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"Introduction and automation of energy performance indicators and energy baselines according to DIN ISO 50006 - A critical evaluation of production facilities in the food industry"

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Abstract:

This study provides a practical example of DIN ISO 50006 for the introduction and application of energy performance indicators (EnPIs) and energy baselines (EnBs). Based on the evaluation of a production process of the food company H. & J. Brüggen KG, the standard is tested for its applicability. An overview is given of the procedure and the requirements proposed or demanded by the standard. Through the subsequent evaluation of the production plants based on regression analyses, the production process is evaluated and the potential for improvement is identified concerning the standard's application descriptions. Also, an automation concept for determining EnPIs and EnBs is presented.

Keywords: DIN ISO 50001, DIN ISO 50006, energy management, energy management system, energy efficiency, energy performance indicator, energy baseline, sustainability.

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1. Introduction

“… We must find a smooth transition to a low-carbon economy. ... By polluting the oceans, not mitigating CO2 emissions and destroying our biodiversity, we are killing our planet. Let us face it: There is no Planet B” (Noack 2018) said French President Emanuel Macron in his speech in Washington in April 2018, emphasizing the seriousness of the issue of climate change. In this context, energy-intensive industrial companies, in particular, are under extraordinary social and economic pressure given the growing awareness of sustainability in politics and economy.

Given this fact, companies are urged to use their resources more efficiently and increase their energy efficiency to meet legal requirements and ensure their competitiveness. Many companies resort to energy management systems for this purpose. The International Organization for Standardization offers a globally recognized standard for implanting such systems within the framework of the standard DIN ISO 50001. In this context, companies' energy efficiency is determined and presented through the introduction and application of energy performance indicators (EnPIs) and energy baselines (EnBs). The EnPIs and EnBs are regulated in DIN ISO 50006 and are mandatory for certification.

Accordingly, an implementation of these is necessary for companies seeking certification according to DIN ISO 50001, such as the company H. & J. Brüggen KG (from now on Brüggen). The internationally active food company wants to evaluate its production processes' energy-based performance by introducing and applying EnPIs and EnBs.

In this study, the background and incentives for integrating an energy management system for German companies are discussed. The recommended procedure and the requirements of DIN ISO 50006 regarding the implementation of EnPIs and EnBs and their application are explained and presented in a clear structure. The subsequent practical implementation of the previously theoretically described implementation is exemplified using crunchy cereal production process. The quantitative analysis carried out provides an energetic evaluation of the individual production plants and a comparison between the plants. Besides, an automation concept for the implementation of EnPIs and EnBs is developed and implemented.

Thus, the present study implements EnPIs and EnBs for one of the company's most energy-intensive production processes as an example, which provides the company with a basis for implementing further EnPIs and EnBs for other plants or processes. Also, the applicability of the DIN ISO 50006 standard is tested by applying it under real conditions.

2. Background

The enormous CO2 emissions produced worldwide present us with one of the most significant challenges of the 21st century, climate change. A large part of these emissions is due to energy production and industrial processes (Maslin 2014, 67). To meet this challenge, the European Parliament has set climate and energy policy targets for all member states to achieve by 2030. The three core targets are to reduce greenhouse gas emissions by 40% compared to the 1990 reference period, to increase the share of renewable energy to at least 32%, and to increase energy efficiency by at least 32.5% compared to an underlying reference development (European Commission 2014).

In December 2019, the Energy Efficiency Strategy 2050 (EffSTRA) was adopted in Germany. This strategy is intended to promote Germany's energy efficiency and contribute to meet the European climate and energy policy goals. The national climate efficiency target 2030 included in it envisages a reduction of 30% in primary energy consumption compared to the reference year 2008, which would correspond to a saving of 1200 TWh (1 TWh = 1 billion kWh). This saving would correspond to the combined energy consumption of the Netherlands and Austria today. Germany is thus not only making an ambitious contribution to European climate and energy policy, but also a disproportionately large one. To achieve this goal, the National Action Plan of Energy Efficiency 2.0 (NAPE) was introduced, which focuses on municipalities, companies, and consumers and aims to encourage these players to use energy more sparingly and efficiently (Federal Ministry for Economic Affairs and Energy 2020).

Industrial companies, in particular, play an essential role here. In 2019, Germany's industrial sector was the largest consumer of electricity, accounting for 45.7%. It was followed by trade, commerce, and services (27.4%) and households (24.6%), which accounted for around a quarter (Statista 2020). Furthermore, the German industrial sector emitted 188 million metric tons of greenhouse gas into the atmosphere in 2019, topped only by the energy industry with 254 million metric tons of greenhouse gas. Germany thus produces the most carbon dioxide emissions in the European Union (Statista 2020).

To incentivize companies to improve their energy efficiency, the German government provides funding to support, among other things, investment in environmentally friendly technologies, the switch to renewable energies, and the implementation of an energy management system (Federal Ministry for Economic Affairs and Energy 2020). A further incentive for the latter is a peak compensation under the Energy and Electricity Tax Act, which grants tax relief to companies that can demonstrate a certified energy management system by DIN ISO 50001 (Environment Federal Office 2020). According to the International Organization of Standardization (ISO), energy management systems help control energy consumption within companies and thus improve their productivity. In the process, an energy policy is developed and implemented. Also, energy consumption targets are defined, and action plans are designed to support the target's achievement (ISO 2018, 2).

Management systems and performance indicators for companies have already been considered for many areas, such as environment (Perotto et al. 2008, 518-520), quality, delivery time, safety, and cost (May et al. 2013, 258). The topic of environmental challenges and energy efficiency has become increasingly important in recent decades, as reports by the European Environment Agency (European Environment Agency 2019, 9-17) and International Energy

Agency (International Energy Agency 2020, 1-6) show. Also, through the introduction of the DIN ISO 50001 standard in 2011 and its dissemination, the area of energy efficiency in terms of energy-related performance control systems and performance indicators became more and more critical. In 2012, one year after introducing the standard, the number of organizations increased from 459 to 1981, which corresponds to an annual growth of 332% compared to the previous year. This growth trend continued so that in 2015, 11985 organizations were certified according to DIN ISO 50001 (Marimon and Casadesús 2017, 1).

Energy-related performance indicators make it possible to identify and evaluate optimization potential by collecting and analyzing energy-related data. The main objectives of this process are to collect the most relevant energy-related information of a system exclusively, to present an overview of the energy performance, which allows identifying savings measures and to enable permanent monitoring of the energy-related performance (Gonzales-Gil et al. 2015, 289). With DIN ISO 50006, practical guidance regarding the creation of energy-related performance indicators was published in 2014, which considers the requirements of DIN ISO 50001.

In addition to the International Organization of Standardization (ISO), other organizations have addressed energy performance measurement. One is Carbon Trust, through a guide to control energy use (Carbon Trust 2019, 4). The other is the Efficiency Valuation Organization, through its energy conservation concepts (Efficiency Valuation Organization 2012, 1-2).

3. Methodology

This work project aims to gain a deeper understanding of how energy performance indicators and energy baselines according to DIN ISO 50006 work and to test their practical applicability. A deductive approach was followed, which aims to test the applicability of an existing theory, presented here in the form of DIN ISO 50006, through practical implementation at the company's selected production facilities.

The quantitative data required for analyzing the production plants concerning the calculation parameters depends on the plants or processes considered. Accordingly, the calculation parameters and the data sources to be collected can change when other plants or processes are considered.

The production facilities' present analysis considers the environmental and production parameters: total product (consisting of primary product and secondary product), working hours, shutdowns, outside temperature, steam, shifts per day and the energy sources electricity and gas. These were identified through analysis of the production process and discussions with the responsible employees. In addition to the parameters mentioned, other parameters were determined, such as layer height, belt speed, product change, and water quantity, which could not be included in the calculations due to a lack of data.

The total product was taken from the ERP system SAP, making it possible to divide it into the primary and secondary products. The average outside temperature values was obtained from an external supplier and represent the only secondary data. The internal monitoring tool called Libra records the energy-related measured values of the individual plants in the company via numerous measuring points. It enables these data to be displayed at different time intervals. Thus, it was possible to determine the measured values of the energy carriers electricity and gas. The amount of steam used is also recorded in Libra. However, this is to be considered as an output factor since it is generated by gas. Besides, the working hours and shutdowns were determined based on the energy-related measured values.

When collecting data for the environmental and calculation parameters, two criteria had to be met. First, a data frequency at a daily level had to be ensured. Second, the data had to be available for the intended calculation period from January 2019 to October 2020.

Before the analysis, the collected data was prepared. Using conditional formatting in Excel, zero production values, and erroneous measured values were eliminated. Also, statistical outliers were excluded from the data set. For this purpose, the interquartile range method was used for the exemplary implementation. Subsequently, after developing and implementing an automation concept, the Cook, Student, and Conf. methods were added. Then, the data were examined by the application of linear regressions.

The practical application of the theoretical standard under real conditions offers the opportunity to uncover ambiguities concerning the requirements as well as implementation difficulties and thus to provide starting points for revising them by expanding or improving the corresponding aspects in the standard.

4. Theoretical basics of DIN ISO 50006

DIN ISO 50001, which provides the basis for the development of DIN ISO 50006, supports companies in establishing processes required for continuous improvement of energy-related performance. In doing so, greenhouse gas emissions and other environmental impacts, such as energy costs, are counteracted through the application of systematic energy management (ISO 50001 2018, 7-9). Thereby, the company must determine energy performance indicators (EnPIs) suitable for measuring and monitoring energy-related performance and enable it to demonstrate an improvement in energy-related performance (ISO 50001 2018, 22). Besides, DIN ISO 50006 guides implementing the establishment and application of the required energy performance indicators (EnPIs) and the corresponding energy baselines (EnBs) (ISO 50006 2017, 4).

Thus, the standard's common goal is to improve energy-related performance supported by the EnPIs and reduce energy costs. Since the implementation of the standard is voluntary, companies must be given incentives. As a rule, the economic benefit is in the foreground. On the one hand, this arises from the energy cost savings due to the regular deviation analyses by the EnPIs (Nissen et al. 2018, 113-114). On the other hand, through the state's peak tax compensation for companies that are certified according to DIN ISO 50001 (Nissen et al. 2018, 3).

4.1 EnPI boundaries

It is necessary to define the area to be evaluated by the energy performance indicators. EnPI boundaries are set to identify the most energy-intensive part of the production processes. After the entire factory's initial consideration, the measurement boundaries are narrowed down to the individual plants. By allocating the energy consumptions, they are divided into primary consumers and secondary consumers. A further subdivision of the plants into the individual plant components is possible (ISO 50006 2017, 30). Even before the EnPI boundaries are defined, it is necessary to determine the EnPI users (ISO 50006 2017, 13). The type and complexity of the EnPI to be determined should be adapted to their needs (ISO 50006 2017, 21).

