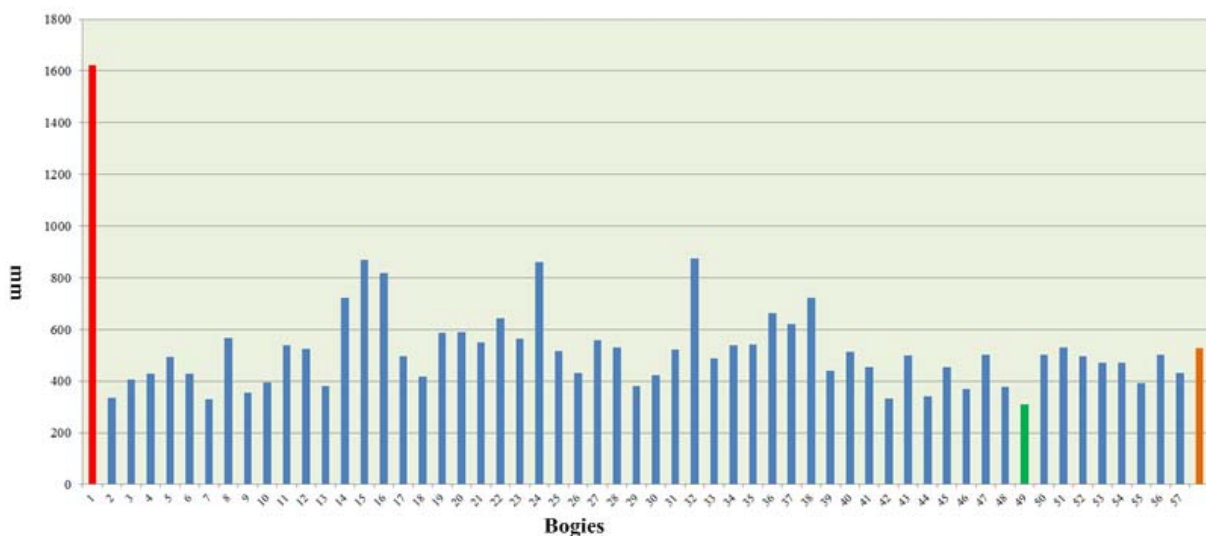


Fig.4.3 Statistics on amount of re-profiling for 57 bogies' wheel-sets\*

(\*: the bogies' number can be found in Table 4.1; the corresponding amount of re-profiling appears in Table 4.2)

Similarly, in Fig.4.3, the horizontal axle represents the 57 bogies (corresponding bogie number in re-profiling system appears in Table 4.1) operating on the Iron Ore Line (Malmbanan). The longitudinal axle of Fig. 4.3 represents the total amount of re-profiling (mm) of the 3 installed wheel-sets (6 wheels) on each bogie. As shown in Fig.4.3 and Table 4.2, during the period in question (January 2010 to May 2013), the wheel-sets installed in bogie 169074 (first column; the first bogie in Fig 4.3 has the bogie number 169074 for re-profiling) have the most re-profiling, a total of 1623.12 mm (red column); the wheel-sets installed in bogie 195908 have the least re-profiling, a total of 310 mm (green column); the average amount for the 57 bogies is 528.65 mm (last column, orange).

Table. 4.1 Bogies' number list

No.	Bogie No.	No.	Bogie No.	No.	Bogie No.	No.	Bogie No.	No.	Bogie No.
1	169074	13	169087	25	169099	37	169111	49	195908
2	169075	14	169088	26	169100	38	169112	50	195909
3	169076	15	169089	27	169101	39	170256	51	195910
4	169077	16	169090	28	169102	40	170257	52	195911
5	169079	17	169091	29	169103	41	195900	53	195912
6	169080	18	169092	30	169104	42	195901	54	195913
7	169081	19	169093	31	169105	43	195902	55	195914
8	169082	20	169094	32	169106	44	195903	56	195915
9	169083	21	169095	33	169107	45	195904	57	198618
10	169084	22	169096	34	169108	46	195905	-	-
11	169085	23	169097	35	169109	47	195906	-	-
12	169086	24	169098	36	169110	48	195907	-	-

Table. 4.2 Statistics on amount of re-profiling for 57 bogies' wheel-sets

No.	Re-profiling (mm)	No.	Re-profiling (mm)	No.	Re-profiling (mm)	No.	Re-profiling (mm)	No.	Re-profiling (mm)
1	1 623.12	13	381.68	25	517.58	37	621.55	49	310
2	336.99	14	723.37	26	432.34	38	721.7	50	502.64
3	406.29	15	869.72	27	559.08	39	441.23	51	529.53
4	429.75	16	819.36	28	531.75	40	512.69	52	496.79
5	492.57	17	496.24	29	379.94	41	455.01	53	469.75
6	428.94	18	417.18	30	422.06	42	332.23	54	471.78
7	328.96	19	585.53	31	521.27	43	498.09	55	391.39
8	567.16	20	589.02	32	873.6	44	340.95	56	503.22
9	356.49	21	549.18	33	487.09	45	453.67	57	432.02
10	394.89	22	643.72	34	539.24	46	368.36	Mean	528.65
11	539.15	23	565.32	35	540.99	47	503.57	-	-
12	523.33	24	860.91	36	664.13	48	378.82	-	-

Although there are total 26 locomotives and each has 2 bogies, the 2 installed bogies could be any from the total 57 bogies.

Comparing Fig. 3.3 with Fig.4.2, we see the gaps between wheels installed in bogies are larger than those installed in locomotives.

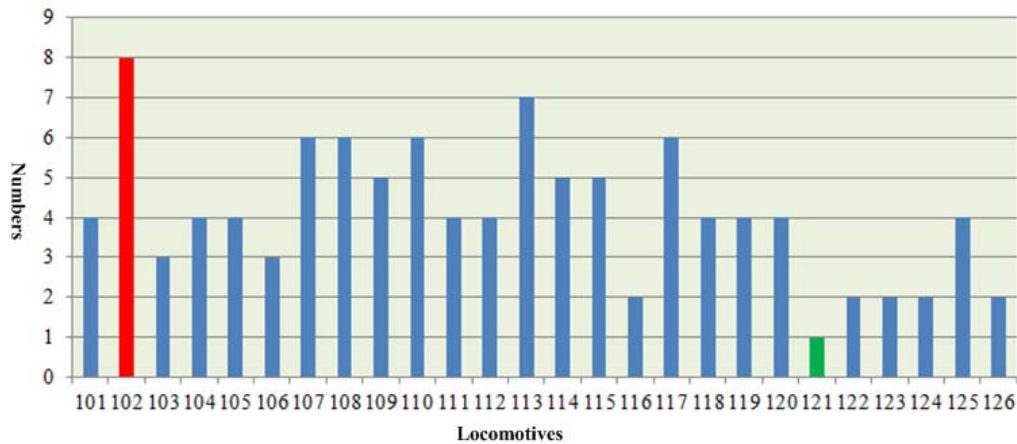


Fig.4.4 Statistics on re-profiling times for 26 locomotives' wheel-sets

Fig.4.4 and Fig. 4.5 show the statistics of the re-profiling times, from the locomotives' perspective and bogies' perspective, respectively. For instance, as seen in Fig.4.4, during the period in question (January 2010 to May 2013), the wheel-sets installed in locomotive 102 have the most re-profiling, a total of 8 times (red column); the wheel-sets installed in locomotive 121 have the least re-profiling, only 1 time (green column). Meanwhile, from the bogies' perspective, the wheel-sets installed in locomotive 169105 (No.31) have the most re-profiling (red), a total of 4 times; the wheel-sets installed in locomotives 195901 and 195908 (No.42 and No.49 respectively) have no re-profiling.

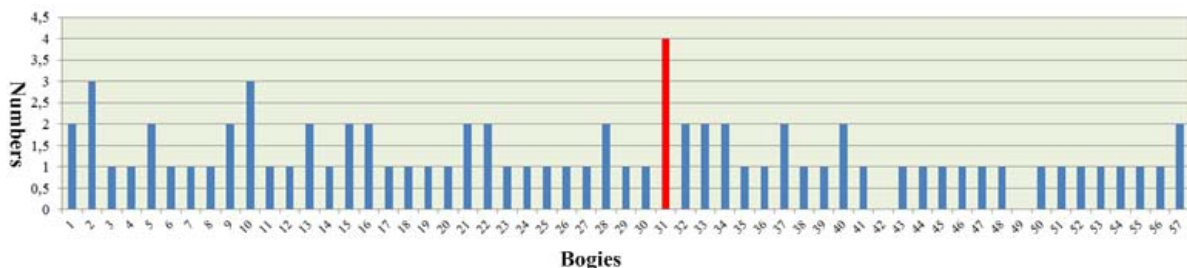


Fig.4.5 Statistics on re-profiling times for 57 bogies' wheel-sets

#### 4.2.2 Comparison of Re-profiling History: four examples

As discussed in Section 4.2.1 (see Fig.4.3), the wheel-sets installed in locomotive 111 have the highest amount of re-profiling, 2108.12 mm; the wheel-sets installed in locomotive 115 have the lowest amount of re-profiling, 747.62 mm. Similarly, the wheel-sets installed in bogie 169074 have the highest amount of re-profiling, 1623.12 mm; at the same time, the wheel-sets installed in bogie 195908 have the lowest amount of re-profiling, 310 mm. To compare gaps in the work orders, four examples (from one wheel installed in Locomotive 111, 115, Bogie 169074 and 195908, respectively) are illustrated here.

Note: Appendix B has all statistics on bogies.

*Example I: one wheel installed in Locomotive 111*

The first example is taken from a wheel installed in Locomotive 111, bogie I, Axel 1, on the right side (see Fig. 4.6).

In Fig.4.6, the horizontal axle represents the corresponding wheel's re-profiling time (the re-profiled date); the longitudinal axle represents the diameters of the wheel before (red) and after (blue) each re-profiling. For instance, in August 2012, before re-profiling, the wheel's diameter is 1249.97mm; after re-profiling, the diameter is 1240.52 mm. It is also obvious that a new wheel is installed in this position around August 2012, since the original value is increasing and close to 1250 mm.

However, as marked in a green circle, in April 2010, there is an abnormal re-profiling history for this wheel. Before re-profiling, the diameter is close to 1195.77mm; after re-profiling, it is only 888.6 mm. This means that 307.17 mm was removed during one re-profiling, which equals 15% of the total re-profiling amount from 2010 to 2013. It has been suggested to LKAB/MTAB that it follow such kinds of abnormal history to discover the reasons.

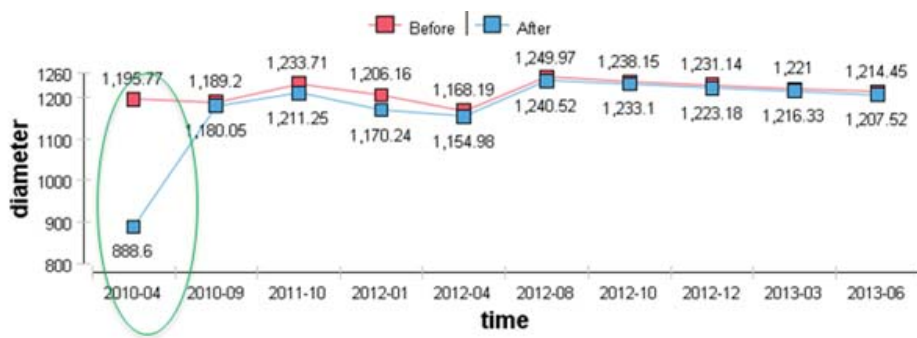


Fig.4.6 Re-profiling history by locomotive (wheel installed in locomotive 111, bogie I, axel 1 on right side)

Table.4.3 Re-profiling history by locomotive (wheel installed in locomotive 111, bogie I, axel 1 on right side)

Time	Bogie No.	Count	Time	Bogie No.	Count
2010-04	169074	2	2012-08	169094	1
2010-09	169074	1	2012-10	169094	1
2011-10	169106	1	2012-12	169094	1
2012-01	169106	1	2013-03	169094	1
2012-04	169106	1	2013-06	169094	1

In this example, three bogies are installed in locomotive 111, bogie 1 (see Table.4.3). The three bogies are numbered 169074, 169106, and 169094. In Table.4.3, the re-profiling times are also listed. For instance, in April 2014, a wheel was installed in bogie 169074 and was re-profiled twice at this time. We suggested that LKAB/MTAB follow such kinds of abnormal history to look for the reasons.

*Example II: one wheel installed in Locomotive 115*

As in Example I, the second example is taken from 1 wheel installed in Locomotive 115, bogie I, Axle 1 on the right side (see Fig. 4.7). In Fig.4.7, it is obvious that a new wheel is installed in this position around June 2012.

It is interesting to note in Fig. 4.7 (marked in a green circle) and Table.4.4, that from February 2010 to April 2013, 5 bogies are installed in locomotive 115, bogie 1, an abnormal observation in this case; we have suggested that LKAB/MTAB follow up on this.

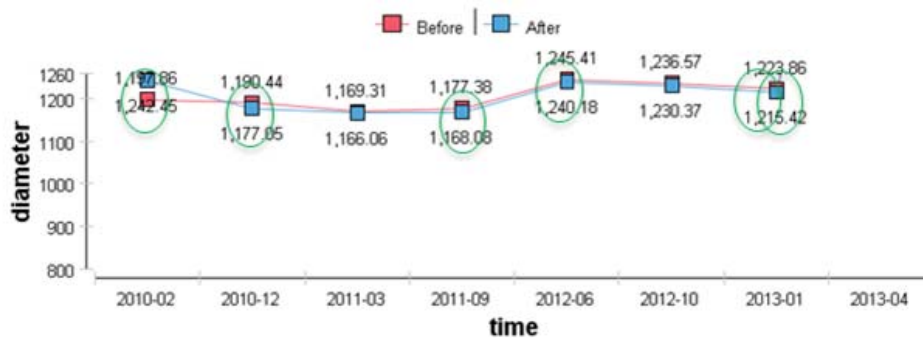


Fig.4.7 Re-profiling history by locomotive  
(wheel installed in locomotive 115, bogie I, axle 1 on the right side)

Table.4.4 Re-profiling history by locomotive  
(wheel installed in locomotive 115, bogie I, axle 1 on the right side)

Time	Bogie No.	Count	Time	Bogie No.	Count
2010-02	169092	1	2012-10	169076	1
2010-12	169081	1	2013-01	169076	1
2011-03	169081	1	2013-04	169076	1
2011-09	169095	1	2013-04	169104	1
2012-06	169076	1	-	-	-

*Example III: one wheel installed in Bogie 169074*

The third example is taken from one wheel installed in Bogie 169074, Axle 1 on the right side (Fig. 4.8). As shown in Fig.4.8, a new wheel is installed in this position around August 2011. It is interesting to see that for this wheel, there are two abnormal values in April 2010 and November 2012. For those two abnormal histories, the total amount removed is 630.21 mm, which equals 39% of the total re-profiling amount. It is also unusual that two abnormal histories are recorded for the same bogie. We suggested that LKAB/MTAB follow such kinds of abnormal history to determine the reasons.

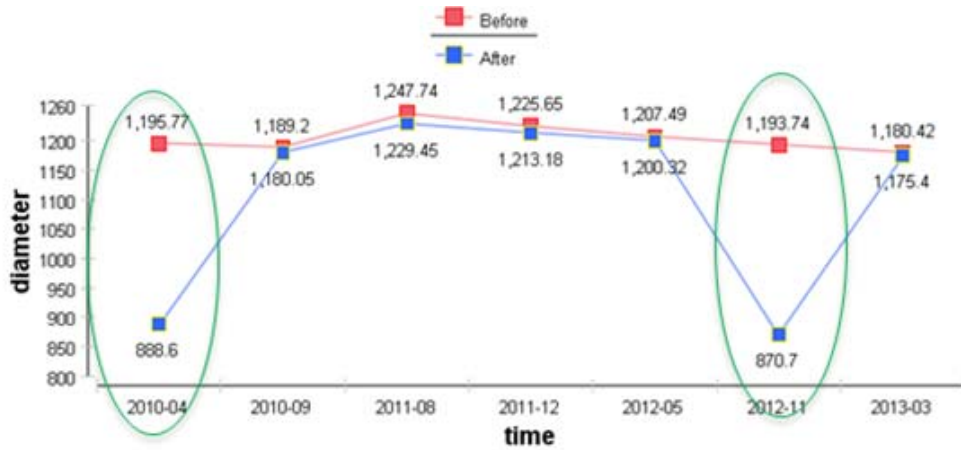


Fig.4.8 Re-profiling history by bogie (wheel installed in bogie 169074, axel 1 on the right side)

Table.4.5 indicates that during the period from April 2010 to March 2013, this bogie was installed in three different locomotives.

Table.4.5 Re-profiling history by bogie (wheel installed in bogie 169074, axel 1 on the right side)

Time	Locomotive No.	Count	Time	Locomotive No.	Count
2010-04	111	2	2012-05	108	1
2010-09	111	1	2012-11	108	1
2011-08	108	1	2013-03	103	1
2011-12	108	1	-	-	-

*Example IV: one wheel installed in Bogie 195908*

The fourth example is taken from 1 wheel installed in Bogie 195908, Axel 1 on the right side (see Fig. 4.9). Fig.4.9 shows the whole lifetime of this wheel, with no abnormal data.

Table.4.6 shows that during the period from December 2010 to November 2012, this bogie was installed in the same locomotive (122) and re-profiled once each time.



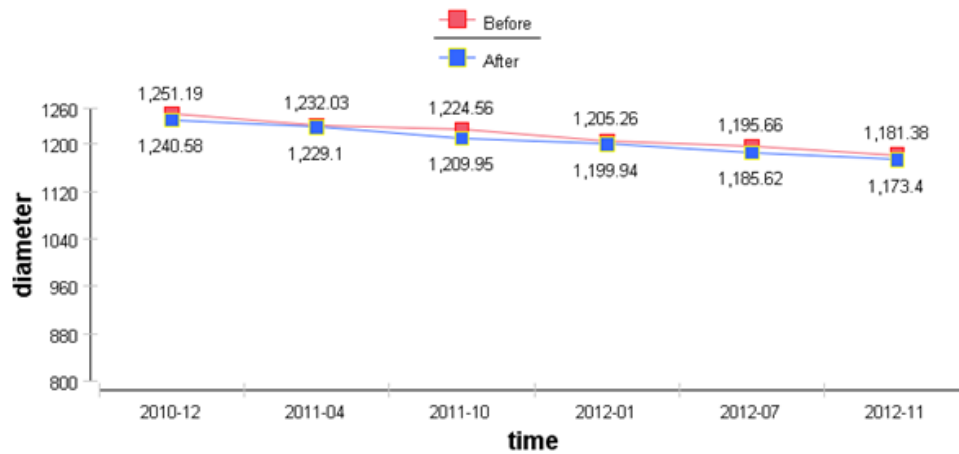


Fig.4.9 Re-profiling history by bogie  
(wheel installed in bogie 195908, axel 1 on the right side)

Table.4.6 Re-profiling history by bogie  
(wheel installed in bogie 195908, axel 1 on the right side)

Time	Locomotive No.	Count	Time	Locomotive No.	Count
2010-12	122	1	2012-01	122	1
2011-04	122	1	2012-07	122	1
2011-10	122	1	2012-11	122	1

*Note: For other researchers' reference, Appendix B has all statistics from the bogies' perspectives.*

### 4.2.3 Re-profiling Statistics by Locomotives

Section 4.2.2 provides four examples of the wheels' re-profiling history, following the results given in section 4.2.1, to illustrate the wheel-sets' re-profiling performance, going from the "best" to the "worst" Mean Time Between Re-profiling statistics.

First, we supply several other normal examples of the re-profiling statistics for the wheels, inspected by re-profiling date (time) and operating distance (kilometres) separately. Second, we note some abnormal points in these statistics to reveal the performance of the work order data from the locomotives' perspective.

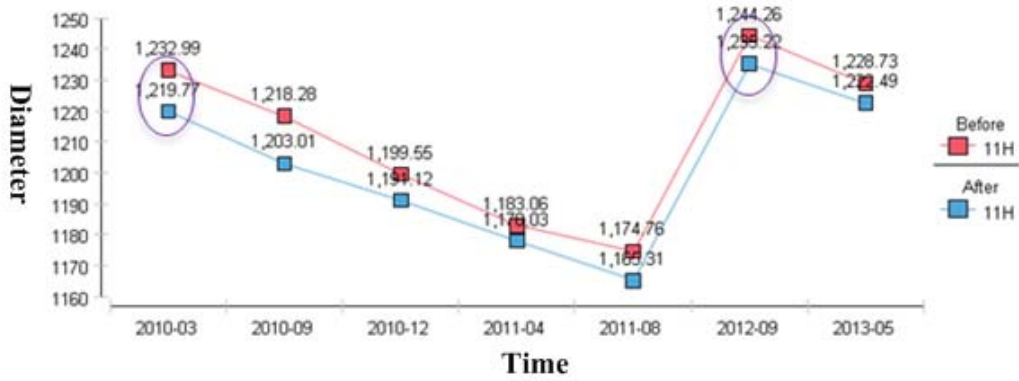


Fig.4.10 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 118, bogie I, axel 1 on the right side)

Table.4.7 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 118, bogie I, axel 1 on the right side)

Time	Bogie No.	Count	Time	Bogie No.	Count
2010-03	169093	1	2011-08	169093	1
2010-09	169093	1	2012-09	169097	1
2010-12	169093	1	2013-05	169097	1
2011-04	169093	1	-	-	-

As illustrated in Section 4.2.2, this example is taken from 1 wheel installed in Locomotive 118, bogie I, Axle 1 on the right side (see Fig. 4.10). In Fig.4.10, the horizontal axis represents the corresponding wheel's re-profiling time (date); the longitudinal axis represents the diameters of the wheel before and after each re-profiling (diameters in mm). In this example, two bogies (169093 and 169097) are changed to be installed in locomotive 118 (the first date is marked in a purple circle in Fig.4.10), bogie 1 (see Table.4.7). In Table.4.7, the re-profiling times are also listed.

In the statistics for the re-profiling history, we found that the wheels installed in the same bogie have quite similar behaviour in their re-profiling performance. Therefore, we include another example in Fig.4.11 and Table 4.8 as a comparison. This wheel is also installed in locomotive 118, but in bogie II.

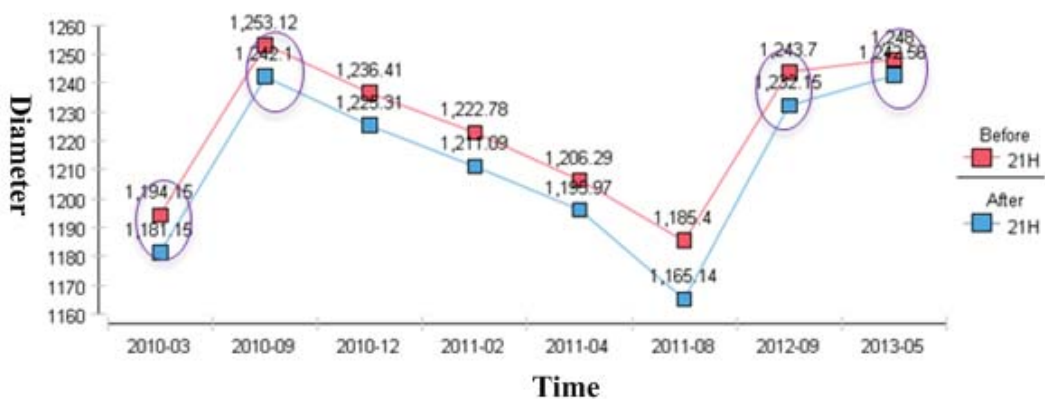


Fig.4.11 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 118, bogie II, axel 1 on the right side)

Table.4.8 Re-profiling history by locomotive and re-profiling date  
(wheel installed in locomotive 118, bogie II, Axel 1 on the right side)

Time	Bogie No.	Count	Time	Bogie No.	Count
2010-03	170257	1	2011-04	169112	1
2010-09	169112	1	2011-08	169112	1
2010-12	169112	1	2012-09	195903	1
2011-02	169112	1	2013-05	195905	1

In this example, four bogies are installed in Locomotive 118, bogie II (also seen in Table.4.7).

In Fig.4.10, see that even for wheels installed in the same locomotive, behaviour can differ due to different installed bogies.

Below we provide the statistics on operating distance (in kilometres, the horizontal axle) for the wheels installed in the same position in Locomotive 118.

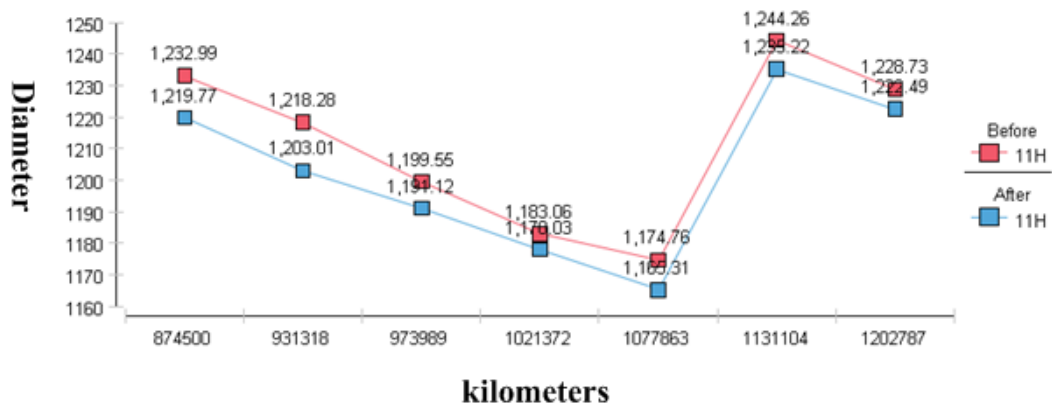


Fig.4.12 Re-profiling history by locomotive and operating distance  
(wheel installed in locomotive 118, bogie I, axel 1 on the right side)

Table.4.9 Re-profiling history by locomotive and operating distance  
(wheel installed in locomotive 118, bogie I, axel 1 on the right side)

Kilometres	Bogie No.	Count	Kilometres	Bogie No.	Count
874,500	169093	1	1,077,863	169093	1
931,318	169093	1	1,131,104	169097	1
973,989	169093	1	1,202,787	169097	1
1,021,372	169093	1	-	-	-

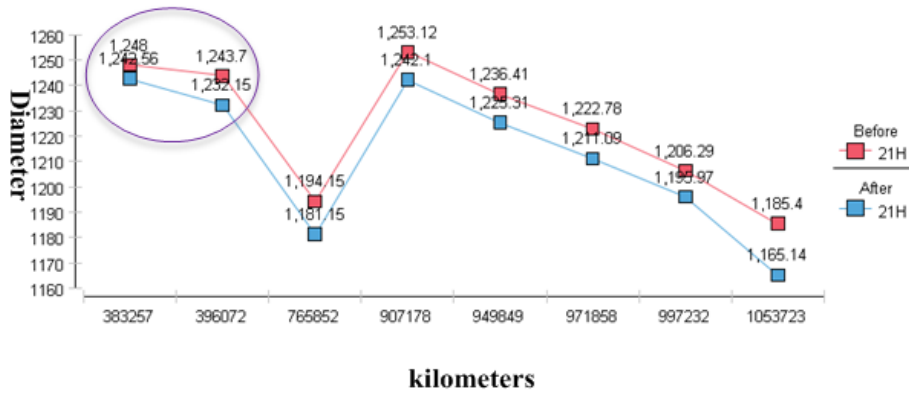


Fig.4.13 Re-profiling history by locomotive and operating distance (wheel installed in locomotive 118, bogie II, axel 1 on the right side)

Table.4.10 Re-profiling history by locomotive and operating distance (wheel installed in locomotive 118, bogie II, axel 1 on the right side)

Kilometres	Bogie No.	Count	Kilometres	Bogie No.	Count
383,257	195905	1	949,849	169112	1
396,072	195903	1	971,858	169112	1
765,852	170257	1	997,232	169112	1
907,178	169112	1	1,053,723	169112	1

Comparing Fig.4.10 – Fig.4.13, we see the figures for the wheel’s re-profiling history are different from those for the wheels installed in Bogie II (marked in a purple circle in Fig.4.13). The record of the operating distance found in Malmbanan’s work orders is a global record for the bogie, not for the specified wheel-sets. This finding is important for our future study.

We now list some abnormal statistics, as shown below.

*Example I: Complex situations to be considered*

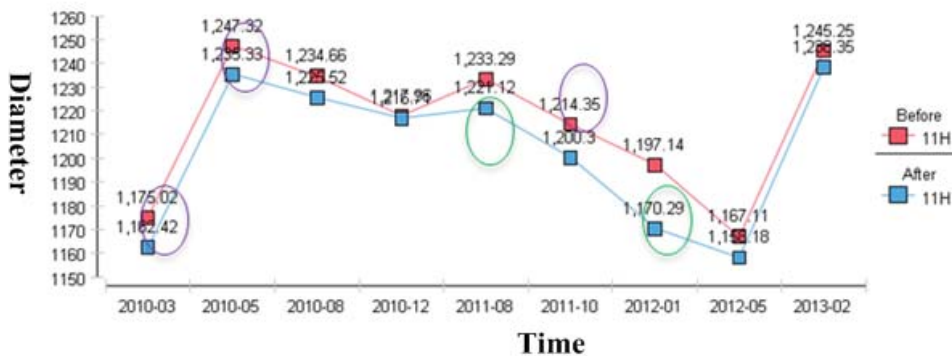


Fig.4.14 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 102, bogie I, axel 1 on the right side)

In Fig.4.14, the bogie (each circle in purple or green represents different bogie numbers) was changed too many times (more than 5 times). In addition, even during the same re-profiling, the bogie could have been changed. As shown in Fig.4.14, the green circle represents the changed bogie for the same

re-profiling, which means the re-profiling statistics at this point actually involve more than two bogies. The purple circles represent the same bogie. In October 2011, the bogie was changed to the purple one, but in January 2011, it was changed back to the green one. Clearly, the situation can be complex.

*Example II: Is smaller before re-profiling than after*

In some cases, the re-profiling history in work orders show that the diameter of the wheel before re-profiling is smaller than the diameter of the wheel after re-profiling. In Fig.4.15, the green circle represents an abnormal value found in the work orders. These data result from incorrect recording of work orders, something to be studied in future research.

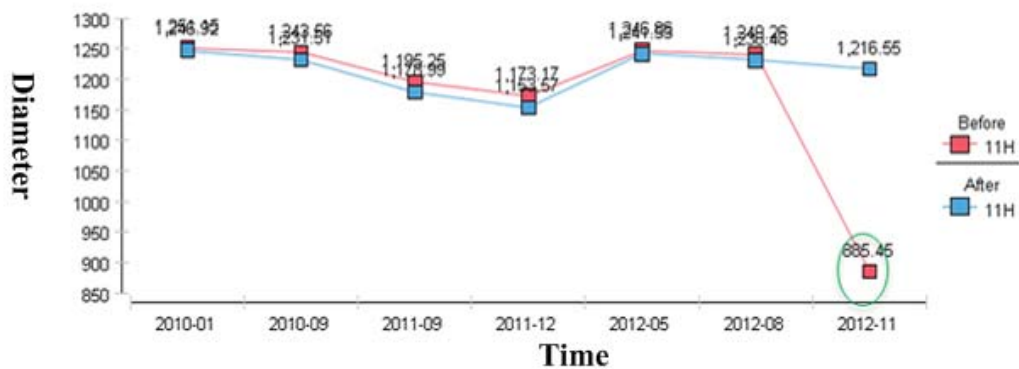


Fig.4.15 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 104, bogie I, axel 1 on the right side)

*Example III: Different behaviour as recorded by re-profiling date and operating distance*

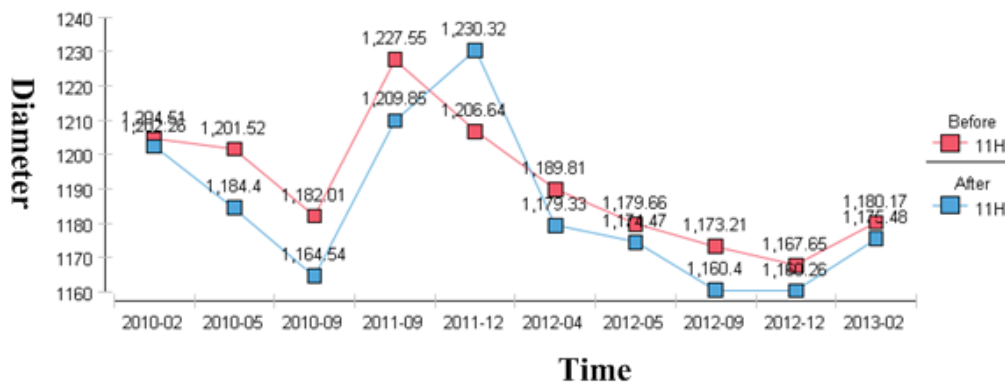


Fig.4.16 Re-profiling history by locomotive and re-profiling date (wheel installed in locomotive 113, bogie I, axel 1 on the right side)

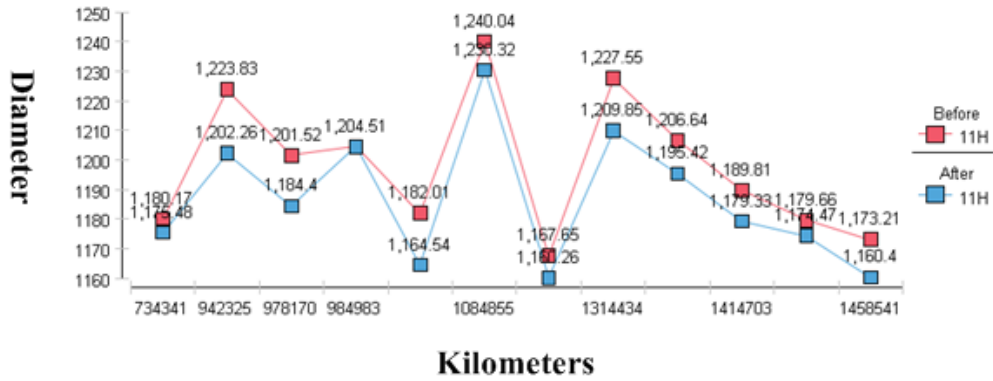


Fig.4.17 Re-profiling history by locomotive and operating distance (wheel installed in locomotive 113, bogie I, axel 1 on the right side)

As mentioned before, because the operating distance in the work order system represents a global record, the figures for re-profiling date and operating distance at the time of re-profiling could vary. Fig.4.16 and Fig.4.17 offer a comparison.

