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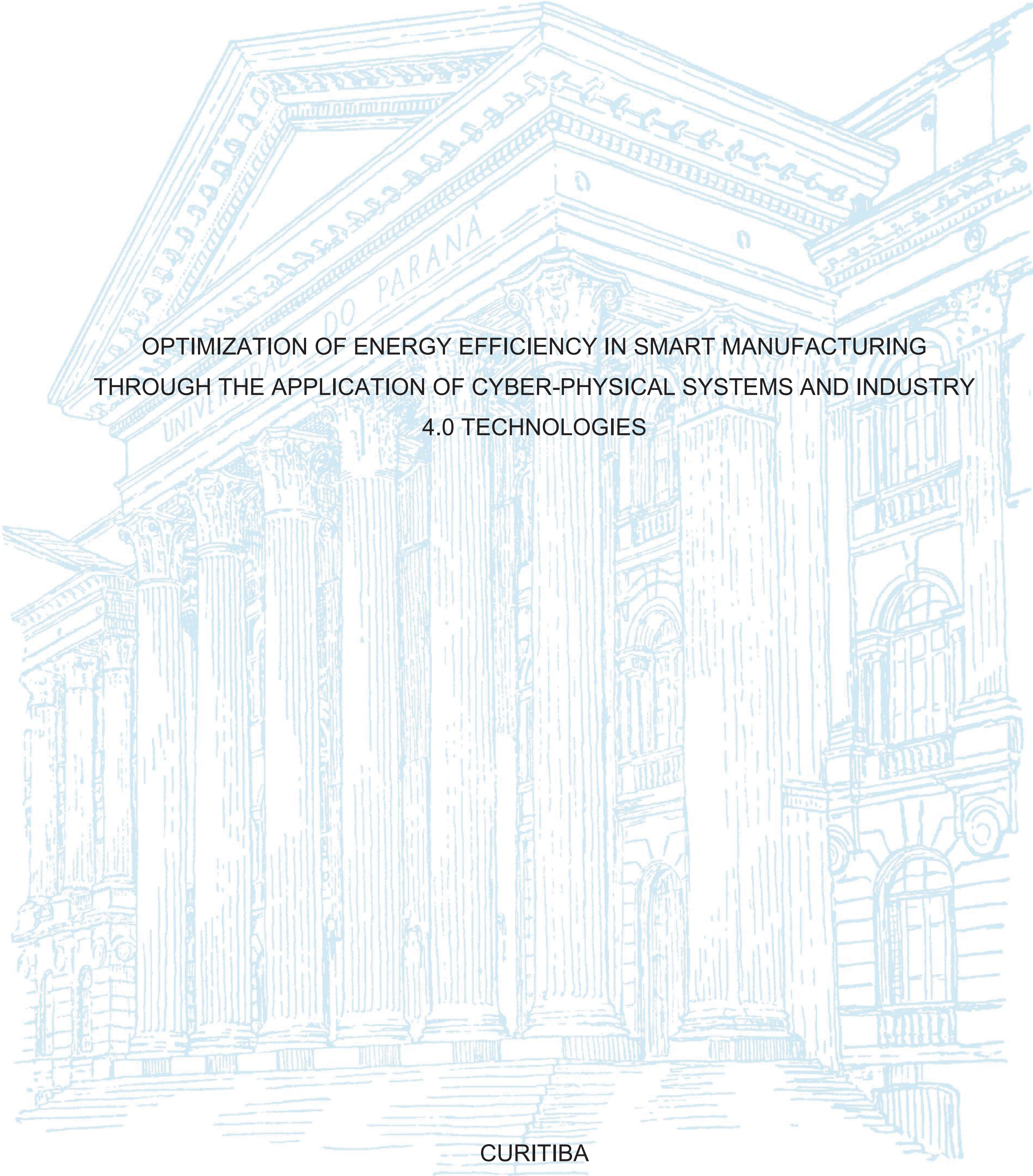
FERNANDO NUNCIARONI MATSUNAGA



OPTIMIZATION OF ENERGY EFFICIENCY IN SMART MANUFACTURING THROUGH THE APPLICATION OF CYBER-PHYSICAL SYSTEMS AND INDUSTRY 4.0 TECHNOLOGIES

CURITIBA

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Dissertação apresentada ao curso de Pós-Graduação em Engenharia de Manufatura, Setor de Tecnologia, Universidade Federal do Paraná, como requisito parcial à obtenção do título de Mestre em Engenharia de Manufatura.

Orientador: Prof. Dr. Pablo Valle
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RESUMO

Sustentabilidade é um tópico que vem sendo endereçado e aprimorado com as diversas oportunidades trazidas pela quarta revolução industrial, o que é uma estratégia essencial no médio e longo prazo para que as indústrias se adaptem a necessidades urgentes da sociedade como: manufatura competitiva e sustentável de bens. Nesse tema eficiência energética é um dos aspectos chave para industrias que querem alcançar um processo sustentável e de neutralidade de carbono em seus processos de produção. Esta dissertação analisa como a aplicação de tecnologias e metodologias pode melhorar substancialmente a eficiência de processos em relação ao consumo de energia. A dissertação foi dividida em uma pesquisa de três etapas, começando com: uma revisão sistemática para identificar como a manufatura inteligente e sistemas cyber-physical estão trazendo resultados para a eficiência energética dentro da manufatura; seguido por experimentos de monitoramento em tempo real e simulações do consumo de energia industrial com objetivo de reduzir o desperdício de energia e otimizar o processo. Como última etapa os resultados foram discutidos demonstrando ganhos no planejamento de produção e potenciais oportunidades de economia de energia e custos e manufatura.

Palavras-chave: quarta revolução industrial; eficiência energética; sistemas cyber; digital twin; sustentabilidade na manufatura;

ABSTRACT

Sustainability is a topic that has been addressed and enhanced with significant improve opportunities by the fourth industrial revolution, which is an essential strategy in the medium- and long-term for industries to adapt to an urgent necessity from society: the competitive and sustainable manufacturing of goods. In that regard, energy efficiency is one of the key aspects for industries that want to achieve a sustainable and carbon neutral production process. This thesis approaches how the application of technologies and methodologies can substantially improve processes overall efficiency in terms of energy consumption. The work is divided in a three-step research, starting with: a systematic review to identify how smart manufacturing and cyber-physical systems are leveraging results in manufacturing energy efficiency; followed by experiments to make real time monitoring and simulation of industrial energy consumption to optimize processes and reduce energy waste and as

a third and final step results are discussed showing gains in production planning and potential saving opportunities in manufacturing energy consumption and costs.

Key-words: the fourth industrial revolution; energy efficiency; cyber physical systems; digital twin; sustainable manufacturing;

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Glossary

SDGs: Sustainable Development Goals.

UN: United Nations.

CPS: Cyber-Physical System.

CPPS: Cyber-Physical Production System.

DT: Digital Twin.

DTS: Digital Twin Shop-floor.

PS: Physical Shop floor.

VS: Virtual Shop floor.

SSS: Shop-floor Service System.

SDTD: Shop-floor Digital Twin Data.

EECM: Equipment Energy Consumption Management.

IIoT: Industrial Internet of Things.

IoT: Internet of Things.

SEC: Machine Specific Energy Consumption.

EC: Energy Consumption.

MMR: Material Removal Rate.

E-KPIS: Energy-related Key Performance Indicators.

OEE: Overall Equipment Efficiency.

ISO: International Standardization Organization.

LCA: Life Cycle Analysis.

LCEA: Life Cycle Energy Analysis.

US: United States of America.

EPE: Embodied Product Energy.

TE: Theoretical Energy.

AE: Auxiliary Energy.

REEL: Remaining Energy-Efficient Lifetime.

CSC: Conservation Supply Curve.

CCE: Cost of Conserved Energy.

MTEF: MAESTRI Total Efficiency Framework.

DoE: Design of Experiments.

e-VSM: energy Value Stream Mapping.

CONTENT

1. INTRODUCTION

1.1. Context

Industrial activity has a considerable share in the total worldwide energy consumption mix, in which industries can account up to 41,9% of total electricity consumption (Ranganadham, 2018). This high-energy consumption factor of the industrial sector leads to great opportunities in energy efficiency, not only for cost reduction purposes, but also to lower the impact of industrial activity in achieving the UN Sustainable Development Goals (SDGs) by 2030. In that matter, industry 4.0 plays a key role in achieving those targets (Nagasawa et al., 2017), enabling the industrial sector to lower its CO_2 footprint along with the competitiveness improvement that results from measures in energy efficiency activities.

1.1.1. Sustainability and Sustainable Development Goals (SDG)

The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. At its heart are the 17 Sustainable Development Goals (SDGs), which are an urgent call for action by all countries - developed and developing - in a global partnership (United Nations, 2021). Figure 1 depicts the seventeen Sustainable Development Goals in which improving energy efficiency in industries leads to the improvement of goals number 7 (affordable and clean energy), number 9 (industry, innovation and infrastructure), number 12 (responsible consumption and production) and more importantly number 13 (climate action).

Figure 1 United Nations - Sustainable Development Goals.

Source: United Nations, 2021

1.2. Problem Situation

Since industries are one of the major consumers of worldwide energy, a common problem that arrives in a practical and theoretical level when starting a systematic approach to improve energy efficiency is: which methodologies, technologies and use cases are provided to significantly improve this topic in an organization? This question is very relevant, since most of the literature proposes the topics in a very focused approach not presenting a practical blueprint on how to organize an efficient approach for the improvement of processes energy efficiency. In that regard, this thesis discusses this problematic in the form of five main questions:

Q1: Which methodologies and approaches are most commonly applied in energy efficiency in smart manufacturing?

Q2: Which smart manufacturing technologies are enhancing significantly the results in energy efficiency?

Q3: What are the use cases of Cyber-physical system technologies in improving energy efficiency in manufacturing?

Q4: Which application models can be utilized in a practical case?

Q5: What are the results and opportunities of an applied study of case in a real industry?

This problematic and approach will be evaluated in a partner company plant that utilizes a manual systematic for forecasting the amount of energy that will be spent in a monthly basis. This systematic is based on an estimation of hours that the machines of the factory will operate depending on the number of items that will be produced on a determined month and evaluating the historical measurements of the plant. This systematic has its limitations, due to several factors, such as: the measurement instruments are located only on the factory main input hence being unable to identify specific energy consumption of buildings and equipment; the consumption data is evaluated only once per month; the consumption base of the factory and sectors are empirically defined and look up for historical data as a reference, so an actual model is not utilized. To improve the known data, the company has installed in the project additional measurement instruments on building and machine level in order to evaluate a possible simulation method for the forecasting of energy consumption of a determined value stream and process.

1.3. Research Targets and Technological Product

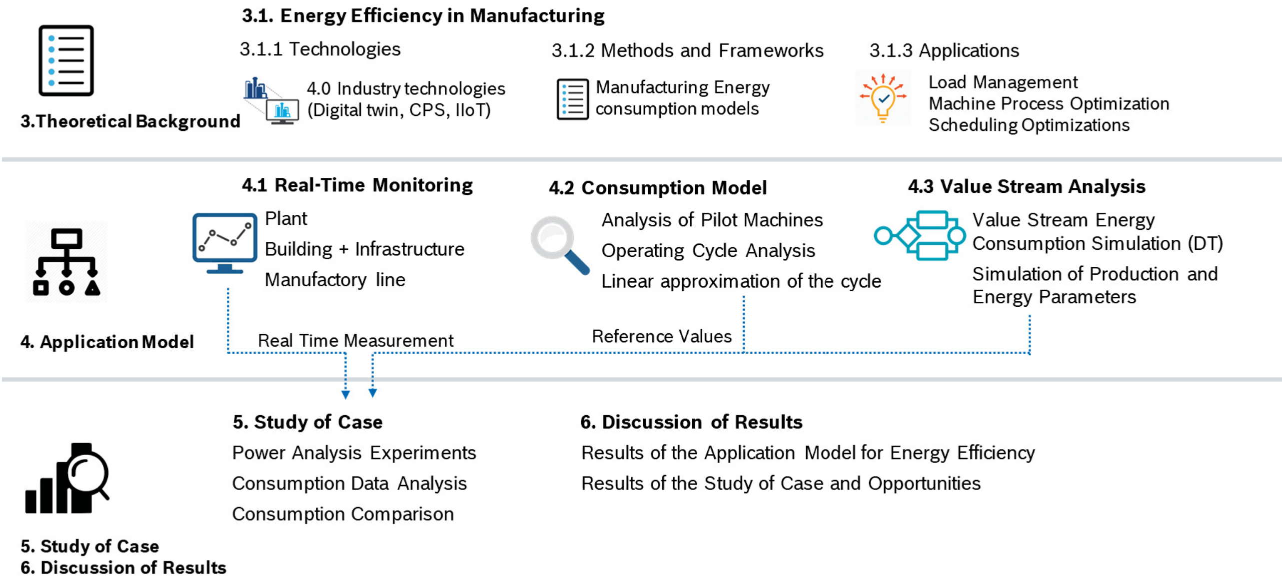
This thesis evaluates a practical case of application of technologies and methodologies to reduce the overall energy consumption of an industrial plant of a multinational automotive company. This systematic approach, coming from a solid theoretical background, allied with a practical application model and a concrete study of case provides a practical blueprint for organizations and companies alike that want to achieve a higher degree of energy efficiency through the application of industry 4.0 concepts and technologies.

As an end-result, this research elaborates and discusses a method that can be applied in order to improve energy efficiency in manufacturing sites and intend to answer the specific questions highlighted in the Problem Situation. This method consists in comparing the energy consumption from a digital twin/simulation of a production cell with the real-time energy consumption that will be measured in every machine.

2. RESEARCH APPROACH

The proposed research follows the diagram shown in Figure 2 which structure can also be found along the thesis' text. Briefly, the research is divided in a THEORETICAL BACKGROUND in Section 3 , followed by the proposed APPLICATION MODEL in Section 4 and a applied practical CASE STUDY in 5. Last but not least, the approach ends with a DISCUSSION OF RESULTS in Section 6 and a brief CONCLUSION in Section 7.

Figure 2 Research framework in three steps.

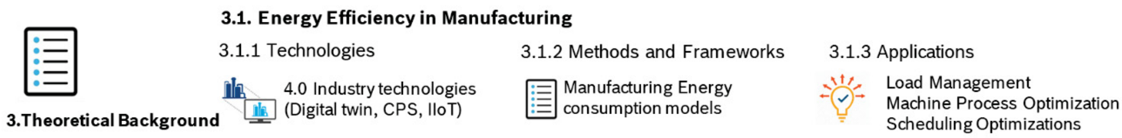


Source: Author, 2020

3. THEORETICAL BACKGROUND

In order to investigate the literature on how energy efficiency in manufacturing is being impacted by new methodologies, technologies and applications, the theoretical background definition was the first step in the proposed research framework. This section intends to answer questions 1 to 3 proposed in section 1.2 Problem Situation. The analysis was divided in the following topics, which will be addressed in section 3.1:

Figure 3 Theoretical background in manufacturing energy efficiency and topics.



Source: Author (2020)

3.1. Energy efficiency in manufacturing

As presented in the INTRODUCTION, energy efficiency in manufacturing has been a very relevant topic throughout the last decades achieving the number of thousands of publications in that regard (Matsunaga et al., 2021). In the context of manufacturing industries, many distinct methodologies for energy efficiency approaches, technologies and measures have been broadly discussed in the literature and those will be summarized in this specific section of the thesis. A summary comparative of methods and frameworks and technologies found in the literature can be found in Annex 1.

3.1.1. Technologies

In this section, a brief discussion of industry 4.0 and cyber-physical technologies applied to energy efficiency will be discussed and summarized. This adds up to section 3.1.2 where methods are described, which serve as a fundamental base and potentialized by new emerging technologies such as CPS, I4.0 and digital twin.

3.1.1.1. Cyber-Physical Systems (CPS)

A cyber-physical system (CPS) is a system that is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and its users. The US National Science Foundation first proposed the term CPS in 2006. In cyber-physical systems, physical and software components are deeply intertwined, each operating on different spatial and temporal scales, exhibiting multiple and distinct behavioral modalities, and interacting with each other in a lot of ways that change with context (Foundation, 2019). Examples of CPS includes smart-grids, autonomous driving systems, medical monitoring, process control systems, robotics systems, pilot avionics and others (Kumar Khaitan Siddhartha ; & D., 2015).

Recently, the cyber-physical system (CPS) and its applications have been widely studied in the field of engineering. Application of a CPS in manufacturing can also be described as a cyber-physical production system (CPPS) which is proposed in process automation and control of dynamic systems. A broader review of the current status and advancement of CPS in manufacturing can be found in many distinct literatures (Wang, L., Torngren, M., Onori, M., 2015). The characteristics of CPS are outlined together with those of big data, cloud technologies and IIoT (Industrial Internet of Things) technologies.

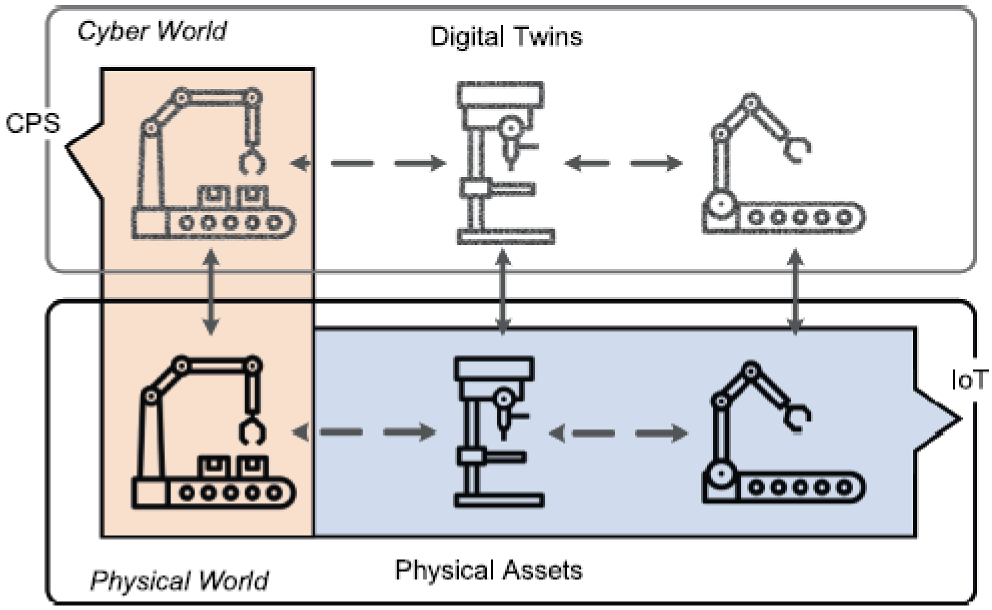
3.1.1.2. Digital Twin (DT) and Digital twin shop-floor (DTS)

A digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object (product) or process (value stream) that helps optimize business performance. The digital twin is based on massive, cumulative, real-time, real-world data measurements across an array of dimensions. These measurements can create an evolving profile of the object (product) or process in the digital world that may provide important insights on system performance, leading to actions in the physical world, such as a change in product design or manufacturing process. (Deloitte University Press, 2017)

With the development of the digital twin (DT), the concept was then introduced into shop-floor and the digital twin shop-floor (DTS) as proposed in 2017 by (F. Tao, M.

Zhang, J. F. Cheng, and Q. L. Qi, 2017). DTS is an extension of DT in the shop floor, aiming at converging the physical and virtual spaces to optimize the existing production activities. It consists of four components, Physical Shop floor (PS), Virtual Shop floor (VS), Shop-floor Service System (SSS) and Shop-floor Digital Twin Data (SDTD). Under this environment, the Equipment Energy Consumption Management (EECM) framework can also be explored (Zhang, Zuo, & Tao, 2018). The main difference between the DTS and the CPPS is that the DTS does not act directly on the machines, being so only a simulation, on the other hand the CPPS acts and controls the machines on the shopfloor. Figure 4 represent a visual diagram of the connection between IOT, CPS and DT.

Figure 4 Digital Twin-CPS-IOT Connection.



Source: (Yuqian Lu et al., 2020)

3.1.1.3. Industrial Internet of Things (IIoT)

Internet of Things (IoT) is a system of interrelated computing devices, mechanical and digital machines, objects, animals or people that are provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction (Tech Target's Internet of Things Network, 2018). The Industrial Internet of Things (IIoT) takes advantage of the IoT connectivity in order to enhance the performance of smart manufacturing and enables the further implementation of industry 4.0 technologies.

3.1.1.4. Big Data

Big data is a term often used to describe sets of data characterized by high volume, high velocity, and high variety (De Mauro, 2015), and for which the use of advanced analytical tools is required in order to process data into actionable information by identifying patterns, trends, and relationships (Lycett, 2013).

Big data is a consequence of the continuous and increasing production of data, spurred in particular by the vast deployment of digital platforms and applications in everyday life. It is estimated that less than 1% of all available data is currently analyzed (Gantz, J. & Reinsel, 2012). Big data therefore creates important challenges and opportunities now and in the coming years.

The main challenges within Big data come from managing its main characteristics, with the high volume of data is necessary to find ways of reducing the amount of data that needs to be stored. As with the high velocity capture of data, is necessary to assure that the speed matches the needs of the process, not being too high or too slow, so that the amount of data do not overwhelm the storage capacities or lack reliability due to the amount of samples. The variety of data needs to be surveyed, as not all data is necessary to be stored. At last, the data quality is a major factor when talking about Big data, so the accuracy of the sensors and the software utilized in data collecting and analyzing process must be taken in to account and be regularly checked (Kristina Wärmefjord et al., 2017).

Big data could support sustainability, for instance by helping produce relevant statistics that enable better informed decision making as much on economic, environmental or societal issues (Nagasawa et al., 2017).