4.2 Relevant variables and static factors

The standard requires identifying factors that influence energy consumption for the primary consumers identified to be able to carry out the normalization necessary (in most cases) in the later course of the analysis. It is essential to isolate the factors that have a high impact on energy consumption from those with little or no impact. Trend diagrams and XY diagrams should be set up to evaluate the influence, thus determining each variable's relevance against energy consumption (ISO 50006 2017, 15-16). The influencing factors should be examined to determine whether they should be considered as relevant variables or static factors. The latter are factors that typically do not vary. Relevant variables are actively involved in determining

EnPIs, while static factors are documented and used to adjust EnPIs in the event of a significant change (ISO 50006 2017, 17).

4.3 Data quality

The quality of the collected data can be reduced by faulty counting or data acquisition and atypical operating conditions. The resulting outliers must be identified and excluded from the database. It is crucial to ensure that the exclusion of outliers does not lead to systematic errors in the generation of EnPIs (ISO 50006 2014, 20).

4.4 Energy performance indicators (EnPIs)

After identifying the relevant variables, appropriate EnPIs should be defined for the primary consumers, divided into four types. The measured energy value, where the total energy consumption is measured and given as an absolute value. This type of EnPI is only used if influencing factors could not be identified, the coefficient of determination is too low, or there is not enough data to be declared as an influencing factor.

The ratio of the measured values expresses the energy efficiency with only one variable as a simple ratio. The energy consumption is divided by the value of the variable, e.g., energy consumption divided by total product. This has the advantage that the normalization is automatic and does not have to be done subsequently. However, it is assumed here that the energy consumption is 100% dependent on the variable used and that there is no baseload.

The statistical model evaluates the relationship between energy consumption and one or more variables through a regression model. This model is used when more than one relevant variable has been identified and/or the process under consideration has a baseload.

The engineering model evaluates the relationship between energy consumption and many relevant variables through an engineering simulation. Given the high complexity, this approach is rarely used in practice (Nissen et al. 2018, 70-73).

4.5 Energy baselines (EnBs)

An energy baseline (EnB) represents a defined period that serves as a quantitative reference point compared to actual EnPI values, thus enabling changes in energy-related performance to be demonstrated (ISO 50006 2017, 7). The basis for this comparison is the determination of the EnPIs for the EnBs described before. A time period should be chosen that is long enough to account for the variability of operational processes. Typically, the period is 12 months to ensure that seasonality is taken into account (ISO 50006 2014, 24).

For the selected period, the energy consumption of the primary consumers and the data of the relevant variables and static factors identified as relevant must now be collected. Based on this database, a comparison could be made between the current EnPI values of the reporting period and the reference period's EnPI values, provided that no changes have taken place in the relevant variables, which is usually not the case (Nissen et al. 2018, 50).

4.6 Concept of normalization

In the likely event that the relevant variables have changed between the reference and reporting periods, normalization of the EnBs is necessary to allow comparison under identical conditions. Normalization occurs automatically when one variable is used by presenting it as a ratio (Nissen et al. 2018, 47). When considering multiple variables, regression models are typically used to normalize energy consumption concerning the variables. Accordingly, normalization through the EnPI occurs by incorporating the changes in the relevant variables into calculating the EnPI values. In other words, it tries to adapt the values set in the past to current conditions. Also, the concept of normalization can be used to forecast future energy consumption (ISO 50006 2017, 36).

5. Analysis and evaluation of crunchy cereal production

In this chapter, the implementation of energy performance indicators (EnPIs) and the corresponding energy baselines (EnBs) for the process of crunchy cereal production is presented. The procedure is explained step by step using an example plant. In addition, an automation concept is presented that was developed for the calculations required in the analysis. Furthermore, by using the developed calculation tool, the plants are compared with each other. All calculations refer to the reference period 2019 and the reporting period of 2020 (Jan - Oct).

5.1 Determination of EnPI users and EnPI boundaries

This analysis primarily serves the energy management team, which thus represents the EnPI users. Their task is to demonstrate energy-related performance improvement, identify potential savings, and develop energy-saving measures.

EnPI boundaries were defined to determine the optimum between setting up EnPIs and the resulting benefits. They help to focus on the most energy-intensive plants or processes. Based on the assumption that the plants with the highest energy consumption also contain the most significant savings potential, they were evaluated according to their total energy consumption. Following the pareto principle, which states that 80% of the output is produced by 20% of the input (Kumar 2015, 54-55), the percentage consumption shares of the total energy consumption were assigned to the individual plants and added until the cumulative consumption share represented around 80%. This procedure is illustrated in table 5.1, "Listing pareto principle."

Looking at the table, it can be seen that the 12 most consumptive plants of the company, which is 19.05% for 63 plants, account for 81.32% of the total energy consumption. These plants are called SEU plants (SEU = Significant Electric Use). The measurement data used for evaluation were collected from an internal monitoring tool, Libra, and refers to the reference period 2019. Libra collects and documents the energy-related data for each plant through numerous measuring points in both production halls. Meanwhile, the monitoring tool records 97% of the company's total energy consumption. The 3% of the energy that is not recorded must be taken into account when interpreting the EnPIs. The company's production processes use electricity and gas as energy sources. Electricity is recorded in kilowatt-hours and gas in cubic meters. For a uniform view of energy consumption, the gas values were converted to kilowatt-hours. Due to the low share of electricity consumption in total energy consumption (about 9.8%), both energy sources were considered together for the analysis. The final subdivision of the EnPI boundaries has placed the energy performance indicator system's focus on the plants determined by the Pareto principle. A pictorial representation of the EnPI boundaries is shown in figure 5.1, "EnPI boundaries."

5.2 Determination of relevant variables and static factors

To identify factors influencing the energy consumption of the example plant 1620 crunchy cereals (hereafter 1620), it was essential to understand the plant's production process. The plant was inspected, relevant documents were analyzed, and discussions were held with the responsible employees to acquire the necessary knowledge. The following influencing factors were derived: Primary product, secondary product (waste), total product, steam, water quantity, layer height, belt speed, product change, outside temperature, working hours, shutdowns, and shifts per day. A more detailed list is shown in table 5.2, "Overview of influencing factors".

Water quantity, product change, layer height, and belt speed were excluded in advance due to a lack of data. Such data should be considered in future data collection. Besides, only the total product was considered, consisting of the primary product and secondary product (waste).

This is because the secondary product (waste) can arise at several points in the production process, and it is not possible to assign it precisely to these points. The subdivision of the influencing factors into variables and static factors showed that only the shifts per day are regarded as static factors since these do not change routinely. All other factors are considered as possible relevant variables**.**

The available measurement data for energy consumption and the influencing factors form the further procedure's data basis. Before the calculations, outliers must be removed. For this purpose, conditional formatting in Excel was used to remove all data points that do not correspond to normal operating conditions, such as zero productions or data that indicate incorrect measurements. Also, the interquartile range method was used to exclude statistical outliers. The adjusted database now includes 277 data points at a daily level, which represent the energy baseline (EnB).

For initial analysis of the data, a trend diagram and an XY diagram were prepared for each potential influencing factor as part of a diagram analysis to assess the relevance compared to energy consumption (see figure 5.2, "Diagram analysis").

As can be seen from the figures, the variables total product, steam, working hours, and shutdowns show similar changes as the energy consumption. It should be noted, however, that the shutdowns show a negative relationship to energy consumption. Moreover, the seasonal dependence of the temperatures can be seen. However, temperature changes very differently from energy consumption, which can be seen in the coefficient of determination (R^2) of 0.0033.

The determination coefficient indicates how much of the total energy consumption can be described by the corresponding variable. Thus, it can be assumed that the temperature has almost no influence on the plant's energy consumption. However, the other variables have a stronger relationship with energy consumption, with 0.7641 for the total product, 0.575 for steam, and 0.9008 for working hours and shutdowns. For the most accurate description of energy-related performance by the EnPIs, a coefficient of determination of 0.95 is targeted (to be determined by the company). Even if the considered variables alone do not show the desired coefficient of determination, simultaneous consideration of several variables can nevertheless lead to a high overall explanation of the energy consumption. Thus, the variables whose combination has the highest coefficient of determination are considered for the compilation of the EnPI.

5.3 Determination of the energy performance indicator

First, it has to be determined which type of EnPI is most appropriate. Since multiple relevant variables have been identified, and the plant has a baseload, a statistical model was used to establish the EnPI. Therefore, it involves using regression analysis to determine which combination of variables has the highest coefficient of determination to provide the most accurate measurement.

The first linear regression analysis performed (linearity is assumed) includes the variable with the highest determination coefficient in the model. In this case, shutdowns (It could also have started with working hours). When using one variable, the regression analysis can be done by an XY diagram. In addition to the coefficient of determination, a function is also shown that describes the plant's energy consumption (see figure 5.3, "Regression with shutdowns").

Formula 5.1: Energy consumption per day in kWh = -918.09 $\frac{kWh}{h}$ * *Shutdowns [h] + 20981 kWh*

A look at the function tells us that the shutdown's coefficient is negative, which means that a higher number of shutdowns leads to lower energy consumption. We can also see that part of the energy consumption cannot be explained only by the change in the shutdowns, but for the calculations of more accurate values, a constant of 20981 kWh per day must be taken into account. It is obvious to consider the constant as the plant's baseload, but this would be correct only in exceptional cases. This may be due to several reasons, among others: the data describe only a subrange of the function, which can be well represented linearly, although the entire function is not linear. Therefore, the constant is primarily used to fit the function to the available data.

Even if the model with relatively high accuracy ($R^2 = 0.9008$) can already estimate the actual values reasonably, there are still partly clear deviations, as shown in figure 5.4, "Comparison of measured and actual values with one variable" at the example of the month February. This indicates that not all relevant variables have been considered yet.

In the next regression analysis, the variables shutdowns and working hours are considered together. The corresponding regression output is shown in figure 5.5, "Regression shutdowns, working hours". When looking at the results, it is noticeable that the column of shutdowns is filled with zeros and the P-values of both variables show an error. This is due to the problem of multicollinearity. The test for collinearity using an XY diagram (see figure 5.6, "Testing for collinearity") shows that there is perfect collinearity ($R^2 = 1$) between the two variables, which makes it impossible to perform a linear regression analysis computationally. This is because both variables were collected based on the same database. This means that only one of the two variables can be integrated into the model. As a result, the variable shutdowns are used for the further exemplary presentation, which is considered together with the total product in the subsequent regression analysis (figure 5.7, "Regression shutdowns, total production").