#### 4.2.4 Re-profiling Statistics by Bogies

In this section, we review the abnormal points noted in Section 4.2.3. First, we provide several normal examples of the re-profiling statistics for the wheels, inspected by re-profiling date and operating distance, separately. Second, we note several abnormal points in these statistics to reveal the performance of the work order data from the bogie's perspective.

As in Section 4.2.3, the first example is taken from 1 wheel installed in bogie 169096, Axel 1 on the right side (Fig. 4.18). In Fig.4.18, the horizontal axle represents the corresponding wheel's re-profiling time; the longitudinal axle represents the diameters of the wheel before and after each re-profiling. In this example, three locomotives (101,119 and 111) are changed to be installed in bogie 169096 (see Table.4.11 and the purple circle in Fig.4.18). In Table.4.11, the re-profiling times are also listed.

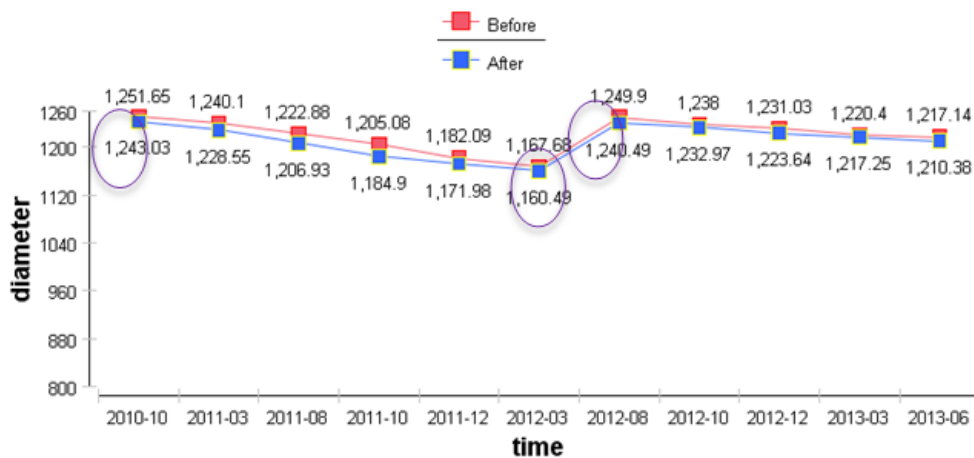


Fig.4.18 Re-profiling history by bogie and re-profiling date (wheel installed in bogie 169096, axel 1 on the right side)

Table.4.11 Re-profiling history by bogie and re-profiling date  
(wheel installed in bogie 169096, axel 1 on the right side)

Time	Locomotive No.	Count	Time	Locomotive No.	Count
2010-10	101	1	2012-08	111	1
2011-03	101	1	2012-10	111	1
2011-08	101	1	2012-12	111	1
2011-10	101	1	2013-03	111	1
2011-12	101	1	2013-06	111	1
2012-03	119	1	-	-	-

In the second example (bogie 169105), five locomotives (127,117,102,113,110) are changed for bogie 169105 (see Table.4.12 and the purple circle in Fig.4.19).

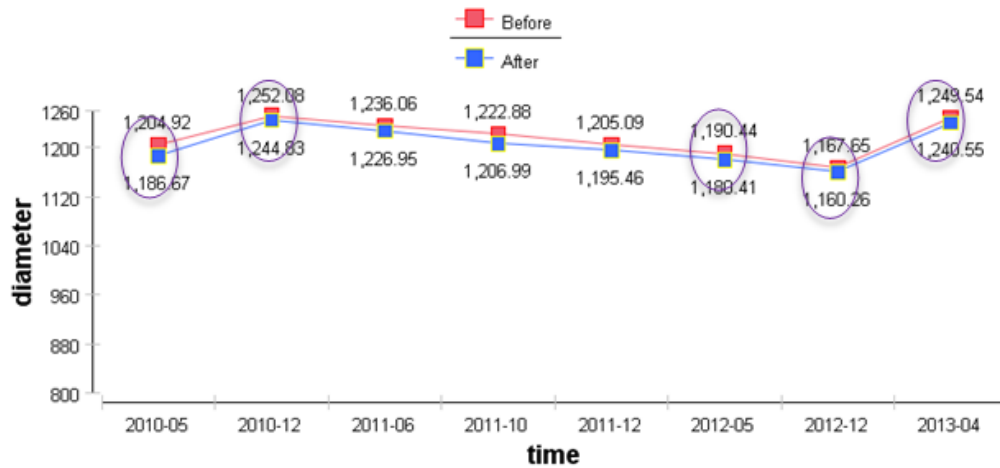


Fig.4.19 Re-profiling history by bogie and re-profiling date  
(wheel installed in bogie 169905, axel 1 on the right side)

Table.4.12 Re-profiling history by bogie and re-profiling date  
(wheel installed in bogie 169905, axel 1 on the right side)

Time	Locomotive No.	Count	Time	Locomotive No.	Count
2010-05	112	1	2011-12	117	1
2010-12	117	1	2012-05	102	2
2011-06	117	1	2012-12	113	1
2011-10	117	1	2013-04	110	1

Below we give the statistics by operating distance (in kilometres, the horizontal axle) for the wheels installed in the same position on bogie 169096 and 169105.

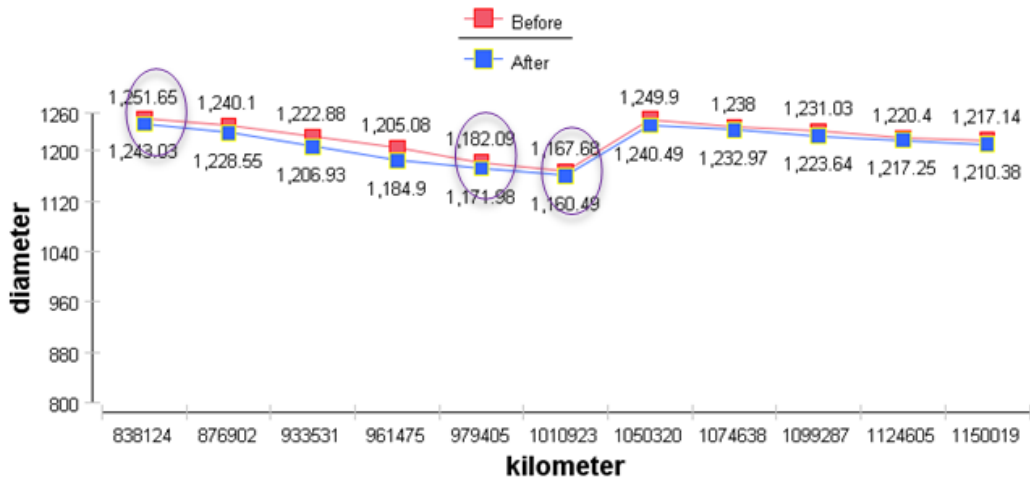


Fig.4.20 Re-profiling history by bogie and operating distance (wheel installed in bogie 169096, axel 1 on the right side)

Table.4.13 Re-profiling history by bogie and operating distance (wheel installed in bogie 169096, axel 1 on the right side)

Kilometres	Locomotive No.	Count	Kilometres	Locomotive No.	Count
838,124	101	1	1,050,320	111	1
876,902	101	1	1,074,638	111	1
933,531	101	1	1,099,287	111	1
961,475	101	1	1,124,605	111	1
979,405	101	1	1,150,019	111	1
1,010,923	119	1	-	-	-

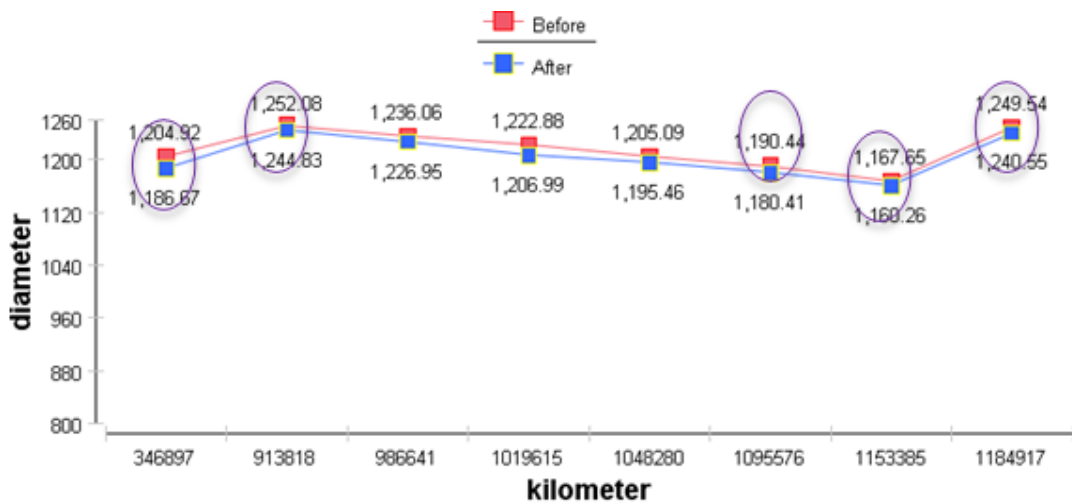


Fig.4.21 Re-profiling history by bogie and operating distance (wheel installed in bogie 169905, axel 1 on the right side)



Table.4.14 Re-profiling history by bogie and operating distance  
(wheel installed in bogie 169905, axel 1 on the right side)

Kilometres	Locomotive No.	Count	Kilometres	Locomotive No.	Count
346,897	112	1	1,048,280	117	1
913,818	117	1	1,095,576	102	2
986,641	117	1	1,153,385	113	1
1,019,615	117	1	1,184,917	110	1

In this section, we also list two abnormal statistics below.

*Example I: Abnormal gaps in the same bogie*

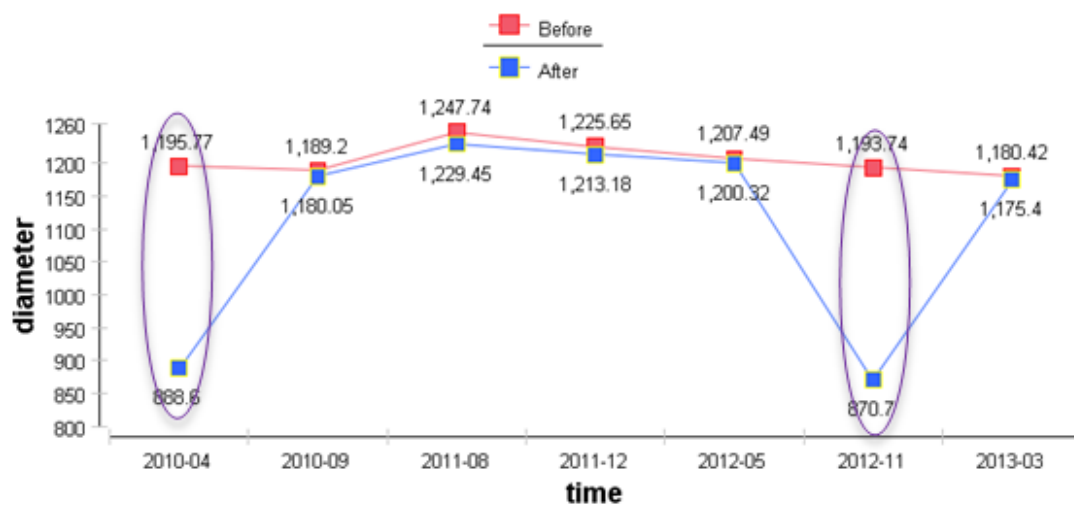


Fig.4.22 Re-profiling history by bogie and time  
(wheel installed in bogie 169074, axel 1 on the right side)

For the wheel installed in bogie 169074, we find two abnormal gaps in “before” and “after” re-profiling statistics. Actually, these two gaps appear as the wheel-set is installed in different locomotives. These two gaps represent almost 92.3% of the total amount of re-profiling, a large number.

*Example II: Is smaller before re-profiling than after*

We find some cases where the diameter of the wheel before re-profiling could be smaller than the diameter of the wheel after re-profiling (Fig.4.23).

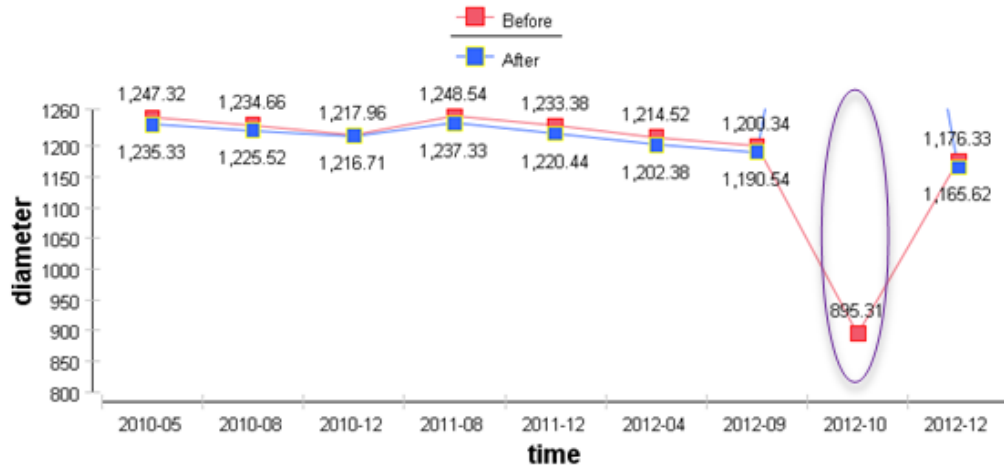


Fig.4.23 Re-profiling history by bogie and time  
(wheel installed in bogie 169082, axel 1 on the right side)

### 4.3 Studies focusing on Wheel-sets and Bogies

This section presents the process and results for the bogie-grouped strategy.

#### 4.3.1 Selection of Bogies

Looking into the statistics of the re-profiling history from the bogies' perspective, we find one obvious discrepancy. Fig.4.18 shows that after March 2012, a new wheel-set was installed, but the re-profiling system did not record the diameter of the replaced wheel. This means we cannot get complete statistics for the wheel-set's entire life. In other words, we don't know if the wheel-set was replaced because the diameter was smaller than 1150mm, something necessary for the wheel's lifetime analysis, or not. Therefore, we examine the work orders for all bogies as the wheel-sets are replaced (Fig.4.24).

Fig.4.24 Wheel-set replacement records

Fig.4.24 shows the wheel-set replacement records for January 2010 to May 2013. The bogies are divided into several groups, shown in different colours. The largest two groups are shown in red and blue (also marked with purple rectangles on the left side); the bogies in the “red” group are numbered “169XXX”, and the bogies in the “blue” group are numbered “195XXX”. As we consider the reasons for the replacements, shown in the last two columns and a purple rectangle on the right side (one of the columns is “Orsak” in Swedish), we find that for the “red” group, the reasons for replacement are complex. Only some cite “low diameter”. Other reasons include “RCF” problems or “Others”. Meanwhile, in the “blue group”, most mention “low diameter”. Hence, in this group, we can assume that all wheel-sets are replaced because their diameters reach 1150 mm.

For further study, we select a group of bogies numbered “195XXX”. There are 16 bogies in this group at Malmbanan.

### 4.3.2 Data preparation

	A	B	C	D	E	F	G	H	I	J	K
1	Bogie number	IORBOG195911	Axel	1	Side	H	Total/Average		122	Total/Average	
2	Installed Locomotive		124						1		
3	Installed position (Bogie)		1						2		
4	Wheel Life Cycle NO.		1								
5	WO reported times in each life cycle		1	2	3	4	5		1*	2	
6	Reported Date (installed* & reprofiled)/ year, month	201010	201102	201109	201201	201206			201210	201303	
7	Reported kilometers /1000km	33,366	87,721	161,346	204,349	268,192	234,826		301,802	357,554	
8	Absolut kilometers /1000km	0	54,355	73,625	43,003	63,843	234,826		0	55,752	
9	Diameters (before)/mm	1251,97	1234,15	1217,22	1201,24	1169,33	/			1245,89	
10	Diameters (after)/mm	1239,04	1225,41	1205,07	1174,66	1160,42	/			1235,44	

Fig.4.25 Examples for data preparation (a)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Bogie number	IORBOG195910	Axle	1	Side	H				Installed	118						Total/Average	
2	Installed Locomotive	123						Total/Average			1						Total/Average	
3	Installed position (Bogie)	2									2							
4	Wheel Life Cycle NO.	1																
5	WO reported times in each life cycle	1	2	3	4	5	6											
6	Reported Date (installed* & reprofiled)/ year, month	201010	201102							201107	201108	201202	201206	201211	201301	201305	21	
7	Reported kilometers /1000km	32,84	87,244					54,404		112,662	139,534	176,587	221,96	274,152	301,625	350,417	210,883	
8	Absolut kilometers /1000km	0	54,404					54,404										
9	Diameters (before)/mm	1251,63	1231,34					/		1237,16	1216,71	1201,32	1186,93	1171,96	/	/		
10	Diameters (after)/mm	1240,05	1221,85					/		1219,22	1206,26	1190,12	1176,22	1160,52	/	/		

Fig.4.26 Examples for data preparation (b)

Figure 4.25 and Figure 4.26 give two examples of how the data are prepared in this study.

Bogie number	IORBOG195901	Axle	1	Side	H		Total/Average	
Installed Locomotive	122							
Installed position (Bogie)	1							
Wheel Life Cycle NO.	1							
WO reported times in each life cycle	1	2	3	4	5	6	6	
Reported Date (installed* & reprofiled)/ year, month	201011	201104	201110	201201	201207	201211	24	
Reported kilometers /1000km	41,334	88,236	161,833	212,06	274,274	324,91	283,576	
Absolut kilometers /1000km	0	46,902	73,597	50,227	62,214	50,636	283,576	
Diameters (before)/mm	1250,52	1229,95	1221,77	1200,78	1190,65	1175,76	/	
Diameters (after)/mm	1238,18	1226,13	1206,95	1195,21	1180,21	1167,59	/	
re-profiling Amount/mm	12,34	3,82	14,82	5,57	10,44	8,17	55,16	
Natural Wear/mm	0	8,23	4,36	6,17	4,56	4,45	27,77	
Total Wear/mm	12,34	12,05	19,18	11,74	15	12,62	82,93	
re-profiling Amount %	1	0,317	0,773	0,474	0,696	0,647	0,665	
Natural Wear Amount %	0	0,683	0,227	0,526	0,304	0,353	0,335	
WearRate_re-profiling/1000km	/	0,081	0,201	0,111	0,168	0,161	0,195	
WearRate_Natural/1000km	/	0,175	0,059	0,123	0,073	0,088	0,098	
WearRate_Total/1000km	/	0,257	0,261	0,234	0,241	0,249	0,292	
ratio of reprofiling and natural		0,464	3,405	0,901	2,289	1,833	1,985	

Fig.4.27 Wear rate statistics (an example)

Figure 4.25 shows the wheel installed in bogie 195911, Axle 1 and on the right side. For the first “complete” lifetime, it is installed in locomotive 124; for the second “incomplete” lifetime, it is installed in locomotive 122. The “incomplete” lifetime means the record is not completed. For each selected lifecycle (marked with a purple rectangle), collected data include the operating history for each re-profiling piecewise, and the diameters' changes at each re-profiling.

Figure 4.26 shows the wheel installed bogie 195910, Axle 1 and on the right side. For this case, the second “complete” lifetime is selected. The number of re-profiling work orders is different between bogies: bogie 195911 has 5 and bogie 195910 has 6. We discover that the start diameters do not exactly equal 1250mm (marked in red circle). LKAB/MTAB says this is a system error. However, in our study, we follow the real values achieved from the above statistics.

Following the above descriptions, we calculate the following wear rate (shown in Fig.4.27 and also in Lin (2013)):

- Absolute kilometres = the current reported kilometres – the previous reported kilometres;
- Re-profiling Amount = Diameters (before) - Diameters (after);
- Natural Wear = previous Diameters (after) – current Diameters (before);
- Total Wear = Re-profiling Amount + Natural Wear;
- Re-profiling Amount % = Re-profiling Amount / Total Wear;
- Natural Wear % = Natural Wear/ Total Wear;
- Wear Rate\_re-profiling = Re-profiling Amount / Absolute kilometres;

- $\text{Wear Rate}_{\text{Natural}} = \text{Natural Wear} / \text{Absolute kilometres}$ ;
- $\text{Wear Rate}_{\text{Total}} = \text{Total Wear} / \text{Absolute kilometres}$ ;
- Average of the total wear rate = the average of  $\text{Wear Rate}_{\text{Total}}$ .

Considering the first re-profiling is implemented before the wheel-sets are used, the statistics show the first natural wear as 0 mm. The final statistics are shown in the figure marked in green.

### 4.3.3 Reliability and Degradation Analysis

The re-profiling statistics for bogie 195902 are abnormal; they only include 3 re-profileings during a whole lifetime; therefore, the data are not included.

Bogie number	IORBOG195902				Axel	1	Side	H	Total/Average			Total/Average	
Installed Locomotive	111									102			
Installed position (Bogie)	2									1			
Wheel Life Cycle NO.	1									2			
WO reported times in each life cycle	0	1	2	3					1*	2			
Reported Date (installed* & reprofiled)/ year, month	201010	201201	201204						201207	201302			
Reported kilometers /1000km	90,767	135,333	162,965				72,198		184,873	231,588			
Absolut kilometers /1000km		0	44,566	27,632			72,198		0	46,715			
Diameters (before)/mm	1233,67	1205,41	1162				/			1245,25			
Diameters (after)/mm	1210,88	1165,3	1154,22				/			1238,35			
re-profiling Amount/mm	22,79	40,11	7,78				70,68	47,89		6,9			
Natural Wear/mm	0	5,47	3,3				8,77	8,77		0			
Total Wear/mm	22,79	45,58	11,08				79,45	56,66		6,9			
re-profiling Amount %		1	0,88	0,702				0,89	0,845		1		
Natural Wear Amount %		0	0,12	0,298				0,11	0,155		0		
WearSpeed_re-profiling/1000km	/	0,9	0,282				0,979	0,663		0,148			
WearSpeed_Natural/1000km	/	0,123	0,119				0,121	0,121		0			
WearSpeed_Total/1000km	/	1,023	0,401				1,1	0,785		0,148			

Fig.4.28 Examples for data preparation: bogie 195902

From the above dataset, we can obtain 3 to 5 measurements of the diameter of each wheel during its lifetime. By connecting these measurements, we can determine a degradation trend.

The first step of the analysis is the selection of the degradation model. In their analyses of train wheels, most studies (Freitas et al. 2009, 2010; Lin et al. 2013) assume a linear degradation path. In our study, we plot the degradation data for the locomotive wheels using Exponential degradation, Power degradation, Logarithmic degradation, and the linear degradation path in Weibull++. The Gompertz model needs a total of more than 5 points to converge; therefore, it was not considered here.

The results (see Figure 4.29) show that the better choices are Linear degradation, Power degradation, and Exponential degradation. The selection should be based on physics of failure (wear or fatigue). In our study, we select the linear degradation model.

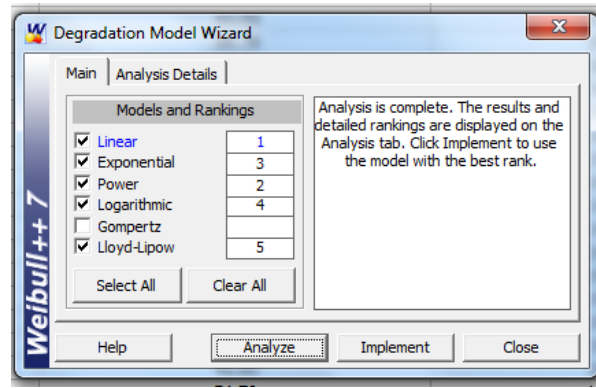


Fig. 4.29 Degradation path analyses

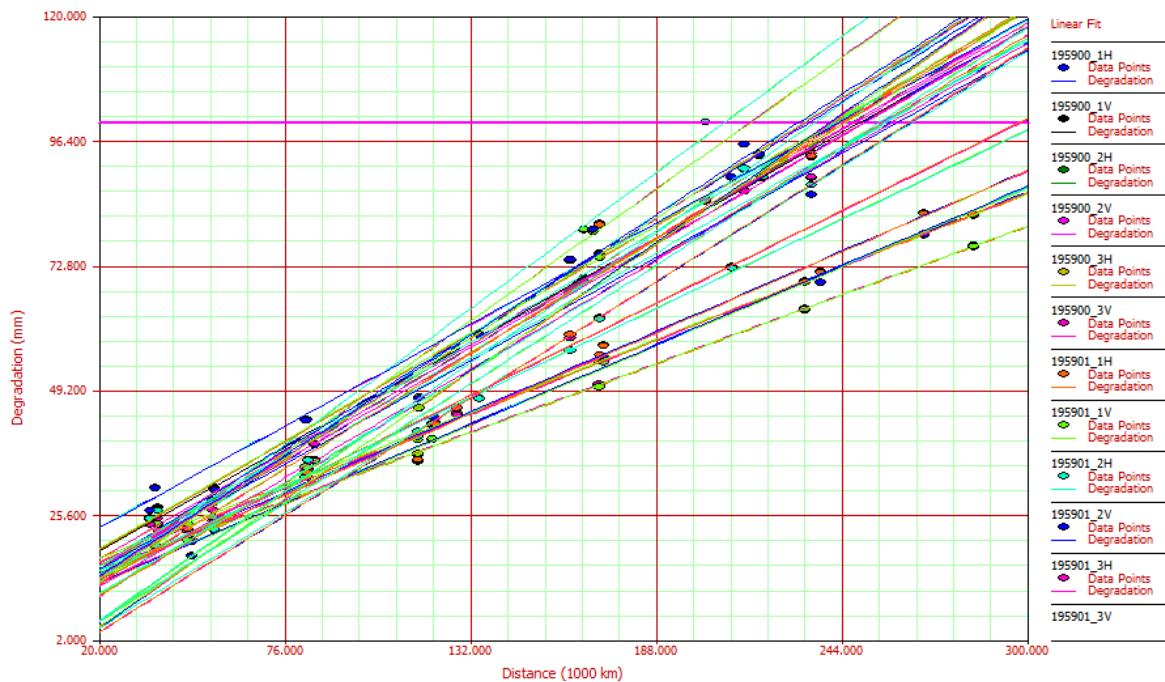


Fig. 4.30 Degradation with Linear function

Let the longitudinal axle represent the performance (here, the diameter of the wheels), and the horizontal axle represent time (here, the running distance of the wheels). Fig.4.30 shows the results of the analysis using a linear function, for a critical degradation level (threshold level  $l_0$ ) of 100mm.

Following the above discussion, a wheel's failure condition is assumed to be reached if the diameter reaches  $l_0$ . We adopt the linear degradation path for all wheels and set  $l_0 = y$ . The lifetimes for these wheels are now easily determined and are shown in Fig. 4.31.

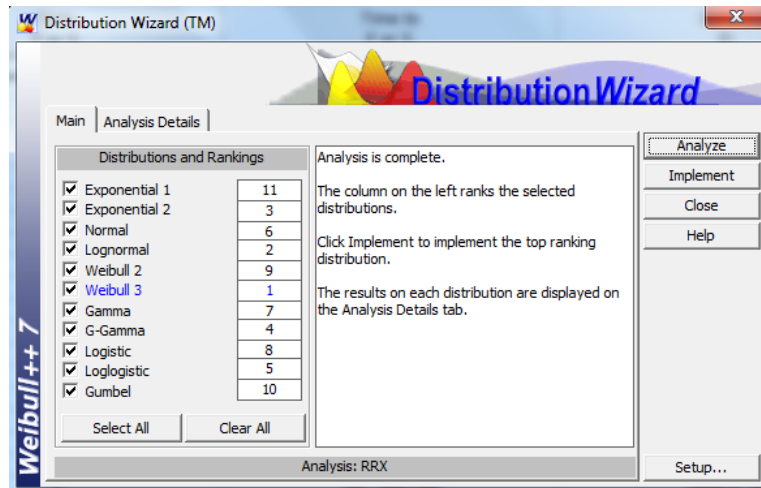


Fig. 4.31 Lifetime distribution

The results (see Fig. 4.31) show that the better choices are 3-parameter Weibull and Log-normal distribution. The selection should be based on physics of failure (wear or fatigue). In our study, based on the type of physics of failures associated with wear and fatigue, we select the 3-parameter Weibull lifetime model. The corresponding parameters' estimation appears in Fig. 4.23.

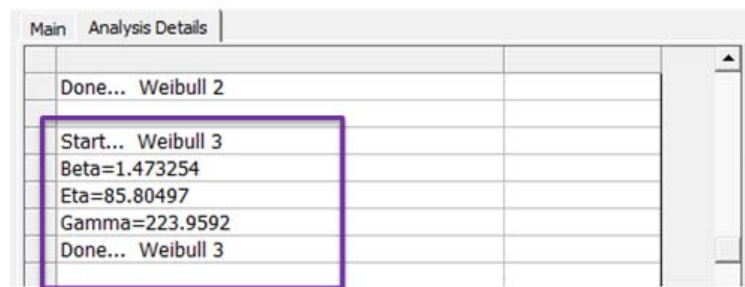


Fig. 4.32 parameters for 3-parameter Weibull

The probability density function (pdf) 3-parameter Weibull distribution is shown in equation (4.1):

$$f(t) = \frac{\beta}{\eta} \left( \frac{t-\gamma}{\eta} \right)^{\beta-1} \exp\left(-\left(\frac{t-\gamma}{\eta}\right)^{\beta}\right) \quad (4.1)$$

where  $t$  is the failure time,  $\beta > 0$  is the shape parameter,  $\eta > 0$  is the scale parameter, and  $-\infty < \gamma < +\infty$  is the location parameter or failure-free life. The probability density function of the wheel-sets' reliability in this holistic study is:

$$f(t) = \frac{1.47}{85.8} \left( \frac{t-223.96}{85.8} \right)^{1.47-1} \exp\left(-\left(\frac{t-223.96}{85.8}\right)^{1.47}\right) \quad (4.2)$$

Other reliability related characteristics could be obtained following equation (4.2).

#### 4.3.4 Comparison Studies on Running Surface Wear

Following each wheel-set's selected lifetime cycle, in this section, we compare various methods of determining running surface wear, including: total wear rate statistics (Fig.4.32), re-profiling statistics

(Fig.4.33), natural wear statistics (Fig.4.34), and the ratio statistics between natural and re-profiling wear rate (Fig.4.34). More details appear in Appendix C.

As mentioned in Section 4.3.3, the re-profiling statistics for bogie 195902 are abnormal; therefore, Table 4,15 shows statistics with bogie 195902 included and excluded. For instance, if we consider the data from bogie 195902, the total wear rate is 0.3542 mm per thousand kilometres; we do not consider it, the wear rate is 0.3262 mm per thousand kilometres. In this research, we recommend excluding the data from bogie 195902.