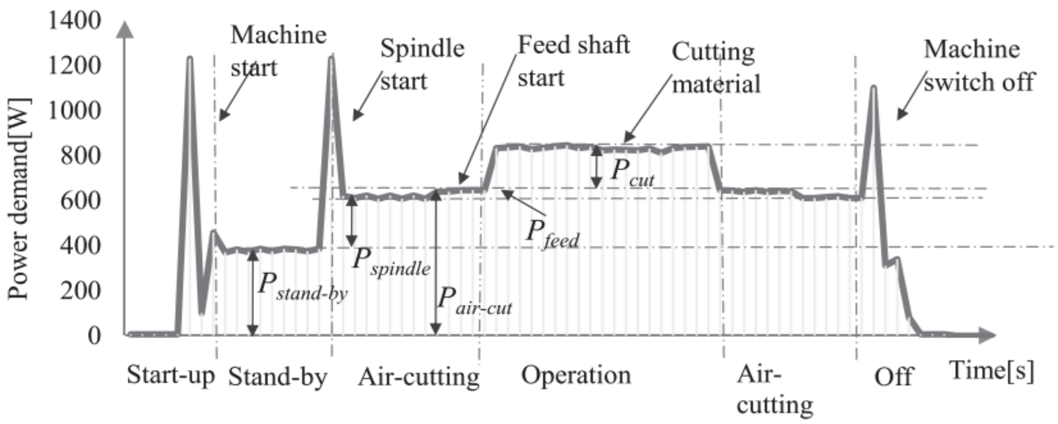
3.1.2. Methods and frameworks

The methodological approaches, frameworks and models of energy consumption in manufacturing serve as an important base for the identification, management and implementation of energy efficiency measures in manufacturing. The results achieved by a methodological approach can be further potentialized with the applications of smart manufacturing technologies (Zhou et al., 2016). In this section a small summary of the methodologies found in the literature are briefly reviewed.

3.1.2.1. Equipment Energy Consumption Management (EECM) and Machine Specific Energy Consumption (SEC)

Equipment Energy Consumption Management (EECM) and Machine Specific Energy Consumption (SEC) are both methods to improve energy consumption of machines and equipment through optimization of processes characteristics, such as machining parameters, scheduling sequences and tool parameters (Zhang et al., 2018). Energy consumption in the machining stages are divided in start-up period, idle periods and cutting periods. Relevant aspects that should be evaluated in a SEC analysis is the design and optimization for energy-efficient, scheduling management and the energy efficiency and environmental impact assessment (Feng, Wang, Gao, Cheng, & Tan, 2018). In Figure 5 we have a typical milling machining process curve. Remembering that the EC is calculated by the multiplication of the time axis with the power demand.

Figure 5 A schematic diagram of power profile of the milling process



Source: (Zhou et al., 2016)

For the analysis of SEC many further models can be used such as model based in linear type of cutting energy consumption, on material removal rate (MMR), main cutting parameters, detailed parameter type of cutting correlation models, metal deformation theory, amount of tool wear, on cutting force, explicit analytical model, neural network black-box model, process-oriented machining. More details on the models can be found in specific machine tool energy efficiency model papers (Zhou et al., 2016).

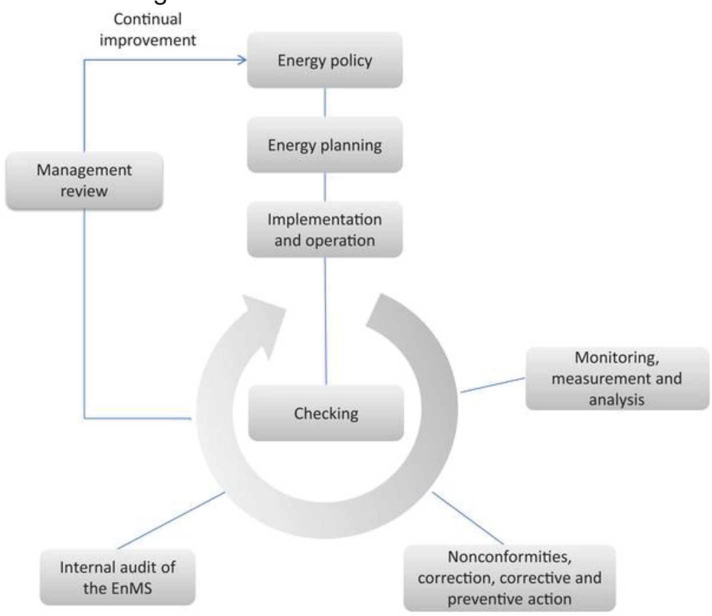
3.1.2.2. Energy-related key performance indicators (e-KPIs)

For the improvement of energy efficiency in manufacturing processes, it is also relevant to have key performance indicators to serve as potential energy efficiency measure identification tool, as whereas a tracking of performance improvement tool in the shop floor. Current indicators such as OEE (Overall Equipment Efficiency) are time based indicators that are not best fit for energy efficiency purposes or also aggregate energy consumption indicators such as kWh/month or kWh/parts that lacks cause-effect relationship, proving to be inefficient for energy efficiency potential identification (May, Barletta, Stahl, & Taisch, 2015). May et al. propose a seven steps approach for e-KPI definition and management.

3.1.2.3. ISO 50.001

ISO (international standardization organization) has established the standard ISO 50.001 to specify requirements for establishing, implementing, maintaining and improving an energy management system, whose purpose is to enable an organization to follow a systematic approach in achieving continual improvement of energy performance, including energy efficiency, energy usage and consumption. It is also based on the common elements of ISO management system standards, ensuring a high level of compatibility notably with ISO 9.001 and ISO 14.001 (International Organization for Standardization, 2018).

Figure 6 ISO 50.001 framework.



Source: (International Organization for Standardization, 2018)

3.1.2.4. Life Cycle Analysis and Life cycle energy analysis (LCA and LCEA)

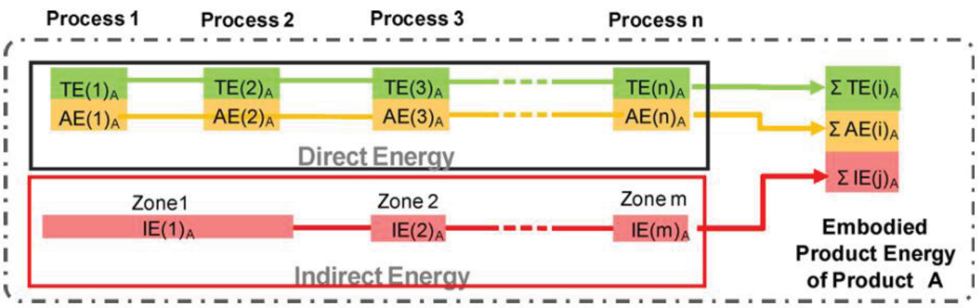
Life-cycle assessment (LCA, also known as life-cycle analysis, ecobalance and cradle-to-grave analysis) is a technique to assess environmental impacts associated with all the stages of a product's life from raw material extraction through materials processing, manufacture, distribution, use, repair and maintenance, and disposal or recycling. Designers use this process to help critique their products (US Environmental Protection Agency., 2010).

Due to the information intensive nature of LCA and the lack of accurate data related to energy demand across a product life cycle (in particular, during the manufacturing phase), significant assumptions and simplifications are often made. This has motivated numerous research programs to investigate energy consumption within a manufacturing facility so as to gain a better understanding of the energy usage and breakdown (Seow & Rahimifard, 2011).

3.1.2.5. Embodied Product Energy (EPE) Framework

Embodied Product Energy (EPE) framework brings more detail to the LCA approach, with the aim of representing the amount of energy attributed to the manufacture of a unit product. For that reason, indirect and direct energy are accounted being defined in this methodology as theoretical energy (TE) (minimum of energy required for direct manufacturing such as melting or machining) and auxiliary energy (AE) (all the indirect energy required for the production of the items) (Seow & Rahimifard, 2011). Further steps of the framework are the modelling embodied product energy and energy simulation as depicted in Figure 7.

Figure 7 Framework for modelling embodied product energy

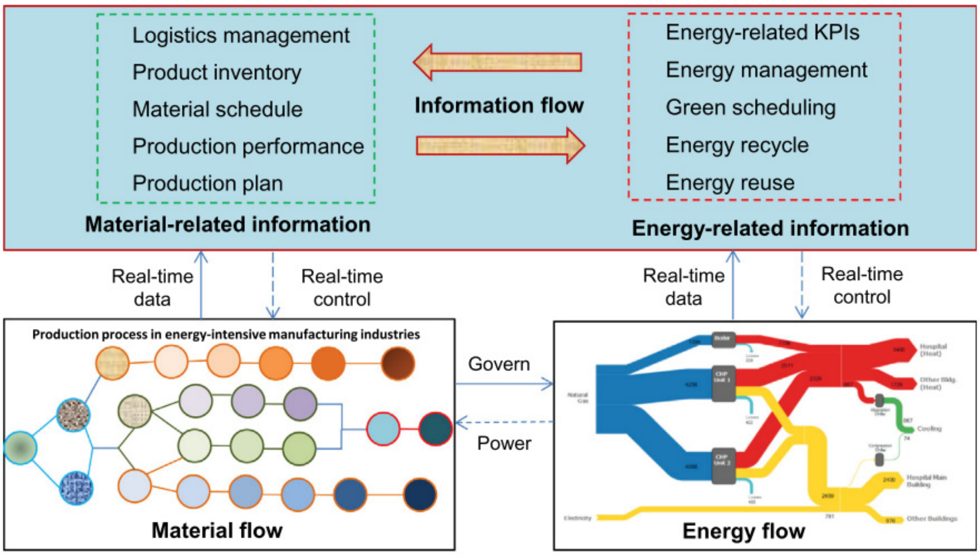


Source: (Seow & Rahimifard, 2011)

3.1.2.6. Material and Energy Flows

Material, energy and information flows are relevant tools for process understanding and management. Therefore, this framework of energy and material flow are usually applied together with Value Stream Mapping techniques in order to understand in a comprehensible approach how information, material, people and machinery correlate to each other in production environment. In Figure 8 we have an example of an energy, material and information flow applied for energy efficiency (Ma, Zhang, Lv, Yang, & Wu, 2019).

Figure 8 Closed-loop structure of energy flow, material flow and information flow.



Source: (Ma et al., 2019)

3.1.2.7. Remaining energy-efficient lifetime (REEL)

REEL is defined as the remaining energy efficient lifetime of a system, in which an equipment or system reaches a non-energy efficient threshold that alerts decision makers of the necessity for the replacement of the asset or renewal. With the development of new smart manufacturing technologies, the prognostics to determine the REEL have become much more precise and realistic through the monitoring and data acquisition, the modelling of energy efficiency and finally the prediction of the REEL. (Hoang, Do, & Iung, 2016).

3.1.2.8. Conservation Supply Curve (CSC) and marginal Cost of Conserved Energy (CCE)

In general, the CSC (Conservation Supply Curve) assesses the cost effectiveness and the technical chances for energy efficiency. The energy conservation potential is shown as a function of the marginal CCE (Cost of Conserved Energy) and provides a clear visualization of energy efficiency. CCE allow for making explicit the impact of maintenance and productivity optimization on energy saving. The application of this model is described in details in distinct literature references (Demichela, Baldissone, & Darabnia, 2018).

3.1.2.9. MAESTRI Total Efficiency Framework (MTEF)

The MTEF represents a flexible and scalable platform, which provides an effective management system that aims to advance the sustainability of manufacturing and process industries. It combines four pillars (Technical/Technological Gaps, Management Gaps and Organizational Gaps) in one holistic platform, which enables an overall efficiency performance assessment from environmental (including resource and energy efficiency), value and cost perspectives. MTEF encompasses Environmental Performance Evaluation with Environmental Influence and Cost/Value assessment models through a life cycle perspective. The aim is to support the decision-making process, by clearly assessing resource and energy usage (valuable / wasteful) of all process elementary flows, and the eco-efficiency performance. It is based in a lean approach, with decision support via value-adding optimization that is also foreseen among the integration of the modules (Paper, Ferrera, Rossini, & Evans, 2017).

3.1.2.10. Empirical Characterization and Industrial surveys for energy analysis

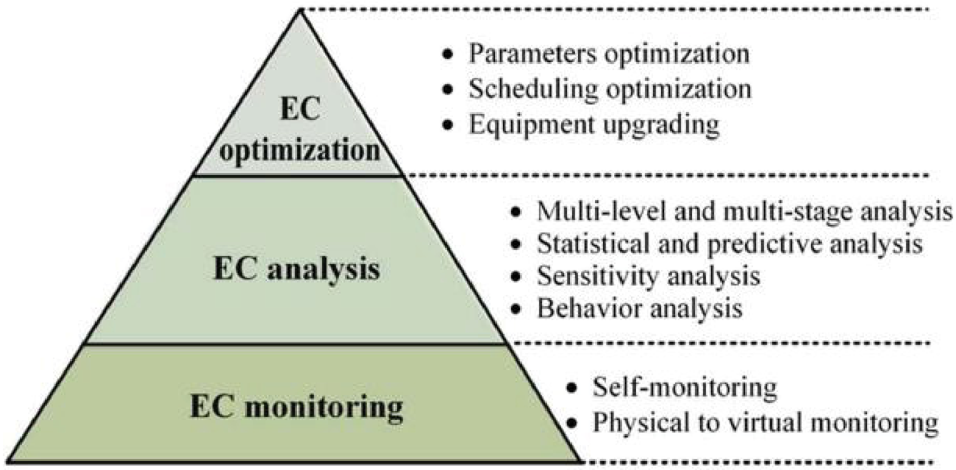
Unlike analytical approaches, empirical modelling uses observations and statistical analysis to characterize the relationship between cause (variables) and effect (responses). The derived relationship can be potentially used to estimate the theoretical limit. It is often used in conjunction with Design of Experiments (DOE) and has been successfully adapted to characterize the energy efficiency of unit processes. However, it is not directly applicable at a factory level. The reasons are twofold: one is that there are numerous potential factors and unknown variables; the other one is that it is impossible and costly to run scheduled experiments at the factory level. (Mahamud, Li, & Kara, 2017).

3.1.2.11. Energy Consumption Monitoring, Analysis and Optimization with application of DTS

With the application of the DTS environment, the evaluation of energy consumption (EC) of a determined equipment becomes much more accurate, following the EC monitoring, analysis and optimization. Since data from both the physical and virtual equipment are available, the equipment energy consumption condition management (EECM) becomes more reliable and more comprehensive. This approach enables better understanding of the monitored object of interest, bringing new insights, approaches and also enabling the identification of upgrades requirements, production scheduling optimizations and parameters optimizations.

Figure 9 depicts the potential applications of DTS as described by Zhang et al., 2018.

Figure 9 Potential applications of DTS for energy equipment consumption management (EECM).



Source: (Zhang et al., 2018)

3.1.3. Applications

In this section, a brief summary is brought in identification and application cases of energy efficiency potentials in manufacturing with the usage of energy efficiency methodologies (section 3.1.2) and smart manufacturing technologies (section 3.1.1).

3.1.3.1. Machine parameters, process and scheduling optimization for Energy Efficiency with CPS application

One relevant application of CPS technology for energy efficiency improvement in manufacturing companies is the integrated energy efficiency optimization strategy and modelling (Li, He, & Li, 2019). The modelling can be divided into four main modelling strategies:

- Energy consumption modelling for machining parameter optimization
- Energy consumption modelling for process planning optimization
- Energy consumption modelling for scheduling optimization
- Energy consumption modelling for tool path optimization

3.1.3.2. Schedule optimization

Utilizing methods and technologies for energy consumption optimization can provide several opportunities for the production environment. Another opportunity that can be mentioned is the power demand optimization. Utilizing the simulation of the production with an energy model as a base, the work schedule of every machine can be changed in order of lowering the demand during peak hours which could lead to savings in costs even if more production hours are needed.

By studying such possibilities of schedule, the simulation can be utilized to provide scheduling optimization of the production cells, in which the energy consumption can be the determining factor.

3.1.3.3. Load management

Another relevant aspect of energy efficiency and energy storage in the manufacturing sector is the possibility of managing peak loads, in order to reduce the costs of energy transmission and usage on times of day when energy is cheaper in the market. That becomes also very relevant with the emergence of smart grids and distributed energy generation technologies.

An interesting usage of energy efficiency simulation and CPS in smart manufacturing is to reduce peak loads with a better understanding of the energy consumption profiles of machinery and value streams in a factory. An interesting application framework can be seen found in (Kohl, Spreng, & Franke, 2014).

In order of specifying the difference between Load Management and Schedule Management is that the first translate to the amount of instant electric power being managed, and the second translate to organize the schedule in a less specific manner, controlling just the energy consumption is an example.

3.1.3.4. Shutdown Management

Another identified opportunity is the monitoring of shutdown management of equipment. Some machines are maintained on a working state even though they are not producing. The solution to this problem can be solved by having a real-time monitoring system coupled with a base-line simulation of the distinct consumption levels of the machine in distinct operating modes. Adding a shutdown management program to value streams and production cells can greatly reduce energy consumption reducing waste in terms of energy demand.

With the possibility of measuring the direct consumption of the machines, the opportunity of the indirect energy (ventilation, lighting, water towers…) consumption analysis also appears. With the energy consumption data of the machines, it is possible in real time to reduce the power of ventilation motors in order to save energy. Premises can be defined such as: proportional degree of power could be displayed by the ventilation motors according to the energy demand that the machines display, or even shutting down sections of the factory ventilation system if the machines power demand is low enough. Such opportunities can help making products more competitive and can prolong the lifetime of those indirect systems.

3.1.3.5. Maintenance Management

The Digital Twin (DT) used together with measurement instruments of high precision can provide a base line for optimal tool mileage, so that when tools become duller its energy consumption increases. By defining an average consumption with the DT and measuring the power consumption in real time, it is possible to set alerts requiring maintenance/change of a specific tool. Nevertheless, the average consumption can also be used to identify problems in the machine and in other parts such as engines by measuring a general difference in consumption that cannot be related in a specific tool path.

This average consumption analysis can be further used as a base for adding new improvements to the machining process, becoming easier to track differences in changes on the process or the machine.

With the measurement of energy consumption in real time allied with other parameters such as machine disturbances, tool consumption, temperature, pressure and other aggregates sensors, it is possible to show correlations that could not be possible without a big data of multiple machine’s parameters or even predict when a failure might occur.

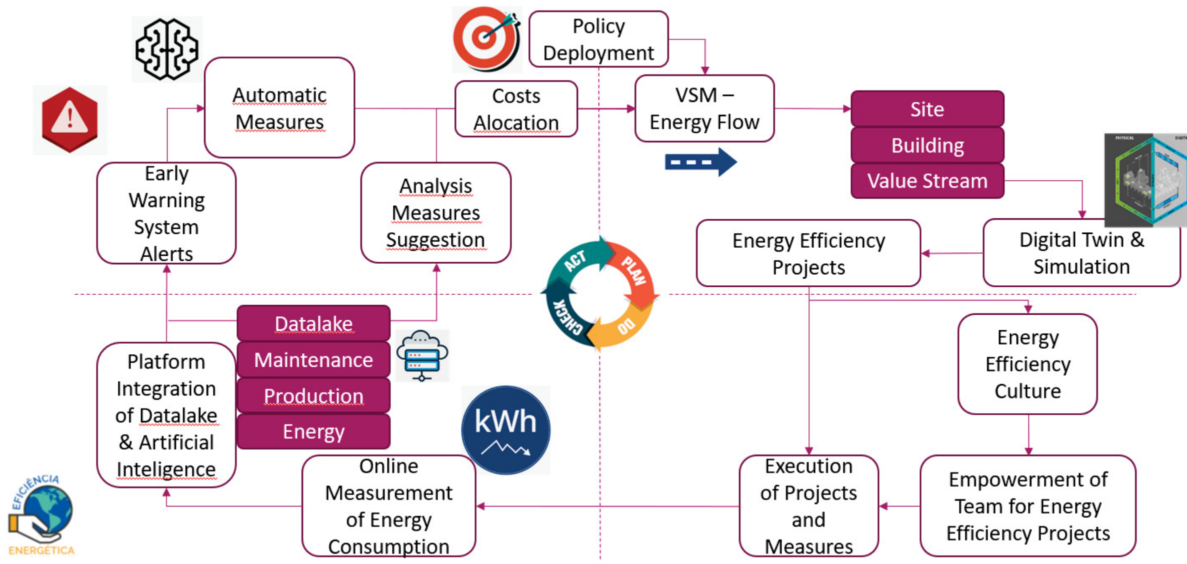
3.2. Theoretical Conclusion

Chapter 3 presented the theoretical basis and defined which methodologies, technologies and approaches are most commonly applied in energy efficiency in smart manufacturing, with this knowledge it possible to answer questions Q1, Q2 and Q3 presented in the INTRODUCTION. The presented concepts where chosen based on the investigation of the most used methodologies, technologies and applications about energy efficiency. The results of this investigation are shown in more detail in Annex 1, which presents a table that links the references to their contribution to the theoretical knowledge presented.

4. APPLICATION MODEL

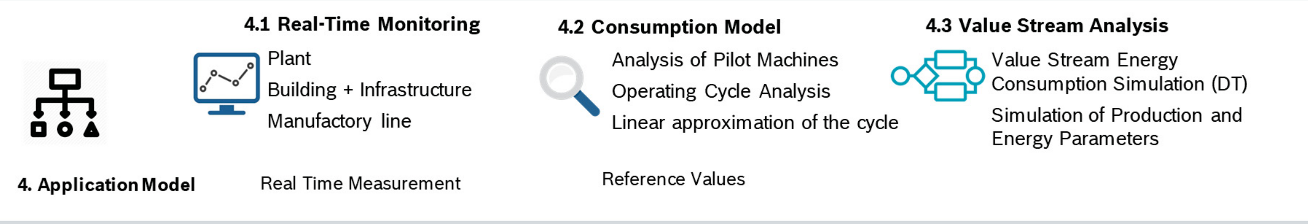
The energy efficiency process workflow being applied in the partner company is shown in Figure 10. For the objective of this research focus was given to implement and improve the following tools and topics of the energy efficiency process shown in Figure 11. This section intends to answer Question number 4 from the Problem Situation section:

Figure 10 Energy efficiency process workflow



Source: Author (2019)

Figure 11 Focuses of the Application Model of this research



Source: Author (2020)

Working and improving the models and technologies applied in those specific topics allied with the companies' tools and workforce can further improve results in energy efficiency and also bring transparency and early correction for unefficient systems.