When considering the regression output of a model with multiple variables, it must be ensured that the adjusted coefficient of determination is taken into account for the evaluation, which also includes the complexity of the model.

Furthermore, the statistical significance of the model and the variables must be checked. The check for the model is done by controlling the F-value and the significance F. The significance F describes the probability that the whole model is not statistically significant and should be below 0.05, which corresponds to a confidence interval of 95%. The F-value is also an indicator of whether a model is statistically significant and should exceed the corresponding theoretical value. The theoretical value was determined using Excel (Excel function: F.INV).

To determine the statistical significance of the variables, on the one hand, the P-value is considered, which indicates the probability that the variable is not significant and should be less than 0.05. On the other hand, the value of the T-statistic is considered. The T-statistic value, which is also used to check the regression coefficients individually, should be greater than the corresponding theoretical value. The theoretical value is determined using the table of T-distribution and considering the type of T-test (here two-sided).

A look at the regression output shows that the adjusted coefficient of determination is now 0.9337 and has increased compared to when only shutdowns were considered. This means that the model can now describe 93.37% of the total energy consumption. The coefficient of shutdowns has decreased to -676.28, as well as the intercept to 15855.23. The additional coefficient states that per kg of total product produced, energy consumption increases by 0.11 kWh. The corresponding values also confirm the statistical significance of the model and the variables. The derived formula is:

Formula 5.2: Energy consumption per day in kWh = -676.28 $\frac{kWh}{h}$ ** shutdowns [h] + 0.11* $\frac{kWh}{Kg}$ ** total production [Kg] + 15855.53 kWh.*

Due to the increased adjusted coefficient of determination, the deviations between the calculated and actual values should be smaller, which is confirmed by the graphical representation in figure 5.8, "Comparison of measured and actual values with two variables".

Third regression analysis is checked whether the addition of the steam allows a further improvement of the determination coefficient. The corresponding regression output is shown in figure 5.9, "Regression shutdowns, total production, steam".

The regression output shows that the adjusted coefficient of determination increased only minimally from 0.9337 to 0.9376. At this point, it should be mentioned that variables that only slightly improve the coefficient of determination could also be omitted since more variables also mean more effort. The resulting improvement in the adjusted coefficient of determination should be commensurate with the effort involved. Accordingly, the variable steam was not integrated into the model.

Furthermore, the deviation's distribution chart (figure 5.10, "Distribution chart") shows that the deviations scatter relatively evenly around 0%. This means that there is no systematic over- or underestimation of the actual values. Also, an average deviation of 0.3% was determined over the 277 underlying daily values, which again underlines the value's accuracy. This indicates that all relevant influencing factors were taken into account, and thus a regression with further variables can be omitted. Accordingly, our EnPI for the plant 1620 in the 2019 reference period is represented by formula 5.2.

When looking at the deviation's distribution chart, it is also noticeable that individual values show larger deviations, which need to be investigated to derive appropriate measures. Thus, the EnPI makes it possible to show deviations that do not arise from the regular fluctuations of the variables and thus form a basis for measuring, monitoring, and presenting the plant's energy-related performance.

5.4 Proof of improvement in energy-related performance

To demonstrate the improvement in energy-related performance required by DIN ISO 50001, the actual EnPI values must be compared with the reference EnPI values of the energy baseline. To ensure that the comparison occurs under identical conditions, it is necessary to normalize the energy baseline using the established EnPI (formula 5.2). The EnPI describes the energy consumption behavior of the 1620 plant over the 277 days used as the energy baseline. Formula

5.2 thus represents the conditions during the reference period. By substituting the relevant variable's actual values into the EnPI (formula 5.2), the normalized energy baseline values for the reporting period are obtained. In other words, for the comparison, the actual daily values for shutdowns and total production are inserted into the EnPI (formula 5.2). The subsequent comparison of the normalized values with the actual values then makes it possible to show the changes in energy-related performance during the reporting period. By analyzing based on daily values, initially, only the daily reference values can be formed. These can then be added up to monthly values, as shown in table 5.3, "Listing of monthly values".

The table shows that concerning the 1620 plant, a saving of 428837 kWh was recorded during the reporting period. This corresponds to a reduction in the energy consumption of the plant of 10.78%. At a price of about 0.15 Euro/ kWh, this corresponds to a monetary saving of 64325.55 Euro. These calculated savings are due to the planned and implemented energy-saving measures.

If the company has planned and implemented energy-saving measures, the difference between the calculated values and the actual values should be clear, as in this case. In the graphical representation in figure 5.11, "Comparison of normalized and actual values", it is clear that the measures implemented were successful. From February onwards, a consistent saving can be seen. Thus, the improvement in the energy-related performance of plant 1620 has been demonstrated and presented in monetary and graphical form, as required from the DIN ISO 50006.

5.5 Automation

To reduce the effort of determining EnPIs and EnBs in the future, an automation concept was developed and implemented in cooperation with the company CBB Software Engineering. The Python-based calculation tool determines the statistical outliers of the imported data set and then provides a listing of the combinations of variables that achieve a previously determined coefficient of determination. Also, the statistical significance of the created model and considered variables is determined and highlighted in non-satisfaction. The input menu (see figure 5.12, "Input menu calculation tool") offers the user a series of input parameters to adapt the calculations to the available data set.

Among other things, the user can choose between several statistical methods for identifying outliers. In addition to the interquartile range method used in Chapter 5, the Cook, Student, and Conf. methods are available for selection. This offers the company the possibility to determine the combinations with the highest possible determination coefficient by excluding different data points by applying different statistical methods. Regarding the example plant 1620, table 5.4, "Comparison of statistical methods" shows that the coefficient of determination varies using different statistical methods. It also can be seen from the table that concerning plant 1620, the highest coefficient of determination (~96%) was obtained using the Student method. This corresponds to an increase in the determination coefficient of ~3% compared to the interquartile range method based on the same database. Thus, this calculation parameter contributes to the optimization of the measurement.

Also, the calculation tool eliminates the need to set cutoffs regarding the relevance of the variables. The calculation tool considers all imported variables, regardless of the coefficient of determination, and excludes those that do not contribute sufficiently to improve the coefficient of determination or are not statistically valid. This prevents influencing factors, which, when considered together with other variables, lead to an increase in the coefficient of determination, from being excluded from the Calculations due to their lower correlation with energy consumption. As an example, the output table for plant 1620 is shown in figure 5.13, "Results table". (The calculation tool only considers the R^2 and not the adjusted R^2. Therefore, small deviations occur).

5.6 Comparison of production facilities

In addition to plant 1620, which has already been discussed, crunchy cereal production also includes plant 1630 and 1640, all of which have been identified as SEU plants and are among the most energy-intensive plants. They account for 19.43% of the total energy consumption, which corresponds to about 12023415 kWh per year. For the analysis of the plants, the calculation tool described in the previous section was applied to clarify the statistical method's impact on the coefficient of determination and, therefore, to provide the most accurate measurement possible ultimately. The results are presented in table 5.5, "Comparison 1620, 1630 and 1640", which shows that all three plant's energy consumption is best described by the EnPI, which considers shutdowns and total product in the model, allowing a direct comparison of the plants. A look at the coefficients of determination obtained shows that the statistical method should be selected individually for each database. For example, for plant 1620 and 1640, the Student method achieves the highest coefficient of determination, while for plant 1630, the Cook method has the highest coefficient of determination.

When looking at the percentage change in energy-related performance, based on the highest coefficient of determination determined, it is noticeable that plant 1620 shows a significant improvement of 10.97%. Plant 1630 shows only about half the energy savings at 5.95%, and plant 1640 shows virtually no change at 0.52%. This shows the company the impact of the planned and implemented energy-saving measures on the individual plants. The task is to investigate why the measures at plant 1640 have not led to any improvement, and accordingly, the measures should be modified or new ones derived.

Also, it is noticeable that despite high coefficients of determination determined for the Student- (9.71%) and Conf.- (8.20%) method as well as for no statistical method used (8.26%), plant 1630 has a significantly higher percentage deviation between the calculated and actual values than the other calculations. This indicates a systematic over- or underestimation of the values, which is a systematic error that affects the measurement's accuracy. Even if the corresponding calculations do not deviate far from the other results, a high percentage deviation can lead to a falsified result. Accordingly, when selecting the EnPI, not only the coefficient of determination but also the percentage deviation should be taken into account to ensure the most accurate measurement possible.

6. Discussion

In this chapter, selected aspects of DIN ISO 50006 are taken up and compared to the analysis carried out in chapter 5. Deficits are addressed, and suggestions for improving or expanding the corresponding aspects are presented.

Concerning point 4.2.6.4 of DIN ISO 50006, it must be ensured that the quality of the underlying database, consisting of the measured energy values and data of the variables, is guaranteed before the calculations of the EnPIs. For this purpose, data points that do not correspond to typical operating conditions must be removed from the database. Care should be taken to ensure that the excluded data points do not lead to systematic errors. The reference to statistical means indicates that statistical methods should be used to identify the outliers. However, the standard does not provide specific instructions for this procedure. This represents a source of error for users in several respects.

First, it makes a difference whether the data points that do not meet the operating conditions, such as zero productions or data indicating mismeasurements, are already removed from the data set before statistical methods are applied, or whether the statistical methods are applied to the raw data. When the statistical methods are applied to the raw data, it can result in data points that do not match the operating conditions not being identified as outliers. To illustrate this, consider the interquartile range method, which determines an upper and lower bound. All data points that are above or below these limits are identified as outliers. However, suppose there are many zero productions or erroneous measured values in the data set. In that case, this will cause the lower bound to take on a negative value, which would mean that zero productions or erroneous measured values are not identified as outliers.

Second, the standard states that care must be taken when excluding data points from the database to avoid systematic errors. However, it does not inform the user how to identify or control these systematic errors. Instead, the standard focuses on providing guidance to the user on determining the desired coefficient of determination and thus performing the most accurate measurement of energy-related performance. Even calculations with a high coefficient of determination can contain systematic errors, as the comparison of production plants in Chapter 5 shows. A systematic error can be represented by the mean value and affects the accuracy of the measurements. In this case, the systematic error is represented by the average percentage deviation of the calculated values and the actual values. Accordingly, when selecting the EnPI used, the coefficient of determination and the average percentage deviation should be considered.

Third, the user is not informed about the possible benefits of using different statistical methods. As shown in chapter 5, applying different statistical methods to the same database leads to different coefficients of determination. Thus, the comparison of several statistical methods can help determine the highest possible coefficient of determination and thus perform a measurement that is as accurate as possible.