Table.4.15 Comparison Studies on Running Surfaces Wearing

mm/1000 kilometres	Average Value		Max Value		Min Value	
	Statistics 1	Statistics 2*	Statistics 1	Statistics 2	Statistics 1	Statistics 2
Total wear rate	0.3542	0.3262	0.785	0.4	0.236	0.236
Re-profiling statistics	0.2425	0.2133	0.70	0.3	0.12	0.12
Natural wear statistics	0.1117	0.1129	0.192	0.192	0.052	0.052
Ratio (natural / re-profiling)	2.45	2.1	10.905	4.236	0.905	0.905

(\*: Statistics 2 represents the results without considering bogie 195902)

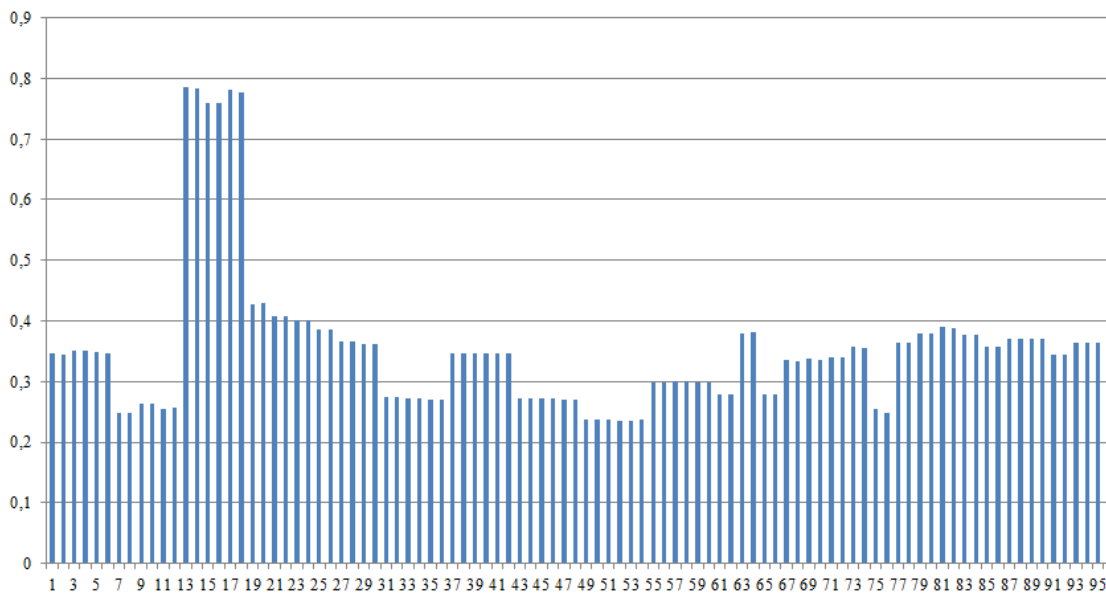


Fig.4.32 Total wear rate statistics

In Figs.4.32, 4.33, 4.34, and 4.35, the horizontal axle represents the different wheels installed in different bogies; the sequence follows Appendix C. The longitudinal axle represents the values.

For example, in Fig.4.32, the first six statistics belong to the six wheels installed in bogie 195900. Their installed position (axel, side) is marked in Appendix C. The longitudinal axle shows the total wear rate. It is obvious that the largest values come from the 13<sup>th</sup> to 18<sup>th</sup> points, which belong to the wheel-sets installed in bogie 195902 with the largest value 0.785 mm/1000 kilometres. Meanwhile, if they are not considered, the largest value is only 0.4 mm/1000 kilometres.



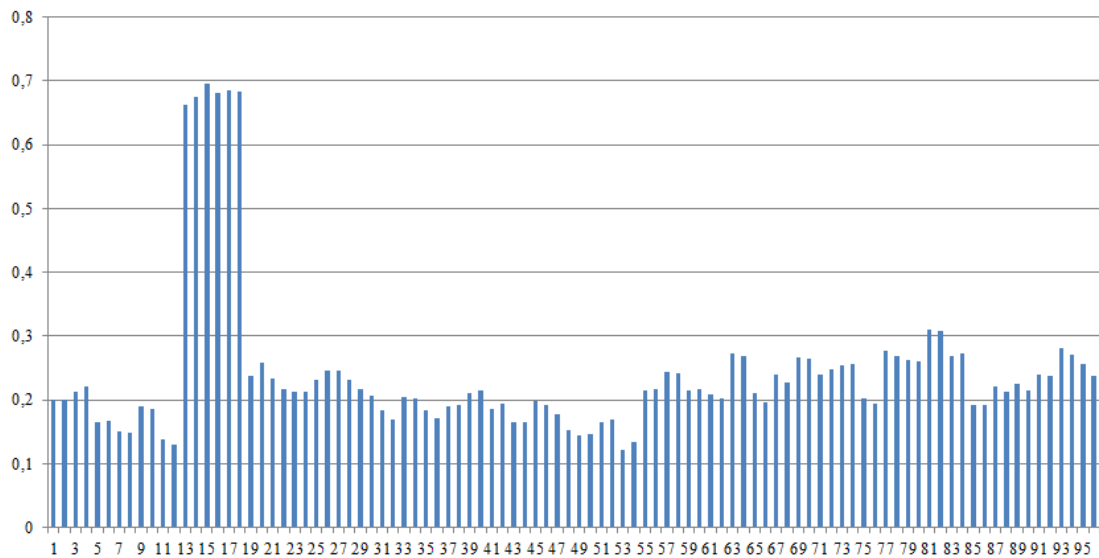


Fig.4.33 Re-profiling statistics

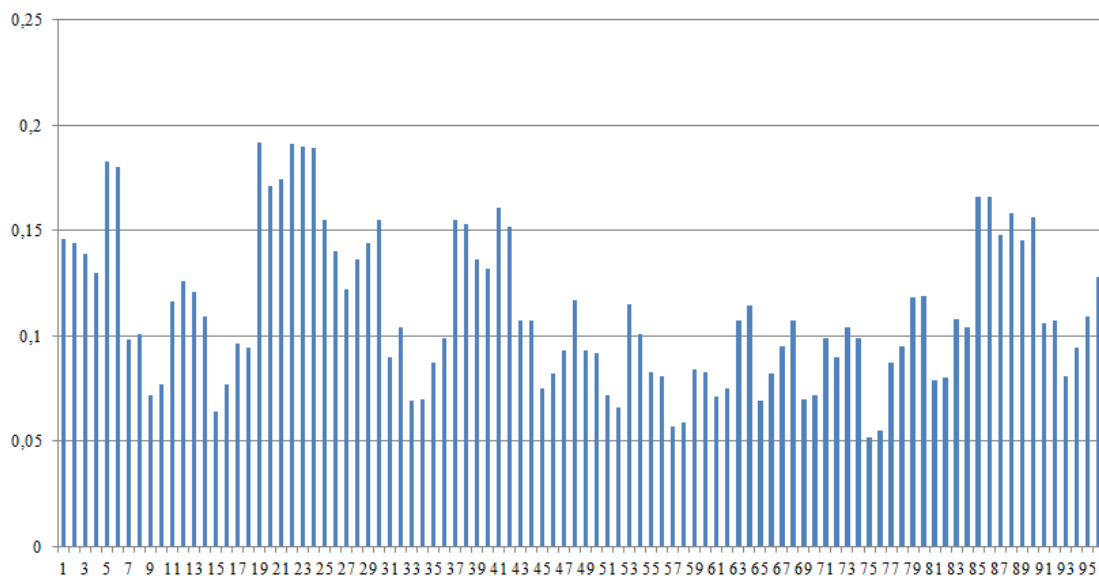


Fig.4.34 Natural wear statistics

Similarly, in Fig.4.34, the largest values come from the 13<sup>th</sup> to 18<sup>th</sup> points, which also belong to the wheel-sets installed in bogie 195902, with the largest value 0.7 mm/1000 kilometres. Meanwhile, if they are not considered, the largest value is only 0.3 mm/1000 kilometres.

When we consider the two results, i.e., including or not including the data from bogie 195902, we find the latter more accurate.

However, in Fig.4.35, showing natural wear rates, the difference between considering bogie 195902 and not considering it is less pronounced. The maximum value does not change. We conclude that the re-profiling frequency influences the re-profiling wear rate and the total wear rate of the wheel-sets, but its influence on natural wear rate is more limited.

The ratio between natural and re-profiling wear rate is also clearly influenced. In Fig.4.35, the maximum value comes from the bogie 195902 and is 10.905; if it is not considered, the maximum value is 4.236. At the same time, the average value decreases from 2.4 to 2.1.

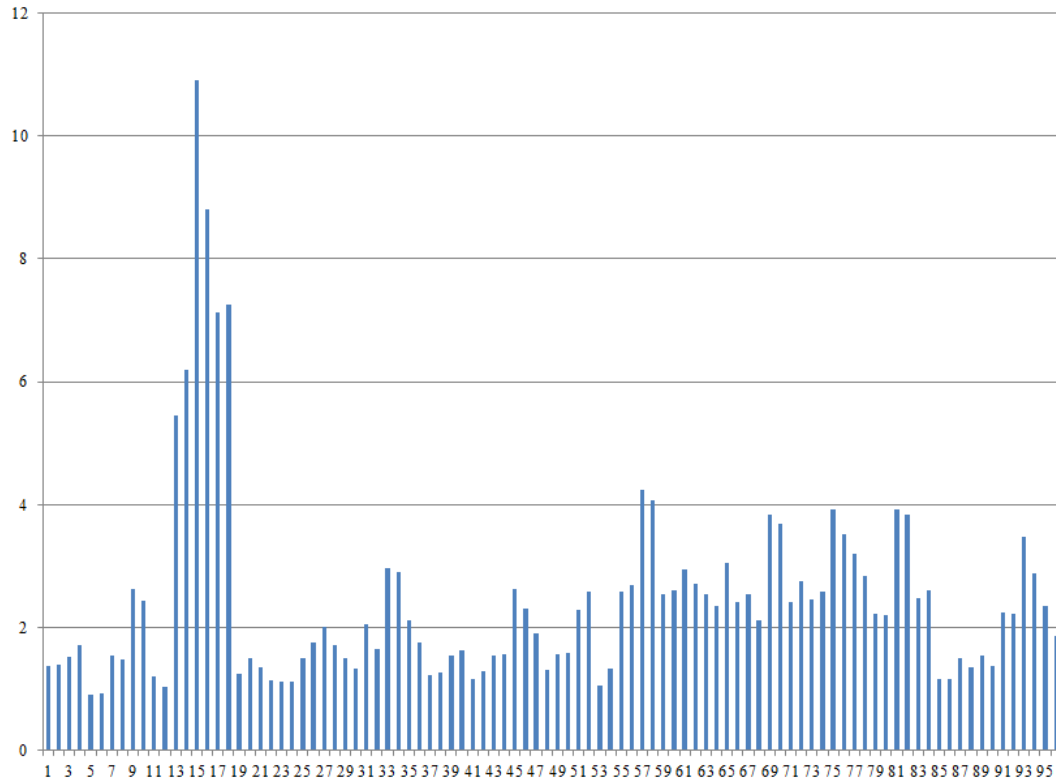


Fig.4.35 Ratio between natural and re-profiling wear rate

If we consider the average statistics from the same point of view, we reach similar conclusions: the re-profiling frequency will obviously influence the average re-profiling wear rate and the average total wear rate of the wheel-sets, as well the ratio between natural and re-profiling wear rate; however, its influence on average natural wear rate is more limited.

Table.4.16 Comparison of total wear rate considering the installed axle

	<b>Axle</b>	<b>I</b>	<b>II</b>	<b>III</b>
Total wear rate	Numbers	7	6	3
	Percentage	43.75%	37.50%	18.75%
Natural wear rate	Numbers	7	1	8
	Percentage	43.75%	6.25%	50%
Re-profiling wear rate	Numbers	2	12	2
	Percentage	12.50%	75%	12.50%
Ratio	Numbers	2	13	1
	Percentage	12.50%	81.25%	6,25%

As for the total wear rate, we recognize the wheel-sets with maximum values with installed axles (I, II, III). For example, for the total wear rate, the maximum values appear in axle I 7 times, 43.75% of the total statistics. For the ratio between natural and re-profiling wear rate, the maximum values appear in axle II 13 times, and 81.25% of the total statistics.

From Table 4.16, we see more natural wear for axel 1 and 3. It is an interesting finding because it is consistent with other conclusions reached at LKAB/MTAB's workshop.

#### **4.4 Results and Discussions of Holistic Study**

In this holistic study, data analysis is carried out from both the locomotives and the bogies' perspective. The results show that Malmbanan should consider wheel-set data from both points of view.

We study the data on wheel-sets' running surface wear for a group of 16 bogies. We derive holistic results from both degradation analysis and wear rate analysis, including the following: first, for the group examined, a linear degradation path is more suitable; following linear degradation, the best life distribution is a 3-parameter Weibull distribution, and the next best is lognormal; second, comparing the wear data of the wheel-sets' running surfaces (including total wear rate, natural wear rate, re-profiling wear rate, the ratio of re-profiling and natural wear) is an effective way to optimise maintenance strategies; finally, more natural wear occurs for the wheels installed in axel 1 and axel 3, a finding that supports related studies at Malmbanan.

In addition, there are some problems with data quality in the work orders.



## 5 Conclusions

As a continuous study of “JVTC project 2012-2013: Using Integrated Reliability Analysis to Optimise Maintenance Strategies”, this research explores the impact of a locomotive wheel-set’s installed position (incl. positions of the installed locomotive, bogie, axel.) on its service lifetime and attempts to predict its reliability related characteristics. In this research, both an integrated procedure for Bayesian reliability inference using Markov Chain Monte Carlo (MCMC) and other traditional statistics theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are applied to a number of case studies using heavy haul locomotive wheel-sets’ running surface wear data from Iron Ore Line (Malmbanan), Sweden. From the discussion of the research questions and results, we reach the following conclusions.

First, the proposed integrated procedure for Bayesian reliability inference using MCMC methods has built a full framework for related academic research and engineering applications to implement modern computational-based Bayesian approaches, especially for reliability inference.

Second, other traditional statistical theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are useful tools for exploring the impact of the locomotive wheel-sets’ installed position (incl. positions of the installed locomotive, bogie, axel.) on their service lifetime and for attempting to predict the reliability related characteristics.

For the above two points, more detailed conclusions and discussions can be found in Section 3 (3.2.3 & 3.3.6).

Third, the holistic study using data from 26 locomotives and 57 bogies at Malmbanan shows that Malmbanan should consider the wheel-set data not only from the locomotives’ but also from the bogies’ point of view.

Fourth, for the studied group, a linear degradation path is more suitable; following the linear degradation, the best life distribution is a 3-parameter Weibull distribution, and the second best is lognormal; comparing the wear data of the wheel-sets’ running surfaces (including total wear rate, natural wear rate, re-profiling wear rate, the ratio of re-profiling and natural wear) is an effective way to optimise maintenance strategy decision making.

Fifth, the results of the case studies show natural wear occurs for the wheels installed in axel 1 and axel 3; this supports findings in related studies at Malmbanan.

Details on the above conclusions can be found in Section 4.

In addition, the case studies’ results reveal that, the wheels’ lifetimes differ according to where they are installed on the locomotive. The differences could be influenced by such factors as the operating environment (e.g., climate, topography, track geometry), configuration of the suspension, status of the bogies and spring systems, operating speeds and applied loads, as well as human influences (drivers’ operations, maintenance policies, lathe operators etc.).

Last but not least, the approach studied in this report can be applied to cargo train wheel-sets or to other technical problems (e.g. other industries, other components).

## 6 Recommendations

Based on the research conducted for this report, for the LKAB / MTAB research workshop, we have the following recommendations:

- Results from this study should be considered for improving daily maintenance strategies.
- Considering the abnormal data found in this project, data quality in both work orders and re-profiling systems needs to be improved.
- In this project, we can only consider one lifecycle's data for each wheel-set due to time limitation. To achieve more convincing results and effectively monitor wheel-set performance, this study should be continuous.
- Results from this study could be used in other research in the internal workshop.

In addition, we suggest the following research:

- In this research, the case studies only focus on locomotive wheel-sets. We should consider more applications, for instance, cargo train wheel-sets, or other technical problems (e.g. other industries, other components).
- The results achieved by this study could be extended to other train wheel-set research topics, e.g., Wheel-set "health diagnostic", RAMS driven Maintenance Strategy Review & Optimization for Rolling Stock Wheels, Precise Maintenance Strategies Making, etc.
- The covariates considered in this report are limited to locomotive wheels' installed positions; more covariates must be considered. These include such factors as operating environment (e.g., climate, topography, track geometry, the braking forces and the curving forces), configuration of the suspension, status of the bogies and the spring systems, operating speeds and applied loads, etc.
- Results from Section 4, incl. Appendix B and Appendix C, should be studied further. For instance, the piecewise for each re-profiling period should be considered separately.
- In subsequent research, we plan to consider using our results to optimise maintenance strategies and the related LCC (Life Cycle Cost) problem considering maintenance costs, particularly with respect to different maintenance inspection levels and inspection periods (long term, medium term and short term).





## References

1. Aslanidou H, Dey D K, Sinha D. Bayesian analysis of multivariate survival data using Monte Carlo methods. *Canadian Journal of Statistics*. 1998, 26: 33-48
2. Bernasconi A, et al. An Integrated Approach to Rolling Contact Sub-surface Fatigue assessment of Railway Wheels. *Journal of Wear*. 2005. 258: 973-980
3. Braghin F, et al. A Mathematical Model to Predict Railway Wheel Profile Evolution Due to Wear. *Journal of Wear*. 2006. 261: 1253-1264
4. Breslow N E. Covariance analysis of censored survival data. *Biometrics*. 1974,30:80-99
5. Clayton D G, Cuzick J. Multivariate Generalizations of the Proportional Hazards Model (with Discussion). *Journal of the Royal Statistical Society A*. 1985, 148: 82-117
6. Clayton D G. A Model for Association in Bivariate Life Tables and its Application in Epidemiological Studies of Familial Tendency in Chronic Disease Incidence. *Biometrika*. 1978, 65: 141-151
7. Clayton P. Tribological Aspects of Wheel-Rail Contact: A Review of Recent Experimental Research. *Journal of Wear*. 1996. 191: 170-183
8. Congdon P. *Applied Bayesian Modeling*. England: John Wiley and Sons. 2003
9. Congdon P. *Bayesian Statistical Modeling*. England: John Wiley and Sons. 2001
10. Crowder M. A multivariate distribution with Weibull connections. *Journal of the Royal Statistical Society B*. 1989, 51: 93-107
11. Donato P, et al. Design and Signal Processing of A Magnetic Sensor Array for Train Wheel Detection. *Journal of Sensors and Actuators A*. 2006. 132: 516-525
12. Freitas M A, et al. Reliability assessment using degradation models: Bayesian and classical approaches. *Pesquisa Operacional*. 2010,30 (1):195-219
13. Freitas M A, et al. Using Degradation Data to Assess Reliability: A Case Study on Train Wheel Degradation. *Journal of Quality and Reliability Engineering International*. 2009, 25: 607-629
14. Hakon K G, Odd O A, Nilslid H. Frailty models based on levy processes. *Advances in Applied Probability*. 2003, 35: 532-550
15. Hougaard P. Frailty models for survival data. *Lifetime Data Analysis*. 1995, 1:255-273
16. Hougaard P. Survival models for heterogeneous populations derived from stable distributions. *Biometrika*. 1986, 73: 387-396
17. Ibrahim J G, Chen M H, Sinha D. *Bayesian Survival Analysis*. New York: Berlin Heidelberg, 2001

18. Johansson A, Andersson C. Out-of-round Railway Wheels- a Study of Wheel Polygonalization through Simulation of Three-dimensional Wheel-Rail Interaction and Wear. *Journal of Vehicle System Dynamics*. 2005, 43(8):539-559
19. Kalbfleisch J D, Prentice R L. Marginal likelihood's based on Cox's regression and life model. *Biometrika*. 1973, 60:267-278
20. Klein J P, Moeschberger M L. *Survival Analysis: Techniques for Censored and Truncated Data*. Springer-Verlag New York, Inc.1997
21. Lawless J F. *Statistical Models and Methods for Lifetime Data*. John Wiley and Sons.1982
22. Levin M A, Kalal T T. *Improving Product Reliability*. John Wiley, 2003
23. Lin J, Using Integrated Reliability Analysis to Optimise Maintenance Strategies – A Bayesian Integrated Reliability Analysis of Locomotive Wheels. Research Report. Published by: Luleå University of Technology. 2013.
24. Liu Y M, et al. Multiaxial Fatigue Reliability Analysis of Railroad Wheels. *Journal of Reliability Engineering and System Safety*. 2008. 93:456-467
25. McGilchrist C A, Aisbett C W. Regression with Frailty in Survival Analysis. *Biometrics*. 1991, 47:461-466
26. Meeker W Q, Escobar L A. *Statistical Methods for Reliability Data*. Wiley, 1998.
27. Palo M. Condition Monitoring of Railway Vehicles: A Study on Wheel Condition for Heavy Haul Rolling Stock. Licentiate Thesis. Luleå University of Technology, Sweden. 2012.
28. Palo M. Condition-Based Maintenance for Effective and Efficient Rolling Stock Capacity Assurance: A Study on Heavy Haul Transport in Sweden. Doctoral Thesis. Luleå University of Technology, Sweden. 2013.
29. Pennell M L, Dunson D B. Bayesian Semi parametric Dynamic Frailty Models for Multiple Event Time Data. *Biometrika*. 2006, 62:1044-1052
30. Pombo J, Ambrosio J, Pereira M. A Railway Wheel Wear Prediction Tool based on A Multibody Software. *Journal of Theoretical and Applied Mechanics*. 2010. 48, 3:751-770
31. Qiou Z, Ravishanker N, Dey D K. Multivariate survival analysis with positive frailties. *Biometrika*. 1999, 55: 637-644
32. Sahu S K, Dey D K, Aslanidou H, Sinaha D. A Weibull regression model with gamma frailties for multivariate survival data. *Lifetime Data Analysis*. 1997, 3:123-137
33. Skarlatos D, Karakasis K, Trochidis A. Railway Wheel Fault Diagnosis Using A Fuzzy-logic Method. *Journal of Applied Acoustics*. 2004. 65:951-966
34. Spiegelhalter D J, et al. Bayesian measures of model complexity and fit. *Journal of Royal Statist. Society Series B*.2002, 64(3):583-639
35. Stratman B, Liu Y, Mahadevan S. Structural Health Monitoring of Railroad Wheels Using Wheel Impact Load Detectors. *Journal of Failure Analysis and Prevention*. 2007. 7(3):218-225

36. Tassini N, et al. A Numerical Model of Twin Disc Test Arrangement for the Evaluation of Railway Wheel Wear Prediction Methods. *Journal of Wear*. 2010. 268: 660-667
37. Yang C, Letourneau S. Learning to Predict Train Wheel Failures. *Conference Proceedings. The 11th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD 2005)*. Chicago, Illinois, USA.



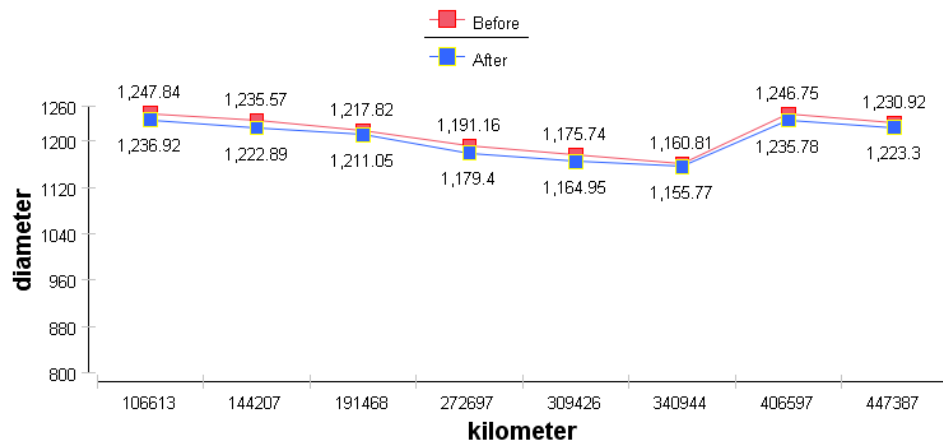
## Appendix A

- Lin J, Asplund M, Parida A. *Reliability Analysis for Degradation of Locomotive Wheels using Parametric Bayesian Approach*. Journal of Quality and Reliability Engineering International. 2013. DOI: 10.1002/qre.1518 (SCI)
- Lin J, Asplund M. *Bayesian Semi-parametric Analysis for Locomotive Wheel Degradation using Gamma Frailties*. Institution of Mechanical Engineers. Proceedings. Part F: Journal of Rail and Rapid Transit. 2013. <http://dx.doi.org/10.1177/0954409713508759> (SCI)
- Lin J, Asplund M. *A Comparison Study for Locomotive Wheels' Reliability Assessment using the Weibull Frailty Model*. Journal of Eksploatacja i Niezawodnosc - Maintenance and Reliability. 2014; 16(2): 276-287 (SCI)
- Lin J. *An Integrated Procedure for Bayesian Reliability Inference using Markov Chain Monte Carlo Methods*. Journal of Quality and Reliability Engineering. 2013. <http://dx.doi.org/10.1155/2013/264920>
- Lin J, Using *Integrated Reliability Analysis to Optimise Maintenance Strategies – A Bayesian Integrated Reliability Analysis of Locomotive Wheels*. Published by: Luleå University of Technology. ISSN: 1402-1528; ISBN: 978-91-7439-600-3 (tryckt); ISBN: 978-91-7439-600-3 (pdf). 2013, May
- Lin J, Pulido J, Asplund M. *Analysis for Locomotive Wheels' Degradation*. Conference Proceedings. The 60th Annual Reliability and Maintainability Symposium (RAMS® 2014). January 27-30, Springs, Colorado, USA. 2014.
- Lin J, Asplund M, Parida A. *Bayesian Parametric Analysis for Reliability Study of Locomotive Wheels*. Conference Proceedings. The 59th Annual Reliability and Maintainability Symposium (RAMS® 2013). January 28-31, Orlando, FL, USA.
- Lin J, Pulido J, Asplund M. *Reliability Analysis for Locomotive Wheels' Degradation: Classical and Bayesian Semi-parametric Approaches*. Submitted to Journal. 2014

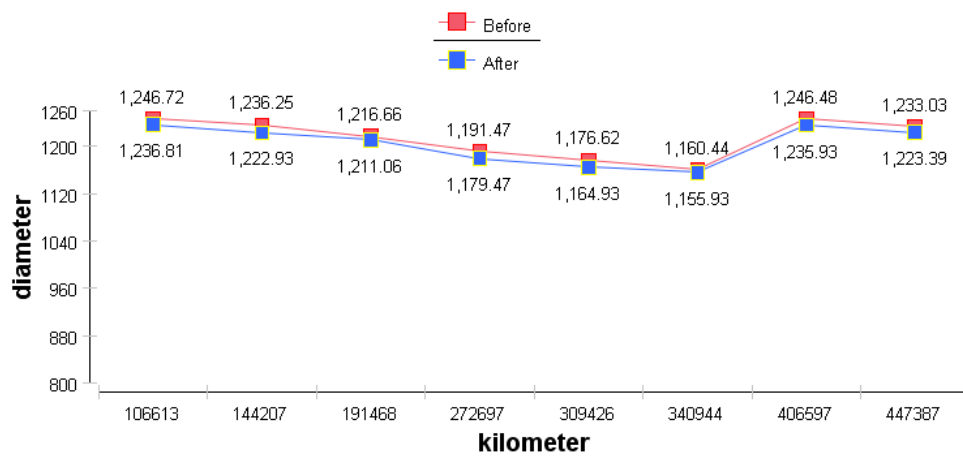


# Appendix B

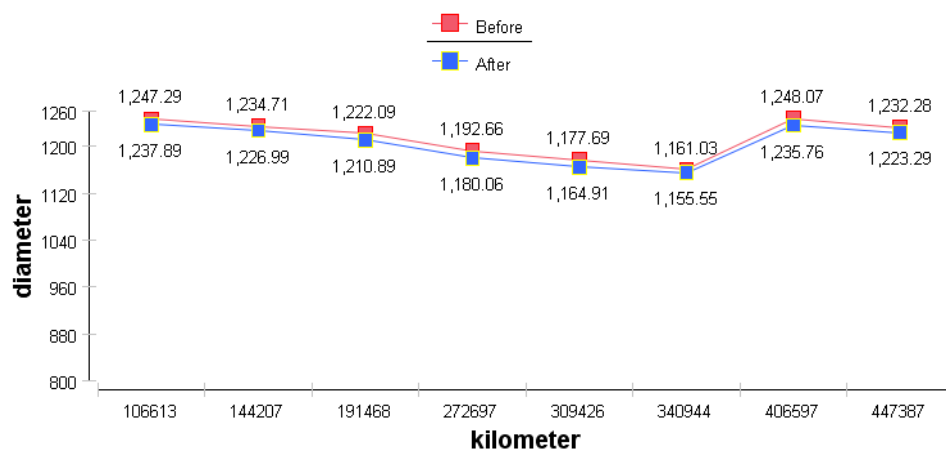
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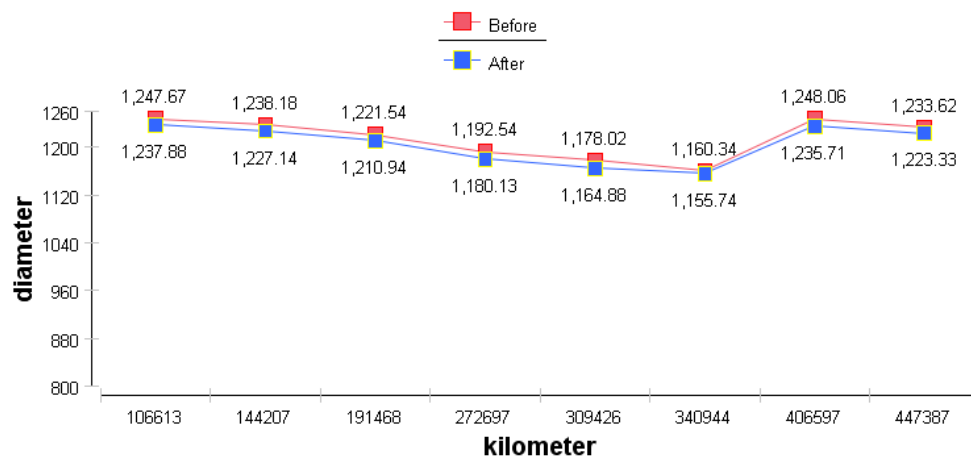
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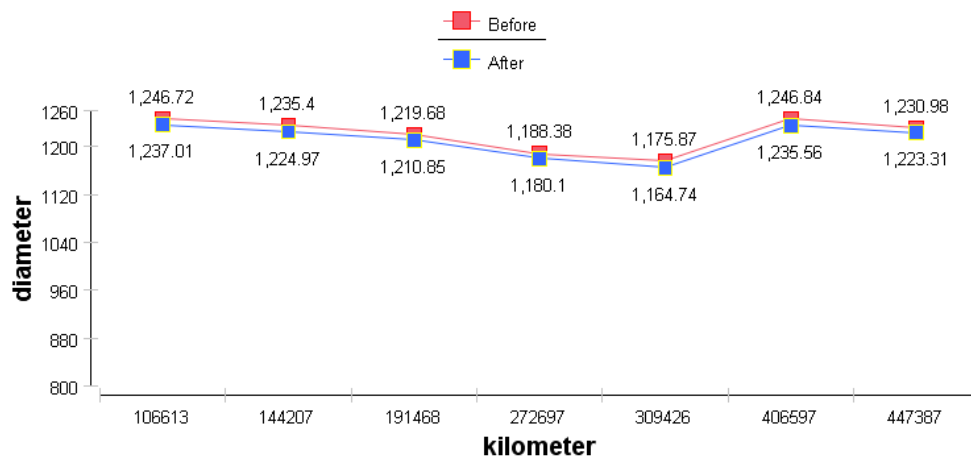
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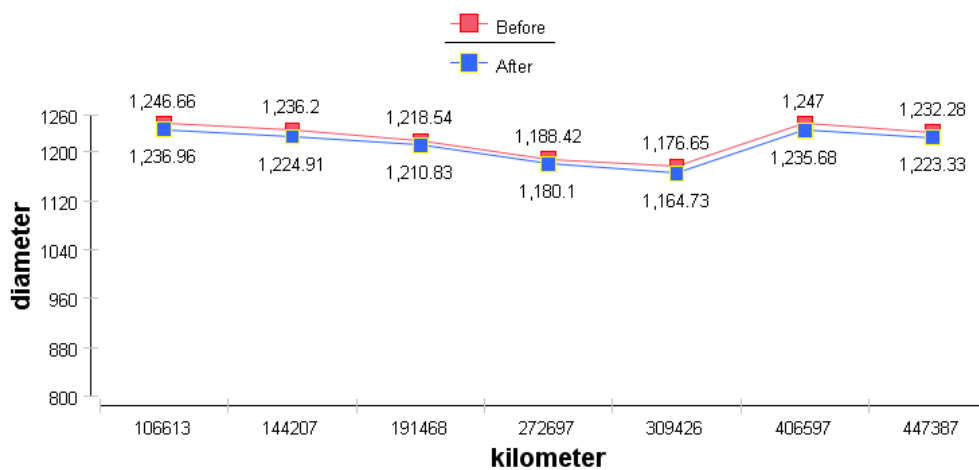
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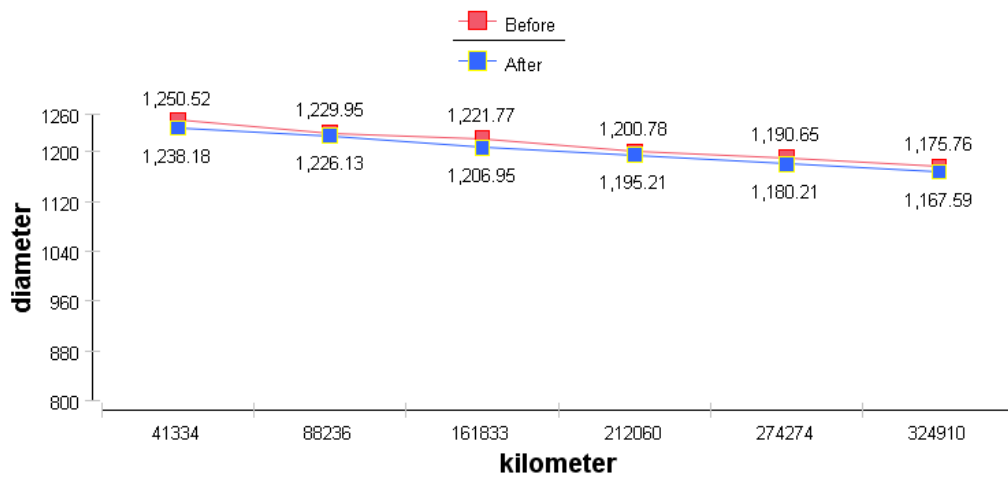