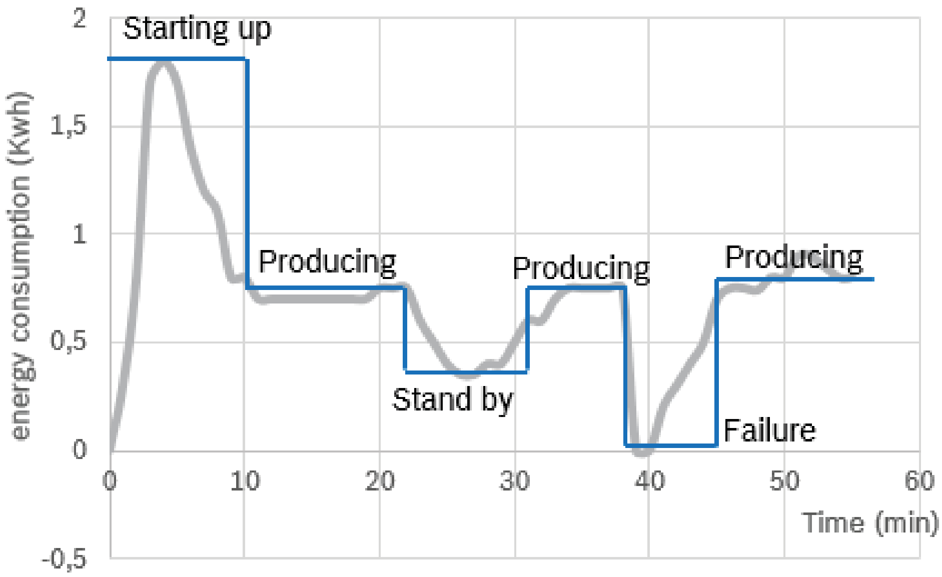
4.1. Real-time monitoring

The online measurement of energy consumption or real-time monitoring is critically important to give fast reaction and automatic diagnosis of systems that show opperative problems or show improvement opportunities regarding energy efficiency. For this purpose, the application of a platform for energy analysis allied with the application of energy consumption meters can help putting light and making clear of the current status of all systems in a factory, be it in site, building, infrastructure or machine level. In this research, since it is being conducted in partnership with a company, it was used the available tools for energy analysis; which will be defined in 5.1.3 Data Collection.

4.2. Consumption model

Measuring data in real time is very important, however if one do not define or give the boundary conditions and reference to which a set of data is relevant, the real-time measurement might not bring its full potential. Therefore, another important aspect of the method definition is setting reference values (statistically defined) and consumption models regarding the energy consumption of machines (in this particular case, machining equipment as the most relevant asset in the partner company). In this regard, a discretization and evaluation of each value stream step will be conducted in order to evaluate models that can give references for the consumption of machining processes. This is already a known methodology applied in the industry as e-VSM (energy value stream mapping), which assess the energy for the production of a certain item in all steps and processes of a value stream.

Figure 12 Example of consumption model of manufacturing machinery



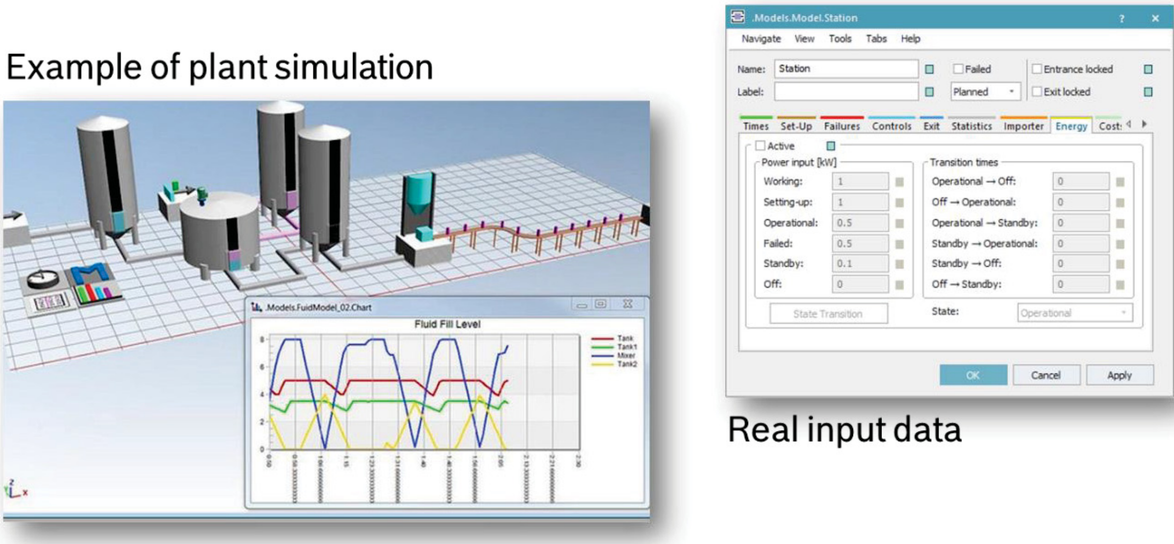
Source: Author (2020)

The application of manual e-VSM assessment is utilized broadly in industries for many years however it is not a dynamic process rendering many of the measurements to become out-of-date whenever there are relevant changes in systems configuration, relevant production volume fluctuations and also technical system improvement. In this regard, a third method step was also defined as relevant being the usage of plant simulation and digital twin models to simulate the energy consumption of process in a dynamic way.

4.3. Value Stream Analysis

Applying plant simulation software to model a certain value stream regarding its specific processes and parameters can lighten the differences in energy consumption reference values in a dynamic way. With this approach, it is possible to assess that a process may be inefficient due to several reasons, such as: scheduling problems, technical problems or distinct volume production conditions. This can lead to machinery of the same type utilizing distinct energy levels even producing similar goods.

Figure 13 Value stream simulation with plant simulation software.



Source: Author (2020)

5. CASE STUDY

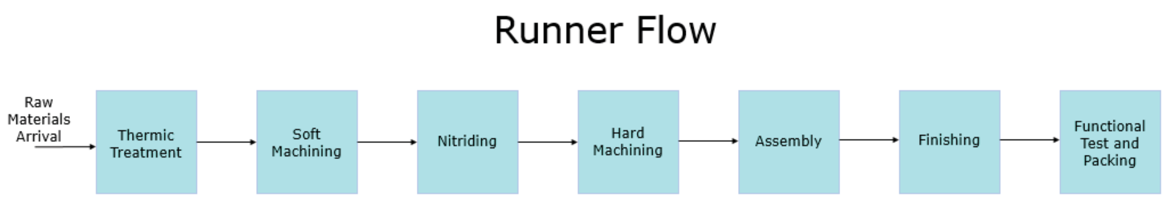
In this section, the practical study of case with the implementation of the APPLICATION MODEL in the partner company is described in details, ranging from the Power Analysis Experiments, followed by the Consumption Data Analysis and ending with Consumption Comparison of the machines in the selected value stream.

5.1. Power Analysis Experiments

5.1.1. Production Cell

In the studied company, the product Runner 483 was chosen as subject for the power consumption analysis of its material flow. This product is one of the most produced in the plant. The Figure 14 represents a flow of the manufacturing process and its steps.

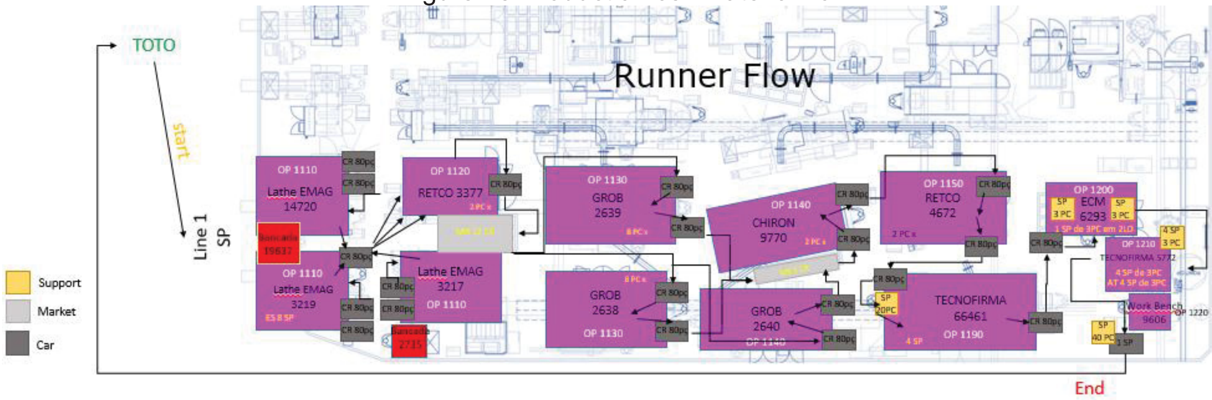
Figure 14 Full processing process



Source: Author (2020)

Since the full process of the Value Stream is very complex and contain many machines, a production cell was chosen as a target for the power analysis experiment; this cell is responsible for the process of soft machining the materials of the Runner 483. The machines that compose this specific value stream are broadly used across the factory, so the results of the experiments can be used as an indicator for other sections of the plant. The process that composes the cell and its machines will be presented in Figure 15.

Figure 15 Production cell material flow

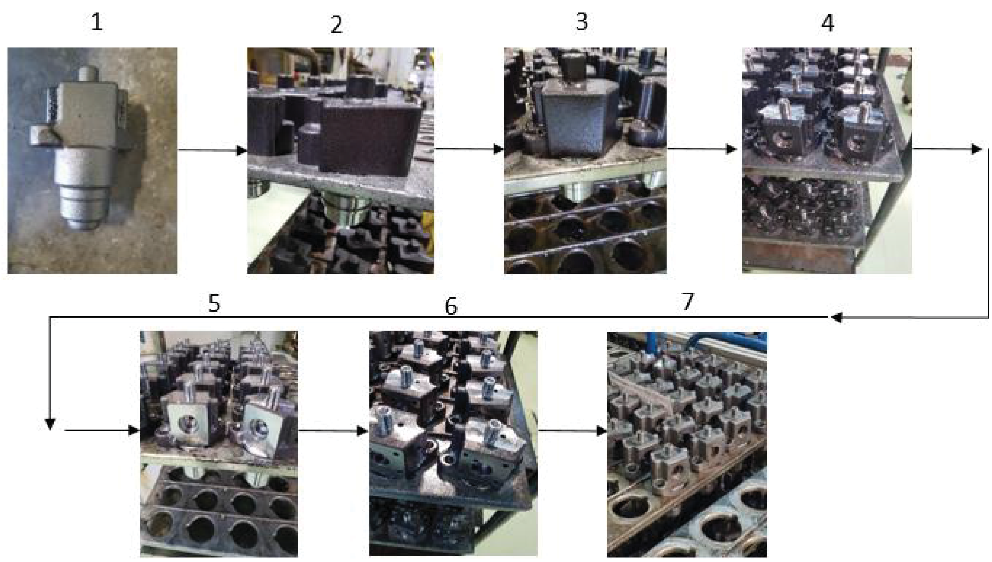


Source: Author (2020)

The material arrives at the cell after the heat treatment (TOTO) (1) and begins being processed by the three lathe EMAG (63kW) which perform the same process (2). After being processed by the lathes, the material follows to the drill RETCO (37kW) (3). Then, it is processed throughout one of the three machining centers GROB (53kW) (4). The resulted product follows throughout the machining center Chiron (39kW) (5). The next step is the processing of the product by a drill RETCO (37kW) (6) and then a washing machine TECNOFIRMA (70kW). After that, the product goes through the Electrolytic grinder ECM (80kW) (7), then to a washing machine TECNOFIRMA (16kW). The last part of this process happens in a workbench where a few samples are checked for quality analysis.

Figure 16 shows the product in every step of the soft machining process.

Figure 16 Product cycle

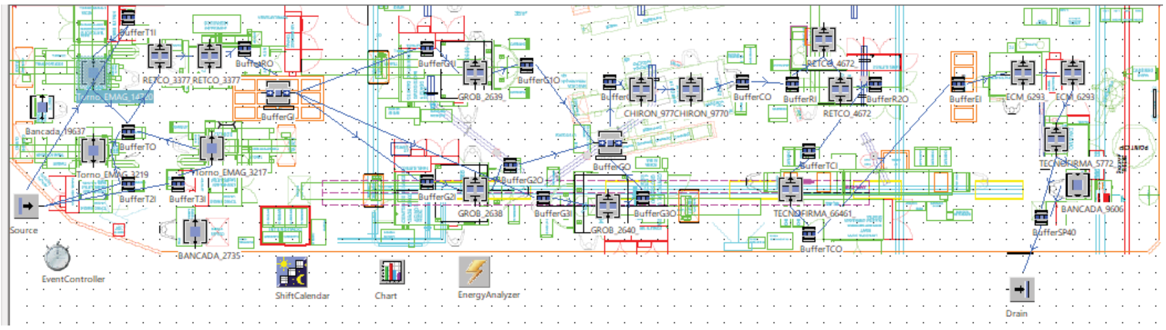


Source: Author (2020)

5.1.2. Value Stream Simulation

For the simulation of the production cell, it was chosen the software Tecnomatix Plant Simulation 15.1. In the software, a digital twin of the production cell was created. This digital twin contains information about every machine, such as: processing time, set-up time, availability and energy parameters. With this information, the software simulates the working process of the production cell. In the experiments a deviation of 5% was observed between the simulation and real number of produced parts. This can occur to disturbances in the process or conservative times of process in the simulation. In Annex 2 Figure 46 the full soft machining cell can be better observed.

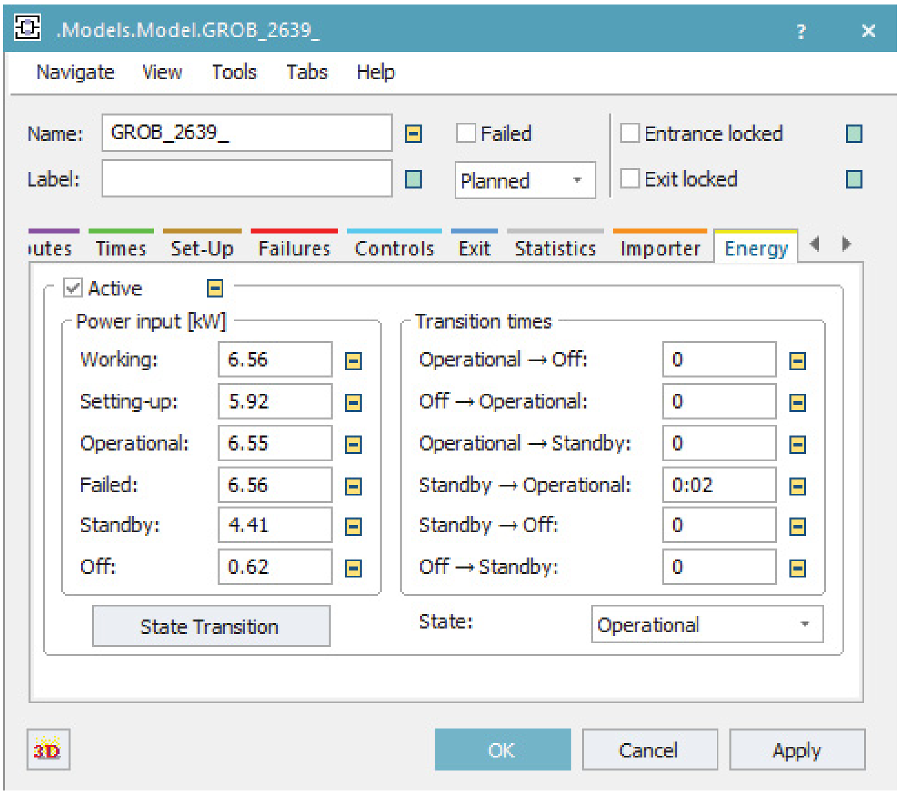
Figure 17 Soft machining production cell



Source: Author (2020)

In the software menus there are energy parameters, so while it simulates the material flow, the energy consumption can be also simulated. Figure 18 shows which data was needed for the simulation. In order to acquire the data for the software, an empirical characterization of every machine was made. Each one had its electrical consumption measured with the Fluke 434 Series II Energy Analyzer for a week.

Figure 18 Energy data example



Source: Author (2020)

With all the parameters defined (material and energy), the simulation displayed the amount of energy the production cell spends for a fixed amount of time. The month of January of 2021 was chosen for this study, due to the fact that all the CCK7200 power multimeters were installed in the machines of the production cell by December 2020, so they could be used as reference for the energy consumption along the previous months. As a result, the simulation displayed the results that are shown in Table 1.

For a more detailed report, the present in Annex 3 presents the full displayed table.

Table 1. Energy Data Example

Energy Consumers	Energy [kWh]
CHIRON_9770	2.968
ECM_6293	8.898
GROB_2638	3.657
GROB_2639	3.334
GROB_2640	4.664
RETCO_3377	4.860
RETCO_4672	4.047
TECNOFIRMA_5772	1.118
TECNOFIRMA_66461	6.288
Torno_EMAG_14720	5.326
Torno_EMAG_3217	5.457

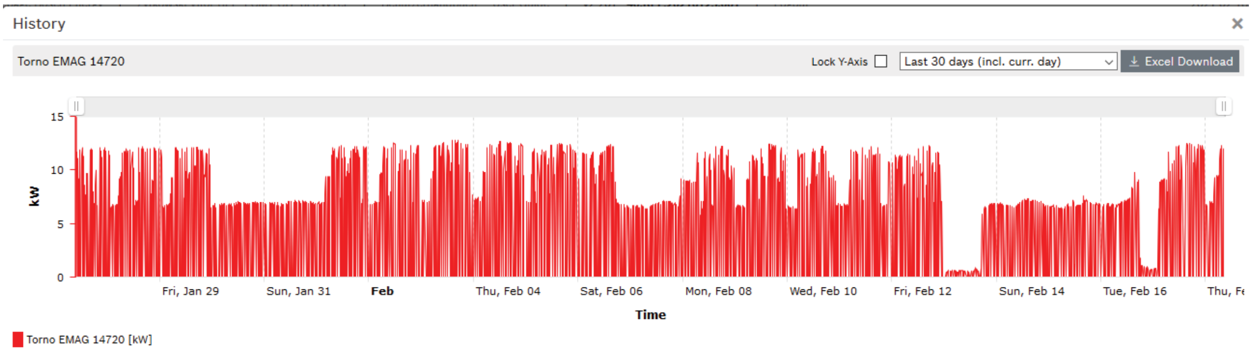
Source: Author (2020)

The software also allows the user to visualize several other information, such as energy consumption by every operational mode of the machines.

5.1.3. Data Collection

For collecting the Machine Specific Energy Consumption (SEC) data, three equipment were used: Fluke 434 Energy Analyzer, Power Multimeter CCK7200 and the Beckhoff CLP. The Fluke Energy Analyzer measured the instant power in a span of 15s, and with it the information needed for the creation of the digital twin was acquired. A portion of the machines listed in this process already had installed the Beckhoff CLP with several sensors. In those machines the installation of the Fluke 434 Energy Analyzer was not necessary, due to the fact that the Beckhoff CLP can provide the necessary information. For a validation of the digital twin model, the instant power sensors CCK were installed in the target defined cell. These sensors are able to measure the active power of each machine in a span of 5 minutes. The collected data is sent to a local data bank, where the information is available for further analysis in the software Energy Platform as shown in Figure 19.

Figure 19 Energy platform

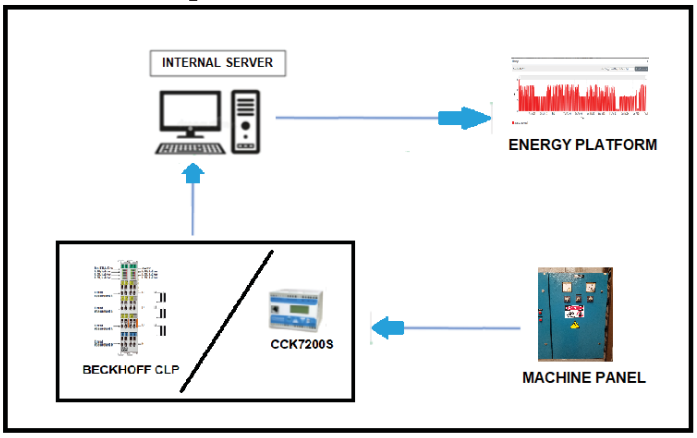


Source: Author (2020)

5.1.4. Data Collecting Devices

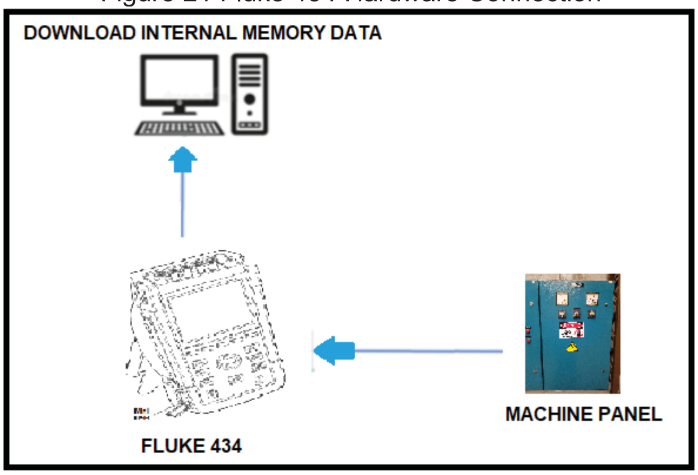
Before presenting the collecting devices, Figure 20 and Figure 21 show the flow chart of how the devices acquire and distribute information.