Furthermore, point 4.2.4 of DIN ISO 50006 defines and quantifies the relevant variables. It is essential to isolate the variables that significantly influence energy consumption from the variables with little or no influence on energy consumption. However, there is no definition of when variables are considered relevant or irrelevant. Nevertheless, the standard provides the user with a rough assessment through the figures shown. Variables with a coefficient of determination of around 0.93 are shown as relevant. In contrast, variables with a coefficient of determination of 0.75 are shown as less relevant or 0.25 as not relevant. This gives the user the erroneous impression that variables with a lower coefficient of determination should always be excluded from the calculations. Even if the variables do not significantly influence energy consumption when considered alone, they can lead to an increase in the coefficient of determination when considered together with other variables and thus contribute to a higher overall explanation of energy consumption. Accordingly, by basically excluding variables with a lower coefficient of determination, the user misses out on possible combinations of variables that would have determined the targeted coefficient of determination.

7. Conclusion

The study aimed to test the practical applicability of DIN ISO 50006 based on the crunchy cereal production process's energy assessment. Based on a quantitative analysis of the individual production plants, it can be concluded that the standard provides the user with a basic understanding of the process of implementing energy performance indicators and energy baselines, but has gaps concerning the calculations to be performed. The results indicate that the standard has room for improvement in identifying and dealing with systematic errors in the calculations, the use of statistical methods to identify outliers, and the selection of relevant variables for building the regression models.

The deductive approach followed, applying the theory under real conditions, has, on the one hand, made it possible to determine the shortcomings in terms of feasibility. On the other hand, it provides the company with an evaluation of energy-related performance according to the standard's requirements for one of the most energy-intensive processes, crunchy cereal production. It also offers starting points in the production process that need to be investigated to derive further measures for energy savings.

When considering the present analysis, it should be noted that the data collection of certain variables, such as working hours and shutdowns, are based on assumptions (see table 5.2, "Overview of influencing factors"). These should also be taken into account when determining EnPIs for other plants or processes of the company.

Based on the results, it would be helpful to expand or amend the relevant standard texts concerning the points listed to bring about a more uniform approach to the calculations of EnPIs and EnBs. This would increase the quality of the calculations to be performed and, thus, the accuracy of the measurement of energy-related performance and enable a more accurate comparison across company boundaries.

Also, the company should strive for more accurate and comprehensive data collection and documentation to ensure the availability of data for all relevant variables of the treated and other plants or processes.

Even if the calculation tool developed significantly reduces the effort required to determine EnPIs and EnBs, these must be reviewed at regular intervals and adjusted if necessary. Accordingly, the company should always set the effort against the savings when further introducing the EnPIs to ensure the economic benefit.

Regarding this study's objective, it can be concluded that the DIN ISO 50006 standard has significant potential for improvement concerning the calculations to be performed. For the company Brüggen, the present analysis evaluated one of the main production processes in terms of energy performance and laid the foundation for the implementation of further EnPIs. The calculation tool developed also represents an automation concept for determining EnPIs and EnBs that can be applied regardless of the company's size and branch.

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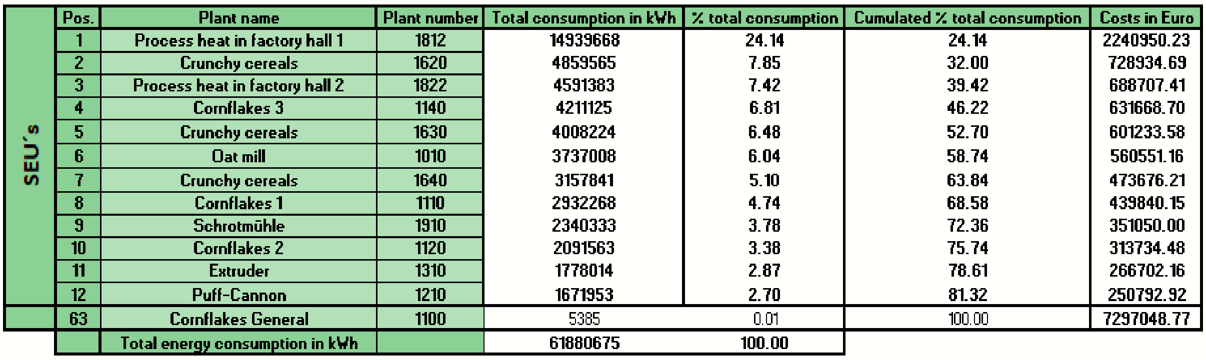
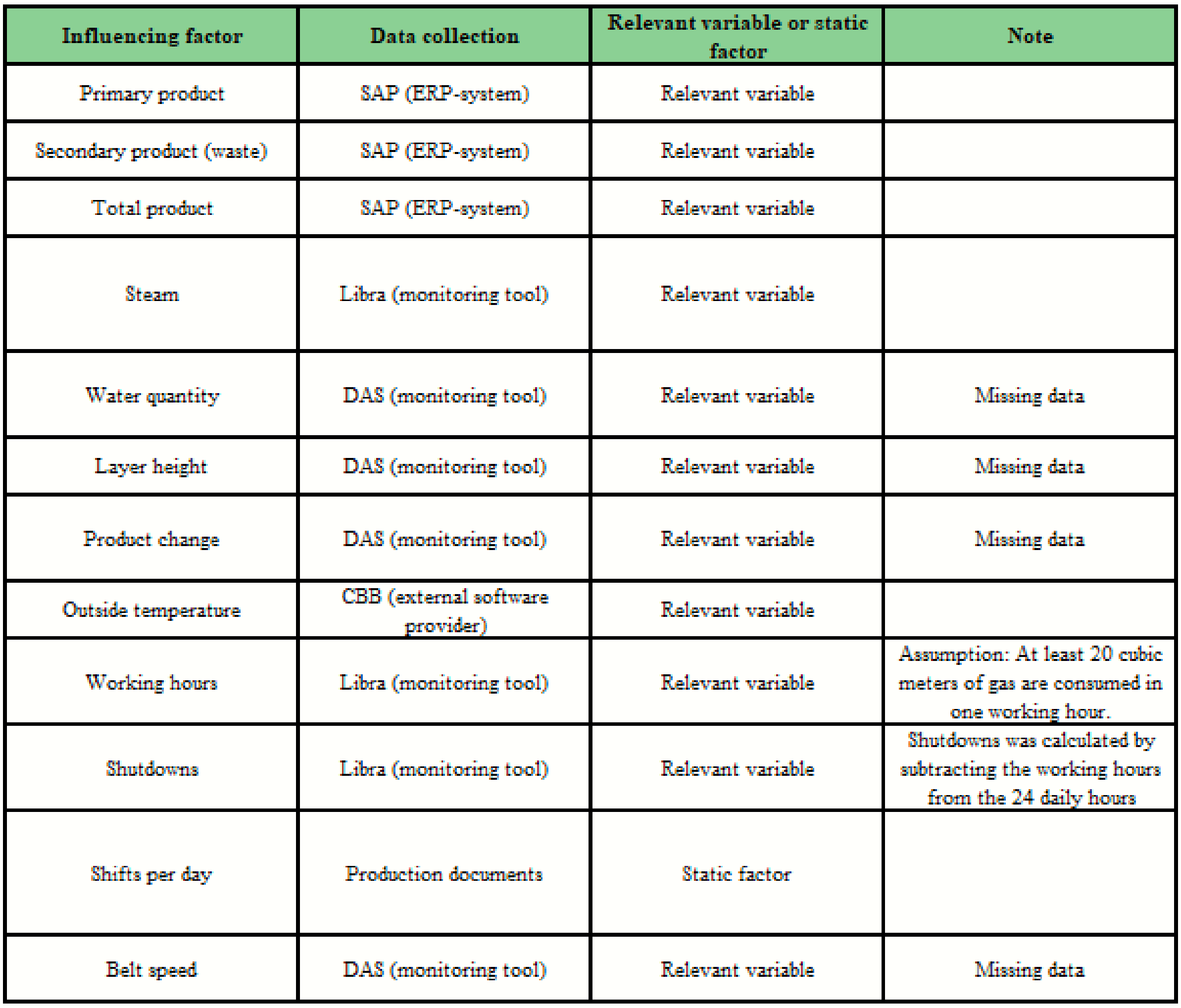
9. Appendix

9.1 Tables:



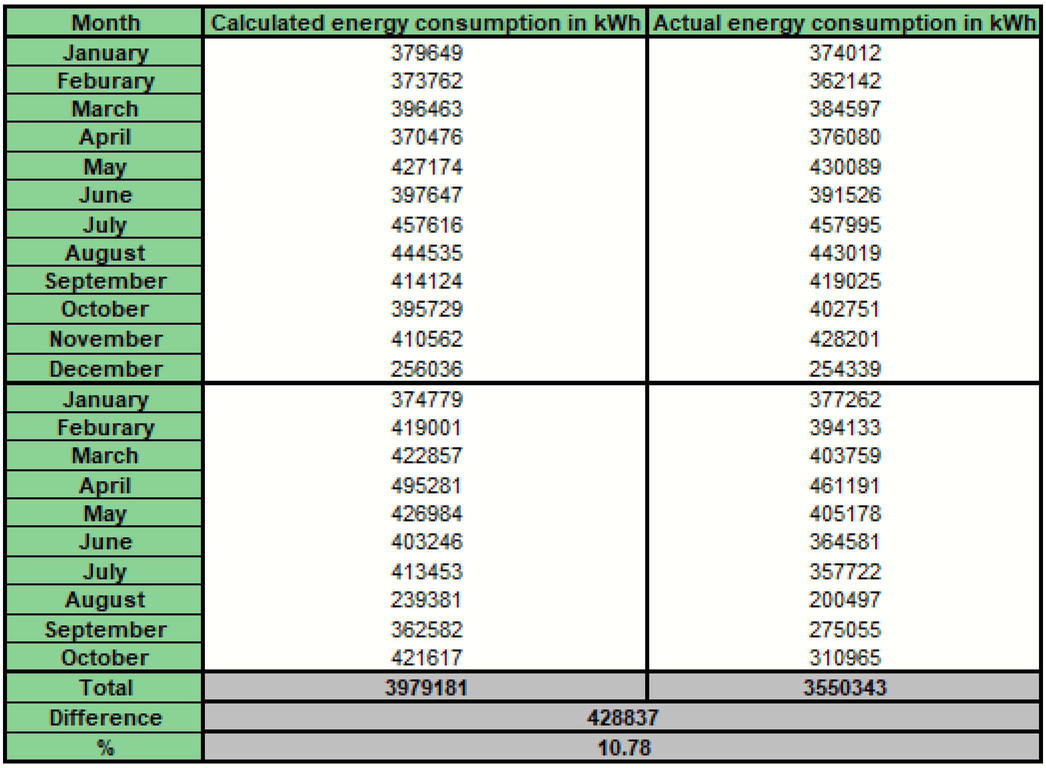
	Pos.	Plant name	Plant number	Total consumption in kWh	% total consumption	Cumulated % total consumption	Costs in Euro
SEU´s	1	Process heat in factory hall 1	1812	14939668	24.14	24.14	2240950.23
	2	Crunchy cereals	1620	4859565	7.85	32.00	728934.69
	3	Process heat in factory hall 2	1822	4591383	7.42	39.42	688707.41
	4	Cornflakes 3	1140	4211125	6.81	46.22	631668.70
	5	Crunchy cereals	1630	4008224	6.48	52.70	601233.58
	6	Oat mill	1010	3737008	6.04	58.74	560551.16
	7	Crunchy cereals	1640	3157841	5.10	63.84	473676.21
	8	Cornflakes 1	1110	2932268	4.74	68.58	439840.15
	9	Schrotmühle	1910	2340333	3.78	72.36	351050.00
	10	Cornflakes 2	1120	2091563	3.38	75.74	313734.48
	11	Extruder	1310	1778014	2.87	78.61	266702.16
	12	Puff-Cannon	1210	1671953	2.70	81.32	250792.92
	63	Cornflakes General	1100	5385	0.01	100.00	7297048.77
		Total energy consumption in kWh		61880675	100.00		