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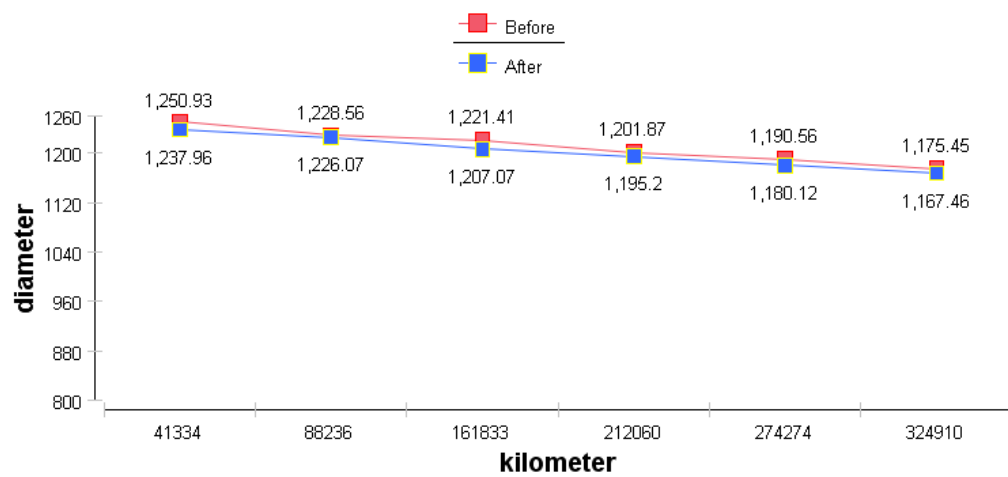




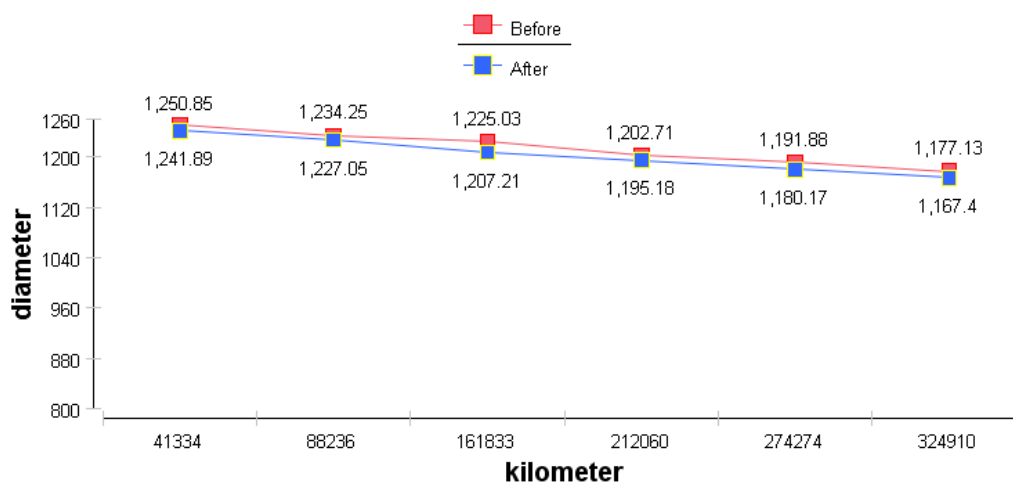
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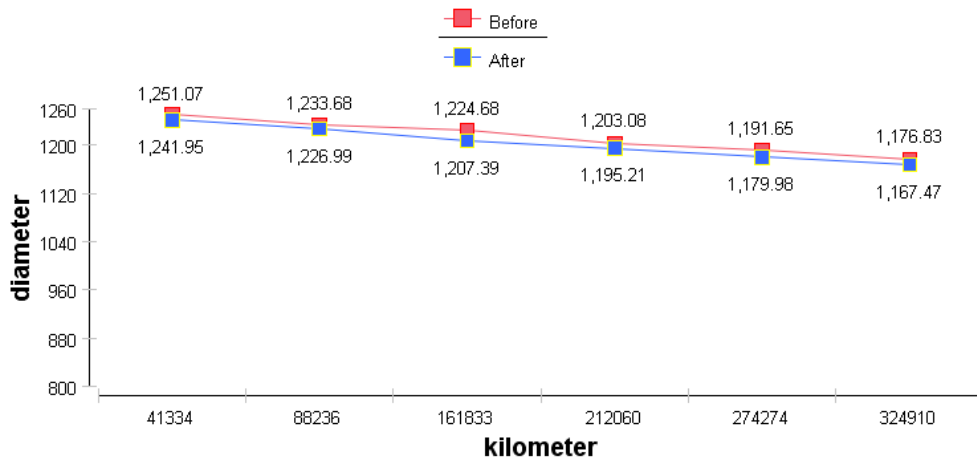
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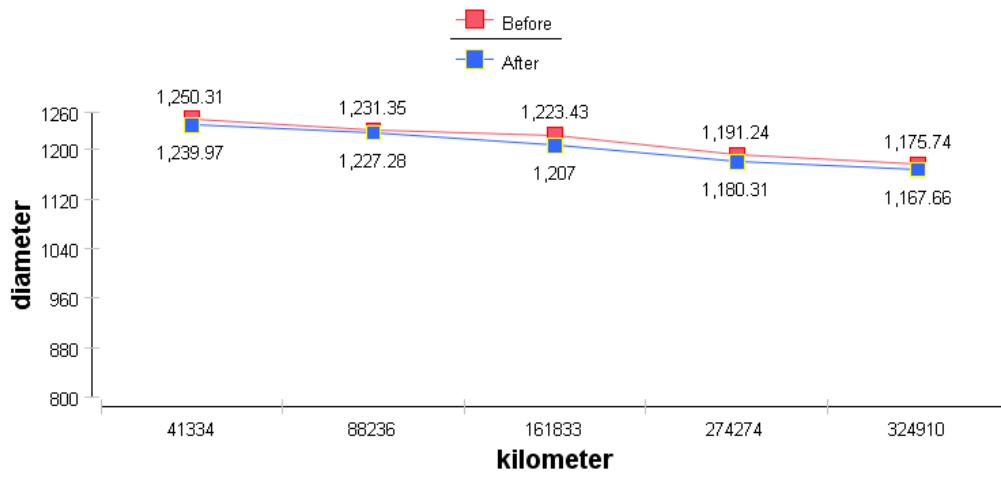
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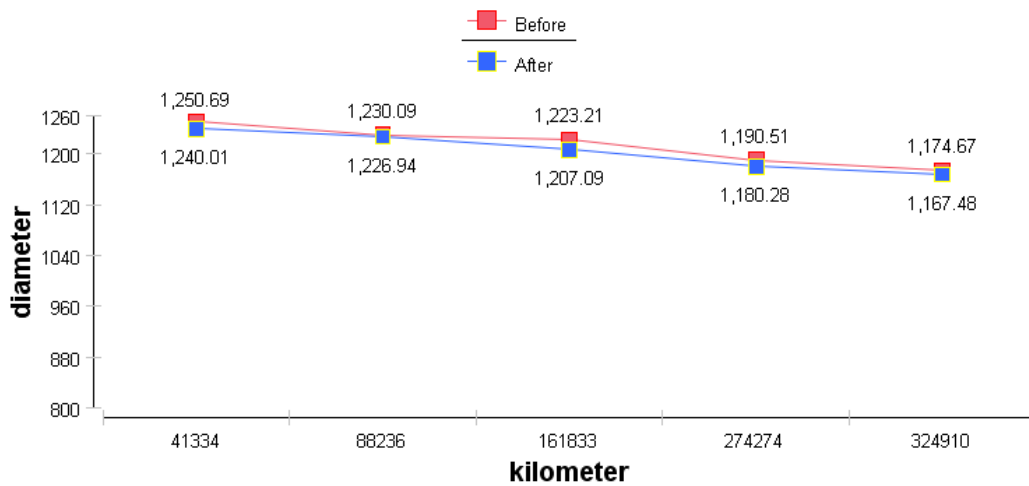
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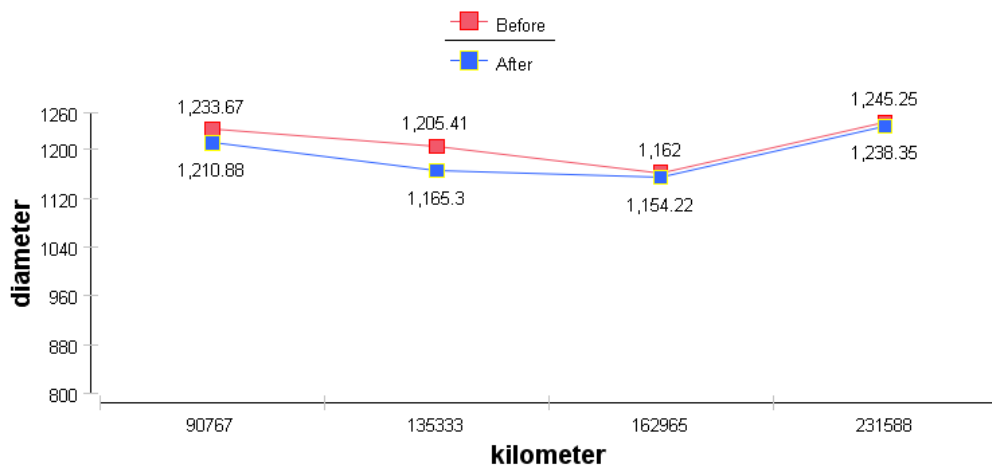
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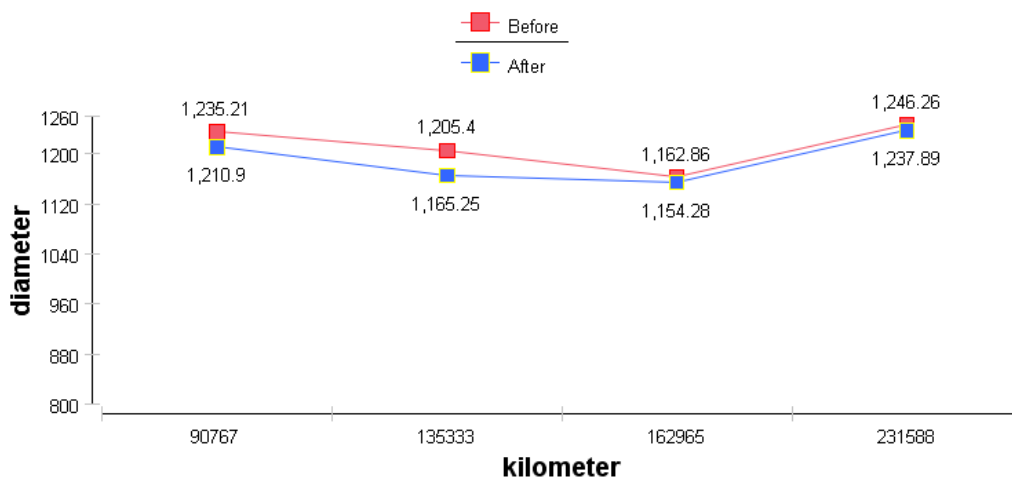
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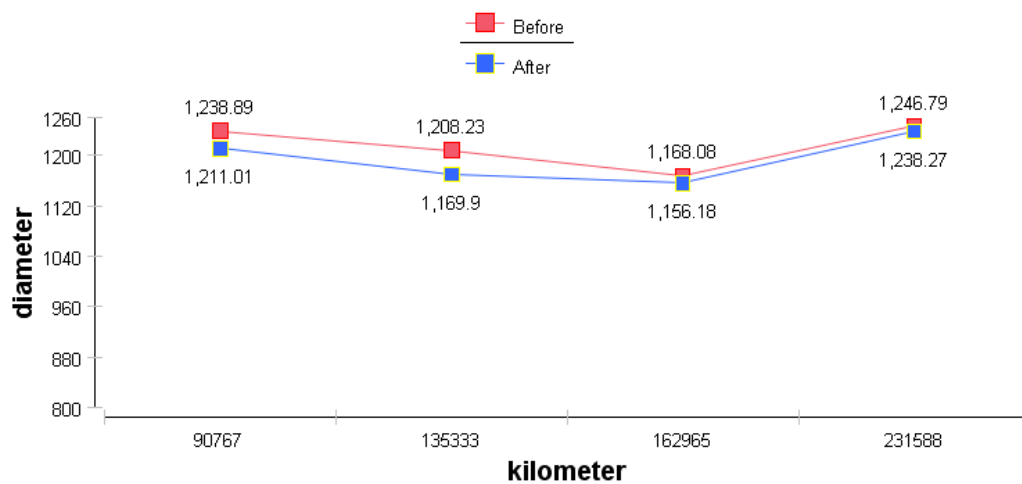
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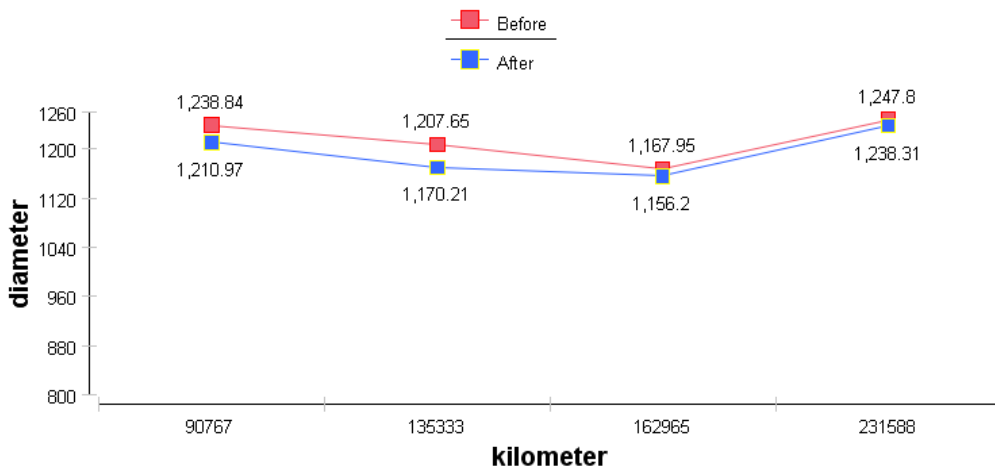
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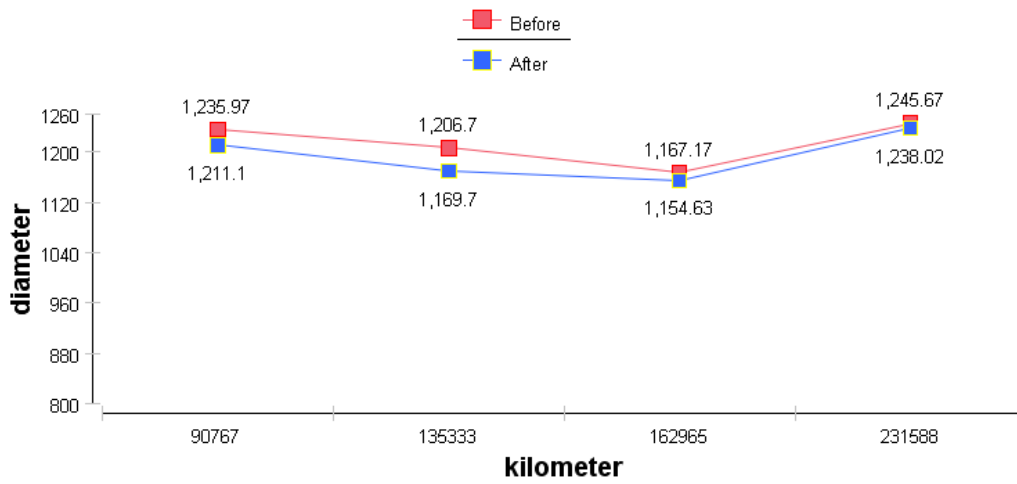
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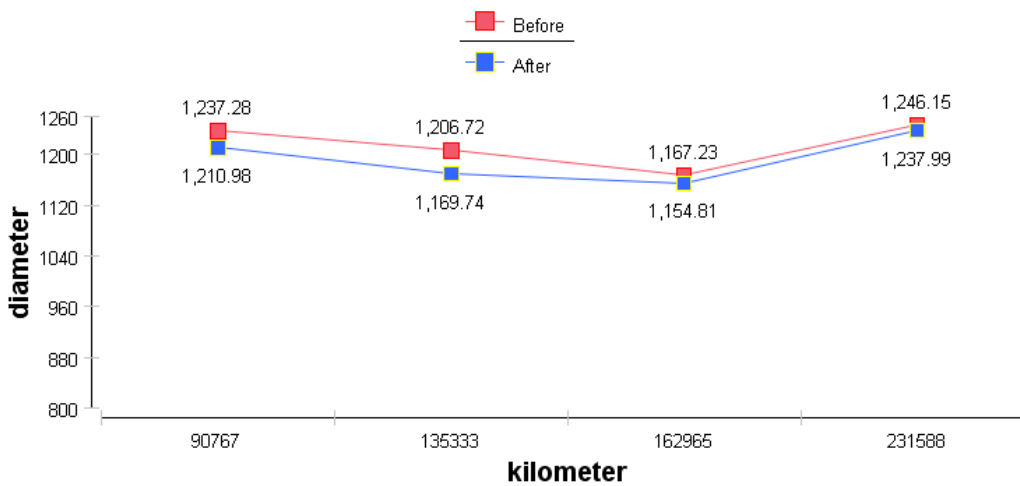
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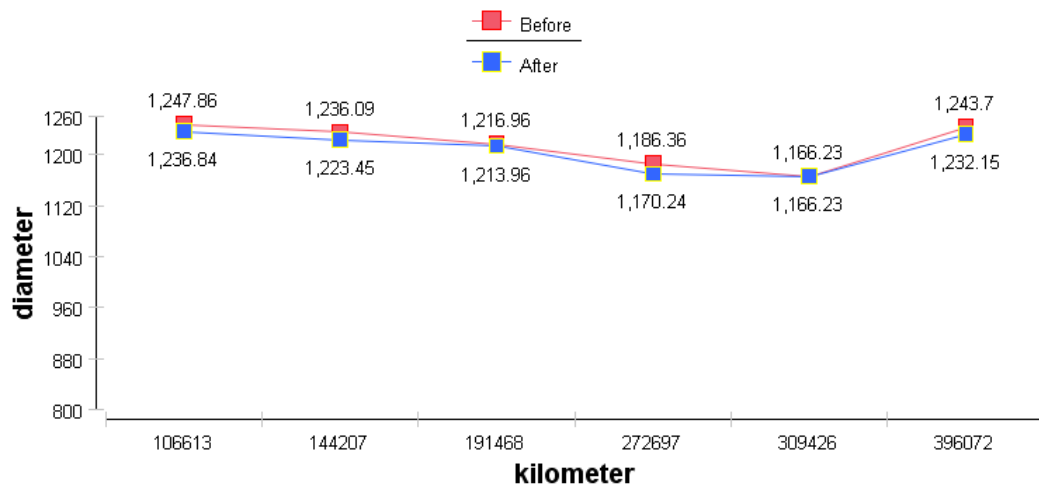
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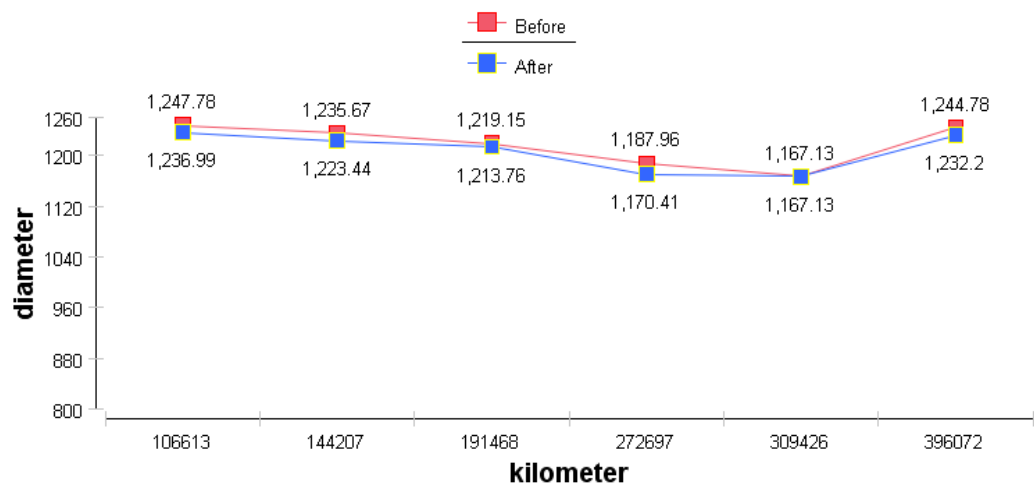
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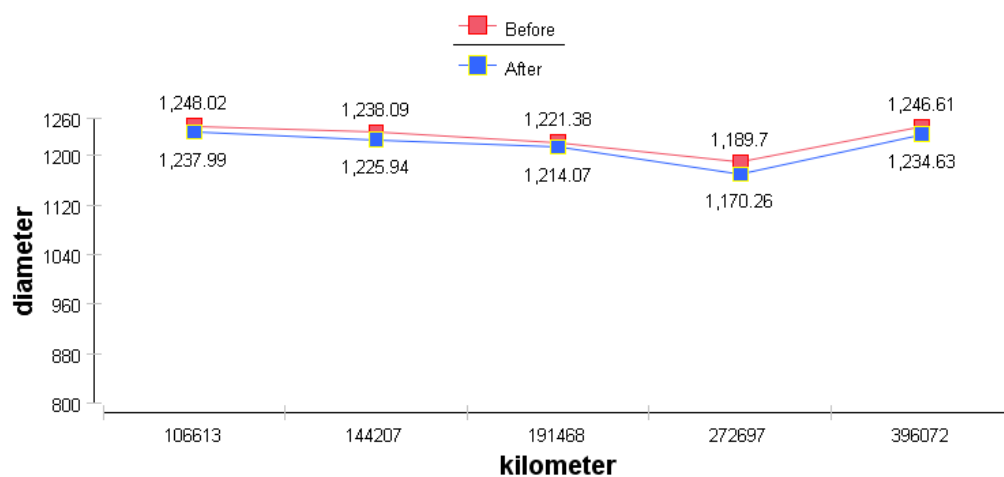
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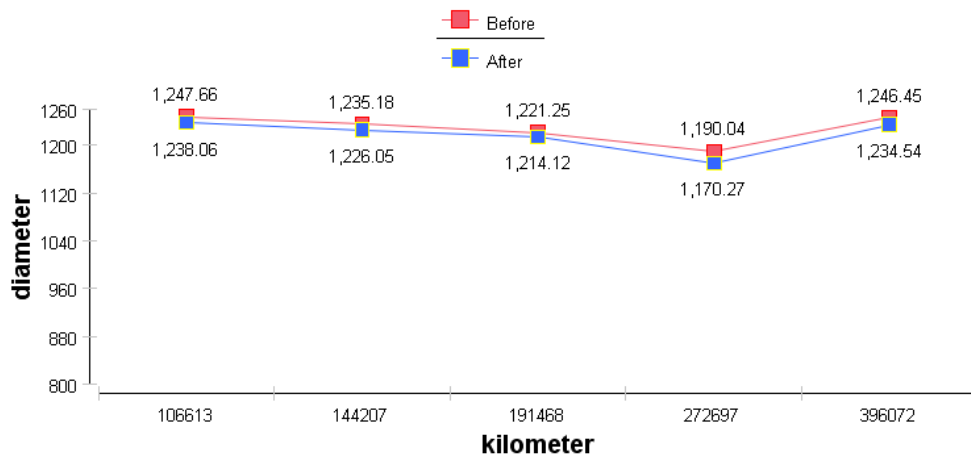
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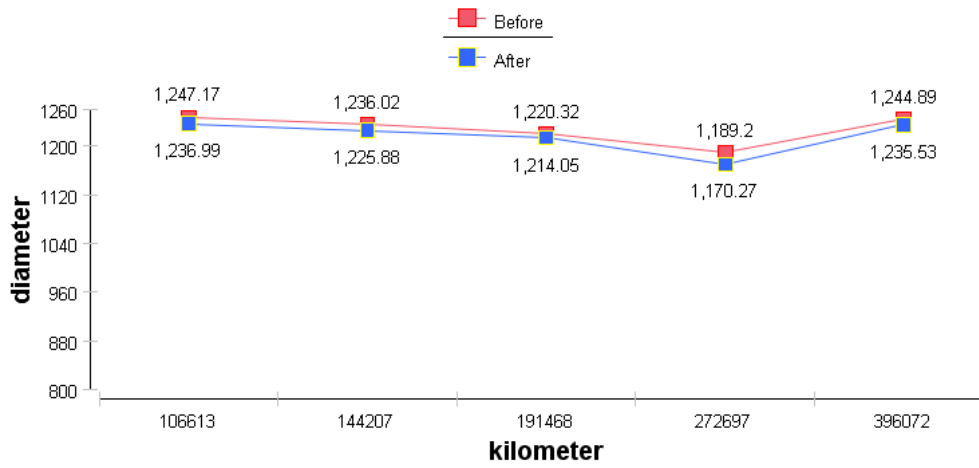
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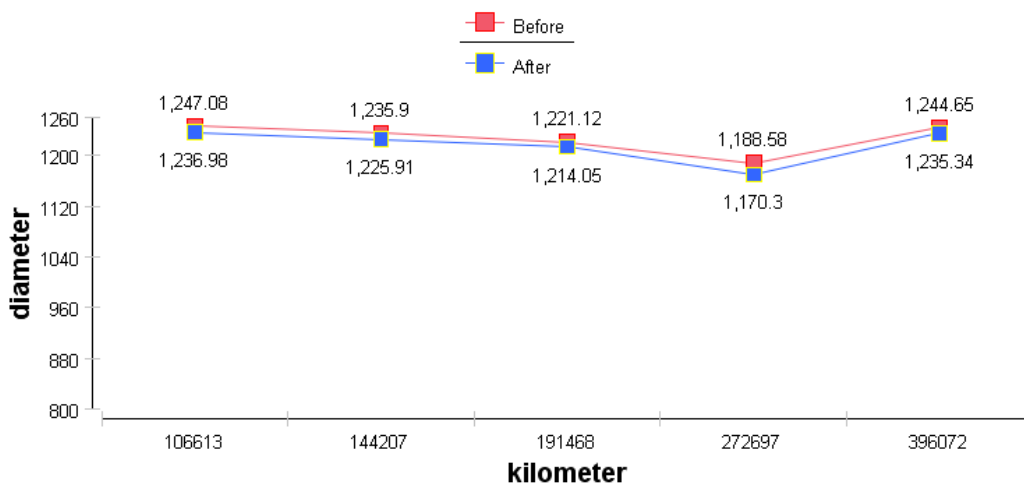
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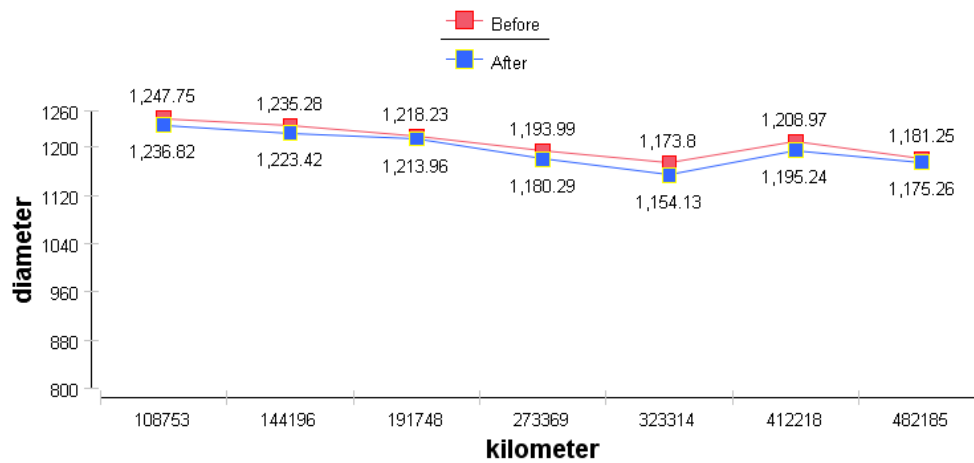
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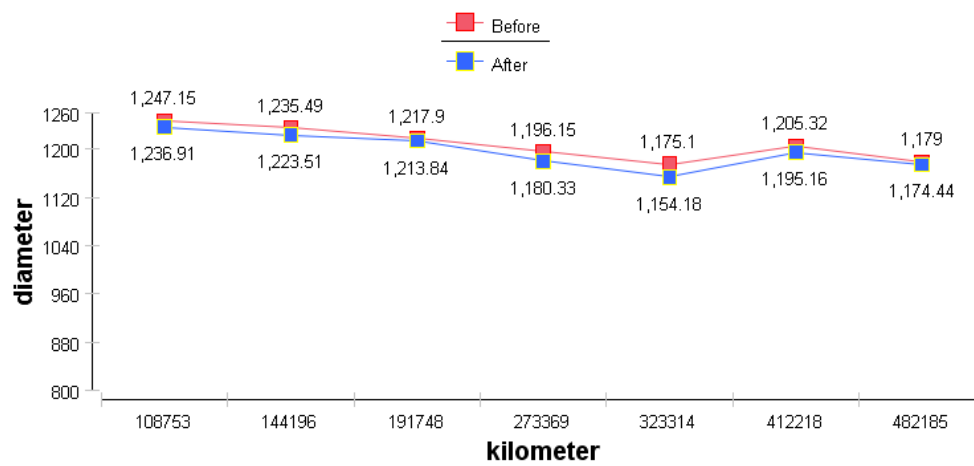
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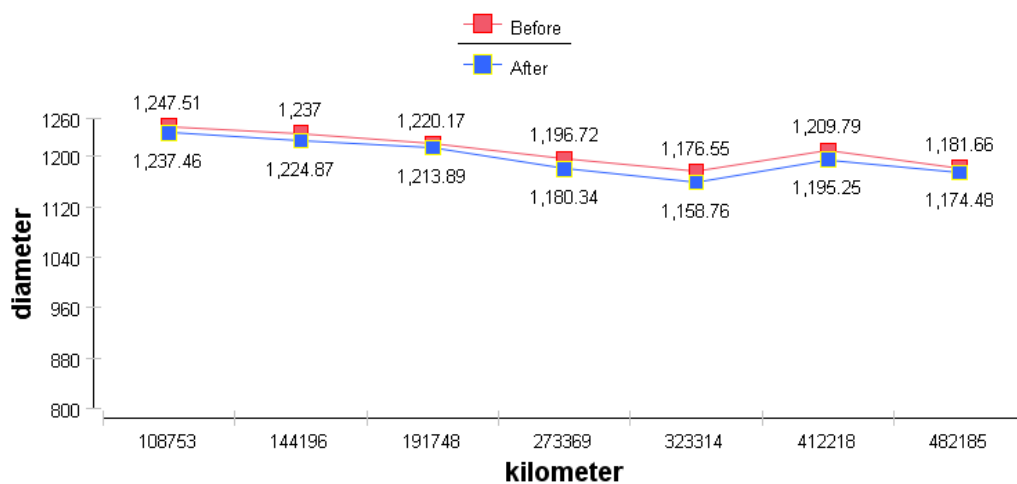
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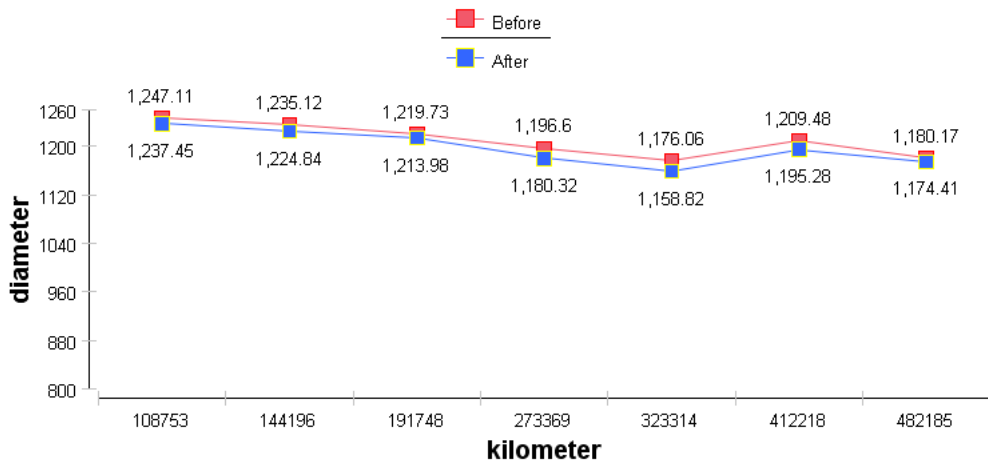
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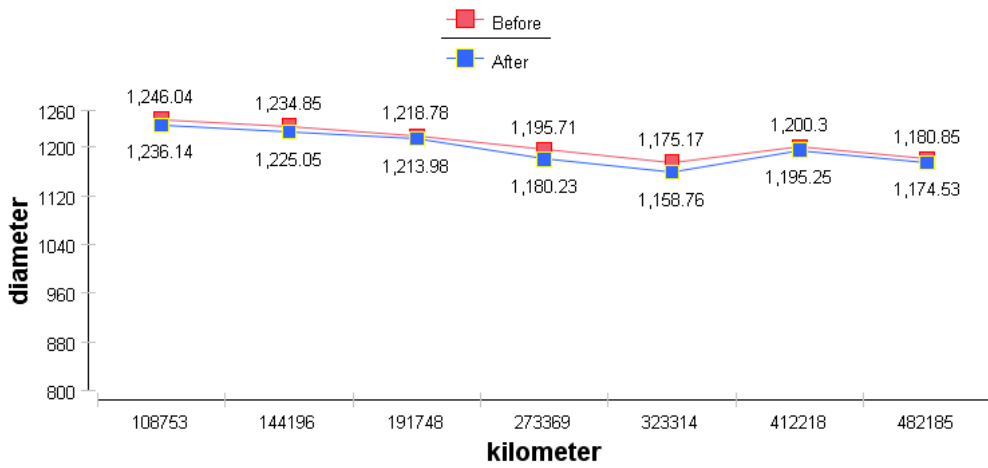
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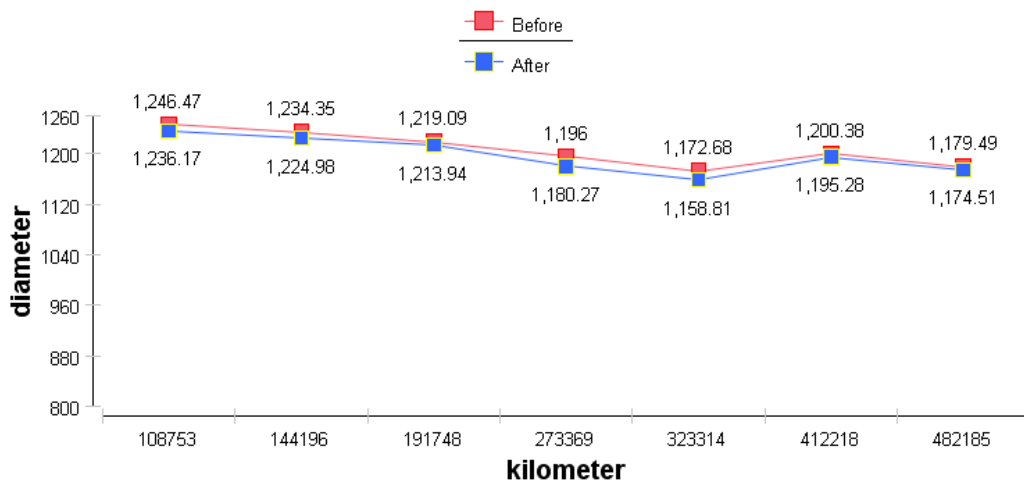
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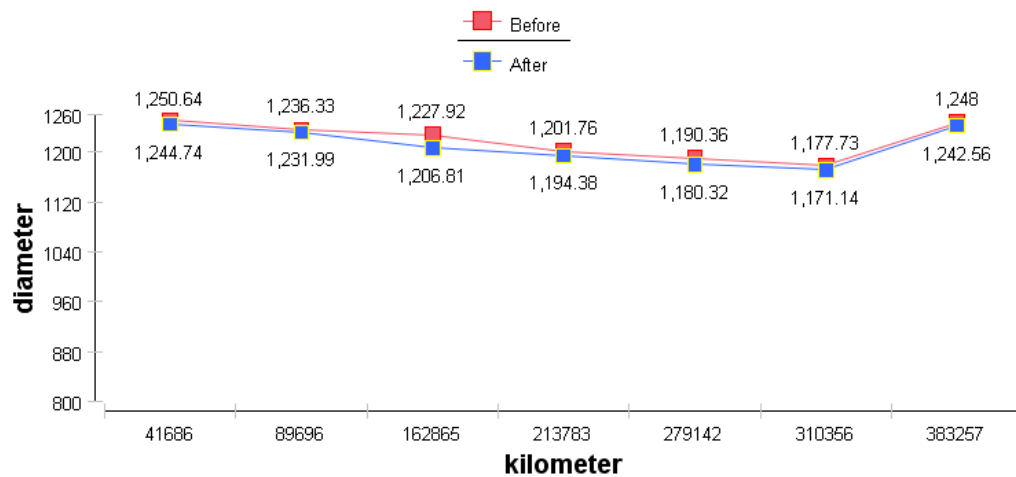