Figure 20 Hardware connection



Source: Author (2021)

Figure 21 Fluke 434 Hardware Connection



Source: Author (2021)

5.1.4.1. CCK7200

Figure 22 CCK7200

Source: Author (2020)

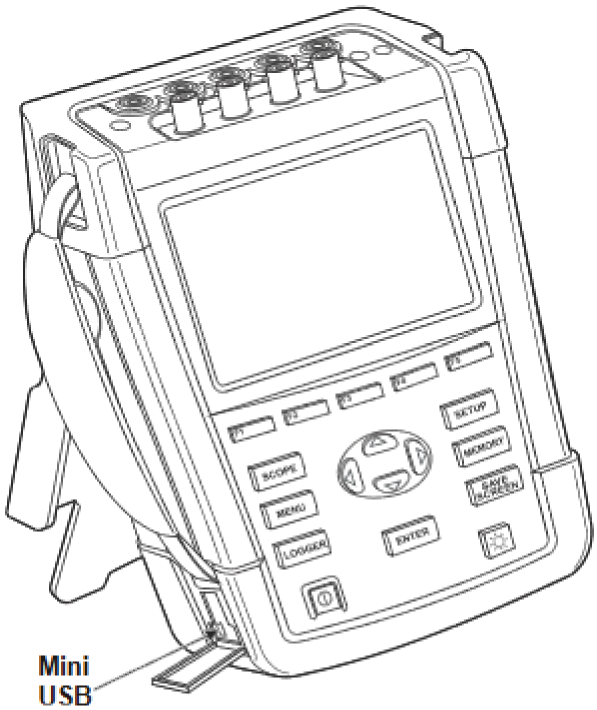
The power multimeter CCK7200 can measure power in a span of 5 minutes. It gives several options of readings, including:

- Voltage
- Electrical Current
- Active Power
- Apparent Power
- Reactive Power
- Power Factor
- Frequency

All the information that is measured with the CCK7200 multimeter is saved on the company's data bank. Then the information is displayed by the software Energy Platform.

5.1.4.2. Fluke 434 Series II Energy Analyzer

Figure 23 Fluke 434 Series II



Source: Author (2020)

The Fluke 434 Series II can measure power in a span of 0.25s. It gives several options of readings, including:

- Voltage
- Electrical Current
- Active Power
- Apparent Power
- Reactive Power
- Energy
- Power Factor
- Frequency
- Harmonics

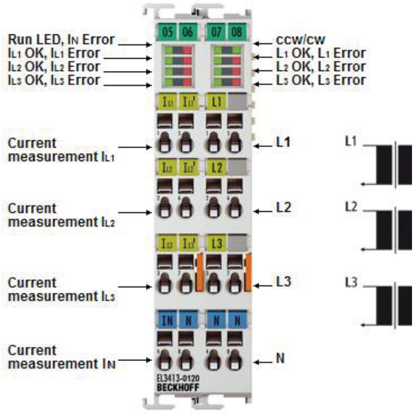
All the information collected with Fluke 434 Series II is saved on its internal SD memory card. The information can be later analyzed by the Fluke software PowerLog Classic V4.6. Its Power Measurement Accuracy is ± 1% ± 10 counts.

5.1.4.3. Beckhoff CLP EL34x3 - 3-phase power measurement terminals

The Beckhoff CLP can measure power in a span of 59,52μs. It gives several options of readings, including:

- Voltage
- Electrical Current
- Active Power
- Apparent Power
- Reactive Power
- Energy
- Power Factor
- Frequency

Figure 24 Beckhoff CLP



Source: Author (2020)

All the information collected with the Beckhoff CLP is saved on the company's internal data bank. The information can later be analyzed by the Energy Platform software or Grafanas's platform. Its Power Measurement Accuracy is 10mW.

Table 2 Data Collecting Instruments

	CCK7200	Fluke 434 Series II	Beckhoff CLP
Measure Span	300 s	0,25 s	59,52 μs
Accuracy	0,2%	+- 1%	10 mW
Memory HD	30 days	7 days	5 days

Source: Author (2020)

5.1.5. Acquired Data

After the Machine Specific Energy Consumption (SEC) of every machine was obtained, the software Plant Simulation was used for creating a Digital Twin (DT) of the chosen production cell. This software opens the possibility of simulating the energy consumption of machines, provided that the SEC is inputted. The software requires the following data of every machine:

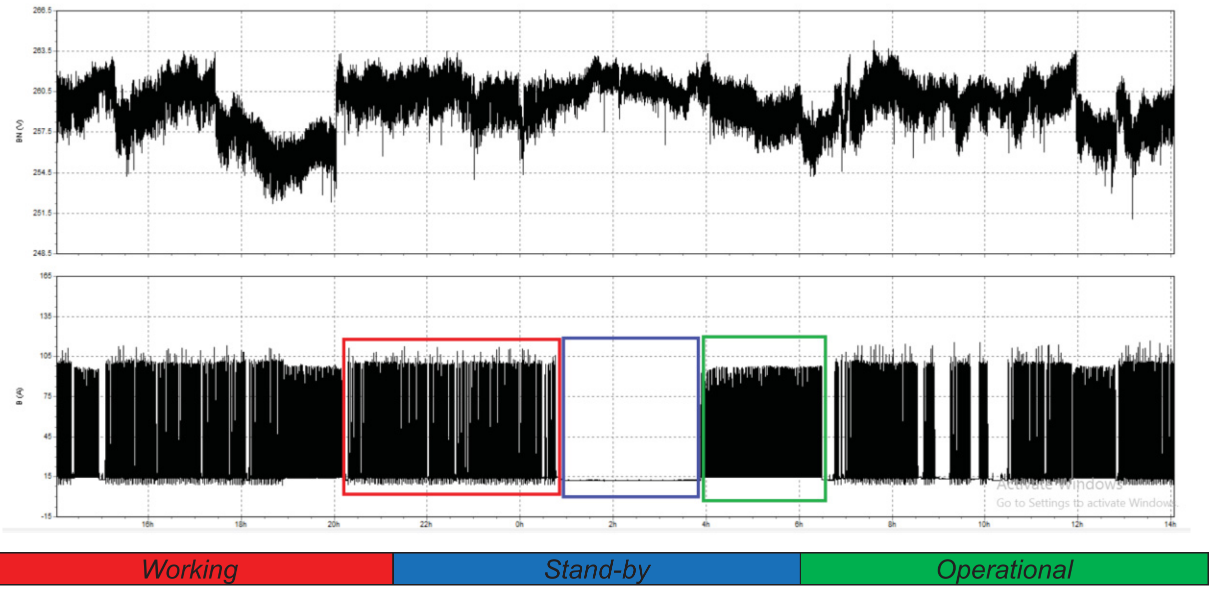
Table 3 Data Required by Plant Simulation

Time	Power
Time working at full power	Power consumption working full power
Time staying off	Power consumption in standby mode
Time in standby	Power consumption at operation mode
Time being operated	Power consumption in off mode
Time in setup mode	Power consumption in setup mode
Number of items that will be done in a simulation row	

Source: Author (2020)

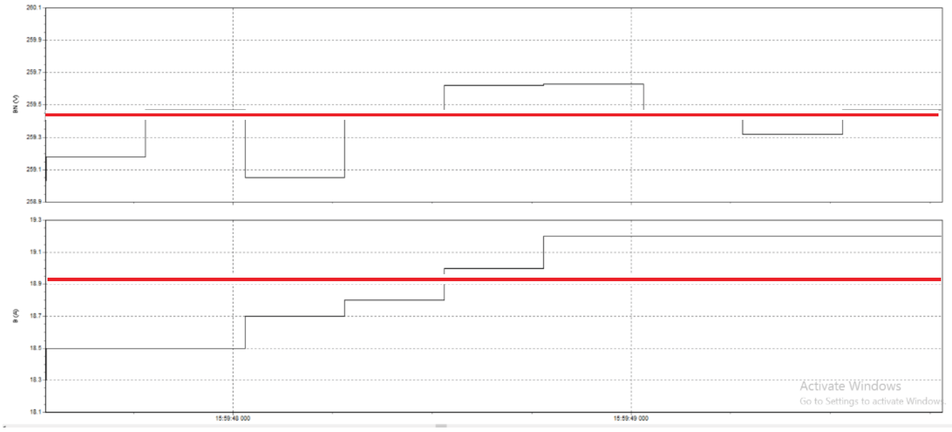
Figure 25 to Figure 28 represents and exemplify the acquired data from the measurements in all the machines that compose the production cell. The measurement instrument collected all the necessary data that is required for the digital twin simulation, on the figures there are trend lines that indicate the medium value, which was utilized on the simulation, these values can be found in Table 4.

Figure 25 Fluke full data analysis example



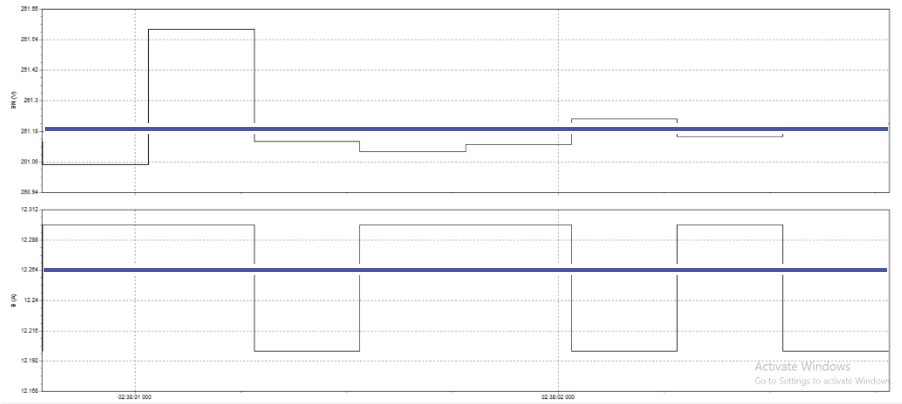
Source: Author (2020)

Figure 26 Power consumption working



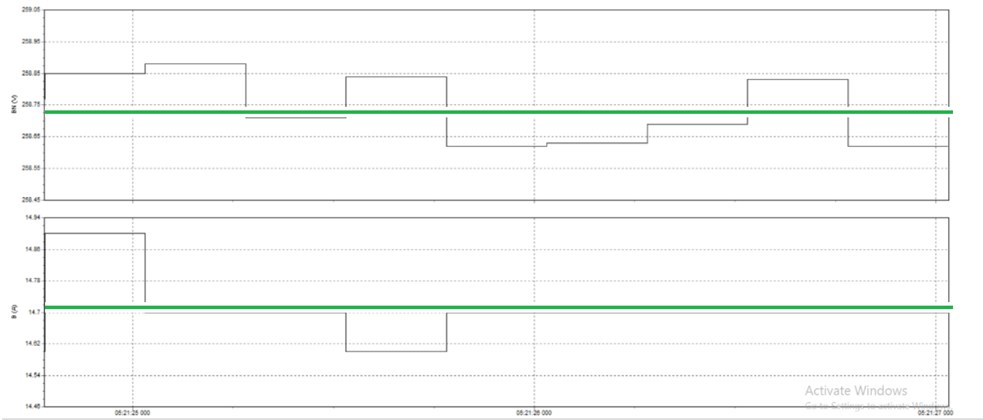
Source: Author (2020)

Figure 27 Power consumption standby



Source: Author (2020)

Figure 28 Power consumption at operational mode



Source: Author (2020)

After this data is inputted, the software simulates the energy consumption of every machine. It also indicates the machines with the biggest consumption for an easier analysis of the process.

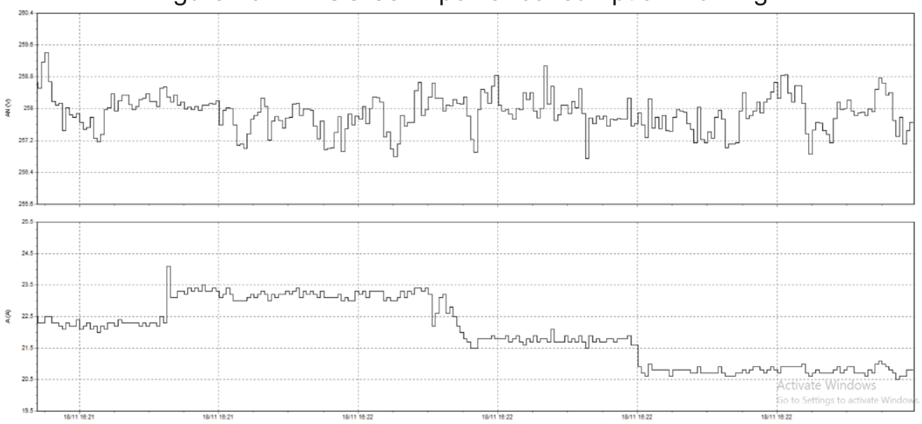
5.2. Consumption Data Analysis

5.2.1. Consumption Curves

Using the power analyzer Fluke 434 and the Beckhoff CLP, the Machine Specific Energy Consumption (SEC) were obtained. For each machine the curves were split in three sections: Power Consumption Working, Power Consumption at Standby Mode, Power Consumption Off.

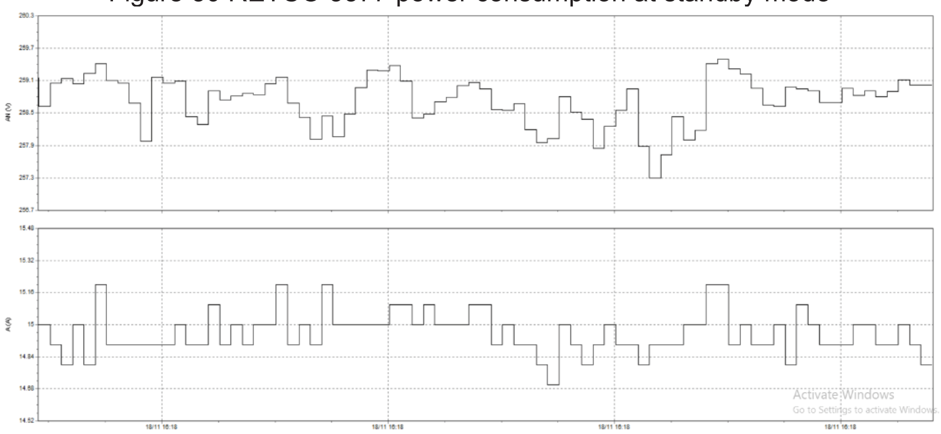
Figure 29 to Figure 34 shows the consumption curves of two machines. The complete data for all the other machinery can be found in Annex 3.

Figure 29 RETCO 3377 power consumption working



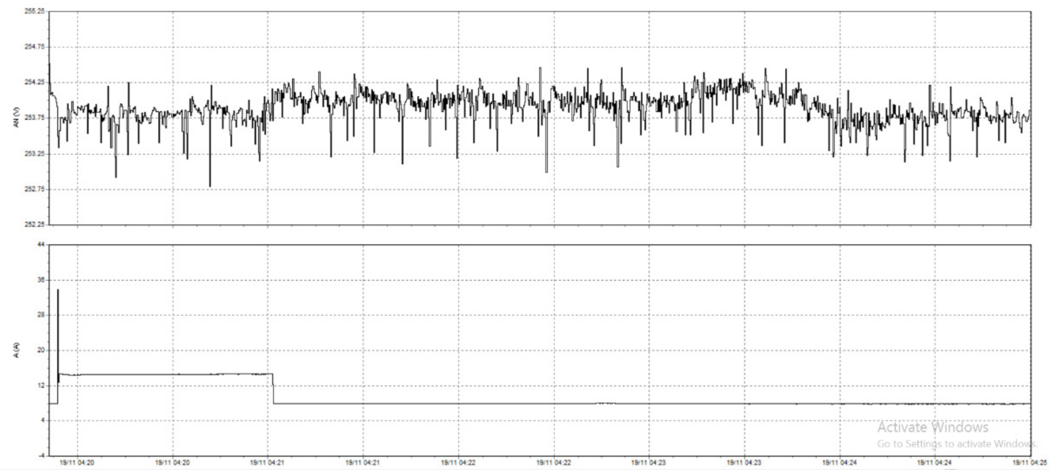
Source: Author (2020)

Figure 30 RETCO 3377 power consumption at standby mode



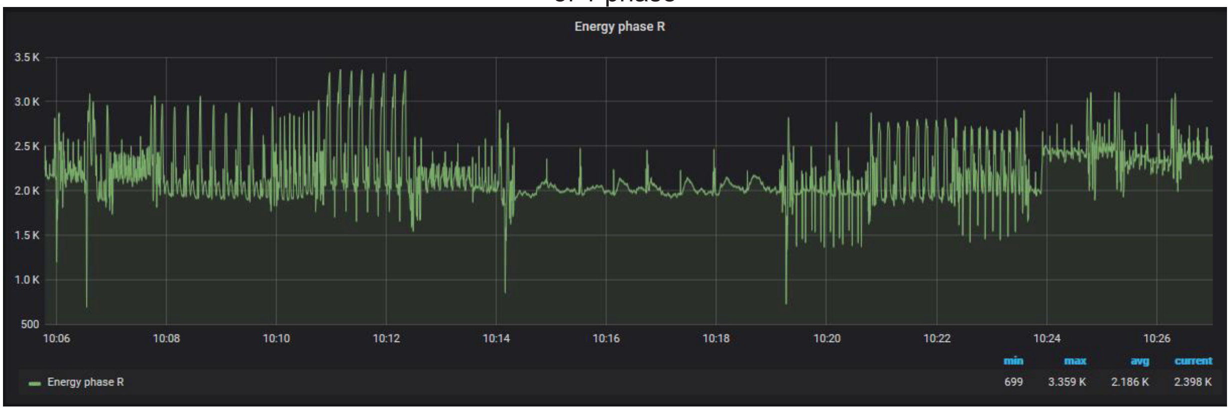
Source: Author (2020)

Figure 31 RETCO 3377 power consumption off



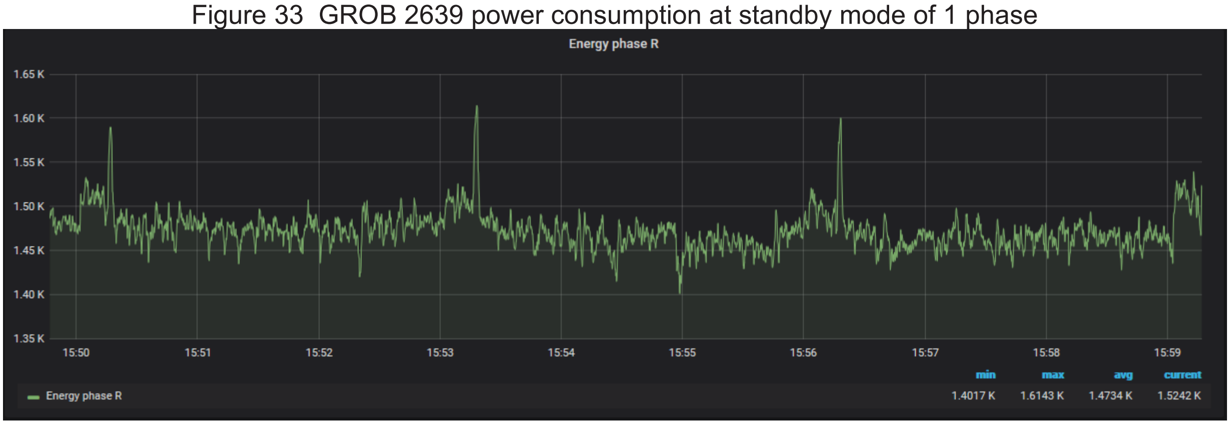
Source: Author (2020)

Figure 32 GROB 2639 power consumption working GROB 2639 power consumption working of 1 phase of 1 phase



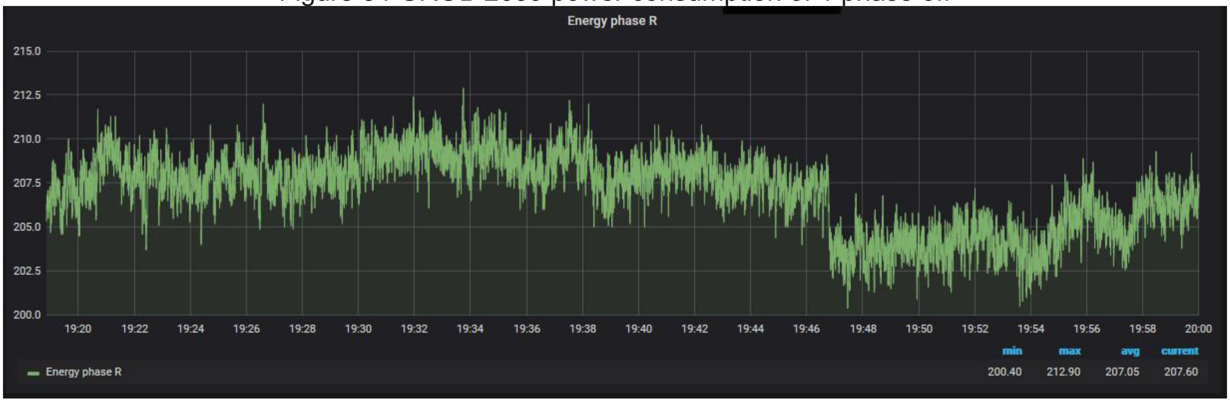
Source: Author (2020)

Figure 33 GROB 2639 power consumption at standby mode of 1 phase



Source: Author (2020)

Figure 34 GROB 2639 power consumption of 1 phase off



Source: Author (2020)

Using these curves and the information provided by the power analyzer Fluke 434 and the Beckhoff CLP the average power consumption was defined. Follow Table 4 with the power values found in the studied machines.