Table 5.1: Listing pareto principle



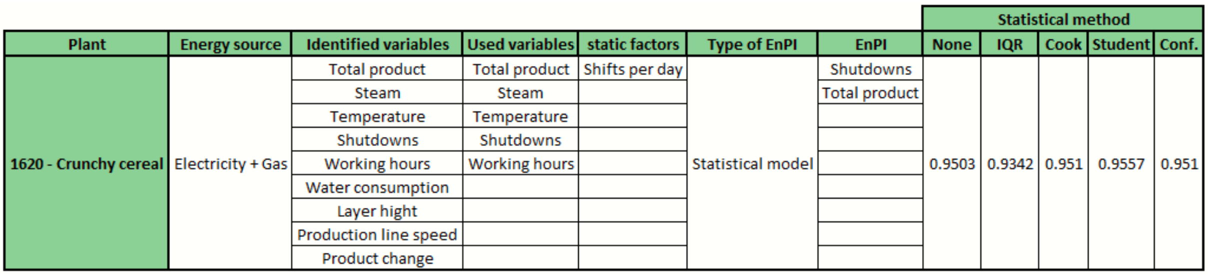
Influencing factor	Data collection	Relevant variable or static factor	Note
Primary product	SAP (ERP-system)	Relevant variable	
Secondary product (waste)	SAP (ERP-system)	Relevant variable	
Total product	SAP (ERP-system)	Relevant variable	
Steam	Libra (monitoring tool)	Relevant variable	
Water quantity	DAS (monitoring tool)	Relevant variable	Missing data
Layer height	DAS (monitoring tool)	Relevant variable	Missing data
Product change	DAS (monitoring tool)	Relevant variable	Missing data
Outside temperature	CBB (external software provider)	Relevant variable	
Working hours	Libra (monitoring tool)	Relevant variable	Assumption: At least 20 cubic meters of gas are consumed in one working hour.
Shutdowns	Libra (monitoring tool)	Relevant variable	Shutdowns was calculated by subtracting the working hours from the 24 daily hours
Shifts per day	Production documents	Static factor	
Belt speed	DAS (monitoring tool)	Relevant variable	Missing data

Table 5.2: Overview of influencing factors



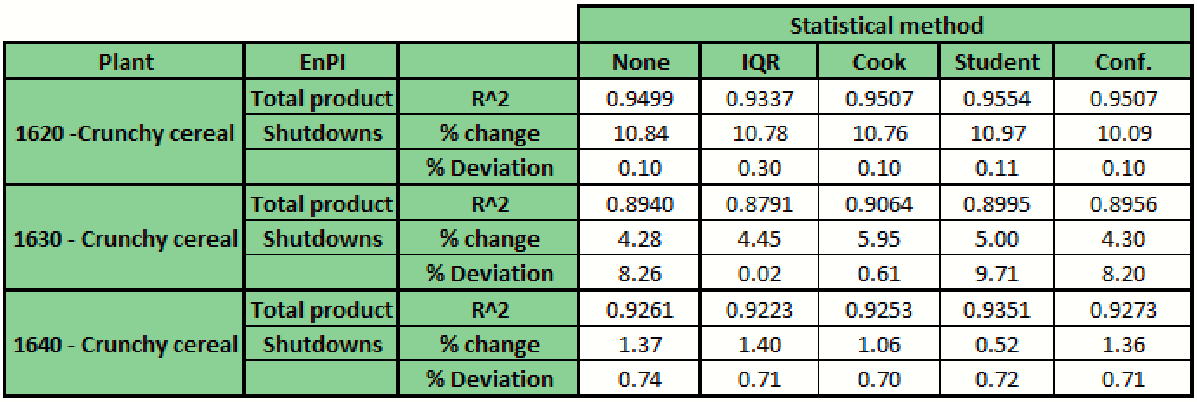
Month	Calculated energy consumption in kWh	Actual energy consumption in kWh
January	379649	374012
Feburary	373762	362142
March	396463	384597
April	370476	376080
May	427174	430089
June	397647	391526
July	457616	457995
August	444535	443019
September	414124	419025
October	395729	402751
November	410562	428201
December	256036	254339
January	374779	377262
Feburary	419001	394133
March	422857	403759
April	495281	461191
May	426984	405178
June	403246	364581
July	413453	357722
August	239381	200497
September	362582	275055
October	421617	310965
Total	**3979181**	**3550343**
Difference	**428837**	
%	**10.78**	

Table 5.3: Listing of monthly values



							Statistical method				
Plant	**Energy source**	**Identified variables**	**Used variables**	**static factors**	**Type of EnPI**	**EnPI**	**None**	**IQR**	**Cook**	**Student**	**Conf.**
1620 - Crunchy cereal	Electricity + Gas	Total product	Total product	Shifts per day	Statistical model	Shutdowns	0.9503	0.9342	0.951	0.9557	0.951
		Steam	Steam			Total product					
		Temperature	Temperature								
		Shutdowns	Shutdowns								
		Working hours	Working hours								
		Water consumption									
		Layer hight									
		Production line speed									
		Product change									

Table 5.4: Comparison of statistical methods



			Statistical method				
Plant	EnPI		None	IQR	Cook	Student	Conf.
1620 -Crunchy cereal	Total product	R^2	0.9499	0.9337	0.9507	0.9554	0.9507
	Shutdowns	% change	10.84	10.78	10.76	10.97	10.09
		% Deviation	0.10	0.30	0.10	0.11	0.10
1630 - Crunchy cereal	Total product	R^2	0.8940	0.8791	0.9064	0.8995	0.8956
	Shutdowns	% change	4.28	4.45	5.95	5.00	4.30
		% Deviation	8.26	0.02	0.61	9.71	8.20
1640 - Crunchy cereal	Total product	R^2	0.9261	0.9223	0.9253	0.9351	0.9273
	Shutdowns	% change	1.37	1.40	1.06	0.52	1.36
		% Deviation	0.74	0.71	0.70	0.72	0.71

Table 5.5: Comparison 1620, 1630 and 1640

9.2 Figures:

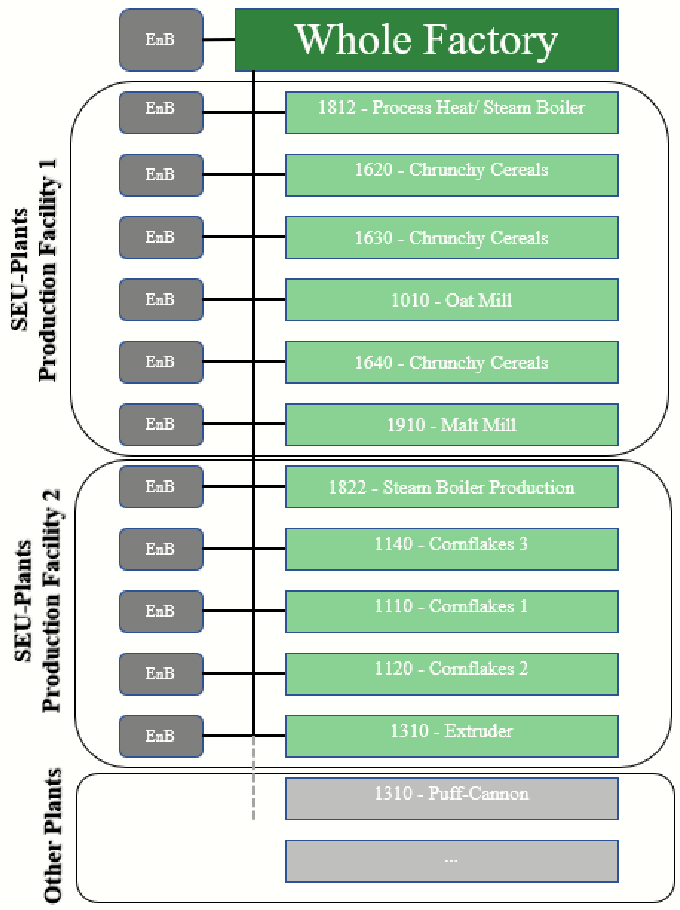
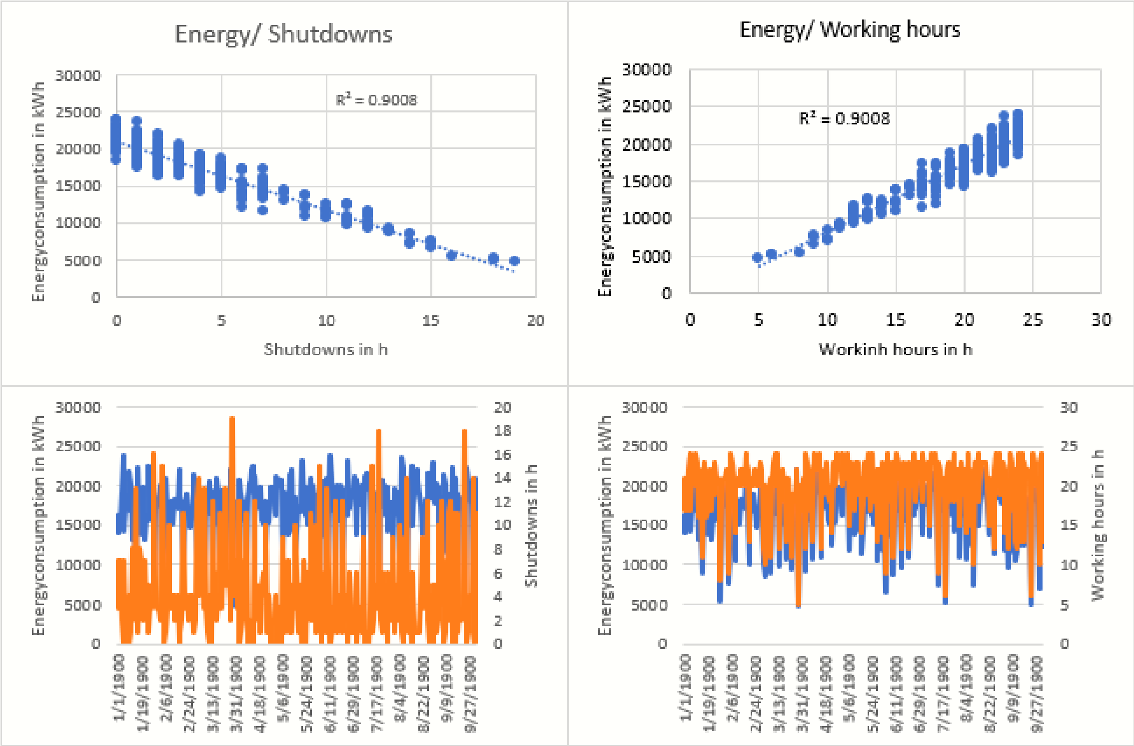