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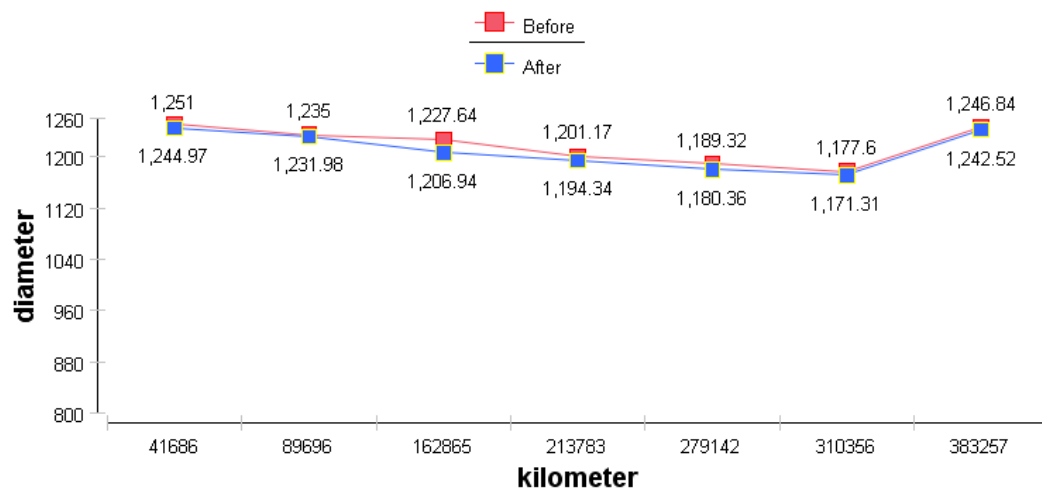




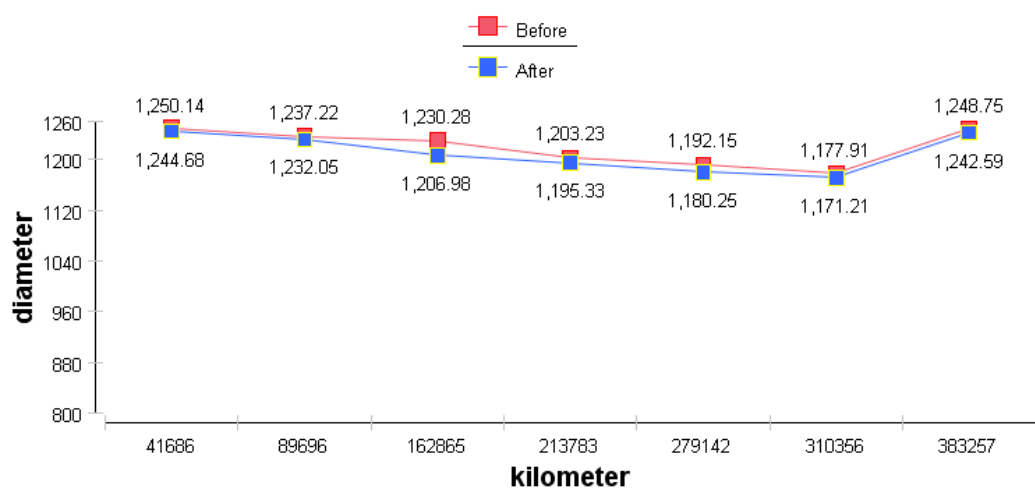
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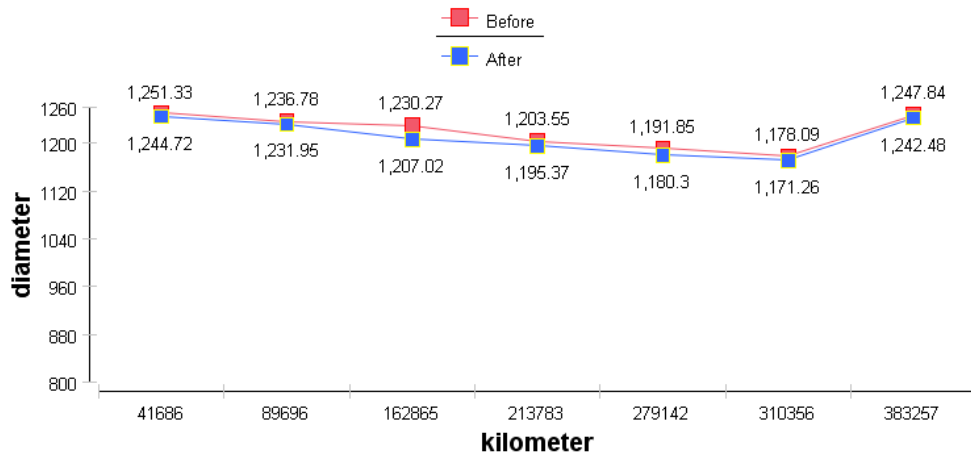
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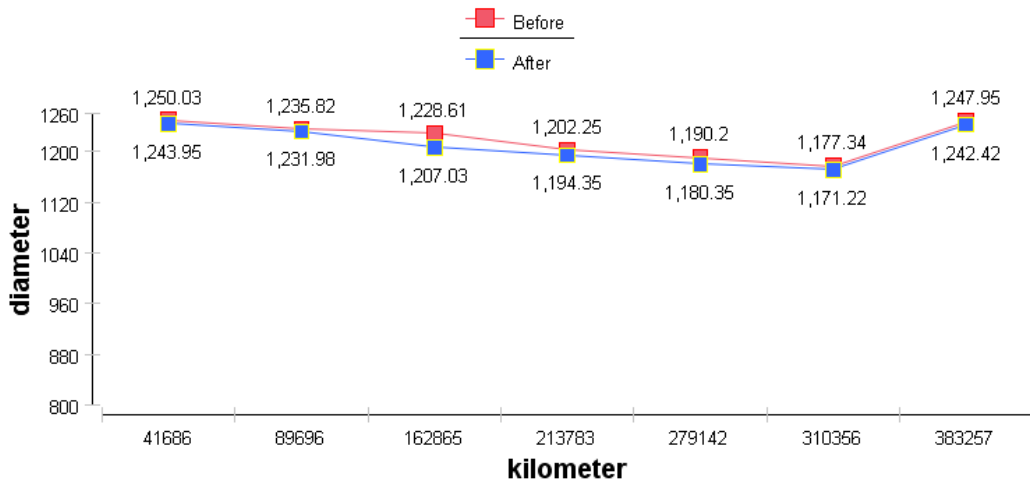
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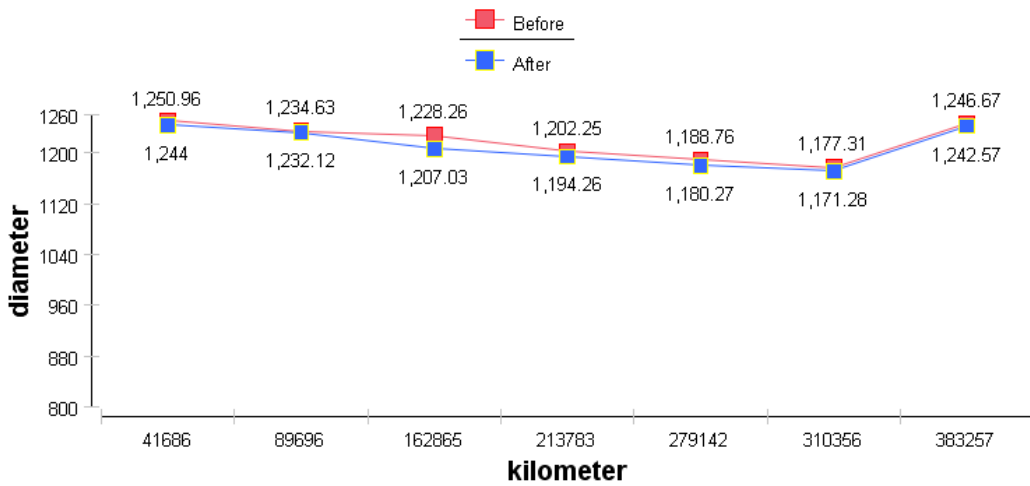
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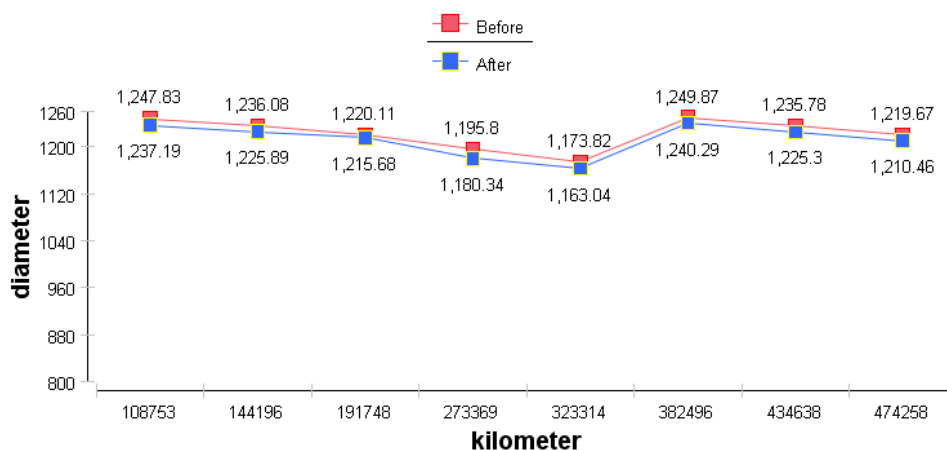
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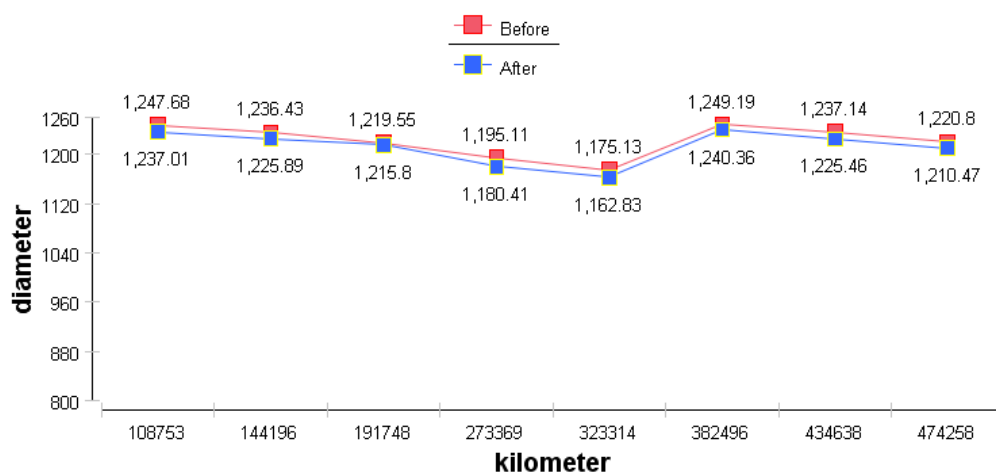
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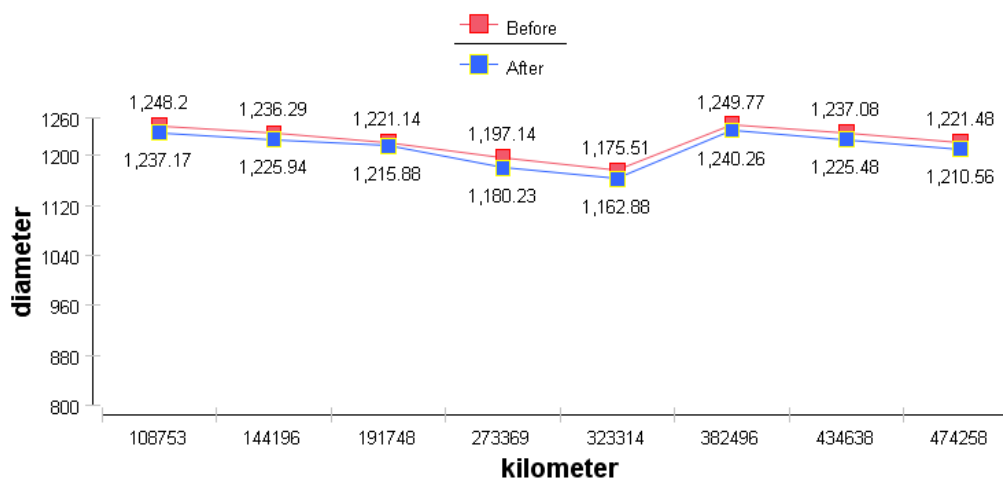
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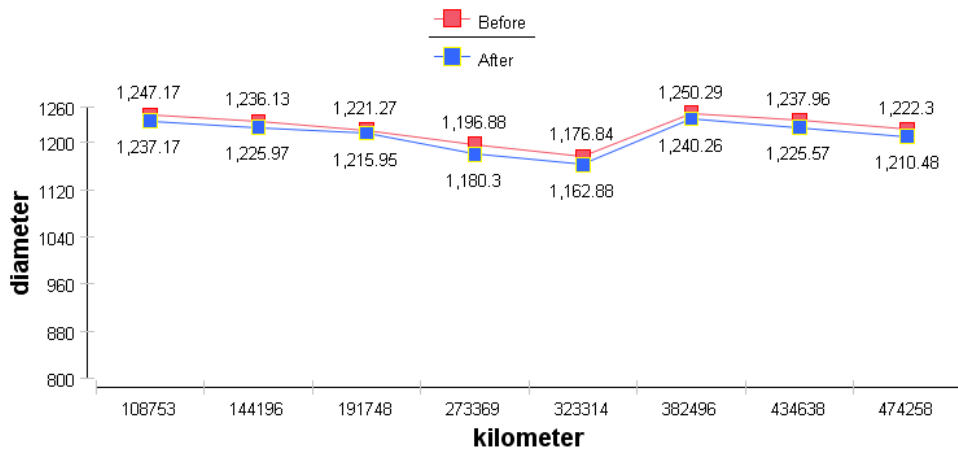
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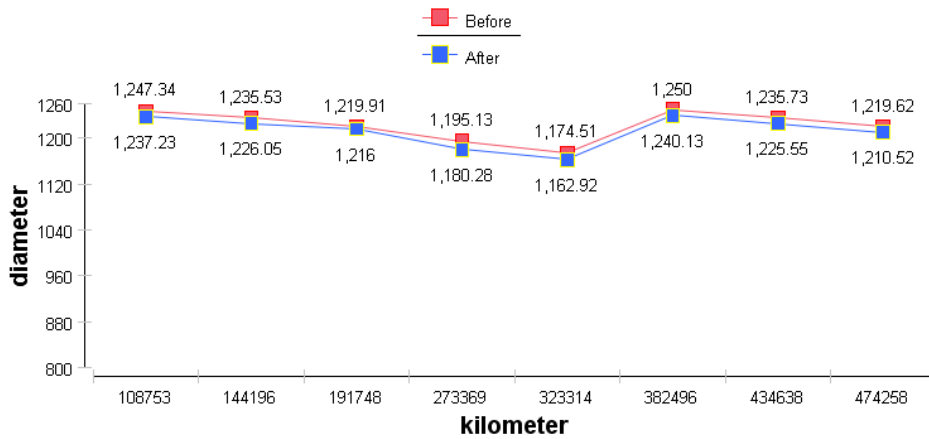
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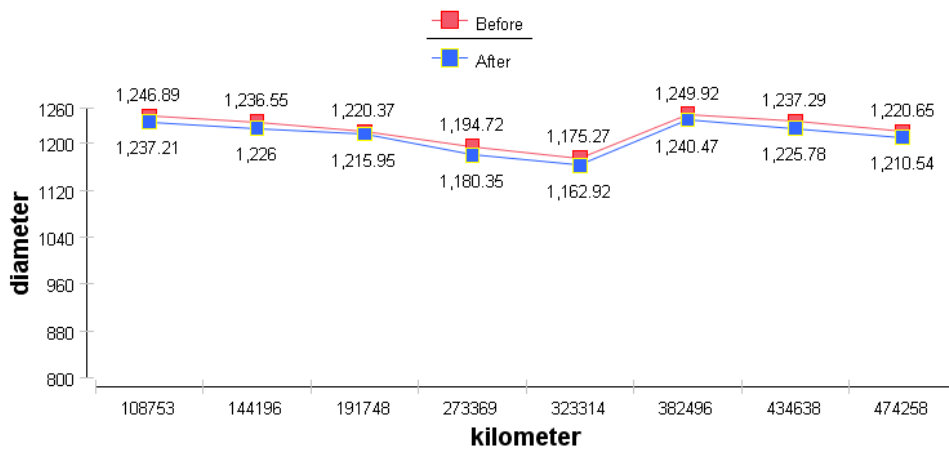
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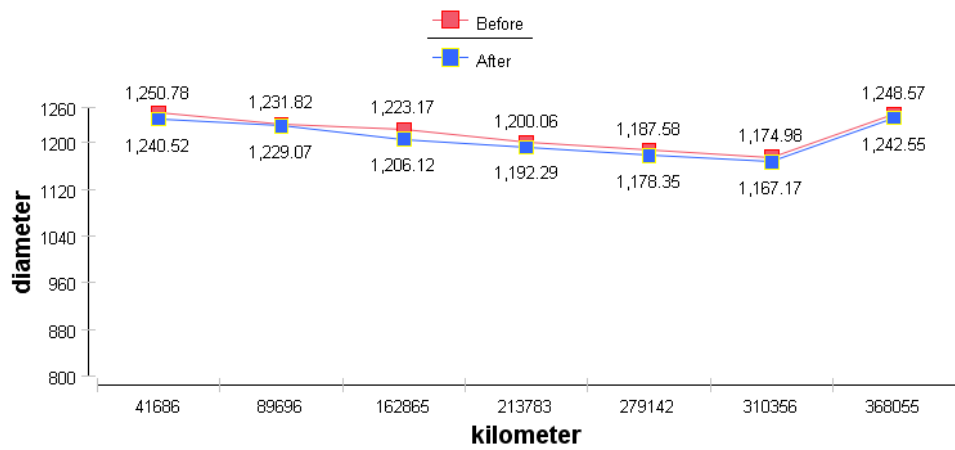
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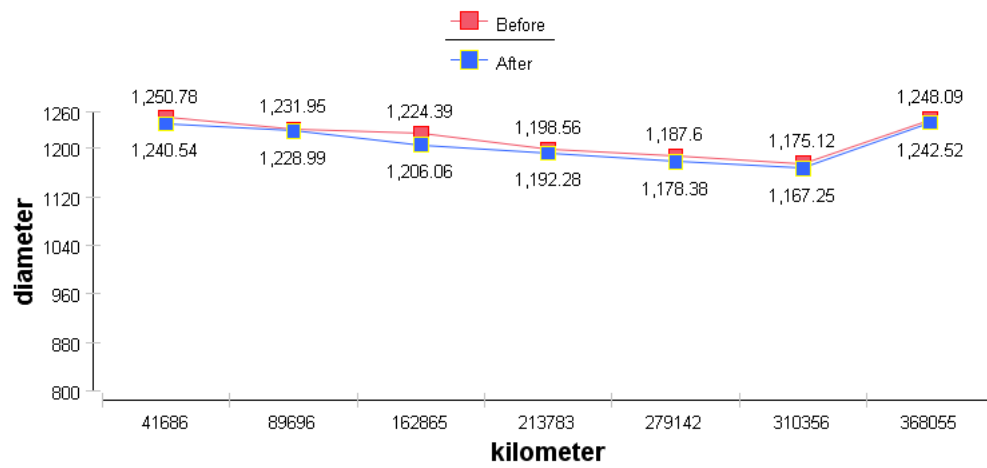
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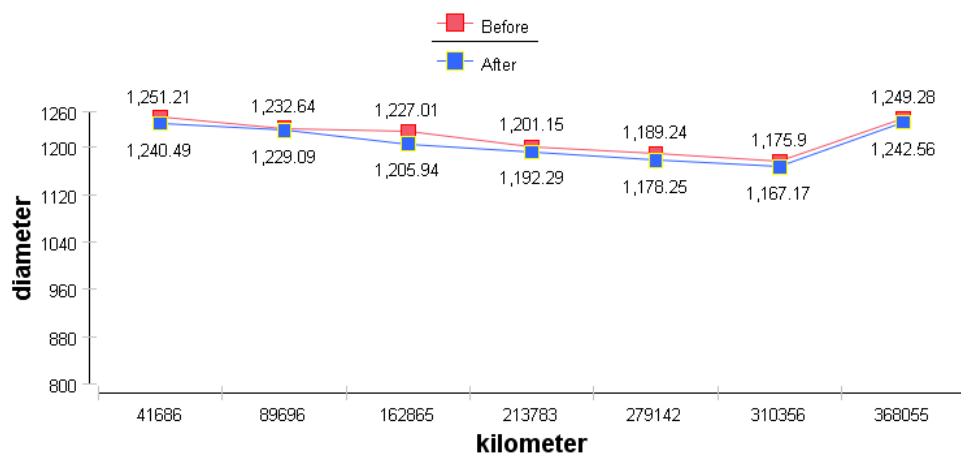
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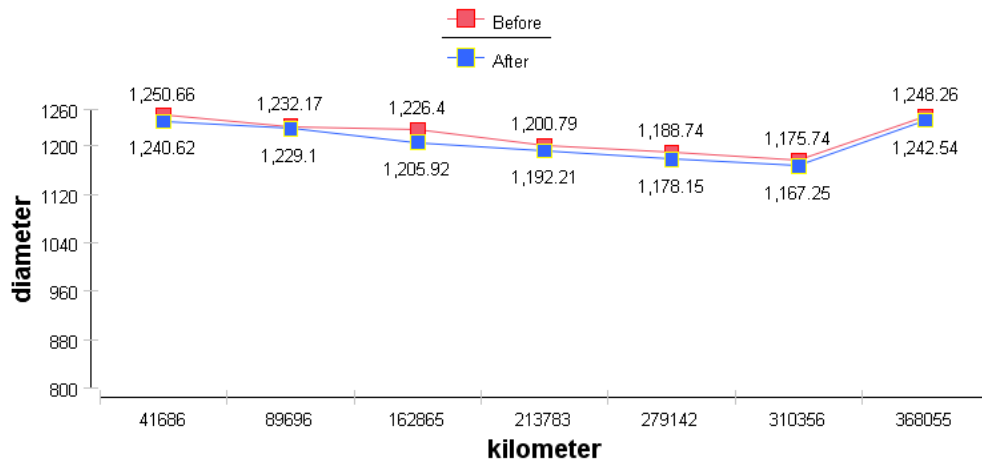
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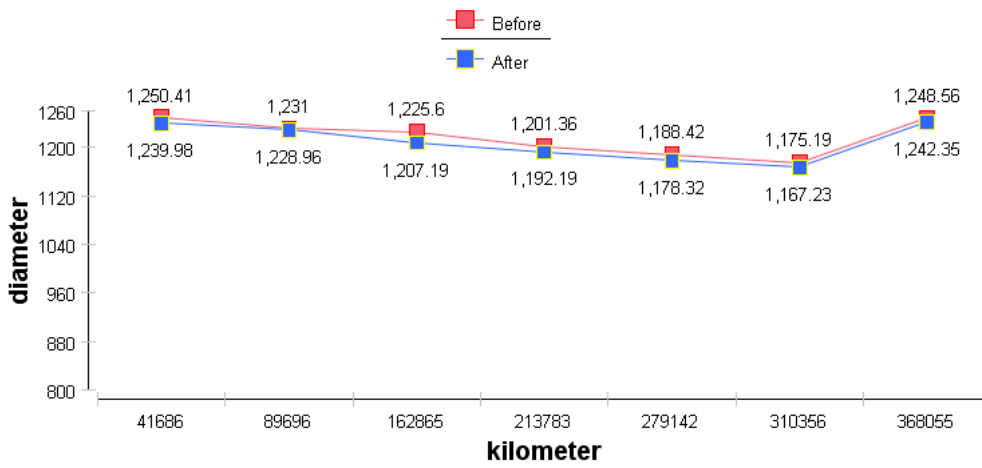
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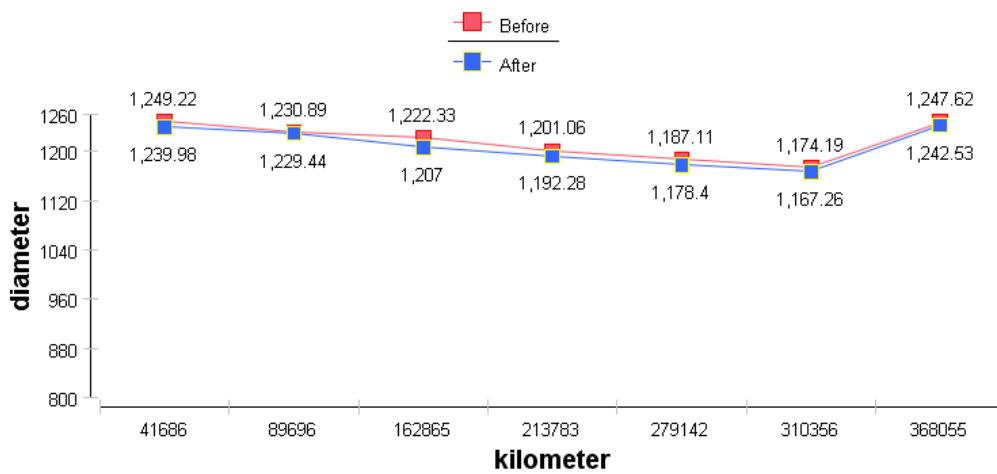
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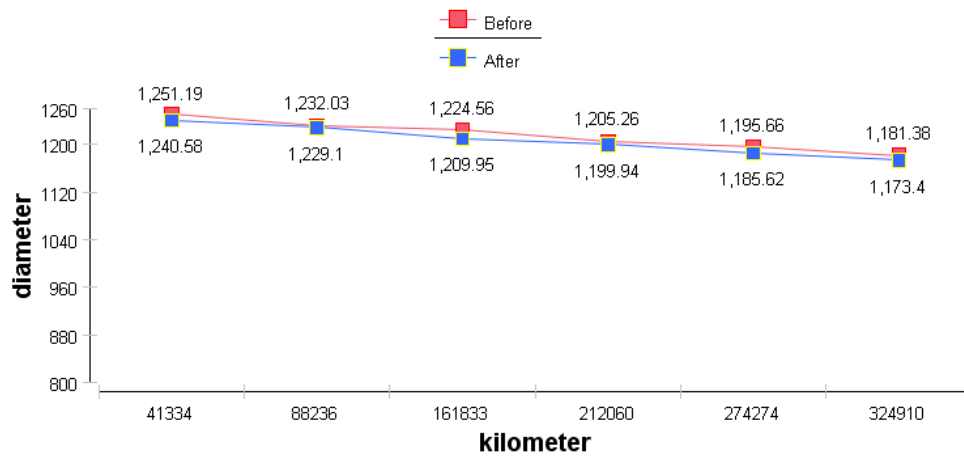
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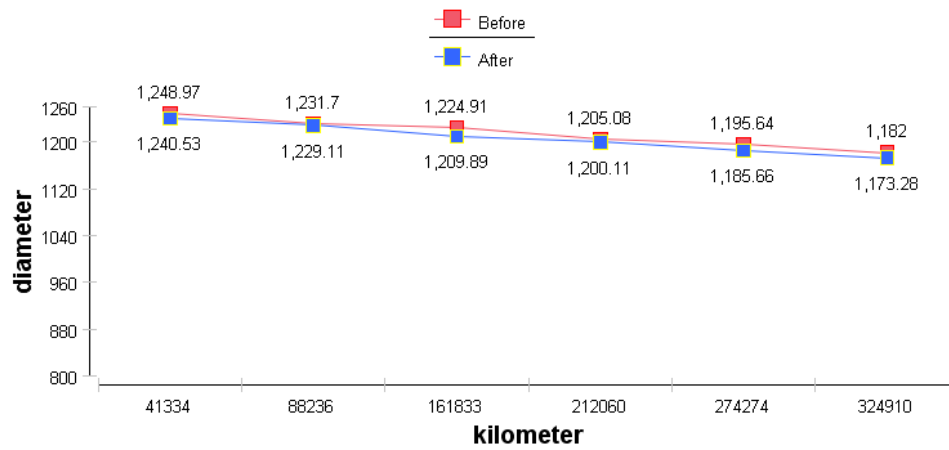
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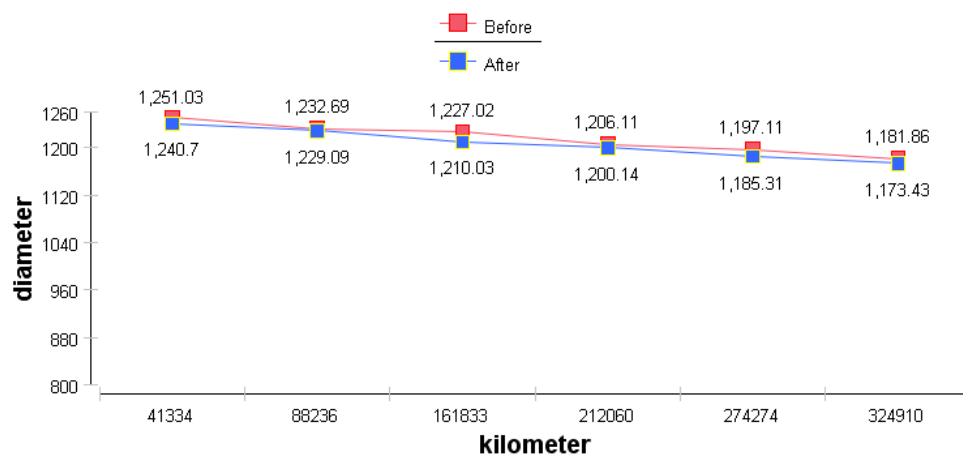
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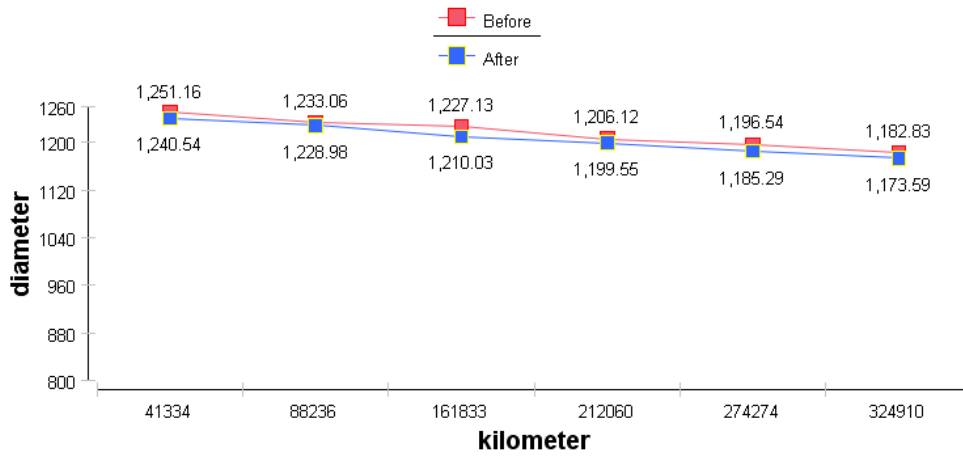
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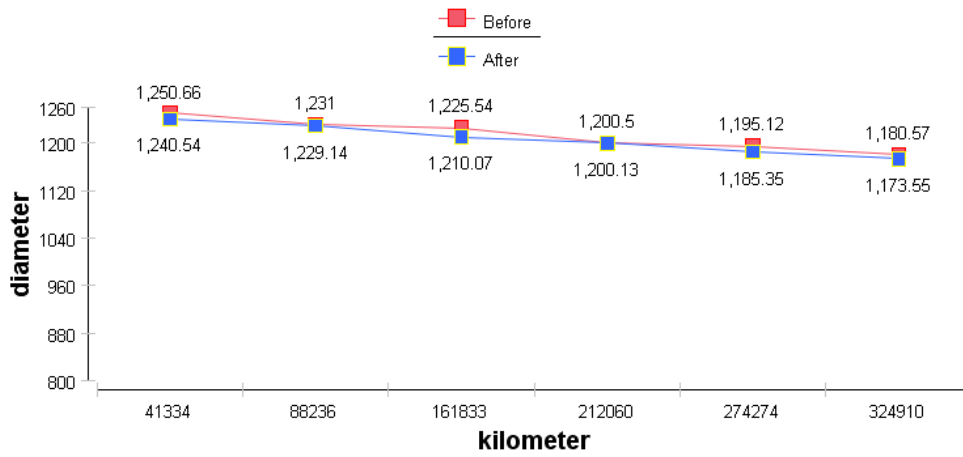
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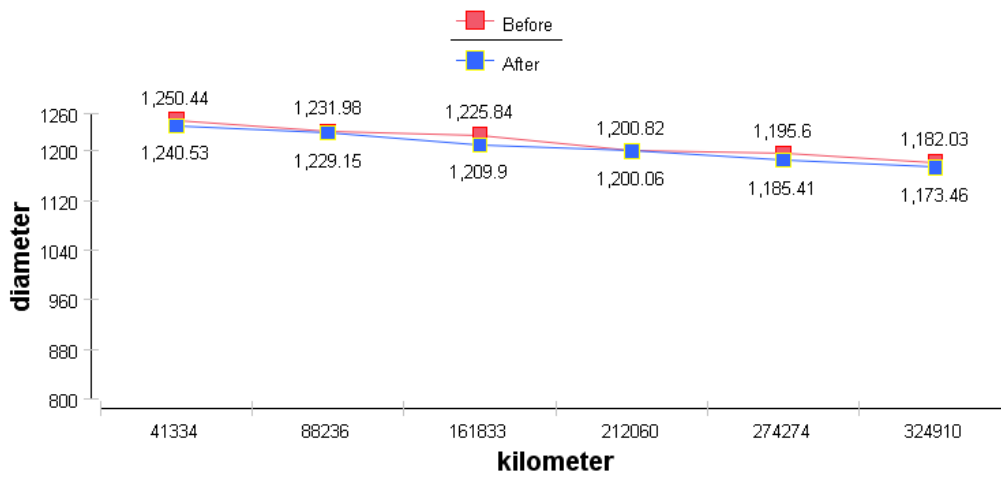
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**IORBOG195908, Axel=3, Side=H**