Table 4 Detailed power consumption

Machine	Power consumption Working (kWh)	Power consumption in setting up mode (kWh)	Power consumption stand-by (kWh)	Power consumption operational mode (kWh)	Power consumption in off mode (kWh)
Lathe EMAG 14720	10,78	7,86	6,26	10,78	0,56
Lathe EMAG 3219	10,98	9,14	7,90	9,33	0,50
Lathe EMAG 3217	11,47	10,06	6,73	9,20	0,50
RETCO 3377	10,03	6,70	7,11	9,09	0,91
GROB 2638	7,14	6,4	5,37	5,37	0,65
GROB 2639	6,56	5,925	4,41	6,55	0,62
GROB 2640	8,97	6,6	8,7	8,7	0,67
CHIRON 9770	6,35	3,73	3,73	5,12	0,53
RETCO 4672	7,76	6,98	7,76	7,76	0,77
TECNOFIRMA 66461	12,02	10,72	3,07	12,02	3,07
ECM 6293	17,82	15,05	15,05	15,05	0,39
TECNOFIRMA 5772	6,45	2,68	0,16	0,38	0,06

Source: Author (2020)

5.3. Consumption Comparison

As an application of the study, the simulation of January 2021 consumption on the production cell was compared to the real consumption. The results are presented in Table 5.

Table 5 Consumption comparison

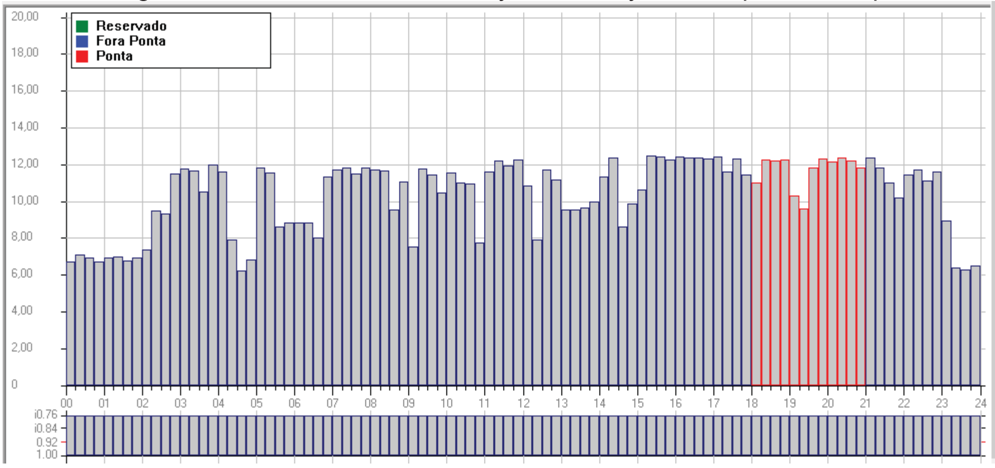
Machine	Real Consumption January (kW)	Simulated Consumption January (kW)	Error (%)	Error (kW)
Lathe EMAG 14720	5.949	4.898	**17,67**	1.051
Lathe EMAG 3219	6.695	5.196	**22,39**	1.499
Lathe EMAG 3217	5.989	5.125	**14,43**	864
RETCO 3377	4.891	4.666	**4,60**	225
GROB 2638	1.390	3.485	**150,72**	-2.095
GROB 2639	4.202	3.129	**25,54**	1.073
GROB 2640	6.670	4.635	**30,51**	2.035
CHIRON 9770	2.950	2.809	**4,78**	141
RETCO 4672	4.191	3.973	**5,20**	218
TECNOFIRMA 66461	5.460	5.442	**0,33**	18
ECM 6293	1.570	8.639	**450,25**	-7.069
TECNOFIRMA 5772	X	1.118	X	X

Source: Author (2020)

By applying the concept of Conservation Supply Curve (CSC) and analyzing the results, it is possible to see a great difference between the simulated and the real energy consumption in some machines of the production cell. Due to that difference, every machine had its processes checked in order to find a reason to its behavior.

The machines Lathe EMAG 14720, Lathe EMAG 3219, Lathe EMAG 3217, GROB 2639 and GROB 2640 present the real consumption 25% higher than the simulated values. Since the base power of every process is the same in both simulation and real machines, a hypothesis was that the difference was due to the lack of proper shutdown procedures after the shifts in certain machines. To confirm this hypothesis the CCK7200S data bank was checked, and with it, we could confirm that the machines were not being turned off in the night shift, despite not being used at that time. The Figure 35 presents the data used to support this affirmation.

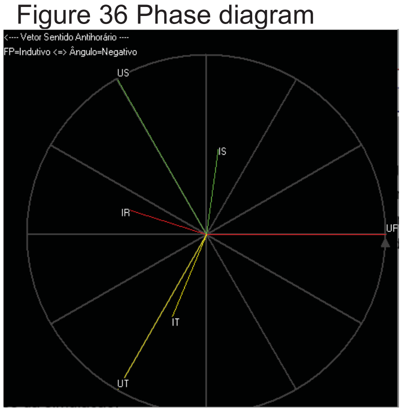
Figure 35 Lathe EMAG 1720 day in January consumption example



Source: Author (2020)

The machine GROB 2638 also presented differences by comparing the real and the simulated data, the odd factor in this machine is that its simulated energy consumption is way higher than its real data. Due to that problem, the machine was analyzed in order to find the reasons for such a difference. After checking many possibilities, it was uncovered that the problem relies with the CCK power multimeter, which has inverted current sensor of two phases, as shown in its diagram bellow.

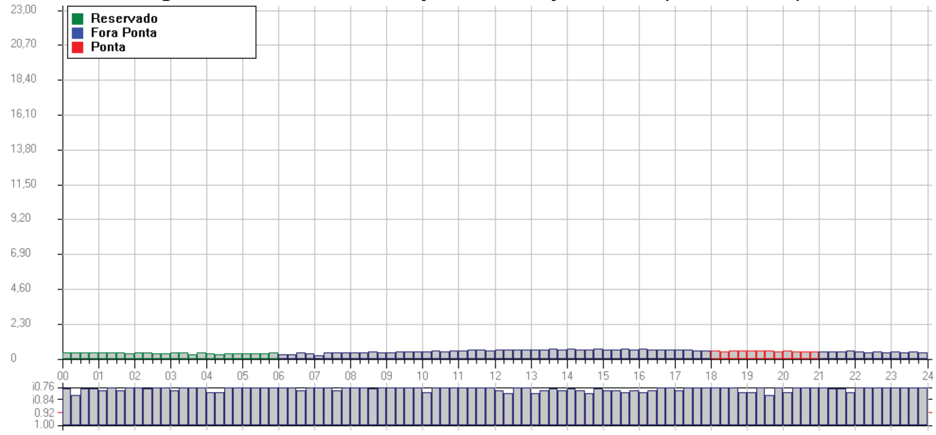
Figure 36 Phase diagram



Source: Author (2020)

The last machine that presented a big difference between the real and simulated energy consumption is the ECM6293. This machine, as GROB2638 has a much lower real consumption than the simulated value. By analyzing the consumption on the CCK software and seeking information with those responsible for the production, it was uncovered that the machine had been off for most of the month due to maintenance reasons.

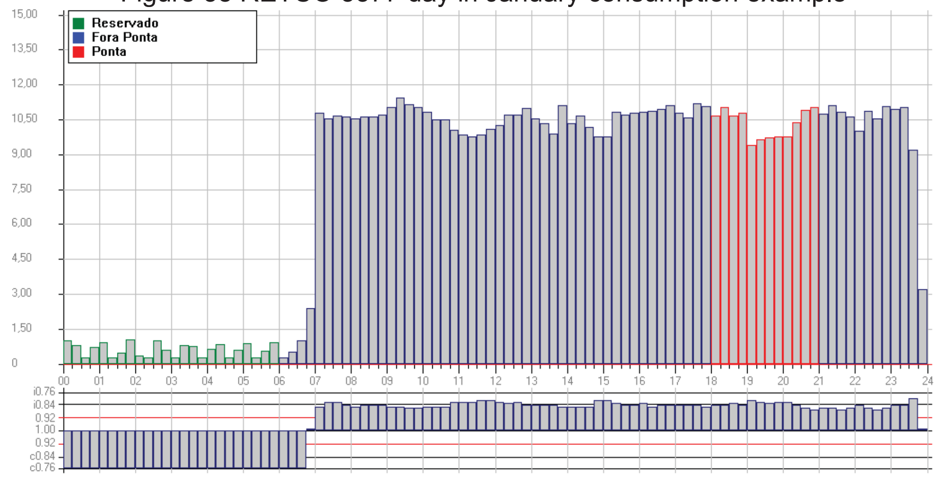
Figure 37 ECM 6293 day in January consumption example



Source: Author (2020)

The machines RETCO 3377, RETCO 4672, TECNOFIRMA 66461 and CHIRON 9770, all had the predicted behavior of turning working only when necessary, due to that they had shown energy consumptions very close to the simulated values.

Figure 38 RETCO 3377 day in January consumption example



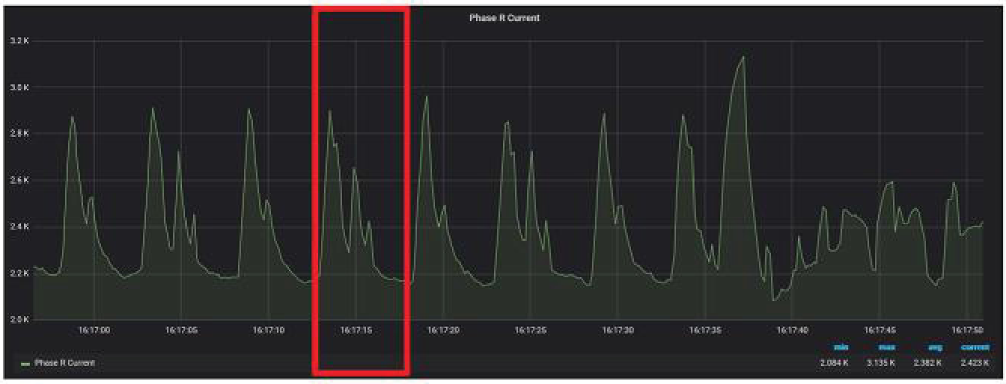
Source: Author (2020)

For a more detailed study of case, the Equipment Energy Consumption Management (EECM) was analyzed.

Three machines were installed with the Beckhoff CLP and had their machining process analyzed; GROB 2638, GROB 2639 and GROB 2640. The objective of this study was to map the consumption of every tool used by the machines, with that information we open possibilities of analysis such as tool quality, tool path optimization and Remaining Energy-Efficient Lifetime (REEL) of each tool became possible.

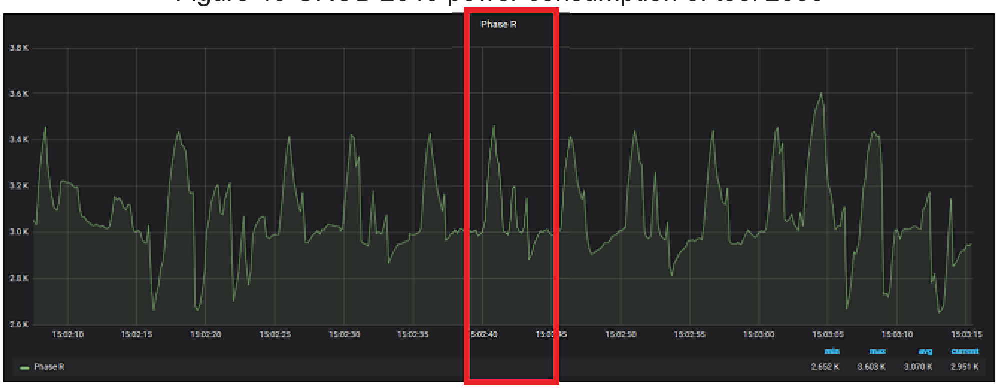
With the detailed study of case this thesis was able to validate the consumption of one set of parts in the simulation software, the compared results along with the power consumption graphic of two tools is shown below, all the graphic data is available in Annex 2. The figures Figure 39 to Figure 44 show the energy consumption on tools 2035 and 2006 while grinding 8 parts. The highlighted section of the figures show the consumption of one part.

Figure 39 GROB 2638 power consumption of tool 2035



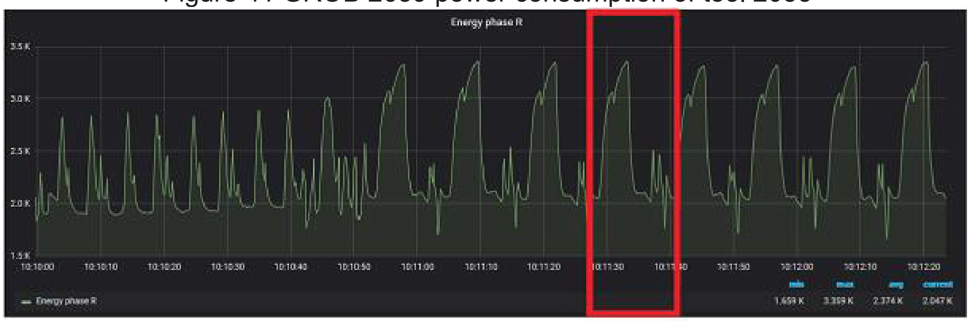
Source: Author (2020)

Figure 40 GROB 2640 power consumption of tool 2035



Source: Author (2020)

Figure 41 GROB 2639 power consumption of tool 2035



Source: Author (2020)

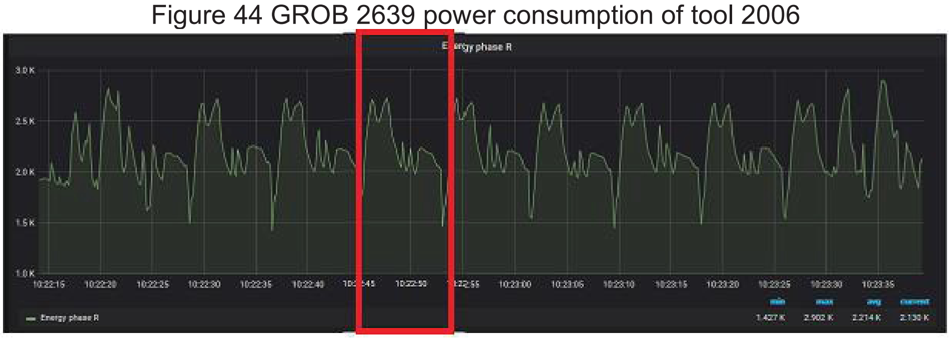
Figure 42 GROB 2638 power consumption of tool 2006

Source: Author (2020)

Figure 43 GROB 2640 power consumption of tool 2006

Source: Author (2020)

Figure 44 GROB 2639 power consumption of tool 2006



Source: Author (2020)

When using the software for the production simulation for simulating only 1 row of parts (8 parts) the Embodied Product Energy (EPE) is defined. Comparing those results with the real consumption, we obtain the Table 6.

Table 6 Energy consumption

	Simulated EPE (kW)	Real EPE (kW)
GROB 2638	0,315	0,311
GROB 2640	0,411	0,411
GROB 2639	0,287	0,286

Source: Author (2020)

6. DISCUSSION OF RESULTS

In this section both the results of the implementation of the APPLICATION MODEL and the practical CASE STUDY will be briefly discussed, answering questions 4 and 5 respectively of the Problem Situation.

6.1. Results of the Application Model for Energy Efficiency

With the application model described in section 4, it was possible to systematically approach the process of the partner company in a structured way, generating a solid digital twin model of the pilot value stream to measure its real-time consumption allied with a reference of the process energy consumption for a determined production volume. This result provides an easy-to-use approach that can be applied in several other value streams inside the partner company and other manufacturing industries, answering question number 4 from the Problem Situation.

6.2. Results of the Study of Case and Opportunities

The practical results and opportunities of the APPLICATION MODEL in an applied CASE STUDY will be discussed in this section, providing a robust answer to question number 5 from the Problem Situation. In this section the results and opportunities of real results in a real industrial manufacturing facility situation will be addressed.

6.2.1. Schedule optimization

After analyzing the consumption comparison, it was identified that this project could provide several opportunities for the production environment. The first opportunity that was brought up was power demand optimization utilizing the concept presented in section 3.1.3.2 Schedule optimization.

The simulation was utilized to provide scheduling optimization of the production cell utilizing energy consumption as the determining factor. In the simulation software two new schedules were defined, both schedules differ from the real one. The first one working through the night shift (00:00 until 6:00) until all the products of the month are produced, then shutting down all the idle machines and the second one works through the night shift and Saturdays, but avoid to work in peak hours (18 until 21)

Table 7 Scheduled consumption present the results.

By using this different schedule of production, the simulation produced the same number of parts and the energy saved in the month of January 2021 was 4.653 kWh by working Full Time. Additionally, by not working on Peak hours the energy spent was more than the Full-Time schedule, but it was the most economical way of working, saving R$ 28.980 on an yearly perspective based in the performance of the month of January.

Table 7 Scheduled consumption

Machine	Full Time Working Simulation January (kWh)	No Night Shift Working Simulation January (kWh)	No Peak Time Working Simulation January (kWh)
Lathe EMAG 14720	4.391	4.898	4.900
Lathe EMAG 3219	4.559	5.196	5.100
Lathe EMAG 3217	4.514	5.125	5.144
RETCO 3377	4.092	4.666	4.536
GROB 2638	3.204	3.485	3.398
GROB 2639	2.924	3.129	3.067
GROB 2640	4.066	4.635	4.476
CHIRON 9770	2.645	2.809	2.765
RETCO 4672	3.551	3.973	3.828
TECNOFIRMA 66461	5.716	5.442	5.226
ECM 6293	7.669	8.639	8.538
TECNOFIRMA 5772	1.078	1.118	1.072

Source: Author (2020)

6.2.2. Shutdown Management

As analyzed in section 5.3 Consumption Comparison, another opportunity was identified. Some machines were maintained on a working state even though they are not producing. The solution to this problem was adding a shutdown management program to the studied production cell. This program divided the machines in groups according to their potential of being turned off during unproductive period. After the program was applied it was noted that the potential energy savings were around 65 MWh/Year.

For helping in the shutdown management program an automation project was applied on the production. This project made changes on the programming setup of the Retco machines, making so that if the machine do not process a part for 30 minutes, it turns off most of its processes, this program by itself has the potential energy savings around 100 MWh/Year.

Another opportunity connected to the shutdown program it is the utilization of warning systems. These systems already exist on the software Energy Platform and can be programmed to send alerts according to the energy demand, in order to monitor the state of the machines at defined times, a user can be alerted if a machine is left consuming energy when it was supposed to be turned off.

6.2.3. Maintenance Management

As analyzed in section 5 CASE STUDY and following the concepts displayed on section 3.1.3.5 Maintenance Management, an example off average tool consumption is shown in the Figure 45, any deviation from the average path may show that the machine is not on optimal condition.

Figure 45 Average Tool Path

Source: Author (2021)

This maintenance analysis can be further used as a base for adding new improvements to the machining process, becoming easier to track differences in changes on the process or the machine.

With the measurement of energy consumption in real time allied with other parameters such as maintenance disturbances, tool consumption, temperature, pressure and other aggregates sensors, it is possible to predict when a failure might occur or even showing value of correlations that could not be possible without a big data of multiple machines' parameters.

7. CONCLUSION

As previously discussed, energy efficiency has a major importance and relevance for the future of sustainable manufacturing, with growing/increasing importance in achieving several KPIs, such as reducing the Co_2 footprint, reducing energy consumption and achieving the United Nations sustainable development goals (SDGs). The main objectives were to answer five research questions as defined in section 1.2 Problem Situation.

Research questions Q1 and Q2 can be answered through the exploration of the methodologies and technologies applied to improve energy efficiency in the industry 4.0 context in order to achieve a sustainable and smart manufacturing (section 3.1.1 and 3.1.2 respectively). To answer research question Q3 use cases were identified (section 3.1.3) where the application of compatible energy efficiency methodologies and smart manufacturing technologies, such as CPS and digital twin, were critical for the success achievement, enabling and potentializing results. As a summary for answering questions 1 to 3 Annex 1 brings a consolidated vision of the filtered repertory referred correlating the publications to topics it addresses.

To answer research question Q4, this thesis proposes a comprehensible application model for the enhancement of energy efficiency in manufacturing, detailed in section 4 and with a practical case study detailed in section 5. The results obtained and opportunities identified in the pilot process are discussed in section 0 and answers the last research question Q5, showing solid results in both the implementation of the proposed application model whereas with real financial and consumption reduction in practical results. This master project showed throughout its tests, that there is a huge potential on energy management in a production level, be that in schedule management, maintenance management, shutdown management or even by predicting possible machine failures and other correlations.

For schedule management, the practical CASE STUDY shows that by rearranging the production schedule we can have energy savings and peak demand management, and by combining this with other analysis such as overtime needs, the results can indicate energy and cost savings without the need of extra expenses.

For maintenance management, with the detailed study of case, analysis such as Remaining Energy-Efficient Lifetime (REEL), Embodied Product Energy (EPE), Life Cycle Energy Analysis (LCEA) are obtained and open opportunities for optimization on mileage of every tool and more control over the quality and commercial process.

For shutdown management, the analysis between the digital twin simulation and the measured values shows when a machine should be turned off, utilizing this information, there are possibilities of alarms that indicate if a machine is on in an inappropriate hour and for developing Energy-related Key performance Indicators (E-KPIs). By delegating a person of correcting and analyzing these situations or by upgrading the equipment for an automatic shutdown, a great amount of expenses can be saved. As seen on section 5.3 Consumption Comparison the machines that are not turned off can spend more than 25% more energy than they supposed to.

The partner company plant is mostly composed by older machines, so besides the potential for energy management and industry 4.0 applications, there is a need for analyzing the machines due to the need of upgrades in order of getting compatibility with the industry 4.0 applications. This compatibility issues can be very costly so the main objective in analyzing the machines is prioritizing the ones with the biggest potential.