Figure 5.1: EnPI boundaries


Energy/ Shutdowns
R² = 0.9008
Energyconsumption in kWh
0
5000
10000
15000
20000
25000
30000
0
5
10
15
20
Shutdowns in h
Energy/ Working hours
R² = 0.9008
Energyconsumption in kWh
0
5
10
15
20
25
30
Workinh hours in h
Shutdowns in h
0
2
4
6
8
10
12
14
16
18
20
Working hours in h
1/1/1900
1/19/1900
2/6/1900
2/24/1900
3/13/1900
3/31/1900
4/18/1900
5/6/1900
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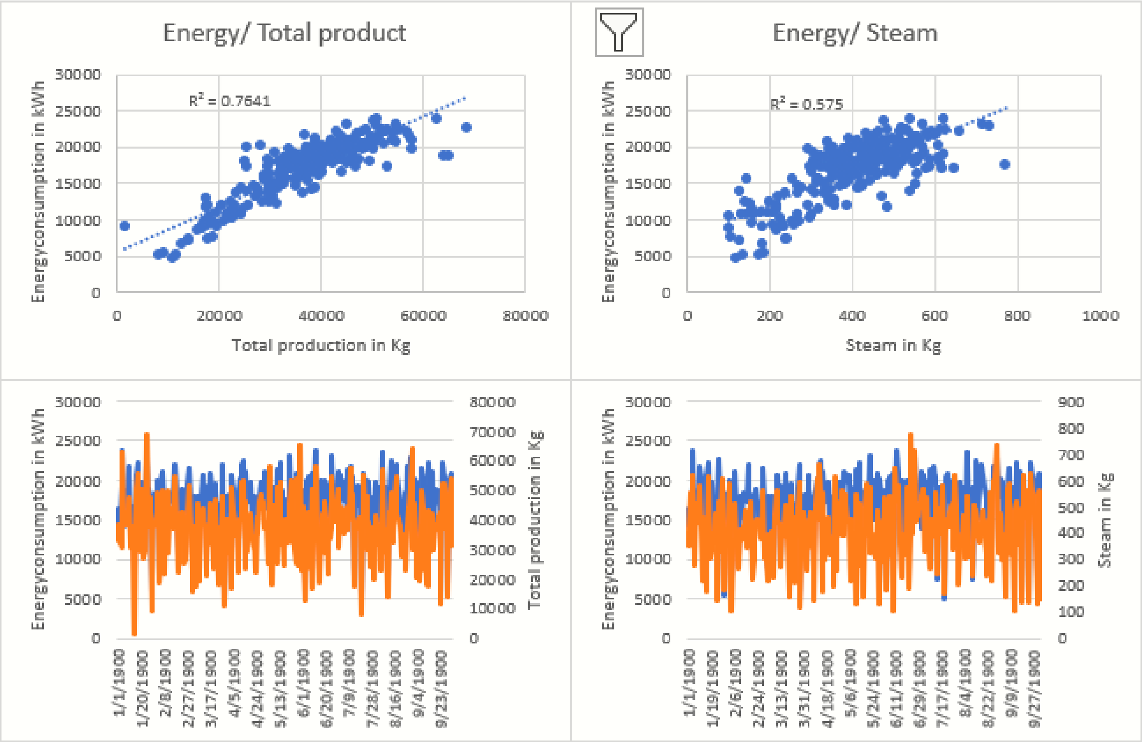
8/22/1900
9/9/1900
9/27/1900


Energy/ Total product
R² = 0.7641
Energyconsumption in kWh
0
5000
10000
15000
20000
25000
30000
0
20000
40000
60000
80000
Total production in Kg
Energy/ Steam
R² = 0.575
0
200
400
600
800
1000
Steam in Kg
0
10000
20000
30000
40000
50000
60000
70000
80000
Total production in Kg
1/1/1900
1/20/1900
2/8/1900
2/27/1900
3/17/1900
4/5/1900
4/24/1900
5/13/1900
6/1/1900
6/20/1900
7/9/1900
7/28/1900
8/16/1900
9/4/1900
9/23/1900
0
100
200
300
400
500
600
700
800
900
Steam in Kg
1/1/1900
1/19/1900
2/6/1900
2/24/1900
3/13/1900
3/31/1900
4/18/1900
5/6/1900
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9/9/1900
9/27/1900

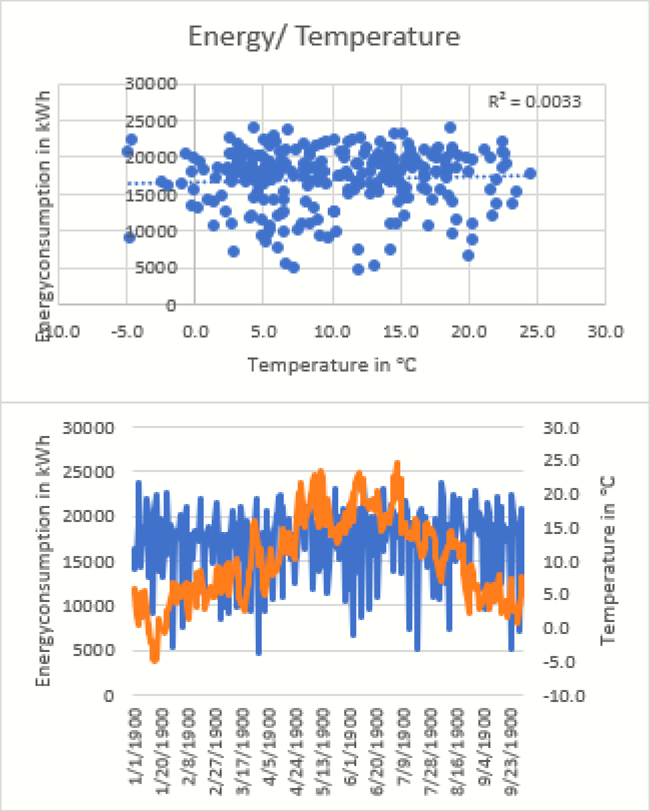


Figure 5.2: Diagram analysis

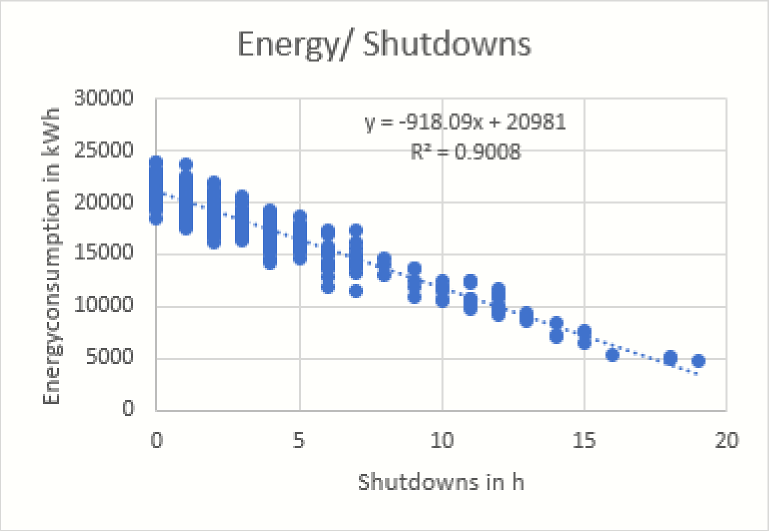


Figure 5.3: Regression with shutdowns

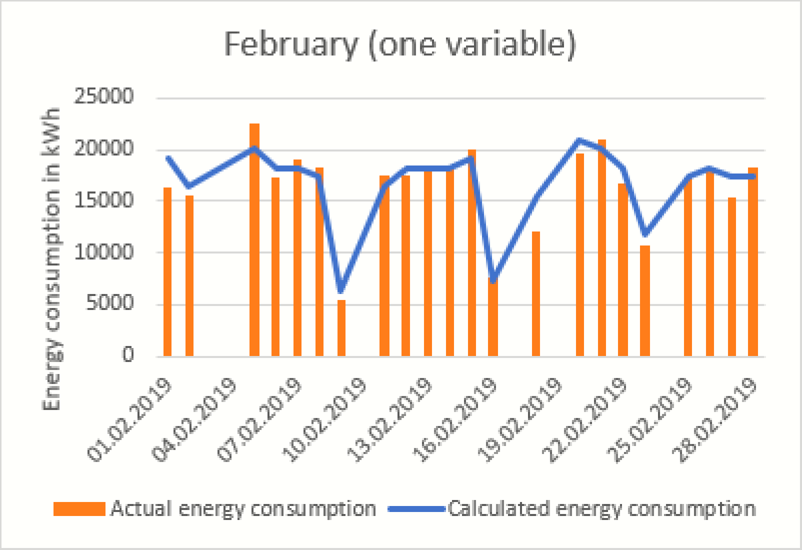
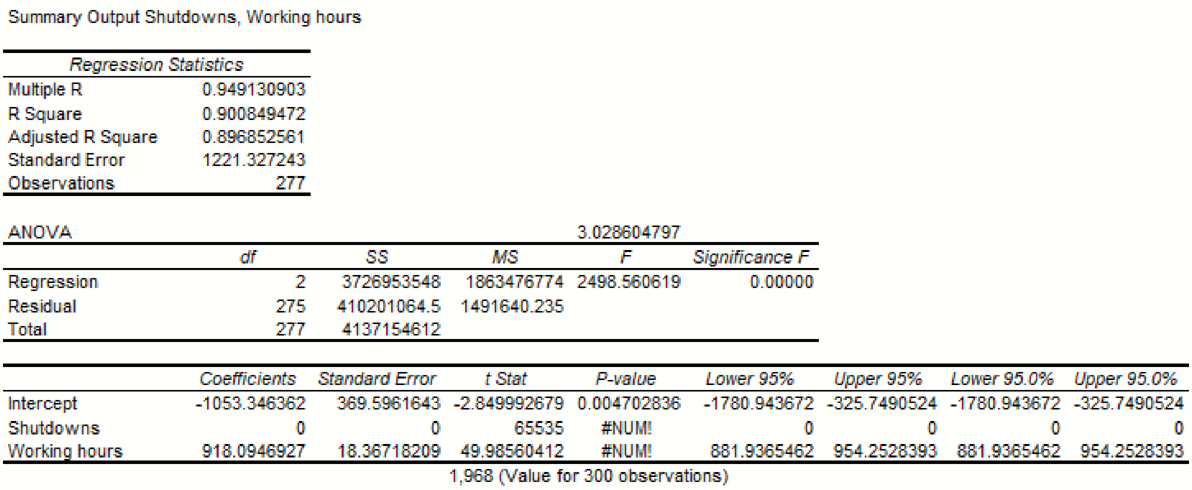