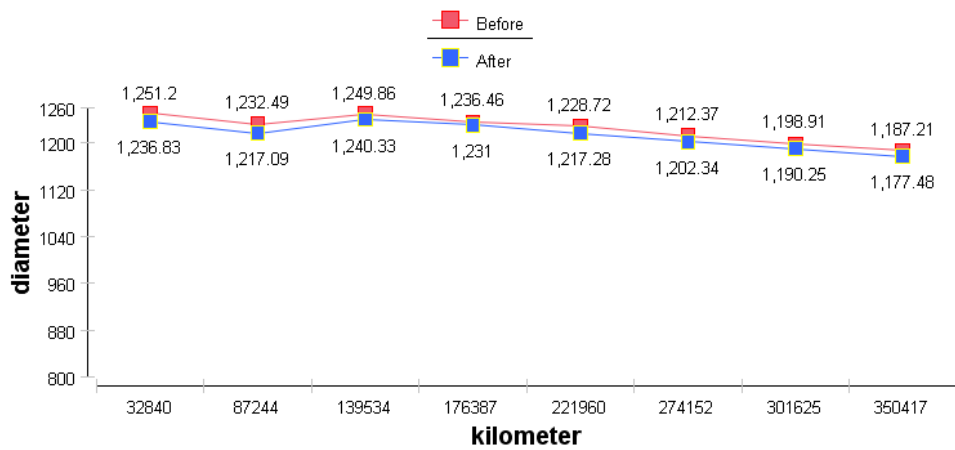


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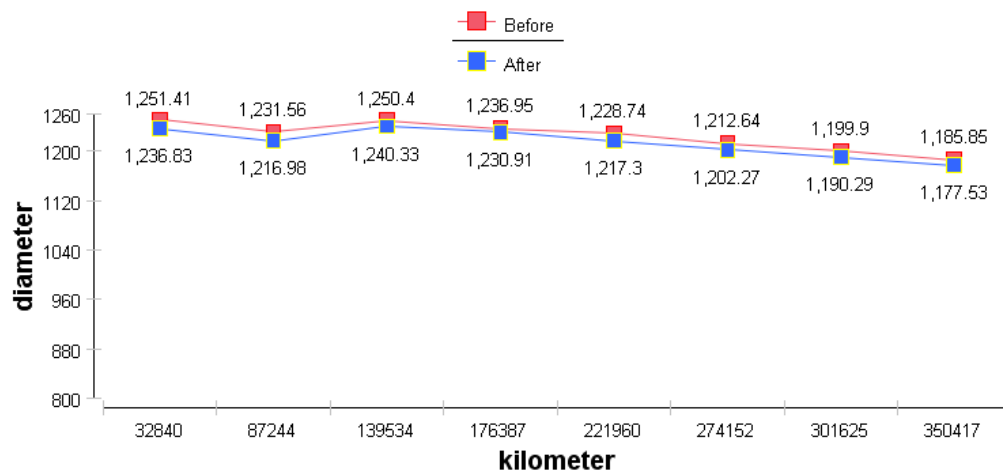




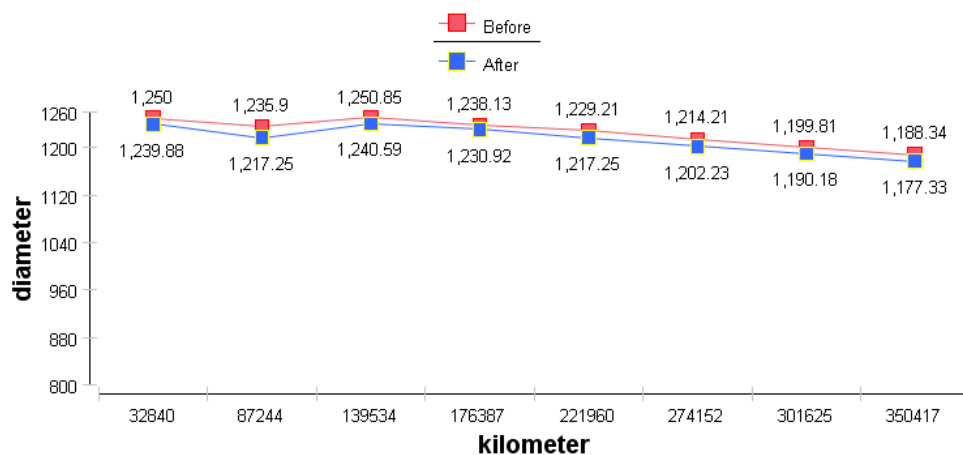
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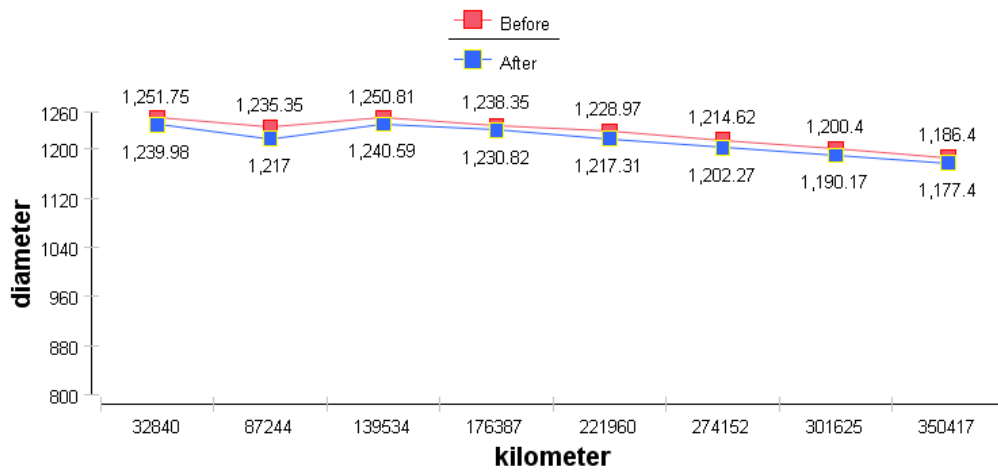
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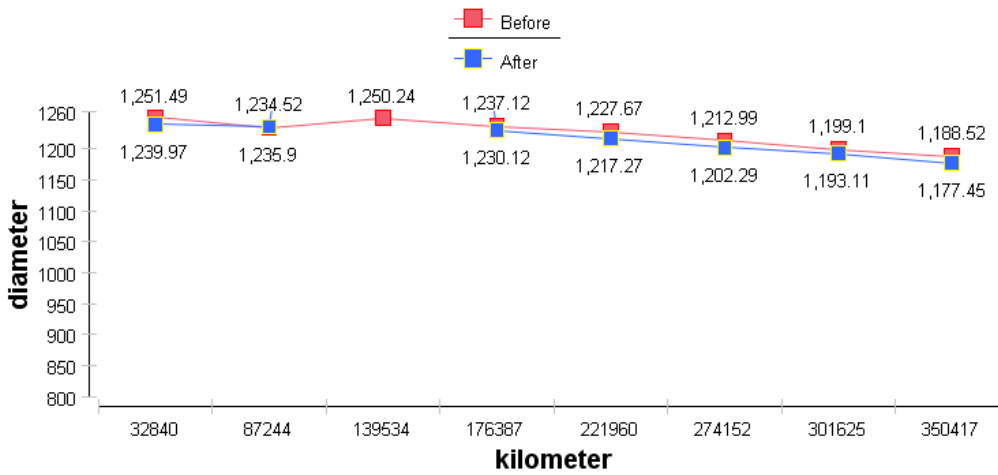
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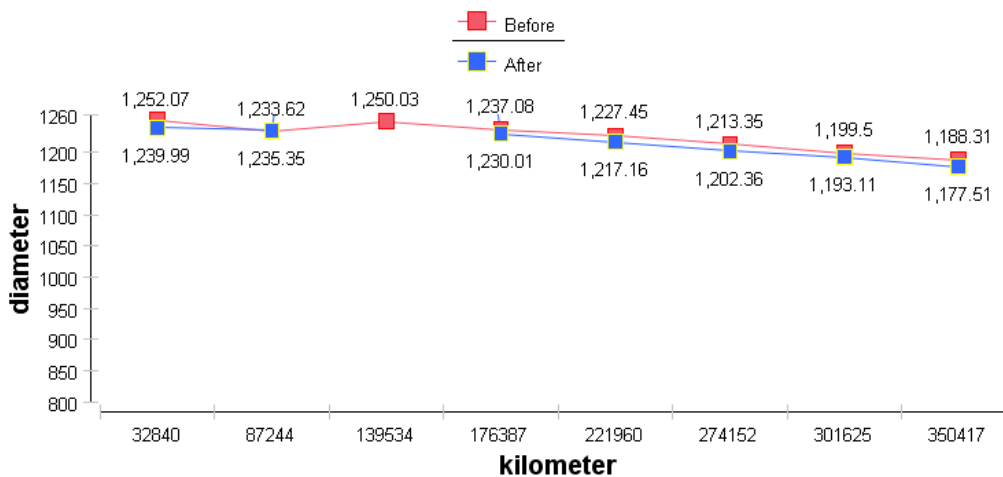
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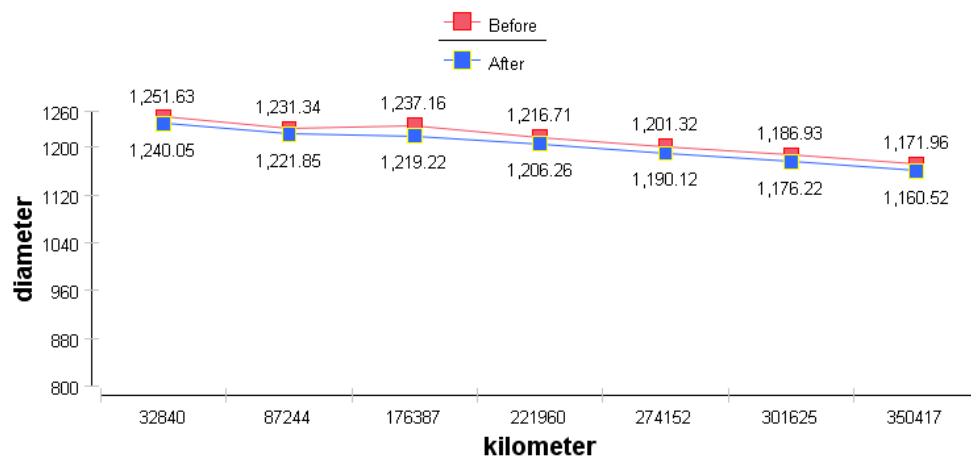
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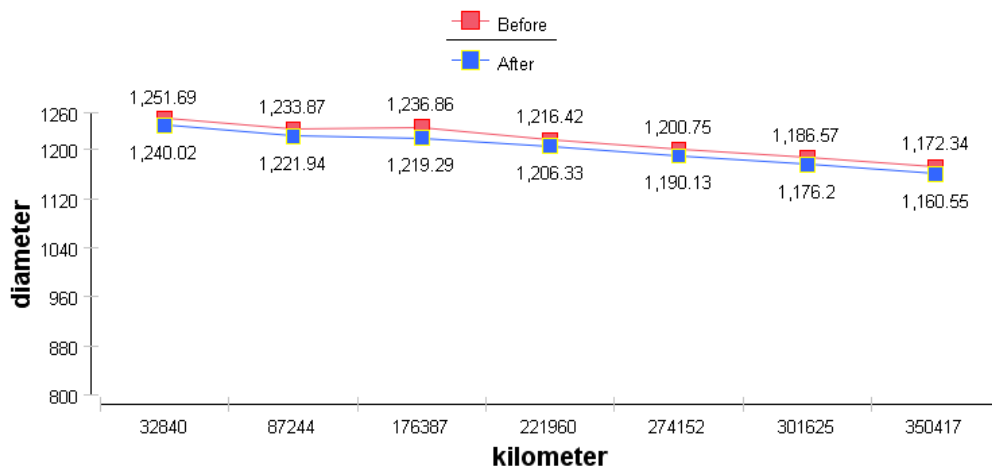
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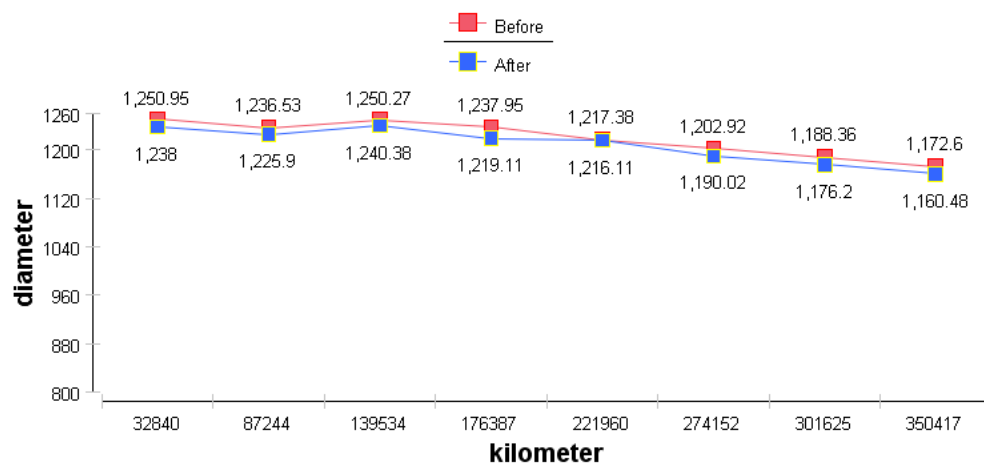
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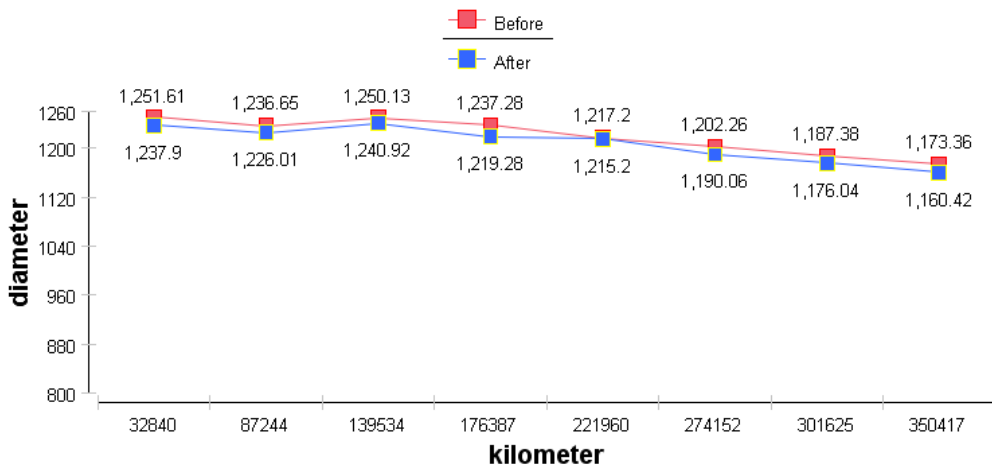
IORBOG195910, Axel=1, Side=V



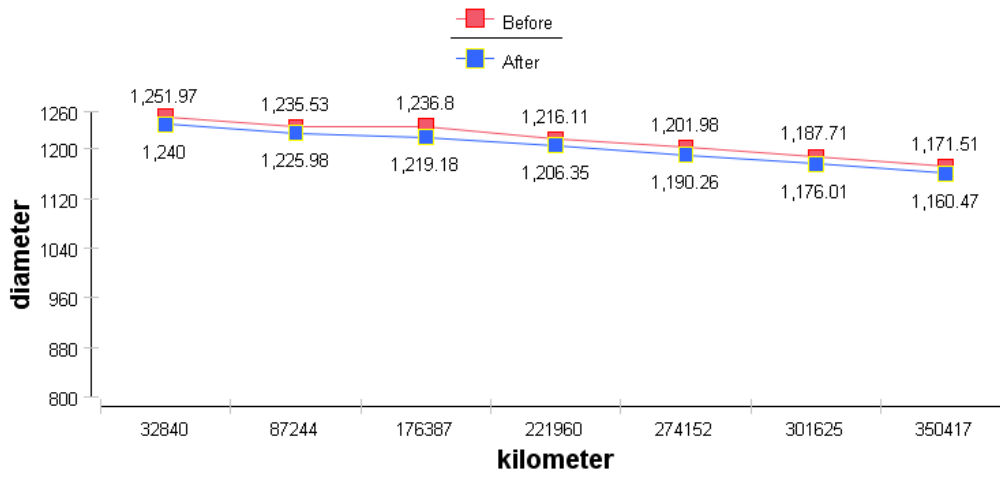
IORBOG195910, Axel=2, Side=H



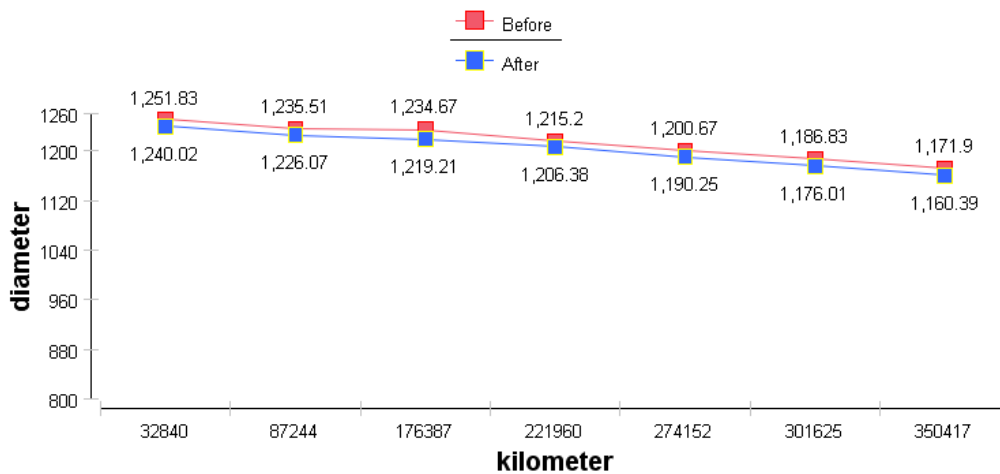
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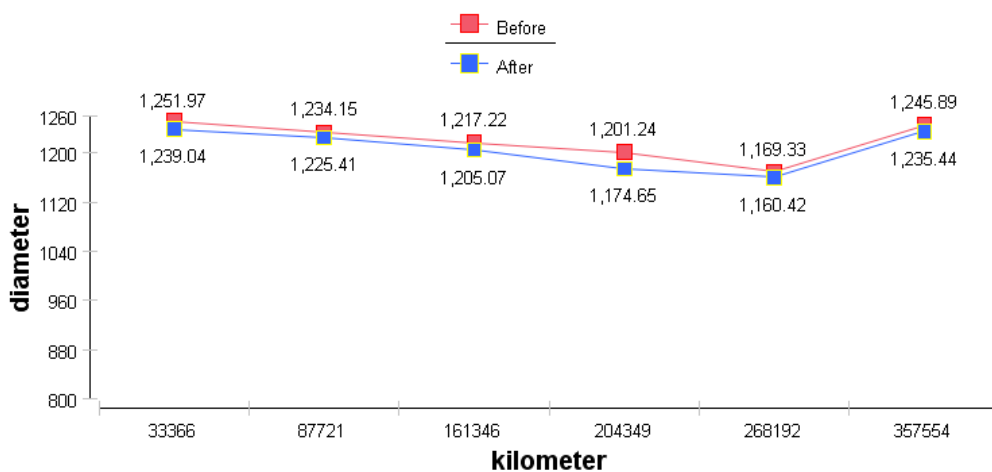
**IORBOG195910, Axel=3, Side=H**