To achieve a lower energy consumption in industry however, it is not enough only applying the correct technical and methodological aspects. A critical element that cannot be left aside is the detailed analysis of the engagement and training of employees on the topic, which is of utmost importance for a successful achievement of good results in energy efficiency in any context. In that regard this topic was not an explored element in this specific work and can be a further investigation focus. One good reference approach can be the learning factory, which has an applied case in energy efficiency found in the work of (Abele, Bauerdick, Strobel, & Panten, 2016).

At last, a topic that needs to be considered is that the evolution of technology is also key to lower energy consumption, being so that over time, better sensors can help identify issues as tool lifetime and overall machine problems and more efficient electrical components will be available.

REFERENCES

De Mauro, A. et al. 2015. (2015). " What is big data? A consensual definition and a review of key research topics." AIP Conference Proceedings, 1644: 97., Available.

Deloitte University Press. (2017). Industry 4.0 and the digital twin.

Demichela, M., Baldissone, G., & Darabnia, B. (2018). Using field data for energy efficiency based on maintenance and operational optimisation. A step towards PHM in process plants. Processes, 6(3). https://doi.org/10.3390/pr6030025

F. Tao, M. Zhang, J. F. Cheng, and Q. L. Qi. (2017). "Digital twin workshop: a new paradigm for future workshop,." Computer Integrated Manufaturing System, 23, n, 1–9.

Feng, Y., Wang, Q., Gao, Y., Cheng, J., & Tan, J. (2018). Energy-Efficient Job-Shop Dynamic Scheduling System Based on the Cyber-Physical Energy-Monitoring System. IEEE Access, 6, 52238–52247. https://doi.org/10.1109/ACCESS.2018.2869048

Foundation, U. N. S. (2019). Cyber-Physical Systems (CPS). 1–27. Retrieved from https://www.nsf.gov/pubs/2019/nsf19553/nsf19553.pdf

Gantz, J. & Reinsel, D. 2012. (2012). "The digital universe in 2020: big data, bigger digital shadows, and biggest growth in the far east." IDC IView.

Hoang, A., Do, P., & Iung, B. (2016). Prognostics on energy efficiency performance for maintenance decision-making: Application to industrial platform TELMA. Proceedings of 2015 Prognostics and System Health Management Conference, PHM 2015. https://doi.org/10.1109/PHM.2015.7380096

International Organization for Standardization. (2018). ISO 50001:2018 Energy management systems - Requirements with guidance for use. International Organization for Standardization.

Kohl, J., Spreng, S., & Franke, J. (2014). Discrete event simulation of individual energy consumption for productvarieties. Procedia CIRP, 17, 517–522. https://doi.org/10.1016/j.procir.2014.01.088

Kristina Wärmefjord, Rikard Söderberg, Lars Lindkvist, Björn Lindau and Johan S. Carlson (2017). "Inspection data to support a digital twin for geometry assurance". Available at ASME publication library.

Kumar Khaitan Siddhartha ;, & D., M. J. (2015). Design Techniques and Applications of Cyber Physical Systems: A Survey. IEEE Systems Journal, 1–15. Retrieved from https://www.academia.edu/23178627/Design_Techniques_and_Applications_of_Cyber_Physical_Systems_A_Survey

Li, X. X., He, F. Z., & Li, W. D. (2019). A cloud-terminal-based cyber-physical system architecture for energy efficient machining process optimization. Journal of Ambient Intelligence and Humanized Computing, 10(3), 1049–1064. https://doi.org/10.1007/s12652-018-0832-1

Lycett, M. 2013. (2013). " 'Datafication': making sense of (big) data in a complex world." European Journal of Information Systems. 22: 381-386. Available at: Https://Link.Springer.Com/ Article/10.1057%2Fejis.2013.10 [Accessed: 26 April 2017] Marscheider-Weidemann,.

Matsunaga, F; Valle P; Deschamps F. (2021). "Maoptimization of energy efficiency in smart manufacturing through the application of cyber-physical systems and industry 4.0 technologies -a systematic review" doi://10.26678/ABCM.COBEF2021.COB21-0259

Ma, S., Zhang, Y., Lv, J., Yang, H., & Wu, J. (2019). Energy-cyber-physical system enabled management for energy-intensive manufacturing industries. Journal of Cleaner Production, 226, 892–903. https://doi.org/10.1016/j.jclepro.2019.04.134

Mahamud, R., Li, W., & Kara, S. (2017). Energy characterisation and benchmarking of factories. CIRP Annals - Manufacturing Technology, 66(1), 457–460. https://doi.org/10.1016/j.cirp.2017.04.010

May, G., Barletta, I., Stahl, B., & Taisch, M. (2015). Energy management in production: A novel method to develop key performance indicators for improving energy efficiency. Applied Energy, 149(2015), 46–61. https://doi.org/10.1016/j.apenergy.2015.03.065

Nagasawa, T., Pillay, C., Beier, G., Fritzsche, K., Pougel, F., Takama, T., … Bobashev, I. (2017). Accelerating clean energy through Industry 4.0: Manufacturing the next Revolution. 56. Retrieved from https://www.unido.org/sites/default/files/2017-08/REPORT_Accelerating_clean_energy_through_Industry_4.0.Final_0.pdf

Paper, C., Ferrera, E., Rossini, R., & Evans, S. (2017). Toward Industry 4 . 0 : Efficient and Sustainable Manufacturing Leveraging Toward Industry 4 . 0 : Efficient and Sustainable Manufacturing leveraging MAESTRI Total Efficiency Framework. (August). https://doi.org/10.1007/978-3-319-57078-5

Ranganadham, M. V. S. (2018). Energy Statistics. 101. Retrieved from http://mospi.nic.in/sites/default/files/publication_reports/Energy_Statistics_2018.pdf

Seow, Y., & Rahimifard, S. (2011a). A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology, 4(3), 258–264. https://doi.org/10.1016/j.cirpj.2011.03.007

Seow, Y., & Rahimifard, S. (2011b). A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology, 4(3), 258–264. https://doi.org/10.1016/j.cirpj.2011.03.007

Seow, Y., & Rahimifard, S. (2011c). A framework for modelling energy consumption within manufacturing systems. CIRP Journal of Manufacturing Science and Technology, 4(3), 258–264. https://doi.org/10.1016/j.cirpj.2011.03.007

Tech Target's Internet of Things Network. (2018). Tech Target's Internet of Things Network.

United Nations, D. of E. and S. A. (2021). Sustainable Development Goals. Retrieved from https://sdgs.un.org/goals

US Environmental Protection Agency. (2010). "Defining Life Cycle Assessment (LCA)."

Wang, L., Torngren, M., Onori, M., 2015. (2015). Current status and advancement of cyber- physical systems in manufacturing.

Yuqian Lu, Chao Liu, Kevin I-Kai Wang, Huiyue Huang, Xun Xu. (2020). " Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues" Retrieved from ScienceDirect library.

Zhang, M., Zuo, Y., & Tao, F. (2018). Equipment energy consumption management in digital twin shop-floor: A framework and potential applications. ICNSC 2018 - 15th IEEE International Conference on Networking, Sensing and Control, 1–5. https://doi.org/10.1109/ICNSC.2018.8361272

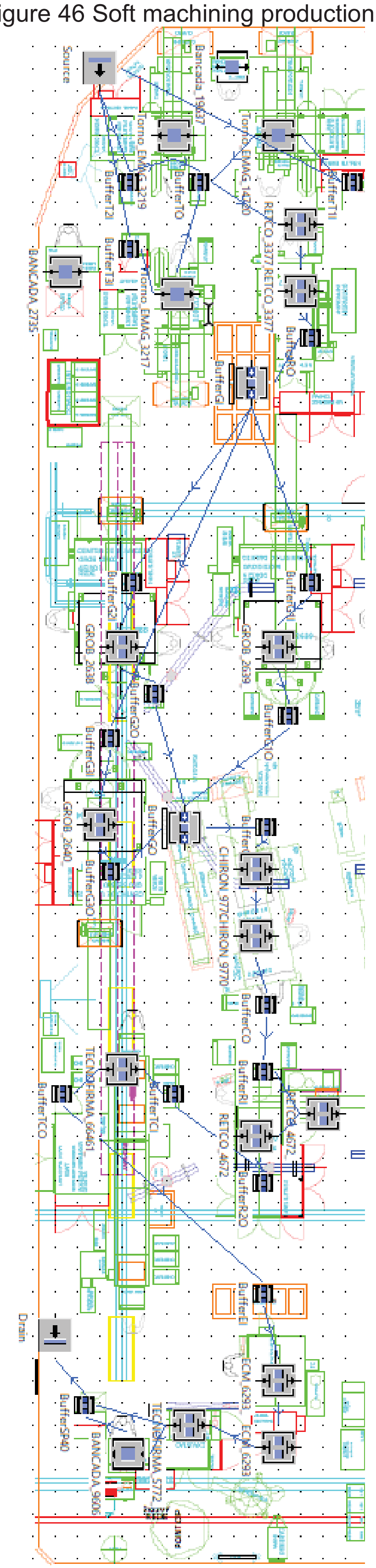
Zhou, L., Li, J., Li, F., Meng, Q., Li, J., & Xu, X. (2016). Energy consumption model and energy efficiency of machine tools: A comprehensive literature review. Journal of Cleaner Production, 112(2014), 3721–3734. https://doi.org/10.1016/j.jclepro.2015.05.093

Annex 1

Index	Reference	Methods and Frameworks	Equipment Energy Consumption Management (EECM) Machine Specific Energy Consumption (SEC)	Energy-related key performance indicators (e-KPIs)	ISO 50001	Life Cycle Analysis and Life cycle energy analysis (LCA and LCEA)	EPE framework Embodied Product Energy	Material and Energy Flows	Remaining energy-efficient lifetime (REEL)	Conservation Supply Curve (CSC) and marginal Cost of Conserved Energy (CCE)	MAESTRI Total Efficiency Framework (MTEF)	Empirical Characterization and Industrial surveys for energy analysis	Energy Consumption Monitoring, Analysis and Optimization	Technologies	Cyber-Physical Systems (CPS)	Digital Twin (DT) and Digital twin shop-floor (DTS)	Industrial Internet of Things (IIoT)	Big Data & Analytics	Load management	Applications	Energy consumption modelling for machining parameter optimization	Energy consumption modelling for process planning optimization	Energy consumption modelling for scheduling optimization	Energy consumption modelling for tool path optimization
1	Abele, E., Bauerdick, C. J. H., Strobel, N., & Panten, N. (2016). ETA Learning Factory: A Holistic Concept for Teaching Energy Efficiency in Production.																							
2	Ahmed, H. (2014). *Applying Big Data Analytics for Energy Efficiency*																	x						
3	Bevilacqua, M., Ciarapica, F. E., Diamantini, C., & Potena, D. (2017). Big data analytics methodologies applied at energy management in industrial sector: A case study.																x	x					x	
4	Cheng, Y., Zhang, Y., Ji, P., Xu, W., Zhou, Z., & Tao, F. (2018). Cyber-physical integration for moving digital factories forward towards smart manufacturing: a survey.														x	x								
5	Cottey, A. (2018). Economic language and economy change: with implications for cyber-physical systems.														x									
6	Darabnia, B., & Demichela, M. (2013). Maintenance an Opportunity for Energy Saving.									x												x		
7	Deloitte University Press. (2017). *Industry 4.0 and the digital twin* .															x								
8	Feng, Y., Wang, Q., Gao, Y., Cheng, J., & Tan, J. (2018). Energy-Efficient Job-Shop Dynamic Scheduling System Based on the Cyber-Physical Energy-Monitoring System		x												x							x	x	
9	Ferrera, E., Rossini, R., Baptista, A. J., Evans, S., Hovest, G. G., Holgado, M., … Estrela, M. A. (2017). Toward industry 4.0: Efficient and sustainable manufacturing leveraging MAESTRI total efficiency framework.										x													
10	He, Y., Li, Y., Wu, T., & Sutherland, J. W. (2015). An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops.																						x	
11	Hoang, A. (n.d.). *Energy efficiency-based prognostics for optimizing the maintenance decision-making in industrial systems* .								x												x			
12	Hoang, A., Do, P., & Iung, B. (2016). Prognostics on energy efficiency performance for maintenance decision-making: Application to industrial platform TELMA.								x													x		
13	Javied, T., Bakakeu, J., Gessinger, D., & Franke, J. (2018). Strategic energy management in industry 4.0 environment.				x								x											
14	Junker, H., & Domann, C. (2017). Towards industry 4.0 in corporate energy management.				x										x							x		
15	Kannan, K., & Arunachalam, N. (2019). A Digital Twin for Grinding Wheel: An Information Sharing Platform for Sustainable Grinding Process.					x										x	x				x			
16	Kohl, J., Spreng, S., & Franke, J. (2014). Discrete event simulation of individual energy consumption for productvarieties.							x							x							x		
17	Leng, J., Zhang, H., Yan, D., Liu, Q., Chen, X., & Zhang, D. (2019). Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop.														x	x								
18	Lenz, J., Wuest, T., & Westkämper, E. (2018). Holistic approach to machine tool data analytics. 3																x	x						
19	Li, X. X., He, F. Z., & Li, W. D. (2019). A cloud-terminal-based cyber-physical system architecture for energy efficient machining process optimization.		x												x			x			x	x	x	x
20	Liu, F., Xie, J., & Liu, S. (2015). A method for predicting the energy consumption of the main driving system of a machine tool in a machining process.																						x	x
21	Lu, X., Wang, S., Li, W., Jiang, P., & Zhang, C. (2015). Development of a WSN based real time energy monitoring platform for industrial applications.												x				x							
22	Ma, S., Zhang, Y., Lv, J., Yang, H., & Wu, J. (2019). Energy-cyber-physical system enabled management for energy-intensive manufacturing industries.							x							x		x	x						
23	Mahamud, R., Li, W., & Kara, S. (2017). Energy characterisation and benchmarking of factories.											x												
24	May, G., Barletta, I., Stahl, B., & Taisch, M. (2015). Energy management in production: A novel method to develop key performance indicators for improving energy efficiency.			x	x																	x		
25	Meng, Y., Yang, Y., Chung, H., Lee, P. H., & Shao, C. (2018). Enhancing sustainability and energy efficiency in smart factories: A review.												x				x	x						
26	Micaela, Demichela; Gabriele, Baldissone; Behnoush, D. (2018). Using Field Data for Energy Efficiency Based on Maintenance and Operational Optimisation. A Step towards PHM in Process Plants.									x														
27	Mohamed, N., Al-Jaroodi, J., & Lazarova-Molnar, S. (2019). Leveraging the Capabilities of Industry 4.0 for Improving Energy Efficiency in Smart Factories.														x		x							
28	Mourtzis, D., Vlachou, E., Milas, N., & Dimitrakopoulos, G. (2016). Energy Consumption Estimation for Machining Processes Based on Real-time Shop Floor Monitoring via Wireless Sensor Networks.														x						x			x
29	Nagasawa, T., Pillay, C., Beier, G., Fritzsche, K., Pougel, F., Takama, T., The, K., Bobashev, I. (2017). *Accelerating clean energy through Industry 4.0* .														x		x	x	x					
30	Pease, S. G., Trueman, R., Davies, C., Grosberg, J., Yau, K. H., Kaur, N., … West, A. (2018). An intelligent real-time cyber-physical toolset for energy and process prediction and optimisation in the future industrial Internet of Things.														x		x				x	x		
31	Pei, W., Ma, X., Deng, W., Chen, X., Sun, H., & Li, D. (2019). Industrial multi-energy and production management scheme in cyber-physical environments: A case study in a battery manufacturing plant.														x								x	
32	Qi, Q., & Tao, F. (2018). Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison.														x	x	x	x						
33	Qi, Q., Tao, F., Zuo, Y., & Zhao, D. (2018). Digital Twin Service towards Smart Manufacturing.														x	x								
34	Seow, Y., & Rahimifard, S. (2011). A framework for modelling energy consumption within manufacturing systems.					x	x	x																
35	Tao, F., & Zhang, M. (2017). Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing.														x	x								
36	Tristo, G., Bissacco, G., Lebar, A., & Valentinčič, J. (2015). Real time power consumption monitoring for energy efficiency analysis in micro EDM milling.							x														x		
37	Uhlemann, T. H. J., Schock, C., Lehmann, C., Freiberger, S., & Steinhilper, R. (2017). The Digital Twin: Demonstrating the Potential of Real Time Data Acquisition in Production Systems.														x	x								
38	Zhang, H., Zhang, G., & Yan, Q. (2018). Digital twin-driven cyber-physical production system towards smart shop-floor.														x	x								
39	Zhang, M., Zuo, Y., & Tao, F. (2018). Equipment energy consumption management in digital twin shop-floor: A framework and potential applications.		x										x		x	x					x	x		
40	Zhou, L., Li, J., Li, F., Meng, Q., Li, J., & Xu, X. (2016). Energy consumption model and energy efficiency of machine tools: A comprehensive literature review.		x			x															x			
41	Zhuang, C., Liu, J., & Xiong, H. (2018). Digital twin-based smart production management and control framework for the complex product assembly shop-floor.														x			x						

Annex 2

Figure 46 Soft machining production cell



Source: Author (2020)

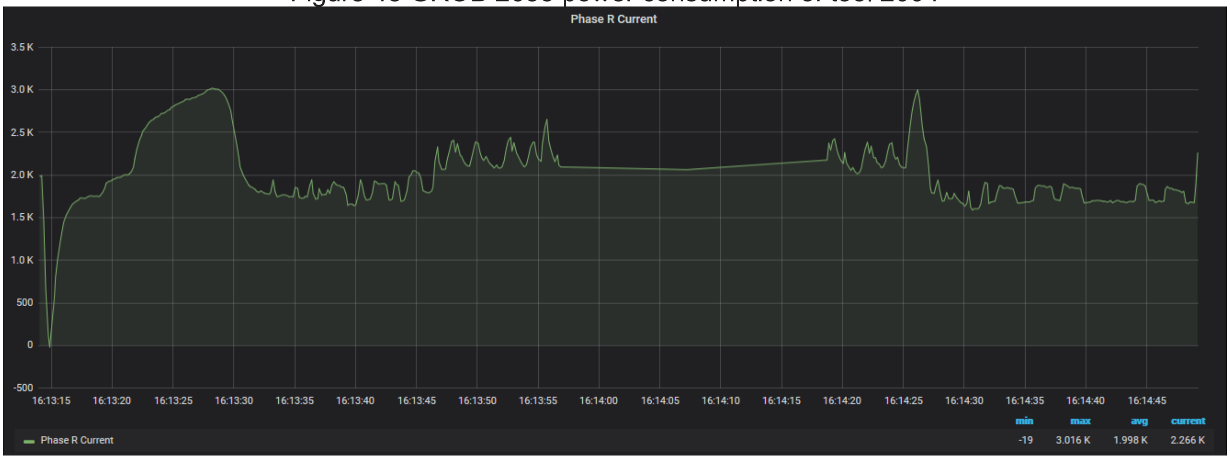
Annex 3

Figure 47 Energy data example

Energy Consumers	Energy [kWh]	Energy operational [kWh]	Current power input [kW]	Working	Setting-up	Operational	Failed	Standby	Off
CHIRON_9770	2968.31	870.93	3.73	1624.79	0.00	870.93	136.81	208.25	127.54
ECM_6293	8898.99	5579.93	15.05	1976.00	0.00	5579.93	406.89	842.31	93.87
GROB_2638	3657.32	460.57	5.37	2479.34	0.22	460.57	263.10	298.19	155.89
GROB_2639_	3334.27	419.87	4.41	2249.05	0.20	419.87	275.73	240.31	149.11
GROB_2640_	4664.25	566.23	8.70	3141.00	0.22	566.23	322.21	473.58	161.01
RETCO_3377	4860.91	2389.92	7.11	1627.54	0.00	2389.92	227.25	397.19	219.00
RETCO_4672	4047.37	1561.99	6.98	1734.23	0.00	1561.99	175.62	390.20	185.34
TECNOFIRMA_5772_	1118.18	112.14	0.16	834.20	0.00	112.14	148.46	8.94	14.44
TECNOFIRMA_66461_	6288.63	3576.51	3.07	1551.67	0.00	3576.51	249.99	171.56	738.90
Torno_EMAG_14720	5326.22	1332.52	6.26	2609.07	0.00	1332.52	921.80	328.20	134.64
Torno_EMAG_3217	5457.67	1304.85	6.73	2889.25	0.00	1304.85	782.75	360.54	120.29
Torno_EMAG_3219	5485.77	1375.39	7.90	2695.96	0.00	1375.39	873.78	420.43	120.20

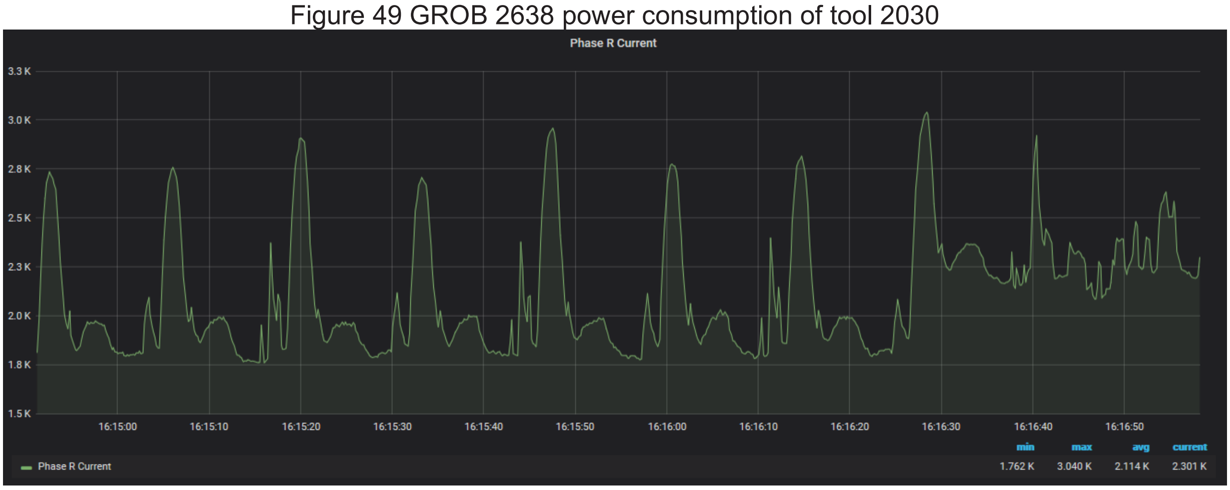
Source: Author (2020)