Figure 5.4: Comparison of measured and actual values with one variable


Summary Output Shutdowns, Working hours

Regression Statistics	
Multiple R	0.949130903
R Square	0.900849472
Adjusted R Square	0.896852561
Standard Error	1221.327243
Observations	277

ANOVA 3.028604797

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3726953548	1863476774	2498.560619	0.00000
Residual	275	410201064.5	1491640.235		
Total	277	4137154612			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-1053.346362	369.5961643	-2.849992679	0.004702836	-1780.943672	-325.7490524	-1780.943672	-325.7490524
Shutdowns	0	0	65535	#NUM!	0	0	0	0
Working hours	918.0946927	18.36718209	49.98560412	#NUM!	881.9365462	954.2528393	881.9365462	954.2528393

1,968 (Value for 300 observations)

Figure 5.5: Regression shutdowns, working hours

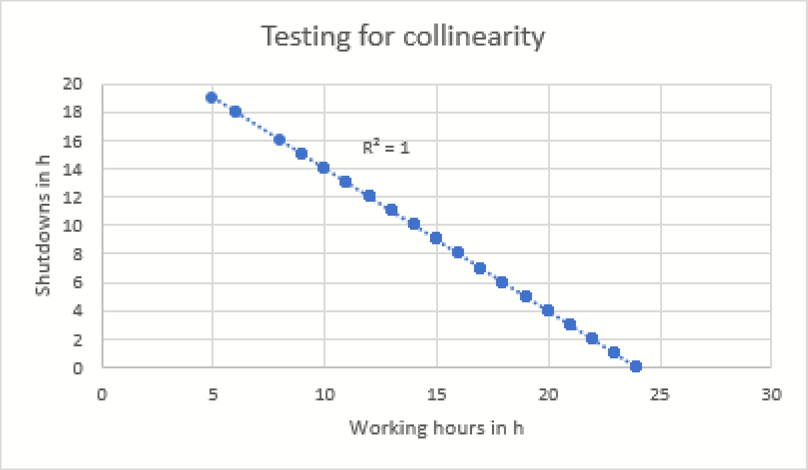
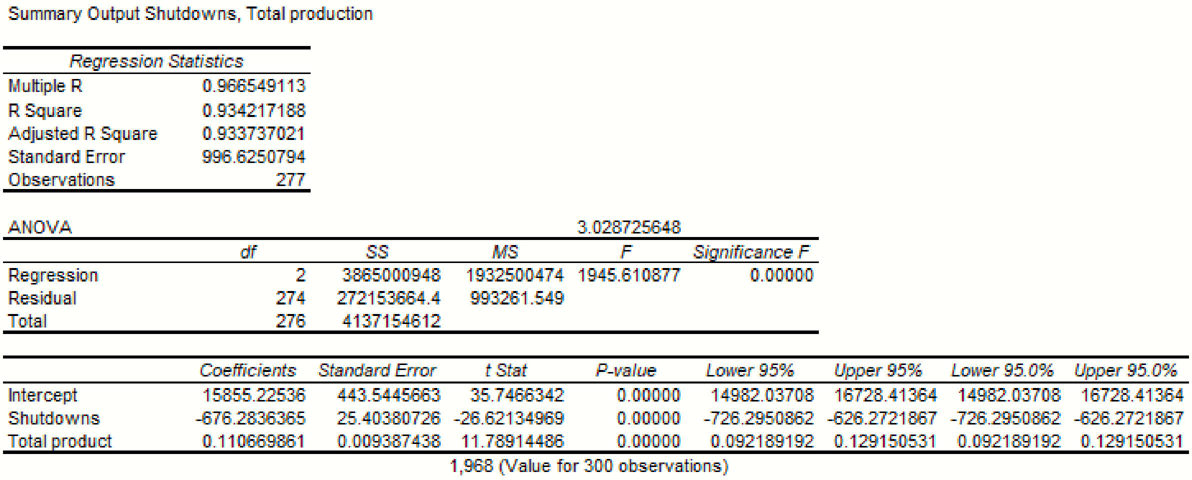


Figure 5.6: Testing for collinearity



Summary Output Shutdowns, Total production

Regression Statistics	
Multiple R	0.966549113
R Square	0.934217188
Adjusted R Square	0.933737021
Standard Error	996.6250794
Observations	277

ANOVA 3.028725648

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3865000948	1932500474	1945.610877	0.00000
Residual	274	272153664.4	993261.549		
Total	276	4137154612			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	15855.22536	443.5445663	35.7466342	0.00000	14982.03708	16728.41364	14982.03708	16728.41364
Shutdowns	-676.2836365	25.40380726	-26.62134969	0.00000	-726.2950862	-626.2721867	-726.2950862	-626.2721867
Total product	0.110669861	0.009387438	11.78914486	0.00000	0.092189192	0.129150531	0.092189192	0.129150531

1,968 (Value for 300 observations)

Figure 5.7: Regression shutdowns, total production

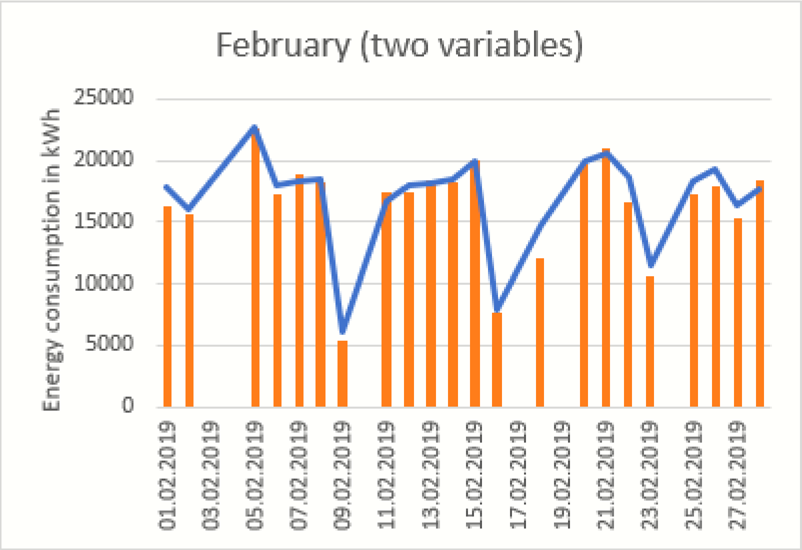
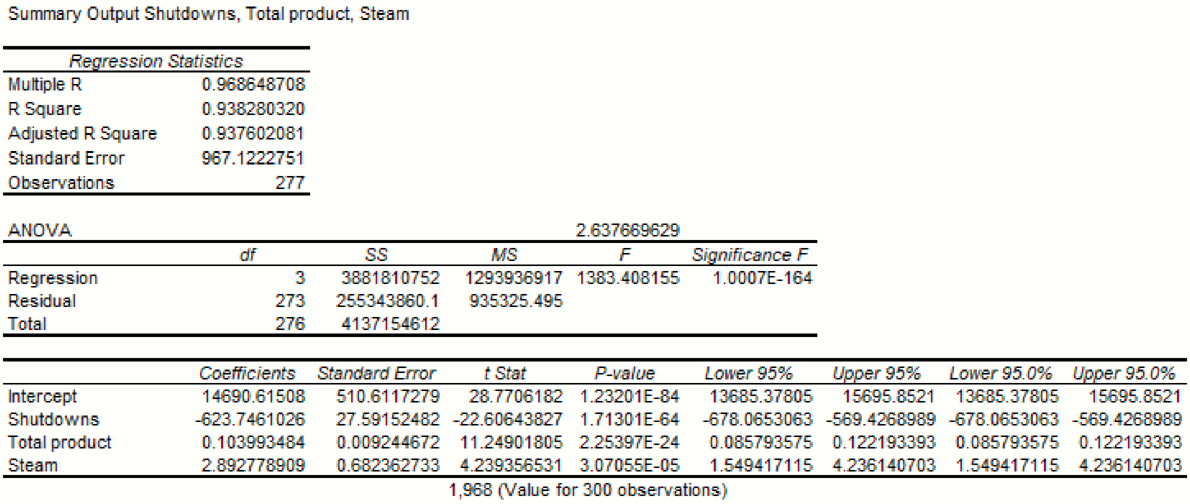


Figure 5.8: Comparison of measured and actual values with two variables


Summary Output Shutdowns, Total product, Steam

Regression Statistics	
Multiple R	0.968648708
R Square	0.938280320
Adjusted R Square	0.937602081
Standard Error	967.1222751
Observations	277

ANOVA 2.637669629

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3881810752	1293936917	1383.408155	1.0007E-164
Residual	273	255343860.1	935325.495		
Total	276	4137154612			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	14690.61508	510.6117279	28.7706182	1.23201E-84	13685.37805	15695.8521	13685.37805	15695.8521
Shutdowns	-623.7461026	27.59152482	-22.60643827	1.71301E-64	-678.0653063	-569.4268989	-678.0653063	-569.4268989
Total product	0.103993484	0.009244672	11.24901805	2.25397E-24	0.085793575	0.122193393	0.085793575	0.122193393
Steam	2.892778909	0.682362733	4.239356531	3.07055E-05	1.549417115	4.236140703	1.549417115	4.236140703

1,968 (Value for 300 observations)