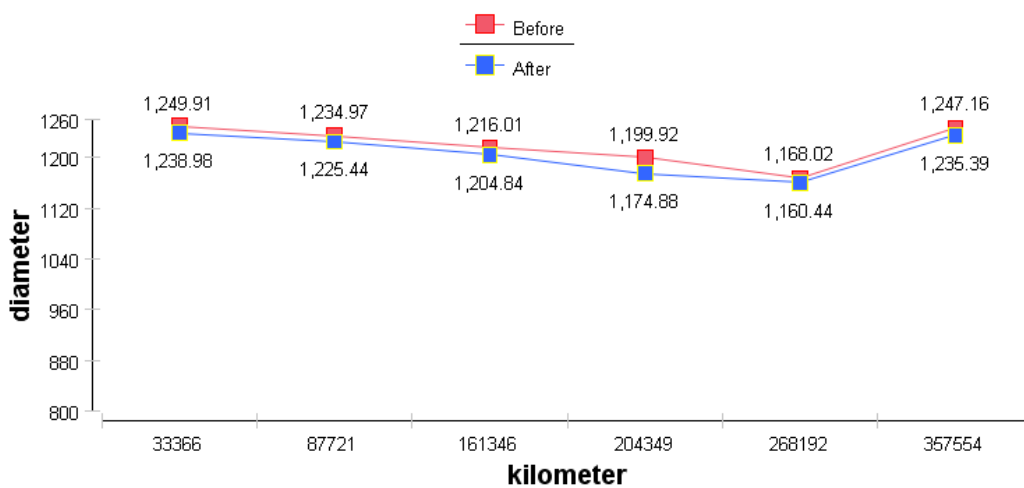
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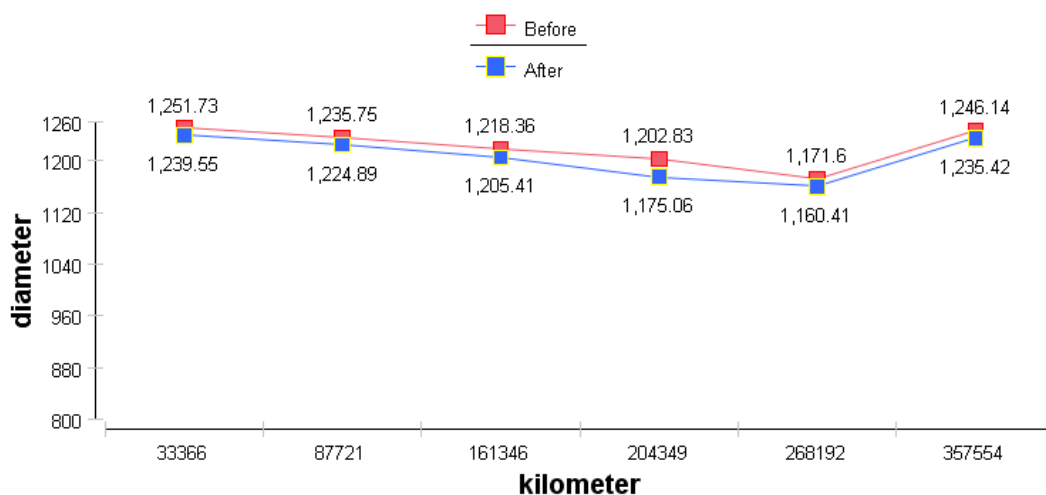
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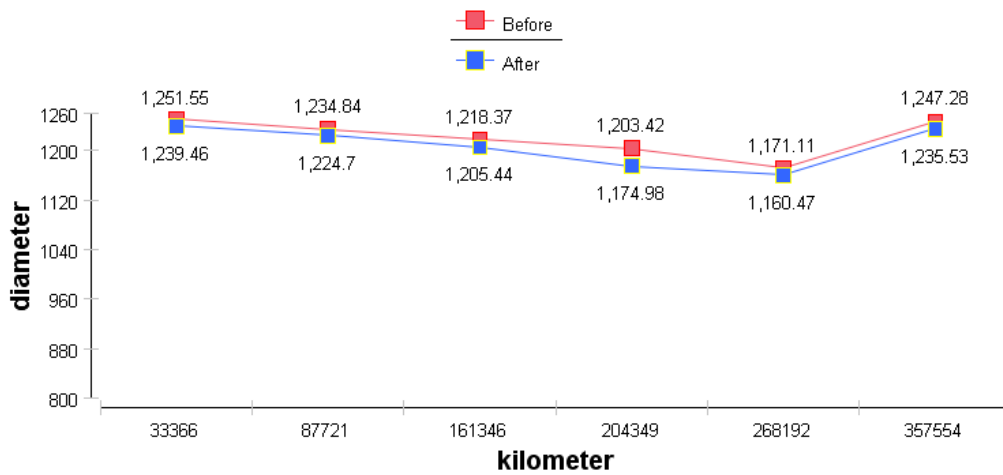
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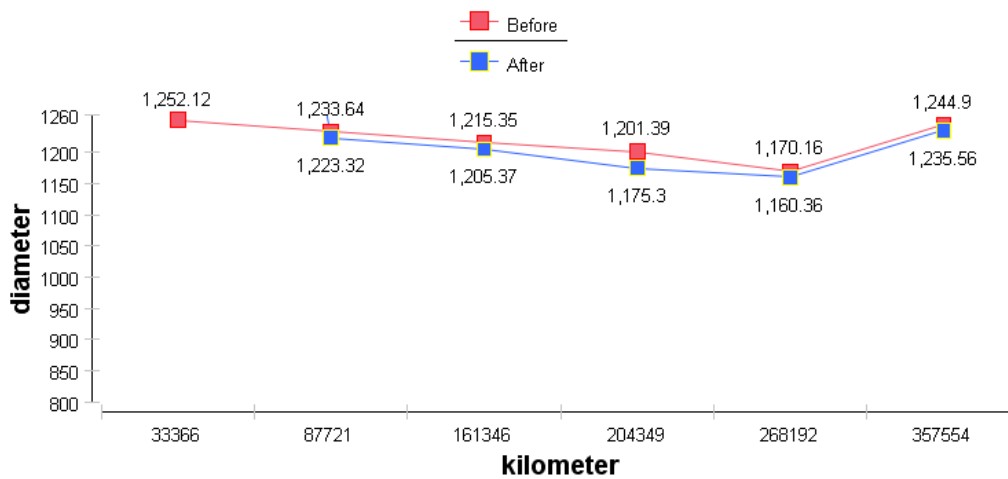
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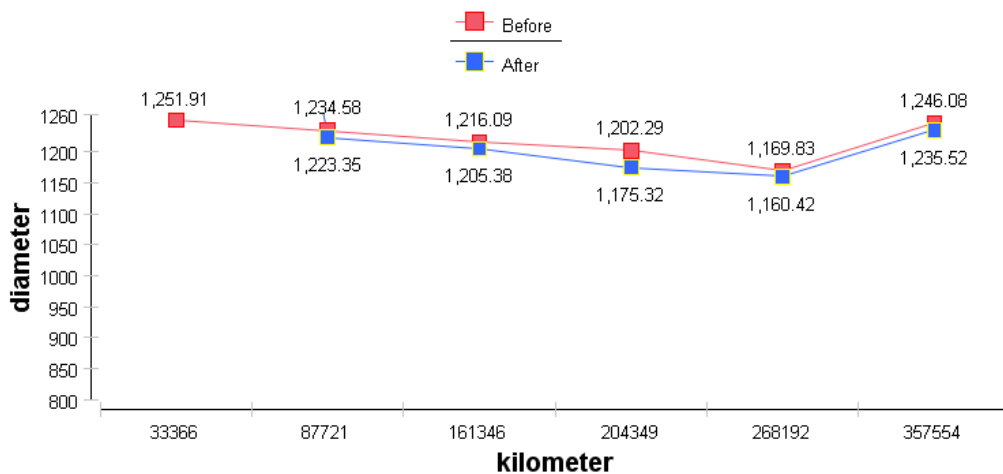
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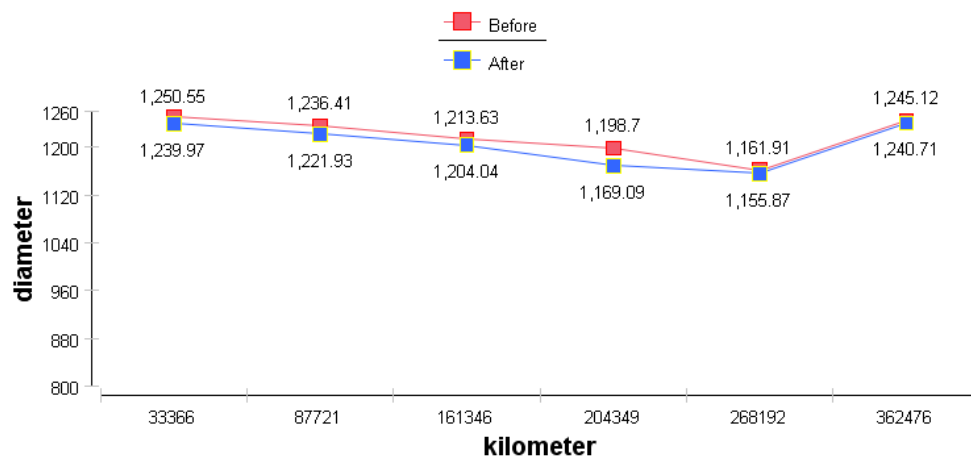
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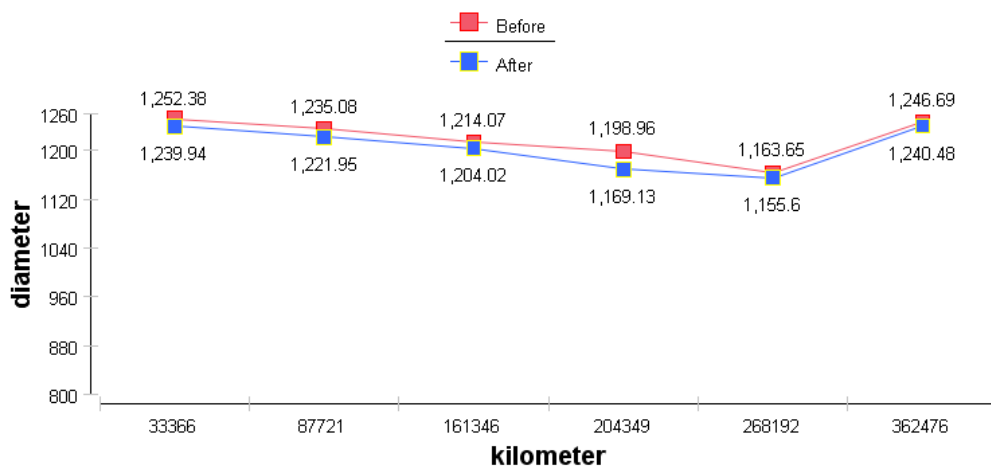
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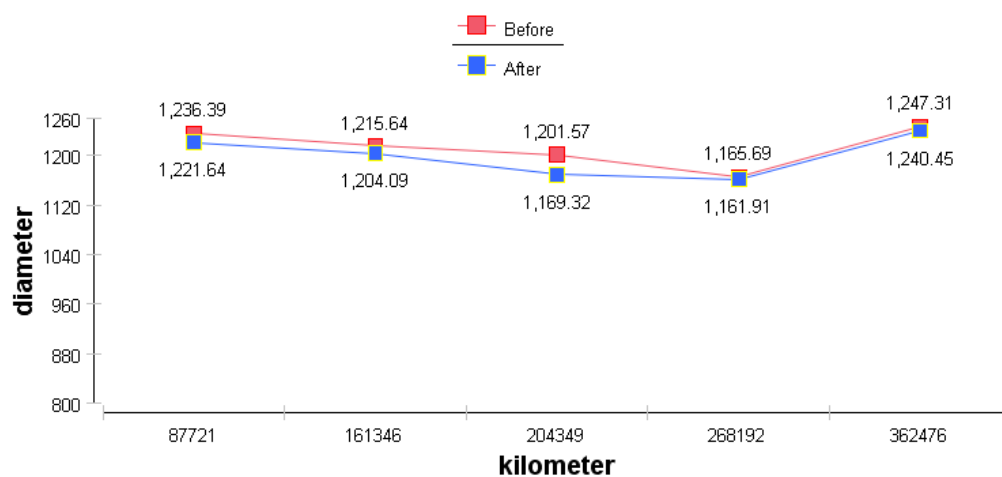
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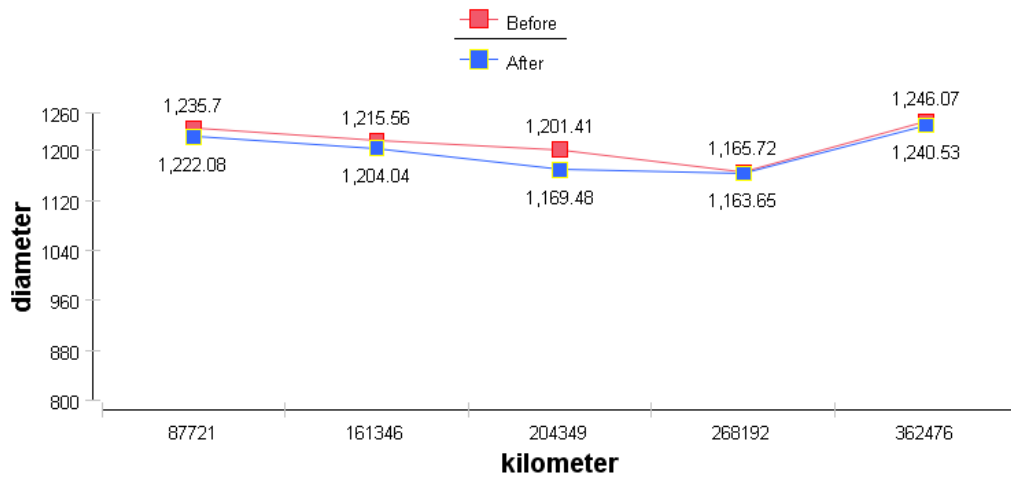
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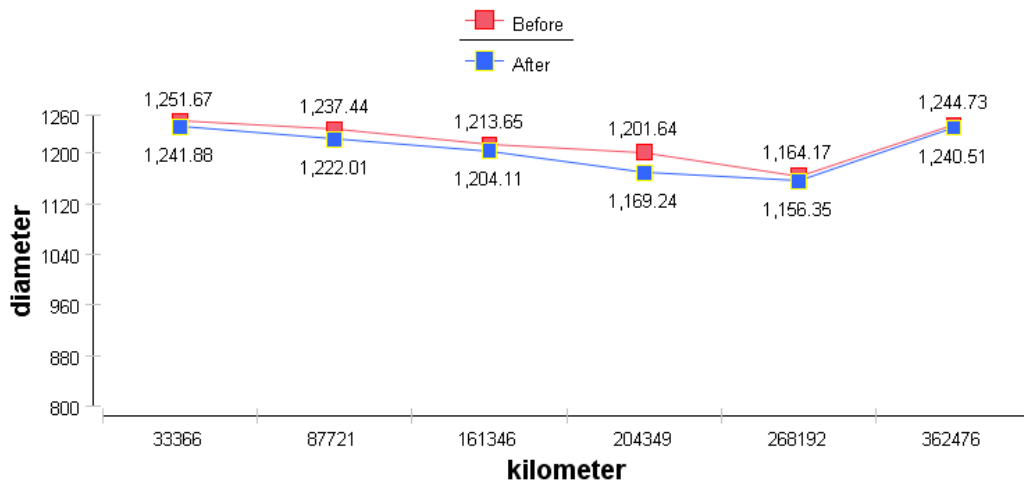
IORBOG195912, Axel=2, Side=H



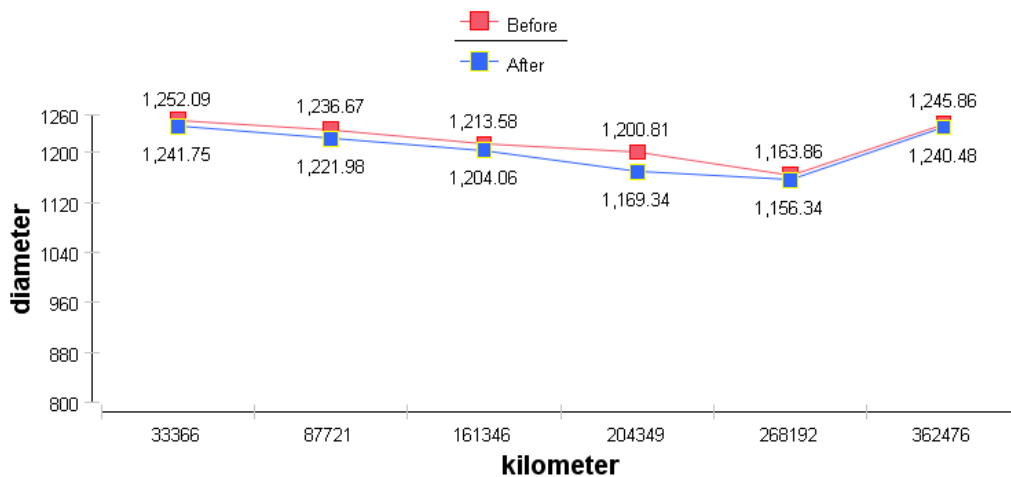
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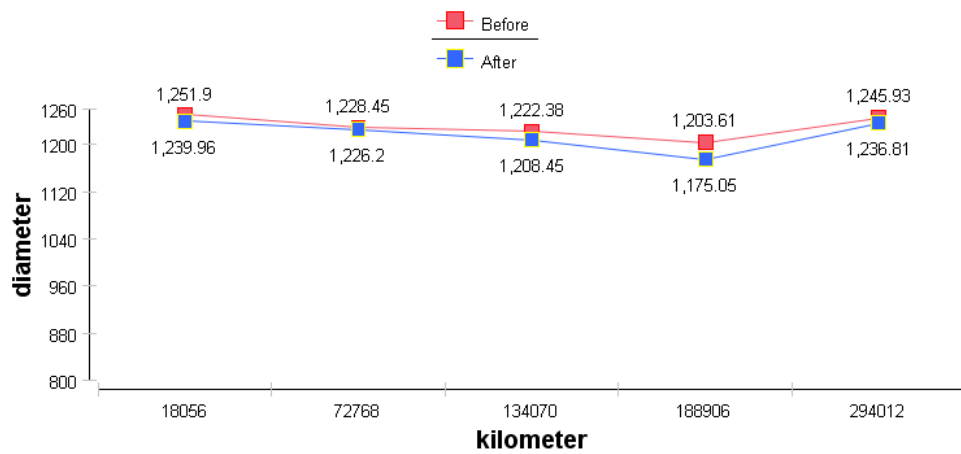


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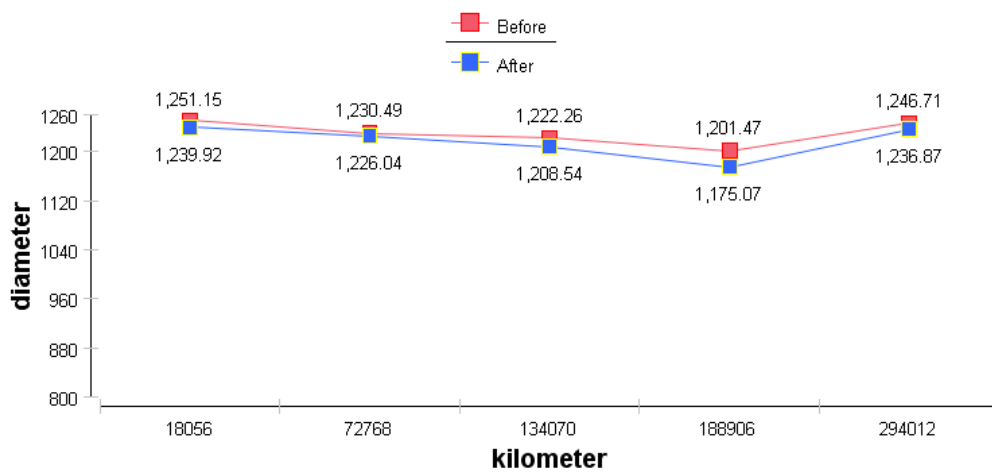




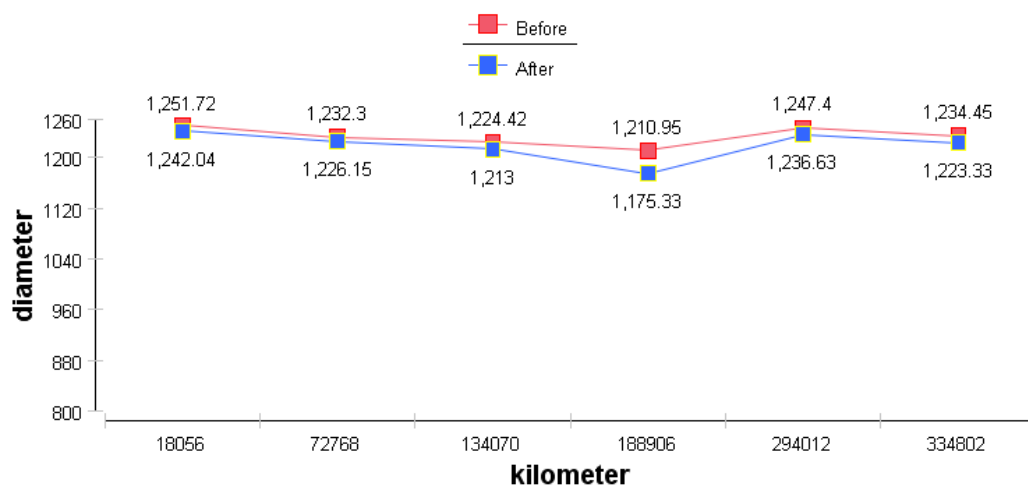
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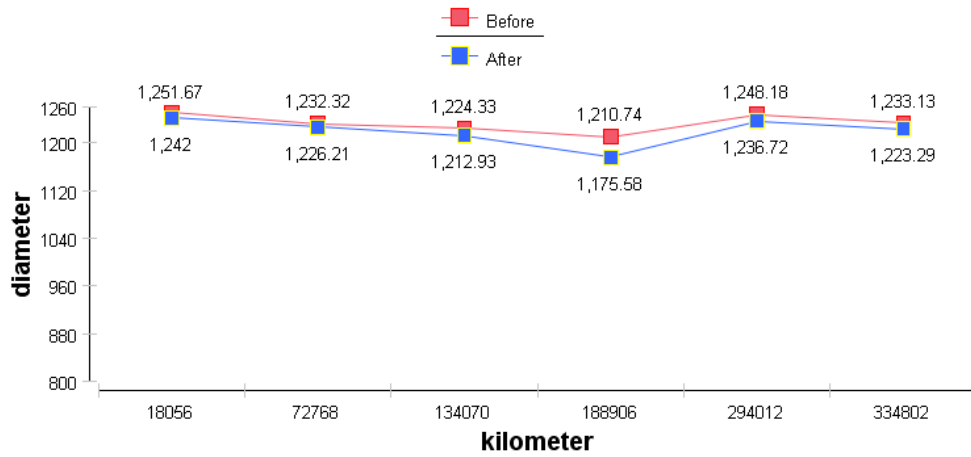
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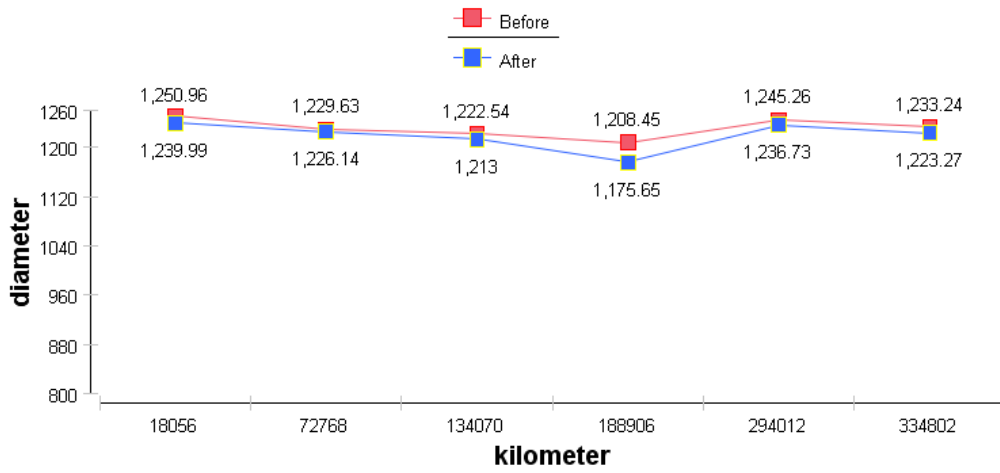
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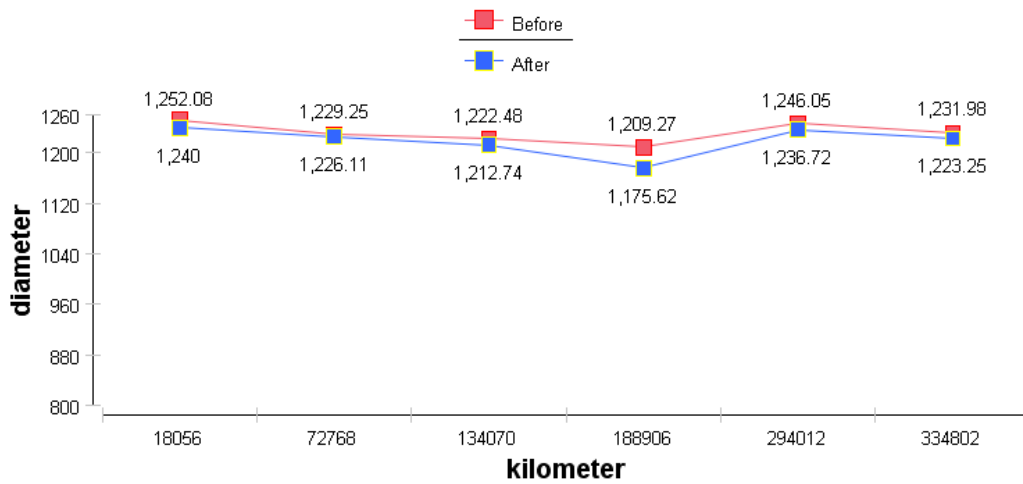
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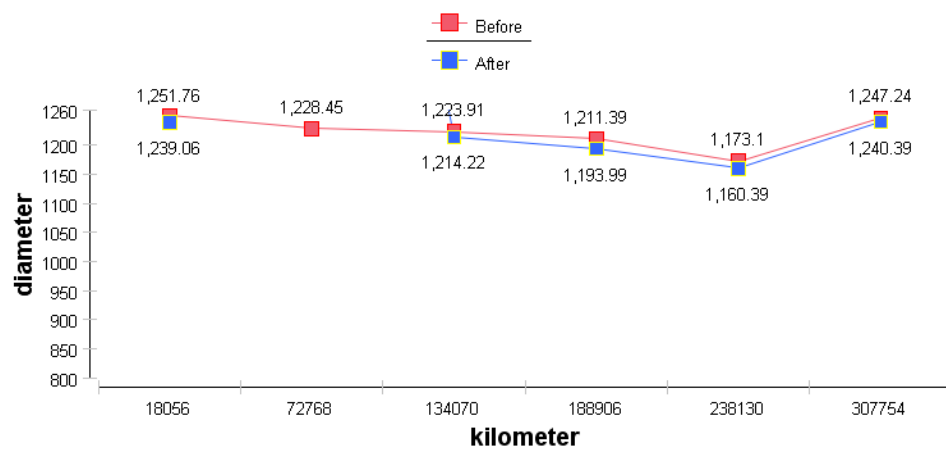
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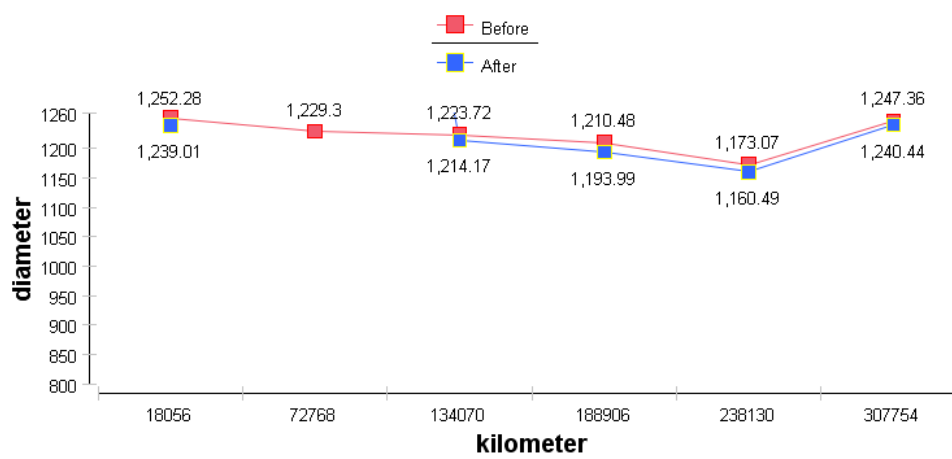
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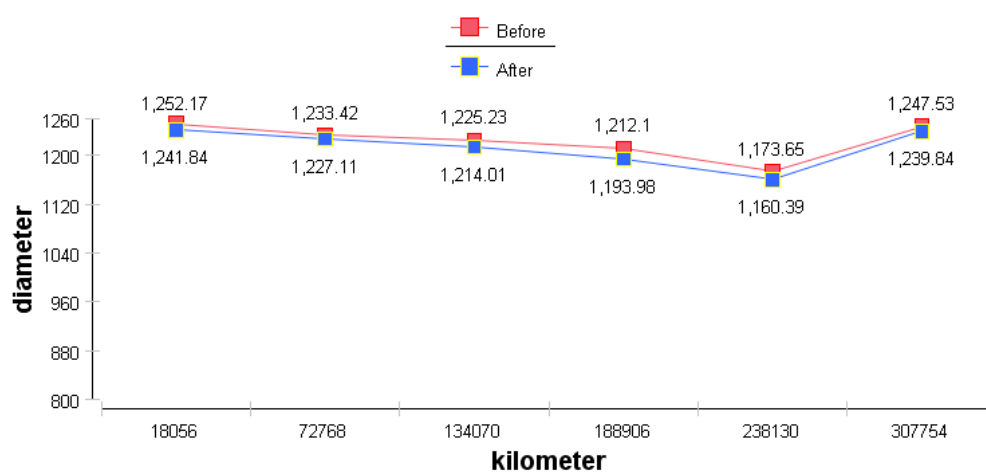
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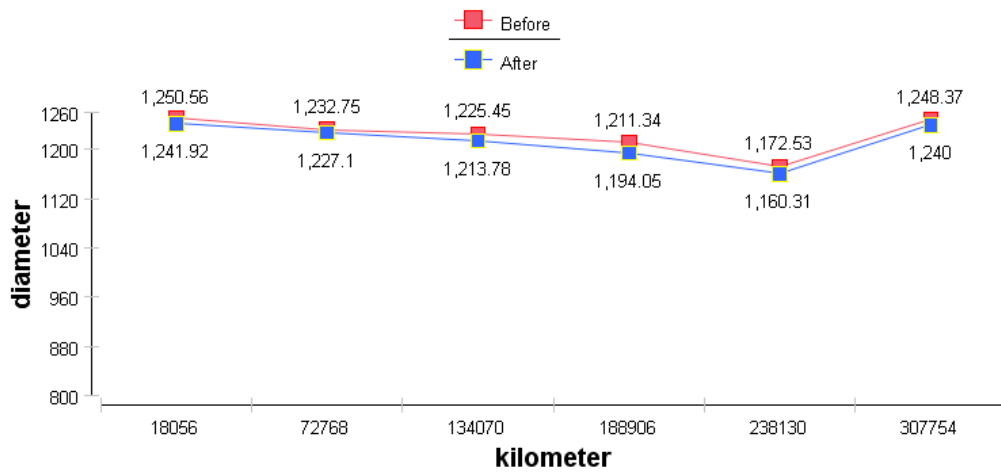
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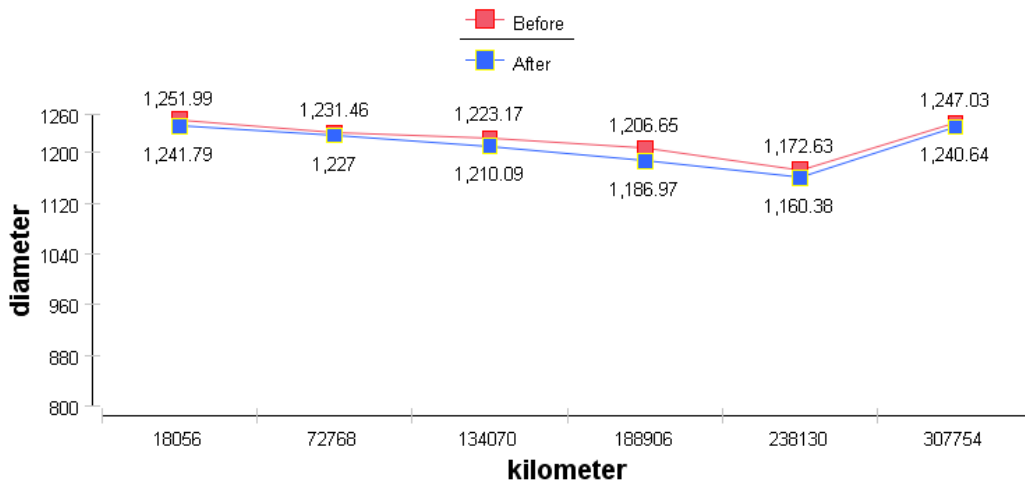
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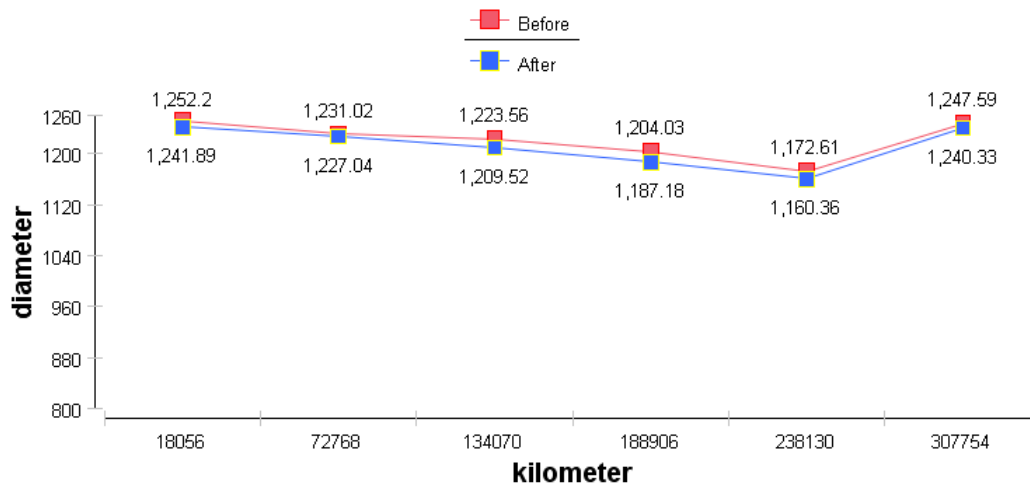
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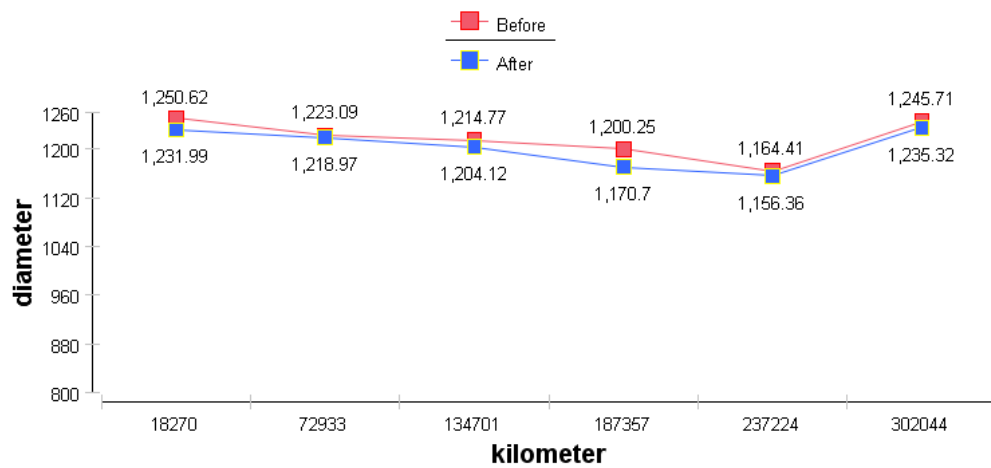
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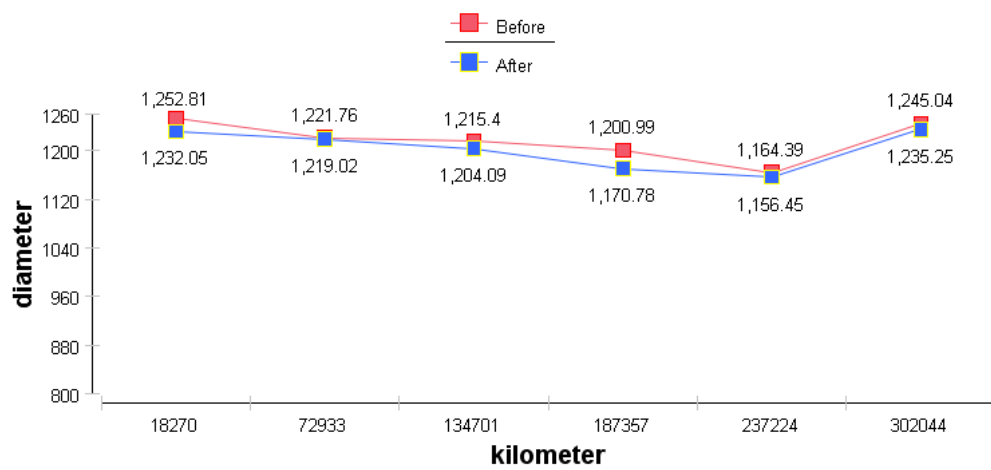
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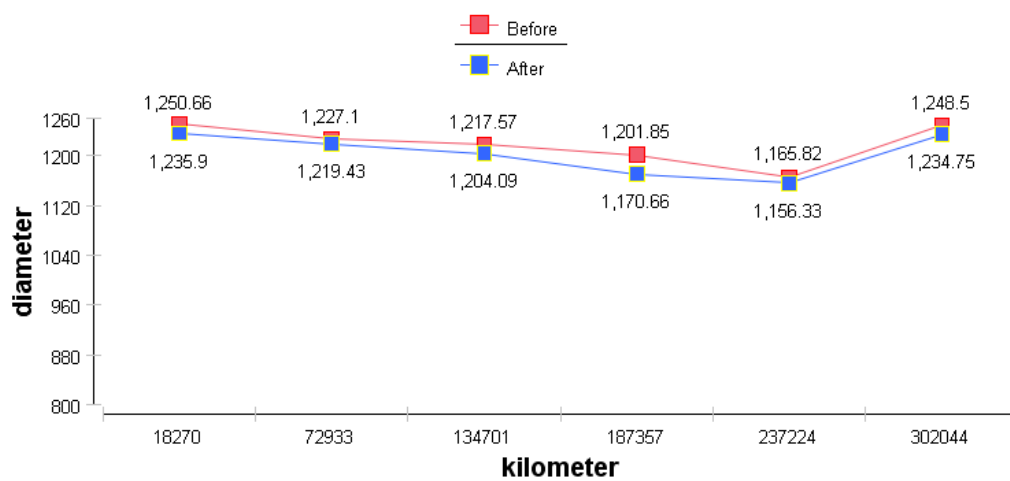
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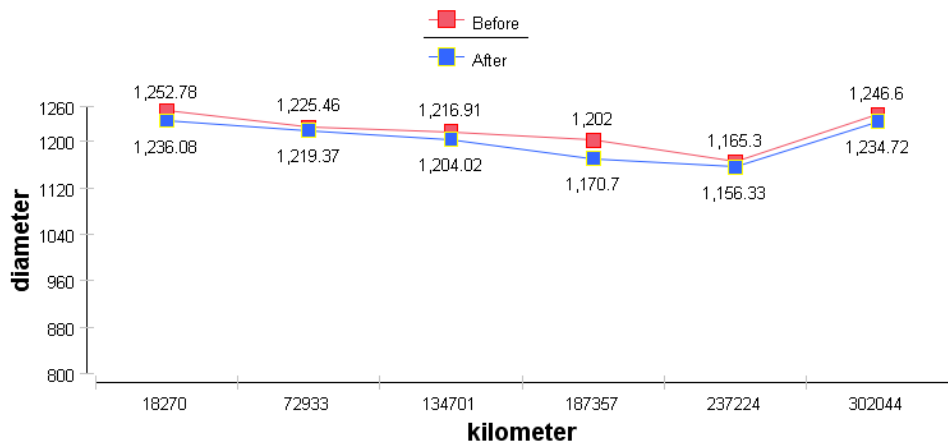
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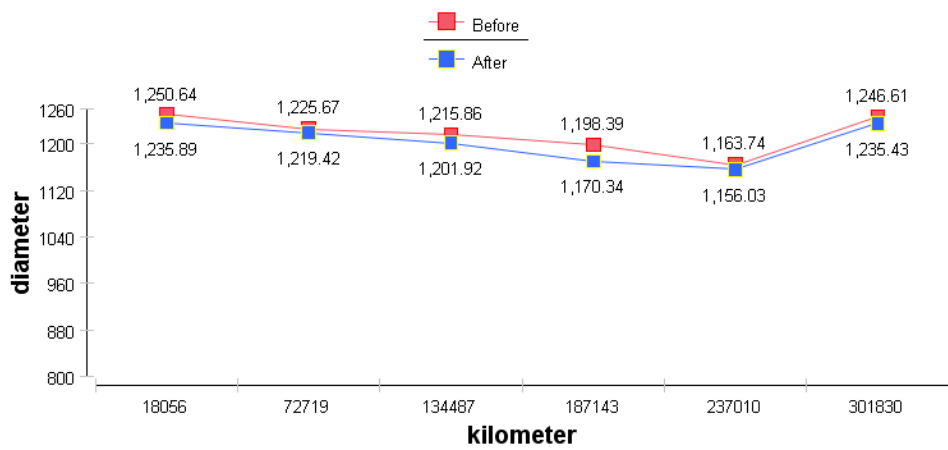
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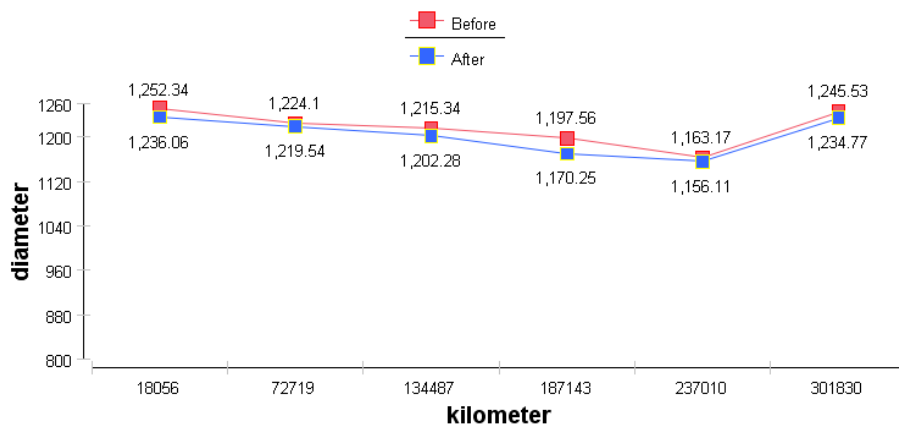
**IORBOG195915, Axel=2, Side=V**