Figure 48 GROB 2638 power consumption of tool 2004



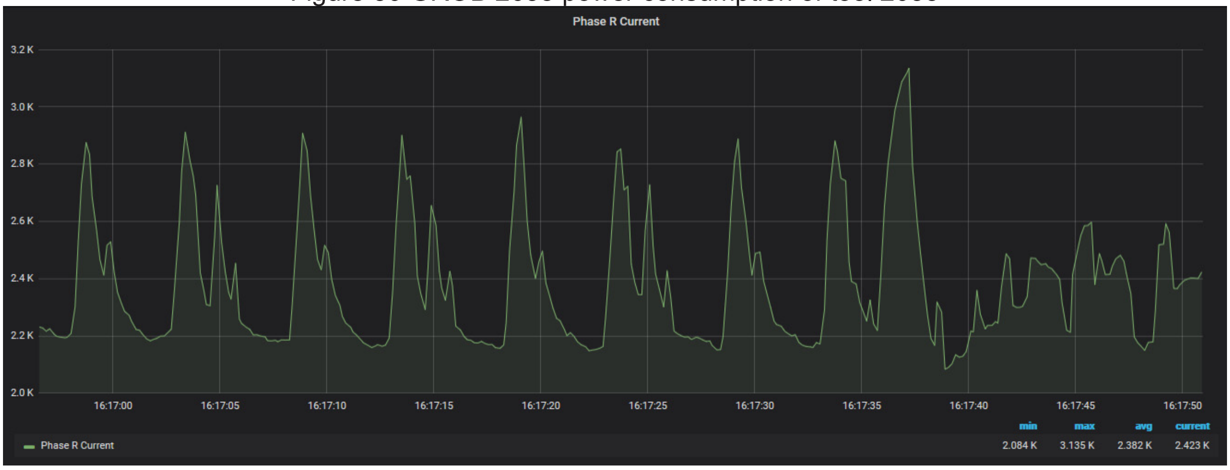
Source: Author (2020)

Figure 49 GROB 2638 power consumption of tool 2030



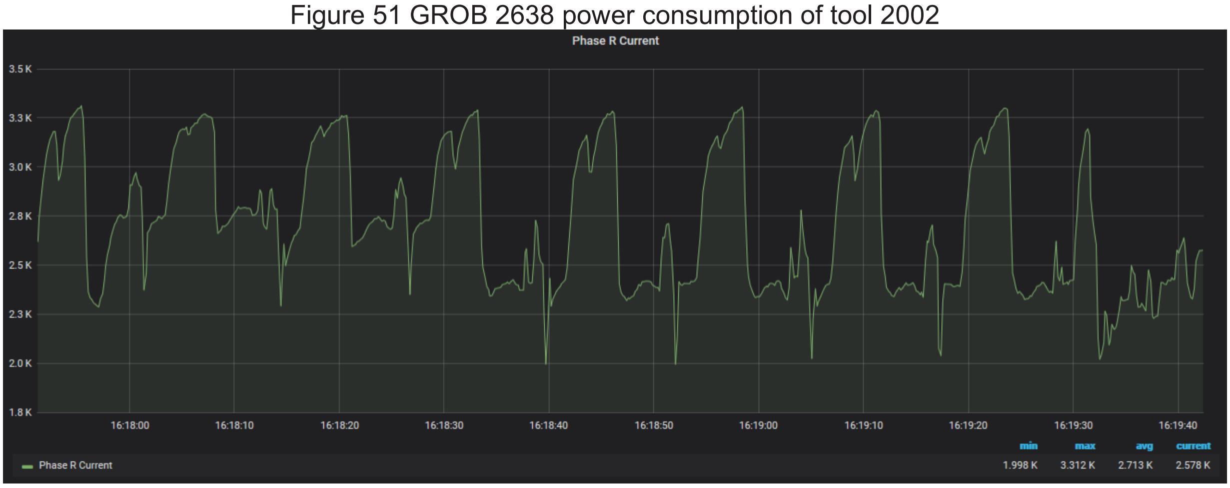
Source: Author (2020)

Figure 50 GROB 2638 power consumption of tool 2035



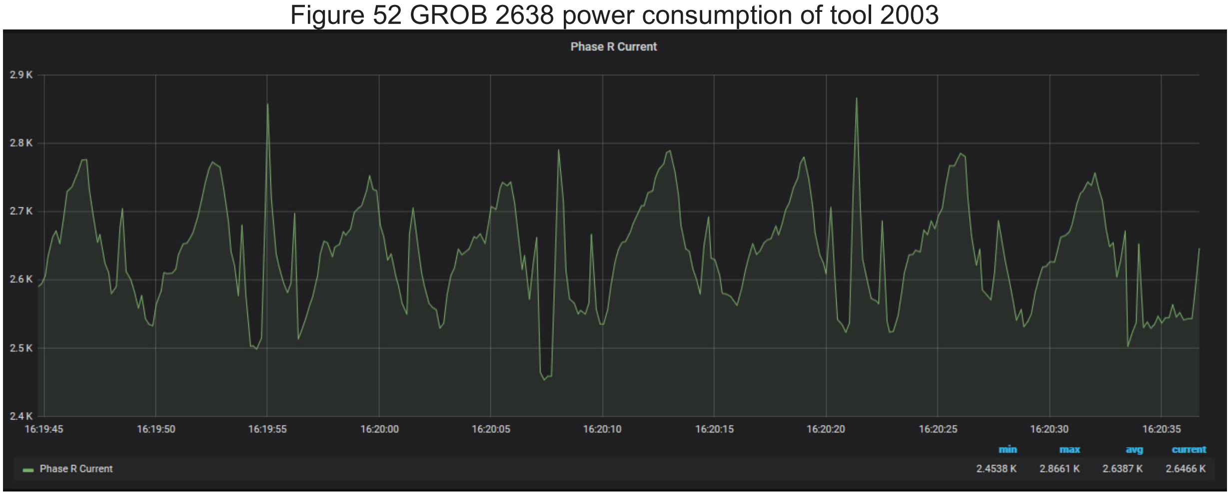
Source: Author (2020)

Figure 51 GROB 2638 power consumption of tool 2002



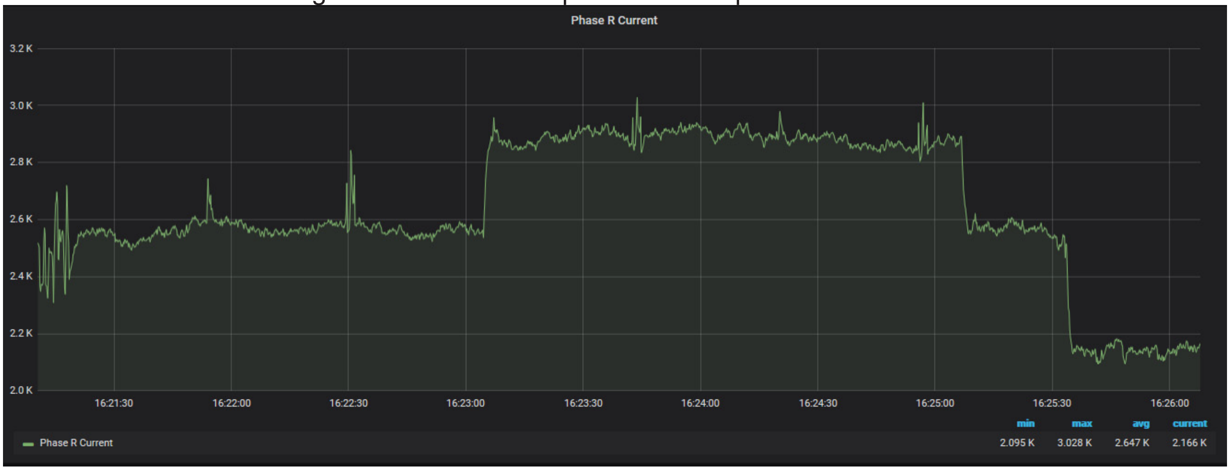
Source: Author (2020)

Figure 52 GROB 2638 power consumption of tool 2003



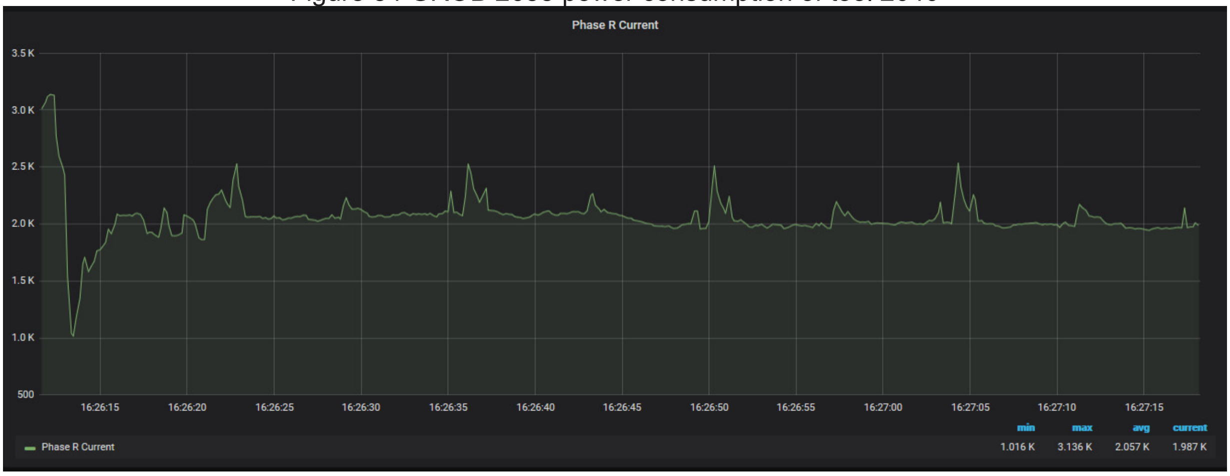
Source: Author (2020)

Figure 53 GROB 2638 power consumption of tool 2026



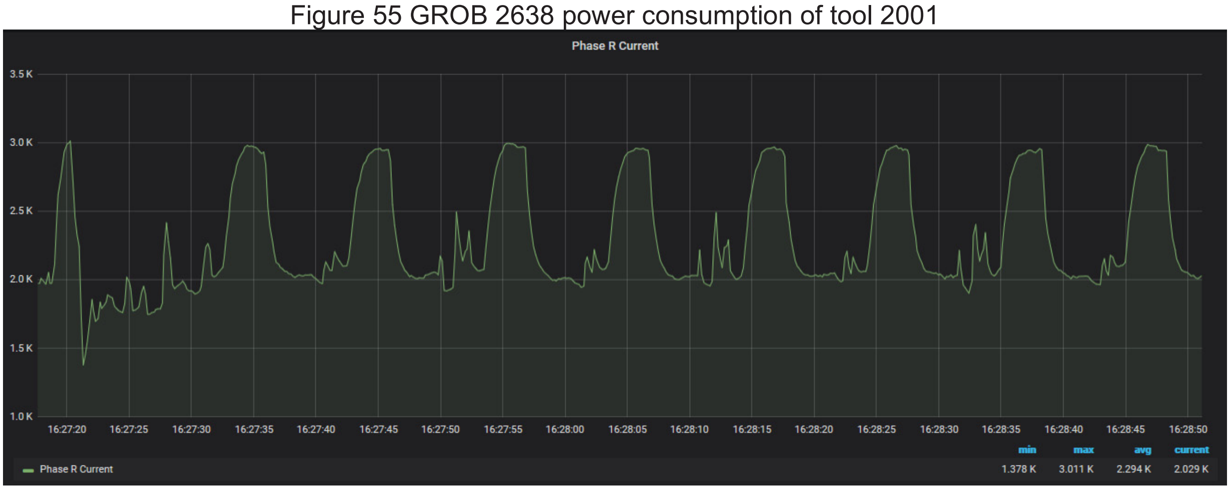
Source: Author (2020)

Figure 54 GROB 2638 power consumption of tool 2040



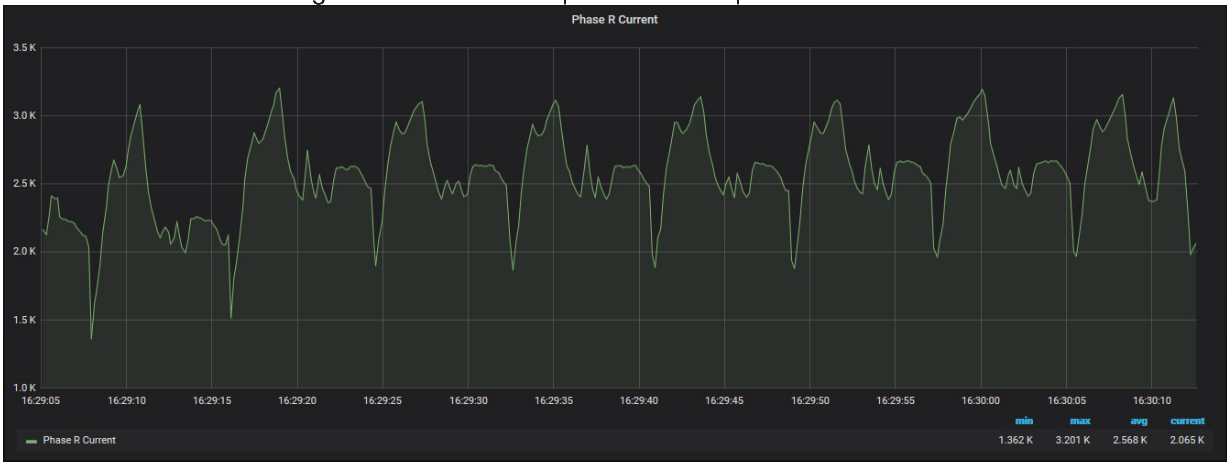
Source: Author (2020)

Figure 55 GROB 2638 power consumption of tool 2001



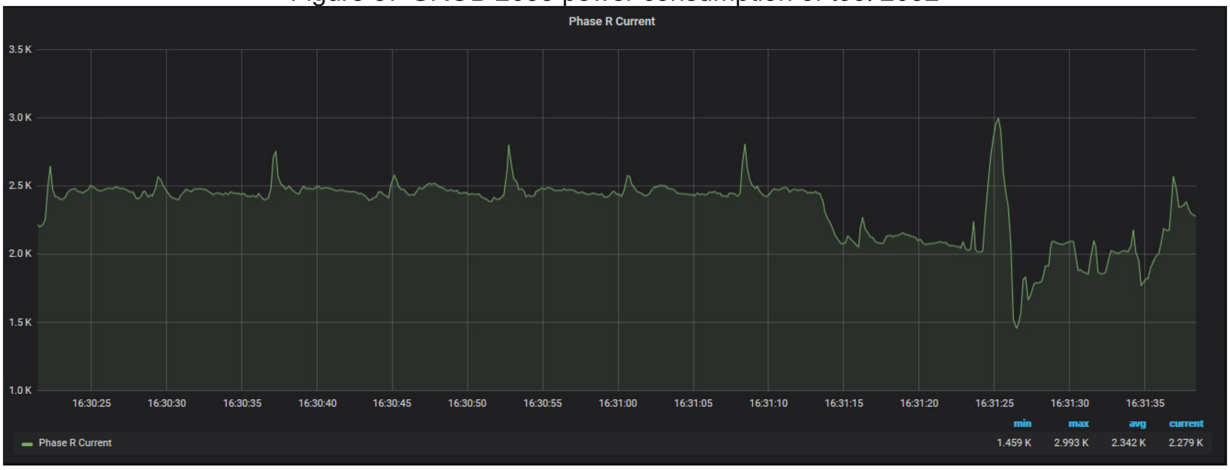
Source: Author (2020)

Figure 56 GROB 2638 power consumption of tool 2006



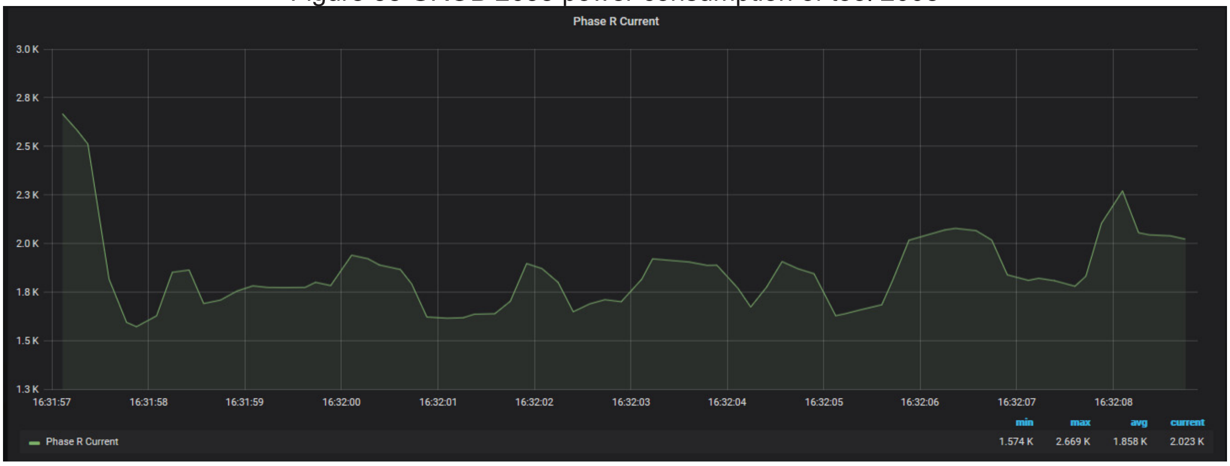
Source: Author (2020)

Figure 57 GROB 2638 power consumption of tool 2032



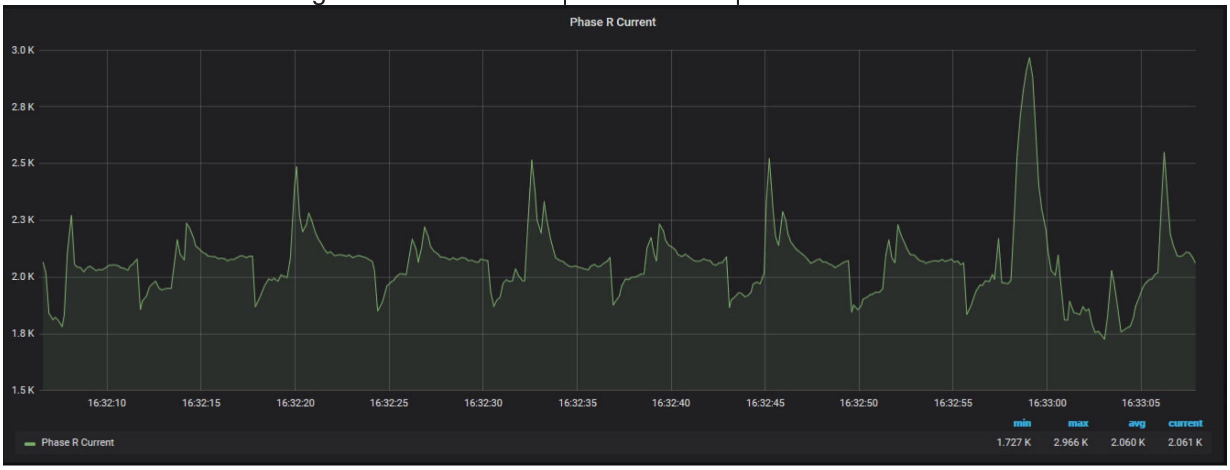
Source: Author (2020)

Figure 58 GROB 2638 power consumption of tool 2008



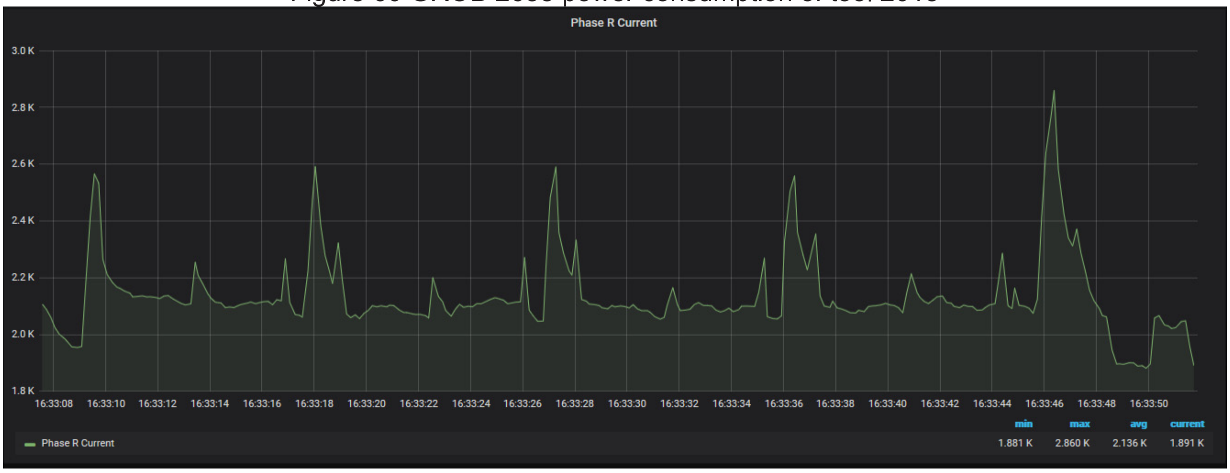
Source: Author (2020)