Figure 5.9: Regression shutdowns, total production, steam

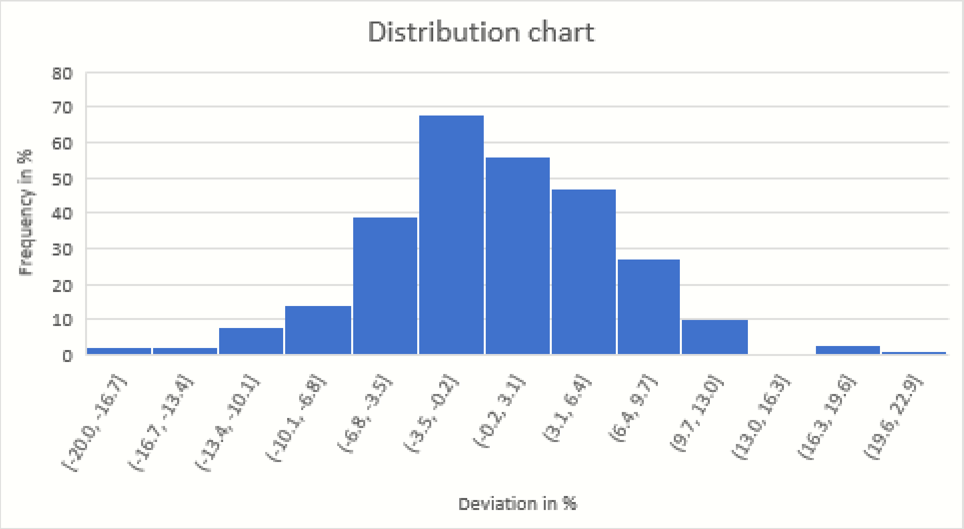


Figure 5.10: Distribution chart

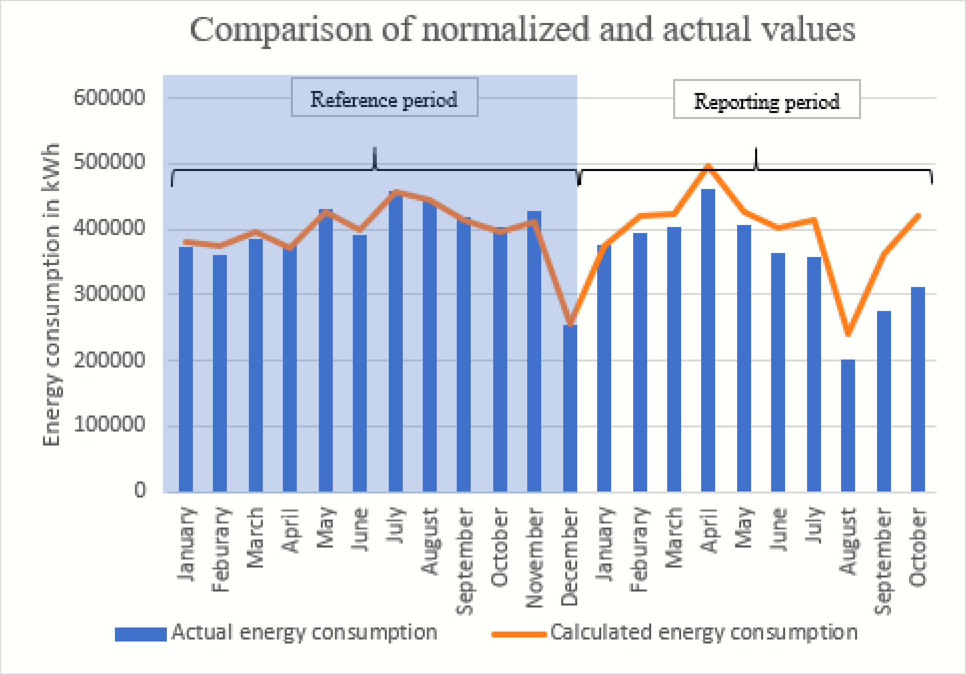
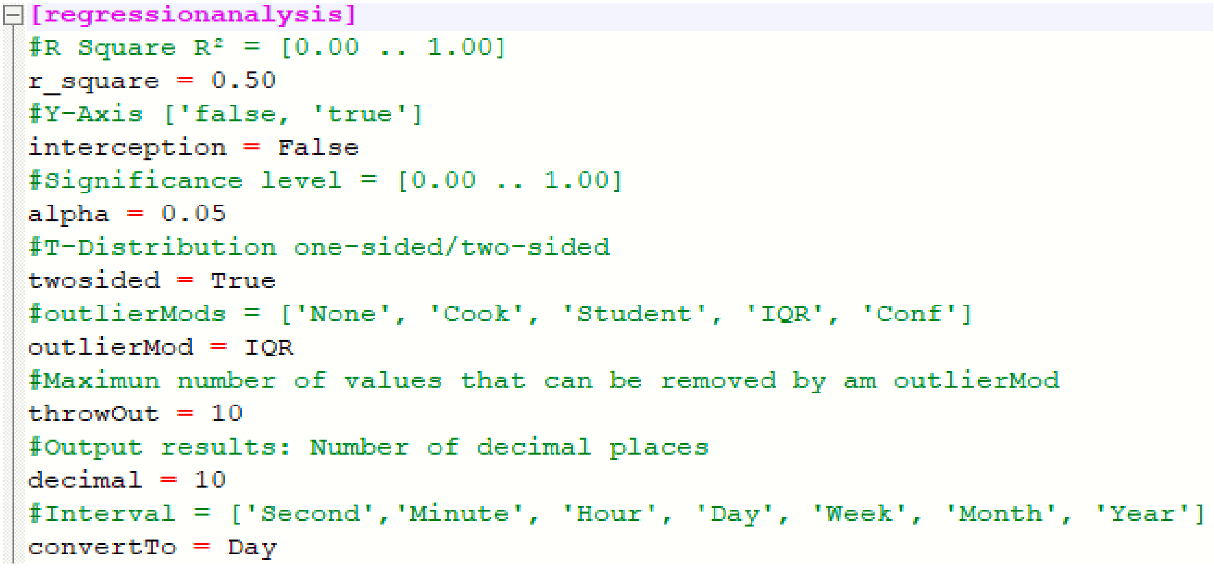
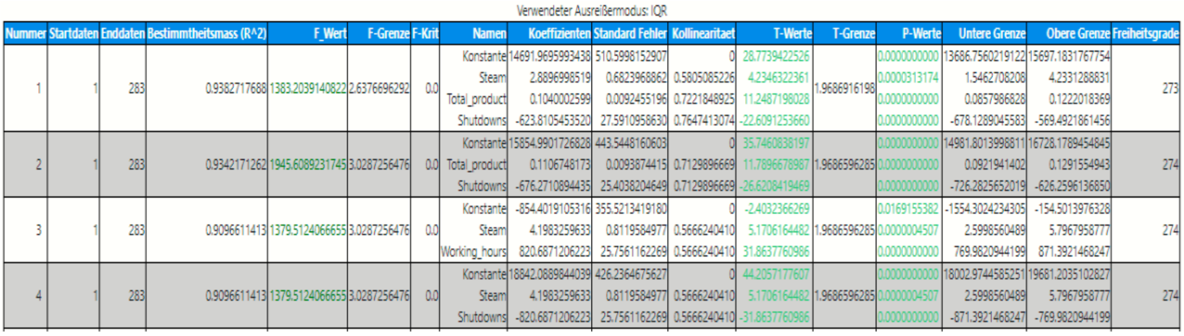


Figure 5.11: Comparison of normalized and actual values



```
[regressionanalysis]
#R Square R² = [0.00 .. 1.00]
r_square = 0.50
#Y-Axis ['false', 'true']
interception = False
#Significance level = [0.00 .. 1.00]
alpha = 0.05
#T-Distribution one-sided/two-sided
twosided = True
#outlierMods = ['None', 'Cook', 'Student', 'IQR', 'Conf']
outlierMod = IQR
#Maximun number of values that can be removed by am outlierMod
throwOut = 10
#Output results: Number of decimal places
decimal = 10
#Interval = ['Second','Minute', 'Hour', 'Day', 'Week', 'Month', 'Year']
convertTo = Day
```

Figure 5.12: Input menu calculation tool



Verwendeter Ausreißermodus: IQR

Nummer	Startdaten	Enddaten	Bestimmtheitsmass (R^2)	F_Wert	F-Grenze	F-Krit	Namen	Koeffizienten	Standard Fehler	Kollinearitaet	T-Werte	T-Grenze	P-Werte	Untere Grenze	Obere Grenze	Freiheitsgrade
1	1	283	0.9382717688	1383.2039140822	2.6376696292	0.0	Konstante	14691.9695993438	510.5998152907	0	28.7739422526	1.9686916198	0.0000000000	13686.7560219122	15697.1831767754	273
							Steam	2.8896998519	0.6823968862	0.5805085226	4.2346322361		0.0000313174	1.5462708208	4.2331288831	
							Total_product	0.1040002599	0.0092455196	0.7221848925	11.2487198028		0.0000000000	0.0857986828	0.1222018369	
							Shutdowns	-623.8105453520	27.5910958630	0.7647413074	-22.6091253660		0.0000000000	-678.1289045583	-569.4921861456	
2	1	283	0.9342171262	1945.6089231745	3.0287256476	0.0	Konstante	15854.9901726828	443.5448160603	0	35.7460838197	1.9686596285	0.0000000000	14981.8013998811	16728.1789454845	274
							Total_product	0.1106748173	0.0093874415	0.7129896669	11.7896678987		0.0000000000	0.0921941402	0.1291554943	
							Shutdowns	-676.2710894435	25.4038204649	0.7129896669	-26.6208419469		0.0000000000	-726.2825652019	-626.2596136850	
3	1	283	0.9096611413	1379.5124066655	3.0287256476	0.0	Konstante	-854.4019105316	355.5213419180	0	-2.4032366269	1.9686596285	0.0169155382	-1554.3024234305	-154.5013976328	274
							Steam	4.1983259633	0.8119584977	0.5666240410	5.1706164482		0.0000004507	2.5998560489	5.7967958777	
							Working_hours	820.6871206223	25.7561162269	0.5666240410	31.8637760986		0.0000000000	769.9820944199	871.3921468247	
4	1	283	0.9096611413	1379.5124066655	3.0287256476	0.0	Konstante	18842.0889844039	426.2364675627	0	44.2057177607	1.9686596285	0.0000000000	18002.9744585251	19681.2035102827	274
							Steam	4.1983259633	0.8119584977	0.5666240410	5.1706164482		0.0000004507	2.5998560489	5.7967958777	
							Shutdowns	-820.6871206223	25.7561162269	0.5666240410	-31.8637760986		0.0000000000	-871.3921468247	-769.9820944199	

Figure 5.13: Result table