**IORBOG195915, Axel=3, Side=H**



**IORBOG195915, Axel=3, Side=V**



## Appendix C

Table.C.1 Studies of Total Wear Rate

No.	Installed locomotive	Installed bogie	Wear Rate ( Total )					Average
			1	2	3	4	5	
1	119	1	0.373	0.251	0.39	0.393	0.291	0.346
2	119	1	0.369	0.251	0.389	0.396	0.286	0.345
3	119	1	0.29	0.341	0.38	0.412	0.297	0.351
4	119	1	0.286	0.343	0.379	0.415	0.29	0.351
5	119	1	0.32	0.299	0.379	0.418	0.292	0.348
6	119	1	0.321	0.298	0.378	0.418	0.291	0.347
7	122	1	0.257	0.261	0.234	0.241	0.249	0.249
8	122	1	0.254	0.258	0.236	0.242	0.25	0.249
9	122	1	0.316	0.27	0.24	0.241	0.252	0.263
10	122	1	0.319	0.266	0.242	0.245	0.247	0.263
11	122	1	0.271	0.276	0.235	0.239	0.25	0.255
12	122	1	0.279	0.27	0.237	0.239	0.253	0.256
13	111	2	1.023	0.401				0.785
14	111	2	1.024	0.397				0.784
15	111	2	0.922	0.497				0.759
16	111	2	0.915	0.507				0.759
17	111	2	0.929	0.545				0.782
18	111	2	0.925	0.54				0.778
19	119	2	0.356	0.201	0.538	0.551		0.428
20	119	2	0.36	0.205	0.534	0.556		0.429
21	119	2	0.321	0.251	0.539			0.408
22	119	2	0.319	0.252	0.54			0.408
23	119	2	0.296	0.25	0.539			0.402
24	119	2	0.294	0.251	0.539			0.401
25	120	1	0.378	0.199	0.413	0.524		0.385
26	120	1	0.378	0.203	0.411	0.524		0.386
27	120	1	0.355	0.231	0.411	0.432		0.367
28	120	1	0.356	0.228	0.412	0.43		0.366
29	120	1	0.313	0.233	0.413	0.43		0.361
30	120	1	0.316	0.232	0.413	0.43		0.361
31	121	2	0.266	0.344	0.244	0.215	0.294	0.274
32	121	2	0.271	0.342	0.247	0.214	0.29	0.274
33	121	2	0.263	0.343	0.229	0.231	0.29	0.273
34	121	2	0.266	0.341	0.229	0.231	0.29	0.273
35	121	2	0.249	0.341	0.249	0.214	0.292	0.271
36	121	2	0.247	0.343	0.251	0.214	0.288	0.271

37	120	2	0.319	0.215	0.433	0.346		0.346
38	120	2	0.314	0.212	0.434	0.352		0.346
39	120	2	0.317	0.212	0.437	0.347		0.346
40	120	2	0.316	0.211	0.437	0.349		0.346
41	120	2	0.315	0.211	0.438	0.348		0.346
42	120	2	0.316	0.211	0.436	0.349		0.346
43	121	1	0.238	0.314	0.272	0.213	0.358	0.273
44	121	1	0.241	0.313	0.271	0.213	0.357	0.273
45	121	1	0.237	0.316	0.268	0.215	0.355	0.273
46	121	1	0.24	0.317	0.269	0.215	0.349	0.273
47	121	1	0.23	0.298	0.295	0.212	0.355	0.271
48	121	1	0.22	0.307	0.289	0.212	0.357	0.271
49	122	2	0.245	0.26	0.199	0.23	0.241	0.237
50	122	2	0.243	0.261	0.195	0.232	0.245	0.237
51	122	2	0.248	0.259	0.197	0.238	0.235	0.237
52	122	2	0.246	0.257	0.209	0.229	0.231	0.236
53	122	2	0.243	0.259	0.198	0.238	0.233	0.236
54	122	2	0.243	0.262	0.196	0.235	0.236	0.237
55	116	2	0.253	0.301	0.286	0.44	0.262	0.298
56	116	2	0.256	0.299	0.288	0.436	0.262	0.298
57	116	2	0.262	0.3	0.288	0.416	0.276	0.3
58	116	2	0.265	0.296	0.288	0.44	0.262	0.3
59	116	2	0.279	0.282	0.287	0.335	0.321	0.299
60	116	2	0.284	0.282	0.284	0.337	0.32	0.299
61	116	1	0.284	0.309	0.506	0.322		0.278
62	116	1	0.284	0.31	0.507	0.321		0.279
63	116	1	0.577	0.066	0.5	0.503	0.322	0.379
64	116	1	0.587	0.09	0.482	0.51	0.32	0.382
65	116	1	0.282	0.308	0.519	0.318		0.278
66	116	1	0.282	0.309	0.518	0.32		0.279
67	124	1	0.251	0.276	0.707	0.223		0.335
68	124	1	0.249	0.28	0.697	0.226		0.334
69	124	1	0.27	0.265	0.706	0.229		0.337
70	124	1	0.272	0.262	0.708	0.227		0.336
71	124	1	0.305	0.244	0.699	0.234		0.339
72	124	1	0.306	0.244	0.699	0.233		0.339
73	124	2	0.332	0.243	0.813	0.207		0.358
74	124	2	0.331	0.244	0.811	0.196		0.355
75	124	2		0.238	0.809	0.116		0.254
76	124	2		0.245	0.804	0.091		0.249
77	124	2	0.366	0.243	0.811	0.202		0.364
78	124	2	0.364	0.243	0.807	0.204		0.364
79	125	1	0.251	0.29	0.609			0.38
80	125	1	0.254	0.285	0.61			0.38
81	125	1	0.29	0.215	0.687			0.39



82	125	1	0.289	0.217	0.681			0.389
83	125	1	0.253	0.214	0.681			0.377
84	125	1	0.254	0.218	0.677			0.377
85	125	2	0.235	0.195	0.369	0.683		0.357
86	125	2	0.218	0.21	0.368	0.681		0.357
87	125	2	0.269	0.214	0.365	0.682		0.37
88	125	2	0.271	0.217	0.36	0.685		0.371
89	125	2	0.27	0.276	0.422	0.54		0.37
90	125	2	0.271	0.286	0.407	0.545		0.37
91	126	1	0.238	0.24	0.635	0.288		0.345
92	126	1	0.238	0.242	0.633	0.287		0.345
93	126	1	0.301	0.248	0.635	0.287		0.363
94	126	1	0.306	0.249	0.633	0.288		0.364
95	126	1	0.301	0.283	0.6	0.287		0.365
96	126	1	0.302	0.279	0.608	0.284		0.365
Average 1								0.354229
Average 2								0.326211

Table.C.2 Studies of Re-profiling Wear Rate

No.	Wheel Position	Installed Locomotive	Installed Bogie	wear rate ( re-profiling)					Average
				1	2	3	4	5	
1	195900_1H	119	1	0.337	0.143	0.145	0.294	0.16	0.201
2	195900_1V	119	1	0.354	0.118	0.148	0.318	0.143	0.201
3	195900_2H	119	1	0.205	0.237	0.155	0.348	0.174	0.212
4	195900_2V	119	1	0.294	0.224	0.153	0.358	0.146	0.221
5	195900_3H	119	1	0.277	0.187	0.102	0.303	0	0.165
6	195900_3V	119	1	0.3	0.163	0.102	0.325	0	0.167
7	195901_1H	122	1	0.081	0.201	0.111	0.168	0.161	0.151
8	195901_1V	122	1	0.053	0.195	0.133	0.168	0.158	0.148
9	195901_2H	122	1	0.154	0.242	0.15	0.188	0.192	0.19
10	195901_2V	122	1	0.143	0.235	0.157	0.186	0.185	0.186
11	195901_3H	122	1	0.087	0.223	0	0.176	0.16	0.139
12	195901_3V	122	1	0.067	0.219	0	0.164	0.142	0.129
13	195902_1H	111	2	0.9	0.282				0.663
14	195902_1V	111	2	0.901	0.311				0.675
15	195902_2H	111	2	0.86	0.431				0.696
16	195902_2V	111	2	0.84	0.425				0.681
17	195902_3H	111	2	0.83	0.454				0.686
18	195902_3V	111	2	0.83	0.449				0.684
19	195903_1H	119	2	0.336	0.063	0.198	0.442		0.237
20	195903_1V	119	2	0.325	0.114	0.216	0.466		0.258
21	195903_2H	119	2	0.323	0.155	0.239			0.234

22	195903_2V	119	2	0.243	0.151	0.243			0.217
23	195903_3H	119	2	0.27	0.133	0.231			0.212
24	195903_3V	119	2	0.266	0.15	0.225			0.213
25	195904_1H	120	1	0.335	0.09	0.168	0.394		0.231
26	195904_1V	120	1	0.338	0.085	0.194	0.419		0.246
27	195904_2H	120	1	0.342	0.132	0.201	0.356		0.245
28	195904_2V	120	1	0.29	0.121	0.199	0.345		0.231
29	195904_3H	120	1	0.277	0.101	0.19	0.329		0.217
30	195904_3V	120	1	0.264	0.108	0.193	0.278		0.206
31	195905_1H	121	2	0.09	0.289	0.145	0.154	0.211	0.184
32	195905_1V	121	2	0.063	0.283	0.134	0.137	0.202	0.17
33	195905_2H	121	2	0.108	0.318	0.155	0.182	0.215	0.205
34	195905_2V	121	2	0.101	0.318	0.161	0.177	0.219	0.203
35	195905_3H	121	2	0.08	0.295	0.155	0.151	0.196	0.183
36	195905_3V	121	2	0.052	0.29	0.157	0.13	0.193	0.172
37	195906_1H	120	2	0.288	0.093	0.189	0.216		0.19
38	195906_1V	120	2	0.297	0.079	0.18	0.246		0.192
39	195906_2H	120	2	0.292	0.111	0.207	0.253		0.21
40	195906_2V	120	2	0.287	0.112	0.203	0.28		0.214
41	195906_3H	120	2	0.267	0.082	0.182	0.232		0.186
42	195906_3V	120	2	0.298	0.093	0.176	0.247		0.194
43	195907_1H	121	1	0.057	0.233	0.153	0.141	0.25	0.166
44	195907_1V	121	1	0.062	0.251	0.123	0.141	0.252	0.166
45	195907_2H	121	1	0.074	0.288	0.174	0.168	0.28	0.198
46	195907_2V	121	1	0.064	0.28	0.169	0.162	0.272	0.191
47	195907_3H	121	1	0.042	0.252	0.18	0.155	0.255	0.177
48	195907_3V	121	1	0.03	0.21	0.172	0.133	0.222	0.153
49	195908_1H	122	2	0.062	0.199	0.106	0.161	0.158	0.144
50	195908_1V	122	2	0.055	0.204	0.099	0.16	0.173	0.146
51	195908_2H	122	2	0.077	0.231	0.119	0.19	0.166	0.165
52	195908_2V	122	2	0.087	0.232	0.131	0.181	0.182	0.17
53	195908_3H	122	2	0.04	0.21	0.007	0.157	0.139	0.122
54	195908_3V	122	2	0.06	0.217	0.015	0.164	0.169	0.135
55	195909_1H	116	2	0.148	0.251	0.192	0.315	0.199	0.215
56	195909_1V	116	2	0.164	0.251	0.199	0.35	0.171	0.217
57	195909_2H	116	2	0.196	0.262	0.23	0.328	0.226	0.243
58	195909_2V	116	2	0.204	0.256	0.237	0.372	0.184	0.241
59	195909_3H	116	2	0.19	0.228	0.205	0.218	0.227	0.214
60	195909_3V	116	2	0.192	0.226	0.211	0.233	0.221	0.216
61	195910_1H	116	1		0.229	0.215	0.39	0.234	0.208
62	195910_1V	116	1		0.221	0.203	0.377	0.242	0.203
63	195910_2H	116	1	0.511	0.028	0.247	0.443	0.248	0.272
64	195910_2V	116	1	0.488	0.044	0.234	0.413	0.265	0.268
65	195910_3H	116	1		0.214	0.225	0.426	0.226	0.21
66	195910_3V	116	1		0.194	0.2	0.394	0.236	0.197

67	195911_1H	124	1	0.161	0.165	0.618	0.14		0.24
68	195911_1V	124	1	0.175	0.152	0.582	0.119		0.227
69	195911_2H	124	1	0.2	0.176	0.646	0.175		0.267
70	195911_2V	124	1	0.187	0.176	0.661	0.167		0.265
71	195911_3H	124	1	0.19	0.136	0.607	0.154		0.239
72	195911_3V	124	1	0.207	0.145	0.627	0.147		0.248
73	195912_1H	124	2	0.266	0.13	0.689	0.095	0.299	0.254
74	195912_1V	124	2	0.242	0.137	0.694	0.11	0.309	0.256
75	195912_2H	124	2		0.157	0.75	0.059	0.265	0.203
76	195912_2V	124	2		0.156	0.743	0.032	0.252	0.194
77	195912_3H	124	2	0.284	0.13	0.753	0.122	0.319	0.278
78	195912_3V	124	2	0.27	0.129	0.732	0.118	0.313	0.269
79	195913_1H	125	1	0.041	0.227	0.521			0.262
80	195913_1V	125	1	0.081	0.224	0.481			0.261
81	195913_2H	125	1	0.112	0.186	0.65			0.311
82	195913_2V	125	1	0.112	0.186	0.641			0.308
83	195913_3H	125	1	0.064	0.156	0.598			0.268
84	195913_3V	125	1	0.057	0.159	0.614			0.272
85	195914_1H	125	2	0.041	0.158	0.317	0.258		0.191
86	195914_1V	125	2	0.063	0.156	0.301	0.256		0.191
87	195914_2H	125	2	0.115	0.183	0.33	0.269		0.222
88	195914_2V	125	2	0.103	0.19	0.315	0.248		0.213
89	195914_3H	125	2	0.082	0.213	0.359	0.249		0.225
90	195914_3V	125	2	0.073	0.229	0.307	0.249		0.214
91	195915_1H	126	1	0.075	0.172	0.561	0.161		0.239
92	195915_1V	126	1	0.05	0.183	0.574	0.159		0.238
93	195915_2H	126	1	0.14	0.218	0.592	0.19		0.282
94	195915_2V	126	1	0.111	0.209	0.594	0.18		0.271
95	195915_3H	126	1	0.114	0.226	0.533	0.155		0.256
96	195915_3V	126	1	0.083	0.211	0.519	0.142		0.237
Average 1									0.242531
Average 2									0.213311

Table.C.3 Studies of Natural Wear Rate

No.	Wheel Position	Installed Locomotive	Installed Bogie	Wear rate ( natural)					
				1	2	3	4	5	Average
1	195900_1H	119	1	0.036	0.107	0.245	0.1	0.131	0.146
2	195900_1V	119	1	0.015	0.133	0.241	0.078	0.142	0.144
3	195900_2H	119	1	0.085	0.104	0.224	0.065	0.123	0.139
4	195900_2V	119	1	0	0.118	0.227	0.057	0.144	0.13
5	195900_3H	119	1	0.043	0.112	0.277	0.115	0.292	0.183
6	195900_3V	119	1	0.02	0.135	0.276	0.094	0.291	0.18
7	195901_1H	122	1	0.175	0.059	0.123	0.073	0.088	0.098

8	195901_1V	122	1	0.2	0.063	0.104	0.075	0.092	0.101
9	195901_2H	122	1	0.163	0.027	0.09	0.053	0.06	0.072
10	195901_2V	122	1	0.176	0.031	0.086	0.059	0.062	0.077
11	195901_3H	122	1	0.184	0.052	0.235	0.063	0.09	0.116
12	195901_3V	122	1	0.212	0.051	0.237	0.075	0.111	0.126
13	195902_1H	111	2	0.123	0.119				0.121
14	195902_1V	111	2	0.123	0.086				0.109
15	195902_2H	111	2	0.062	0.066				0.064
16	195902_2V	111	2	0.074	0.082				0.077
17	195902_3H	111	2	0.099	0.092				0.096
18	195902_3V	111	2	0.096	0.091				0.094
19	195903_1H	119	2	0.02	0.137	0.34	0.109		0.192
20	195903_1V	119	2	0.035	0.091	0.318	0.089		0.171
21	195903_2H	119	2	0	0.096	0.3			0.174
22	195903_2V	119	2	0.077	0.102	0.296			0.191
23	195903_3H	119	2	0.026	0.118	0.308			0.19
24	195903_3V	119	2	0.029	0.101	0.314			0.189
25	195904_1H	120	1	0.043	0.109	0.245	0.13		0.155
26	195904_1V	120	1	0.04	0.118	0.217	0.105		0.14
27	195904_2H	120	1	0.013	0.099	0.21	0.076		0.122
28	195904_2V	120	1	0.066	0.107	0.213	0.085		0.136
29	195904_3H	120	1	0.036	0.132	0.224	0.101		0.144
30	195904_3V	120	1	0.051	0.124	0.22	0.152		0.155
31	195905_1H	121	2	0.175	0.056	0.099	0.062	0.083	0.09
32	195905_1V	121	2	0.208	0.059	0.113	0.077	0.088	0.104
33	195905_2H	121	2	0.155	0.024	0.074	0.049	0.075	0.069
34	195905_2V	121	2	0.165	0.023	0.068	0.054	0.071	0.07
35	195905_3H	121	2	0.169	0.046	0.094	0.063	0.096	0.087
36	195905_3V	121	2	0.195	0.053	0.094	0.084	0.095	0.099
37	195906_1H	120	2	0.031	0.122	0.244	0.131		0.155
38	195906_1V	120	2	0.016	0.133	0.253	0.106		0.153
39	195906_2H	120	2	0.025	0.101	0.23	0.095		0.136
40	195906_2V	120	2	0.029	0.099	0.234	0.069		0.132
41	195906_3H	120	2	0.048	0.129	0.256	0.116		0.161
42	195906_3V	120	2	0.019	0.118	0.26	0.102		0.152
43	195907_1H	121	1	0.181	0.081	0.119	0.072	0.108	0.107
44	195907_1V	121	1	0.179	0.063	0.147	0.072	0.104	0.107
45	195907_2H	121	1	0.164	0.028	0.094	0.047	0.076	0.075
46	195907_2V	121	1	0.176	0.037	0.101	0.053	0.077	0.082
47	195907_3H	121	1	0.187	0.046	0.114	0.058	0.1	0.093
48	195907_3V	121	1	0.189	0.097	0.117	0.079	0.135	0.117
49	195908_1H	122	2	0.182	0.062	0.093	0.069	0.084	0.093
50	195908_1V	122	2	0.188	0.057	0.096	0.072	0.072	0.092
51	195908_2H	122	2	0.171	0.028	0.078	0.049	0.068	0.072

52	195908_2V	122	2	0.159	0.025	0.078	0.048	0.049	0.066
53	195908_3H	122	2	0.203	0.049	0.191	0.081	0.094	0.115
54	195908_3V	122	2	0.182	0.045	0.181	0.072	0.067	0.101
55	195909_1H	116	2	0.105	0.05	0.094	0.125	0.062	0.083
56	195909_1V	116	2	0.092	0.048	0.089	0.086	0.091	0.081
57	195909_2H	116	2	0.067	0.038	0.058	0.088	0.05	0.057
58	195909_2V	116	2	0.061	0.041	0.052	0.068	0.077	0.059
59	195909_3H	116	2	0.089	0.054	0.082	0.116	0.094	0.084
60	195909_3V	116	2	0.092	0.056	0.073	0.104	0.098	0.083
61	195910_1H	116	1		0.055	0.095	0.116	0.087	0.071
62	195910_1V	116	1		0.063	0.107	0.13	0.079	0.075
63	195910_2H	116	1	0.066	0.038	0.253	0.06	0.074	0.107
64	195910_2V	116	1	0.099	0.046	0.248	0.098	0.055	0.114
65	195910_3H	116	1	0.067	0.084	0.093	0.092	0.069	0.069
66	195910_3V	116	1	0.088	0.109	0.124	0.084	0.082	0.082
67	195911_1H	124	1	0.09	0.111	0.089	0.083		0.095
68	195911_1V	124	1	0.074	0.128	0.114	0.107		0.107
69	195911_2H	124	1	0.07	0.089	0.06	0.054		0.07
70	195911_2V	124	1	0.085	0.086	0.047	0.061		0.072
71	195911_3H	124	1	0.115	0.108	0.093	0.081		0.099
72	195911_3V	124	1	0.099	0.099	0.072	0.086		0.09
73	195912_1H	124	2	0.065	0.113	0.124	0.112		0.104
74	195912_1V	124	2	0.089	0.107	0.118	0.086		0.099
75	195912_2H	124	2		0.081	0.059	0.057		0.052
76	195912_2V	124	2		0.089	0.061	0.059		0.055
77	195912_3H	124	2	0.082	0.114	0.057	0.079		0.087
78	195912_3V	124	2	0.093	0.114	0.076	0.086		0.095
79	195913_1H	125	1	0.21	0.062	0.088			0.118
80	195913_1V	125	1	0.172	0.062	0.129			0.119
81	195913_2H	125	1	0.178	0.028	0.037			0.079
82	195913_2V	125	1	0.177	0.031	0.04			0.08
83	195913_3H	125	1	0.189	0.059	0.083			0.108
84	195913_3V	125	1	0.196	0.059	0.063			0.104
85	195914_1H	125	2	0.194	0.037	0.052	0.424		0.166
86	195914_1V	125	2	0.156	0.055	0.067	0.425		0.166
87	195914_2H	125	2	0.154	0.031	0.035	0.413		0.148
88	195914_2V	125	2	0.168	0.027	0.044	0.437		0.158
89	195914_3H	125	2	0.189	0.062	0.063	0.291		0.145
90	195914_3V	125	2	0.199	0.057	0.1	0.296		0.156
91	195915_1H	126	1	0.163	0.068	0.073	0.126		0.106
92	195915_1V	126	1	0.188	0.059	0.059	0.128		0.107
93	195915_2H	126	1	0.161	0.03	0.043	0.097		0.081
94	195915_2V	126	1	0.194	0.04	0.038	0.108		0.094
95	195915_3H	126	1	0.187	0.058	0.067	0.132		0.109

96	195915_3V	126	1	0.219	0.068	0.09	0.142		0.128
Average1									0.111688
Average2									0.1129

Table.C.4 Studies of the Ratio of Wear Rate (Re-profiling / Natural)

No.	Wheel Position	Installed Locomotive	Installed Bogie	Ratio of wear rate (re-profiling / natural)					
				1	2	3	4	5	Average
1	195900_1H	119	1	9.417	1.336	0.592	2.953	1.217	1.381
2	195900_1V	119	1	24	0.894	0.613	4.102	1.004	1.398
3	195900_2H	119	1	2.425	2.289	0.692	5.41	1.41	1.532
4	195900_2V	119	1	0	1.89	0.675	6.246	1.012	1.71
5	195900_3H	119	1	6.463	1.667	0.368	2.636	0	0.905
6	195900_3V	119	1	14.873	1.212	0.372	3.464	0	0.931
7	195901_1H	122	1	0.464	3.405	0.901	2.289	1.833	1.545
8	195901_1V	122	1	0.264	3.082	1.283	2.247	1.71	1.469
9	195901_2H	122	1	0.942	8.804	1.674	3.545	3.202	2.636
10	195901_2V	122	1	0.808	7.475	1.825	3.167	2.968	2.436
11	195901_3H	122	1	0.473	4.263	0	2.774	1.77	1.203
12	195901_3V	122	1	0.318	4.319	0	2.195	1.283	1.024
13	195902_1H	111	2	7.333	2.356				5.452
14	195902_1V	111	2	7.333	3.587				6.194
15	195902_2H	111	2	13.706	6.519				10.905
16	195902_2V	111	2	11.346	5.211				8.804
17	195902_3H	111	2	8.434	4.952				7.13
18	195902_3V	111	2	8.709	4.952				7.264
19	195903_1H	119	2	16.857	0.462	0.585	4.051		1.237
20	195903_1V	119	2	9.309	1.257	0.681	5.211		1.506
21	195903_2H	119	2	0	1.604	0.799			1.347
22	195903_2V	119	2	3.167	1.488	0.821			1.132
23	195903_3H	119	2	10.494	1.128	0.748			1.114
24	195903_3V	119	2	9.204	1.475	0.718			1.128
25	195904_1H	120	1	7.696	0.821	0.686	3.032		1.494
26	195904_1V	120	1	8.434	0.724	0.894	4		1.762
27	195904_2H	120	1	26.027	1.336	0.953	4.682		2.012
28	195904_2V	120	1	4.405	1.123	0.938	4.051		1.703
29	195904_3H	120	1	7.621	0.767	0.848	3.237		1.506
30	195904_3V	120	1	5.135	0.873	0.876	1.825		1.326
31	195905_1H	121	2	0.515	5.173	1.463	2.497	2.546	2.049
32	195905_1V	121	2	0.302	4.78	1.183	1.786	2.279	1.646
33	195905_2H	121	2	0.692	13.085	2.106	3.739	2.861	2.968
34	195905_2V	121	2	0.608	13.925	2.356	3.274	3.098	2.906
35	195905_3H	121	2	0.473	6.407	1.653	2.378	2.03	2.106

36	195905_3V	121	2	0.267	5.494	1.674	1.545	2.04	1.747
37	195906_1H	120	2	9.204	0.767	0.776	1.653		1.227
38	195906_1V	120	2	18.231	0.592	0.709	2.333		1.257
39	195906_2H	120	2	11.821	1.096	0.901	2.676		1.551
40	195906_2V	120	2	9.753	1.132	0.869	4.025		1.625
41	195906_3H	120	2	5.579	0.637	0.712	2.012		1.155
42	195906_3V	120	2	15.949	0.786	0.678	2.436		1.278
43	195907_1H	121	1	0.316	2.891	1.283	1.959	2.322	1.551
44	195907_1V	121	1	0.344	3.975	0.838	1.967	2.413	1.558
45	195907_2H	121	1	0.451	10.111	1.849	3.608	3.695	2.636
46	195907_2V	121	1	0.362	7.621	1.674	3.049	3.525	2.311
47	195907_3H	121	1	0.227	5.494	1.571	2.676	2.546	1.899
48	195907_3V	121	1	0.16	2.155	1.475	1.688	1.646	1.309
49	195908_1H	122	2	0.342	3.219	1.132	2.344	1.882	1.558
50	195908_1V	122	2	0.294	3.566	1.033	2.236	2.39	1.591
51	195908_2H	122	2	0.449	8.174	1.525	3.902	2.448	2.289
52	195908_2V	122	2	0.546	9.204	1.681	3.739	3.762	2.584
53	195908_3H	122	2	0.195	4.291	0.038	1.95	1.469	1.062
54	195908_3V	122	2	0.332	4.814	0.083	2.289	2.534	1.331
55	195909_1H	116	2	1.41	5.024	2.04	2.521	3.202	2.584
56	195909_1V	116	2	1.786	5.289	2.226	4.051	1.874	2.69
57	195909_2H	116	2	2.937	7	3.95	3.717	4.464	4.236
58	195909_2V	116	2	3.367	6.299	4.587	5.452	2.39	4.076
59	195909_3H	116	2	2.135	4.236	2.497	1.882	2.413	2.546
60	195909_3V	116	2	2.086	4.025	2.891	2.236	2.247	2.61
61	195910_1H	116	1	4.155	2.268	3.367	2.69		2.937
62	195910_1V	116	1	3.525	1.907	2.906	3.049		2.704
63	195910_2H	116	1	0.733	0.976	7.333	3.367		2.534
64	195910_2V	116	1	0.961	0.942	4.236	4.814		2.356
65	195910_3H	116	1	3.184	2.676	4.587	2.448		3.049
66	195910_3V	116	1	2.195	1.825	3.167	2.802		2.413
67	195911_1H	124	1	1.786	1.481	6.937	1.674		2.534
68	195911_1V	124	1	2.378	1.183	5.098	1.105		2.115
69	195911_2H	124	1	2.861	1.985	10.765	3.237		3.831
70	195911_2V	124	1	2.195	2.04	14.152	2.745		3.695
71	195911_3H	124	1	1.653	1.252	6.576	1.907		2.413
72	195911_3V	124	1	2.086	1.475	8.709	1.717		2.745
73	195912_1H	124	2	4.076	1.155	5.536	0.842		2.448
74	195912_1V	124	2	2.704	1.278	5.897	1.288		2.584
75	195912_2H	124	2	1.924	12.889	1.041			3.926
76	195912_2V	124	2	1.77	12.158	0.55			3.525
77	195912_3H	124	2	3.484	1.141	13.085	1.545		3.202
78	195912_3V	124	2	2.891	1.132	9.638	1.37		2.846
79	195913_1H	125	1	0.196	3.651	5.897			2.215
80	195913_1V	125	1	0.473	3.63	3.739			2.195

81	195913_2H	125	1	0.631	6.576	17.519			3.926
82	195913_2V	125	1	0.631	6.042	15.949			3.831
83	195913_3H	125	1	0.337	2.65	7.197			2.472
84	195913_3V	125	1	0.292	2.676	9.753			2.61
85	195914_1H	125	2	0.212	4.236	6.143	0.608		1.151
86	195914_1V	125	2	0.401	2.846	4.464	0.603		1.151
87	195914_2H	125	2	0.748	5.944	9.526	0.653		1.5
88	195914_2V	125	2	0.616	7.065	7.065	0.567		1.347
89	195914_3H	125	2	0.433	3.425	5.711	0.855		1.551
90	195914_3V	125	2	0.366	4.025	3.065	0.842		1.37
91	195915_1H	126	1	0.462	2.534	7.621	1.278	3.049	2.247
92	195915_1V	126	1	0.266	3.132	9.753	1.242	3.115	2.226
93	195915_2H	126	1	0.873	7.264	13.925	1.959	4.319	3.484
94	195915_2V	126	1	0.572	5.25	15.393	1.66	3.695	2.891
95	195915_3H	126	1	0.61	3.926	7.929	1.169	2.953	2.344
96	195915_3V	126	1	0.381	3.115	5.803	0.996	2.436	1.857
Average 1									2.4515
Average 2									2.1