Figure 59 GROB 2638 power consumption of tool 2009



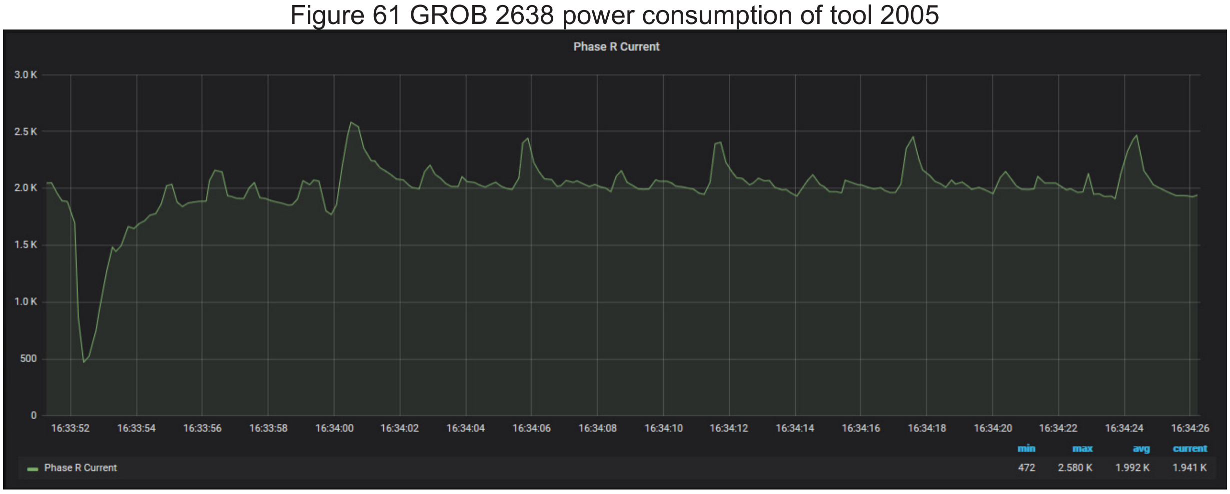
Source: Author (2020)

Figure 60 GROB 2638 power consumption of tool 2015



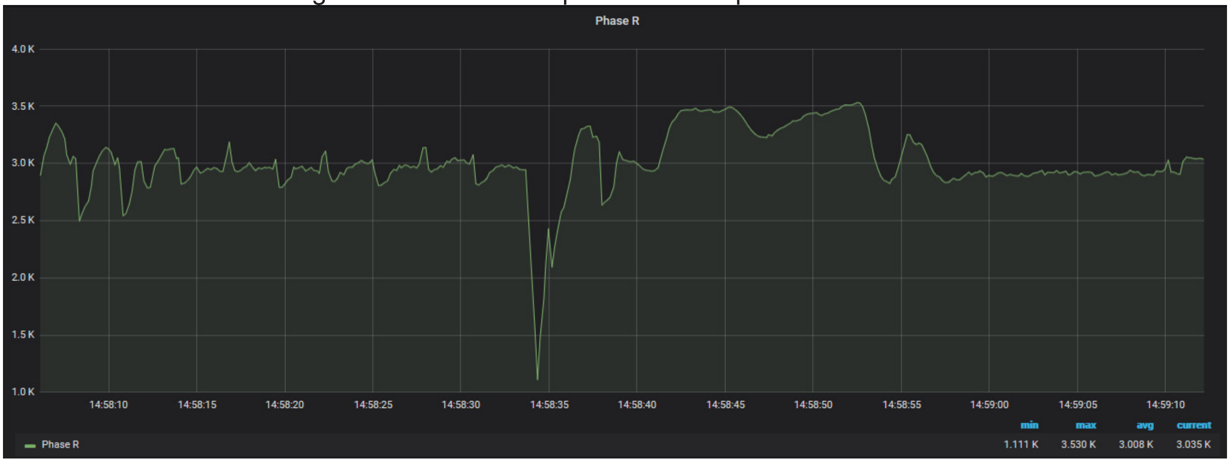
source: author (2020)

Figure 61 GROB 2638 power consumption of tool 2005



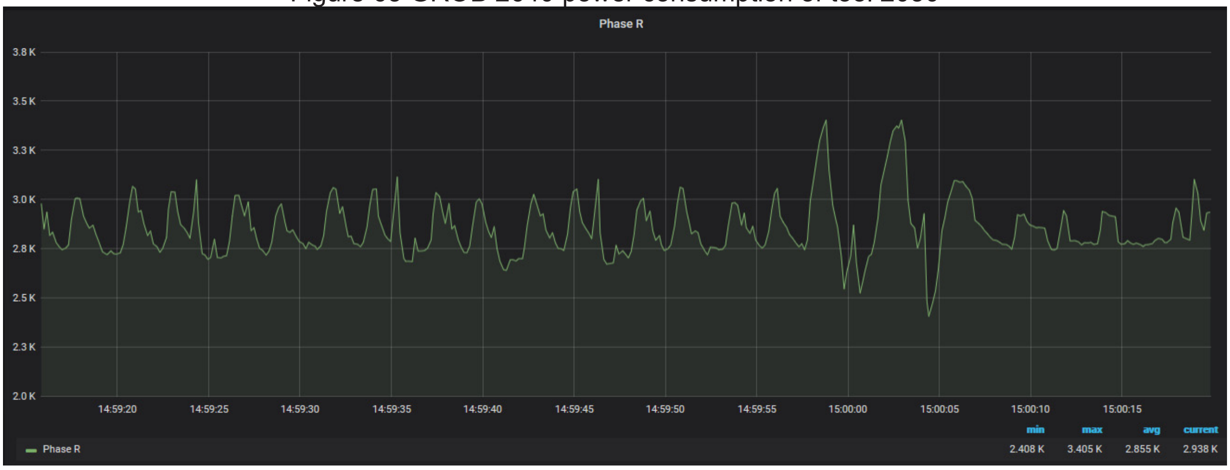
Source: Author (2020)

Figure 62 GROB 2640 power consumption of tool 2004



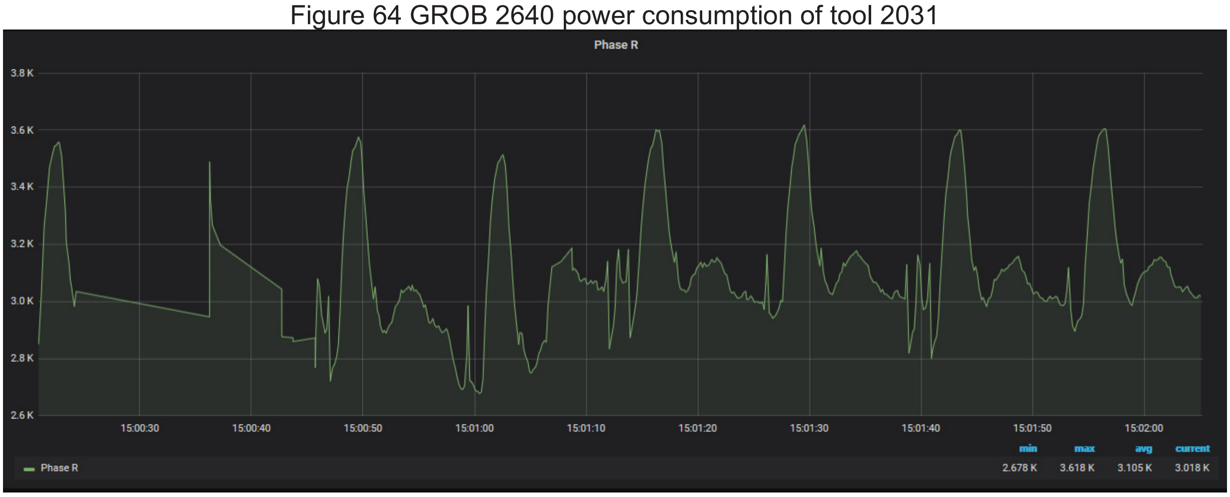
Source: Author (2020)

Figure 63 GROB 2640 power consumption of tool 2030



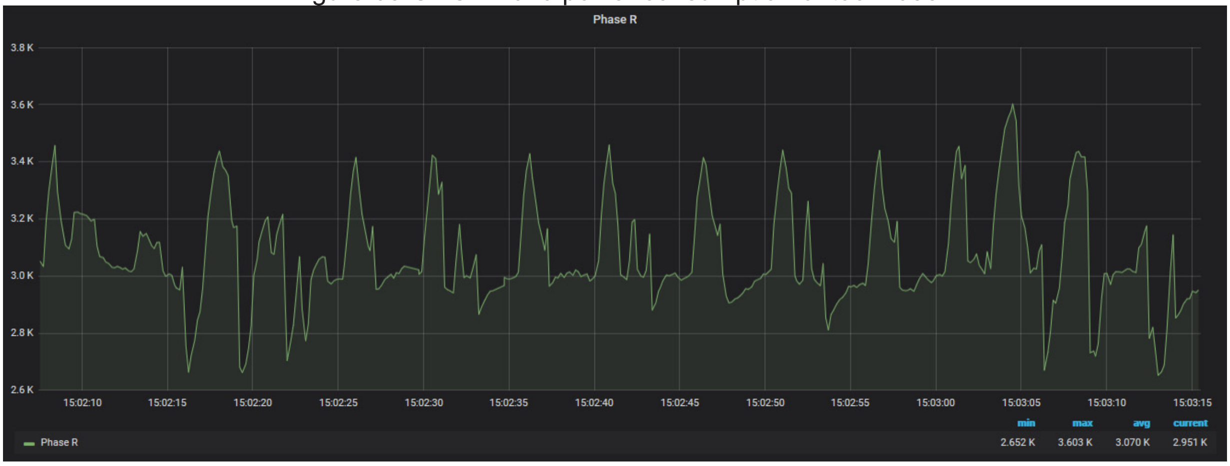
Source: Author (2020)

Figure 64 GROB 2640 power consumption of tool 2031



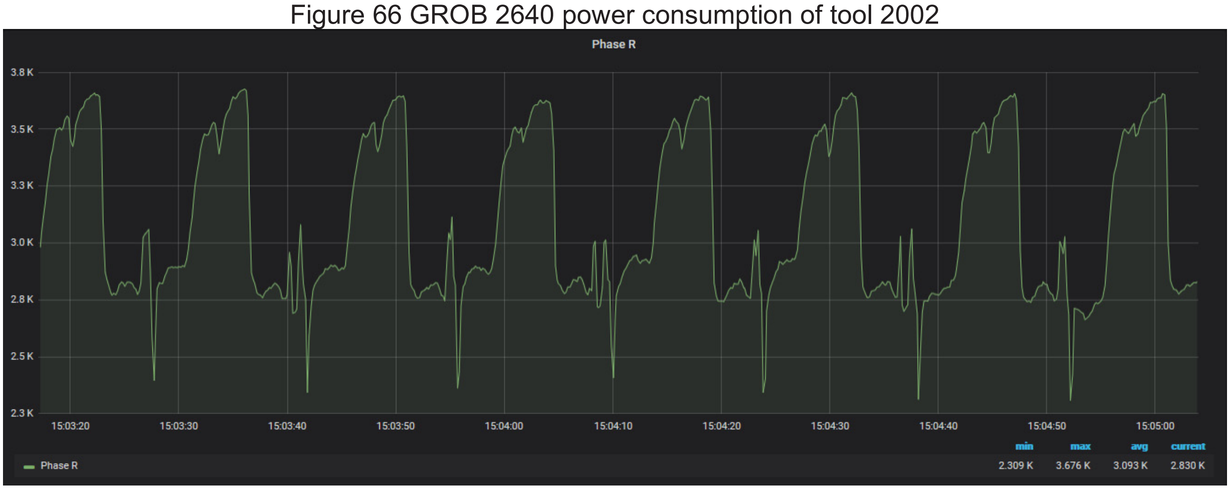
Source: Author (2020)

Figure 65 GROB 2640 power consumption of tool 2035



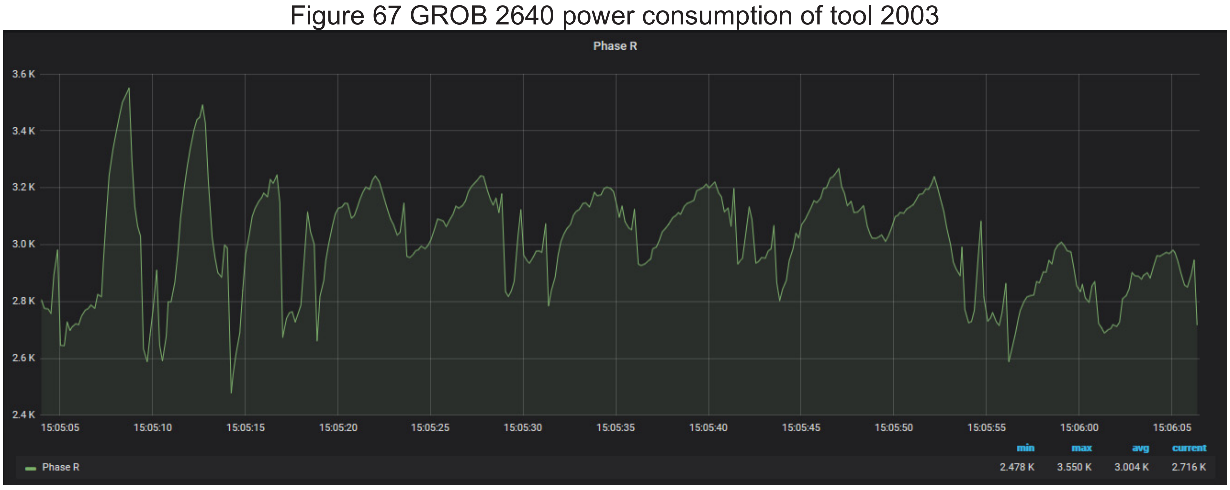
Source: Author (2020)

Figure 66 GROB 2640 power consumption of tool 2002



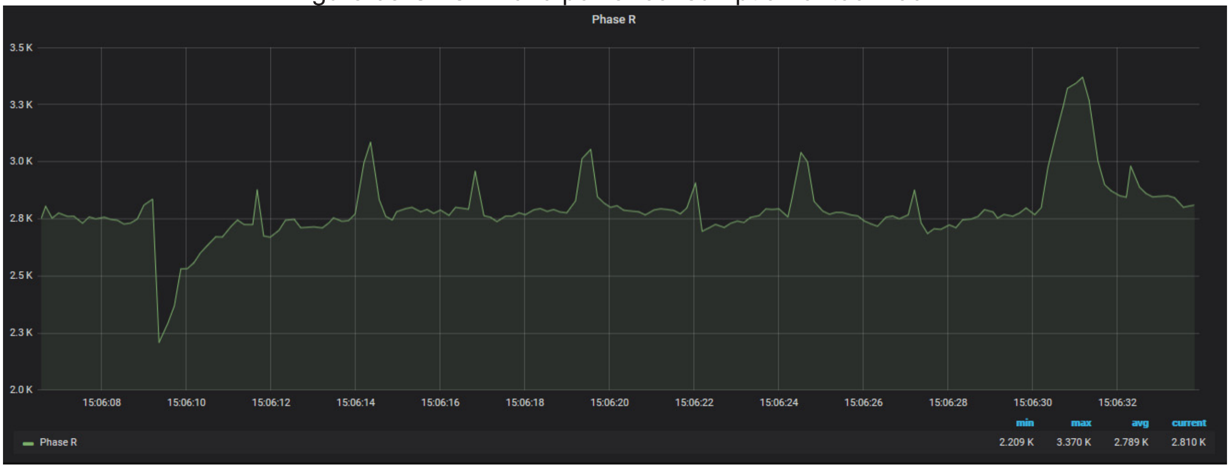
Source: Author (2020)

Figure 67 GROB 2640 power consumption of tool 2003



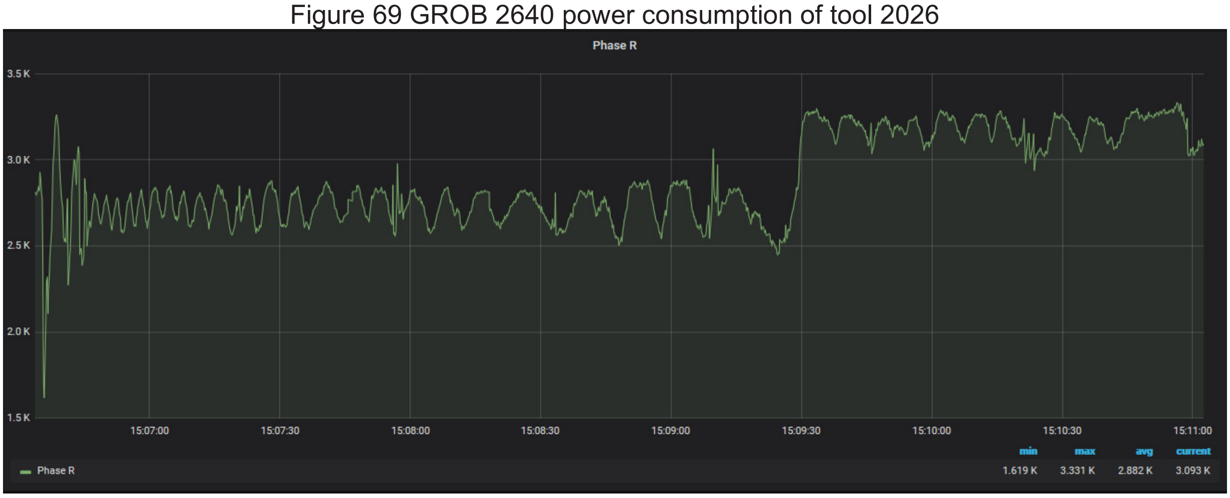
Source: Author (2020)

Figure 68 GROB 2640 power consumption of tool 2001



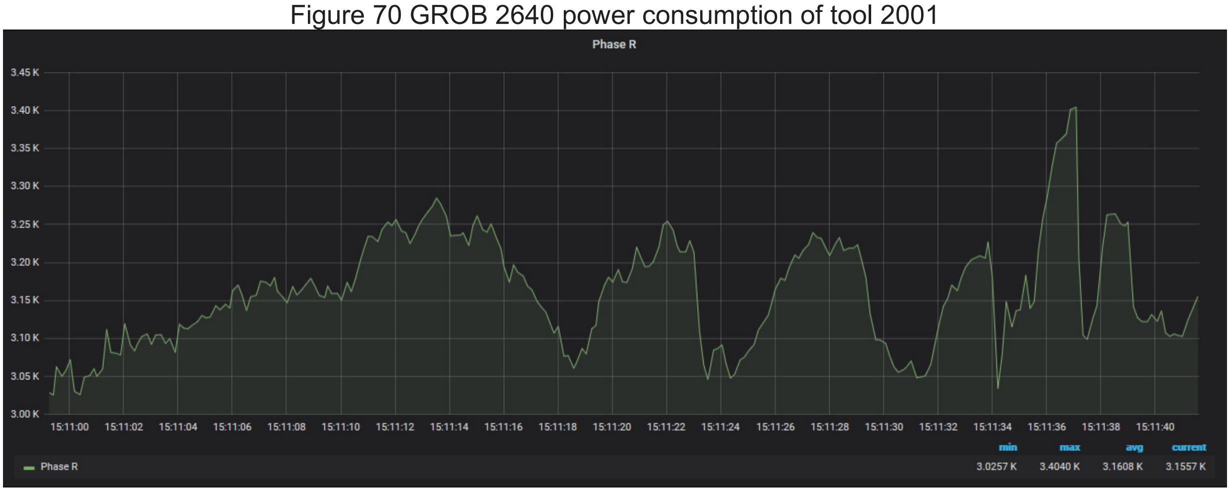
Source: Author (2020)

Figure 69 GROB 2640 power consumption of tool 2026



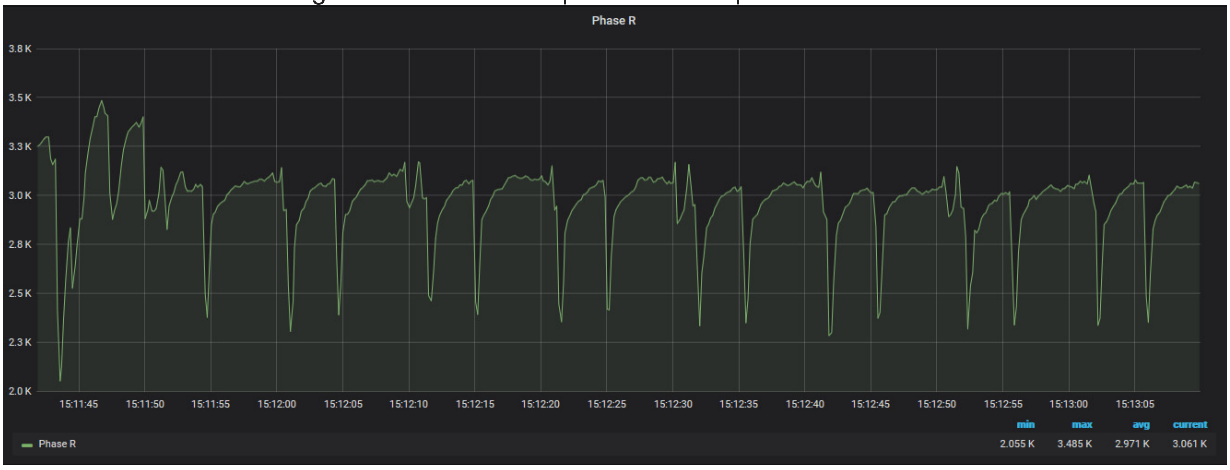
Source: Author (2020)

Figure 70 GROB 2640 power consumption of tool 2001



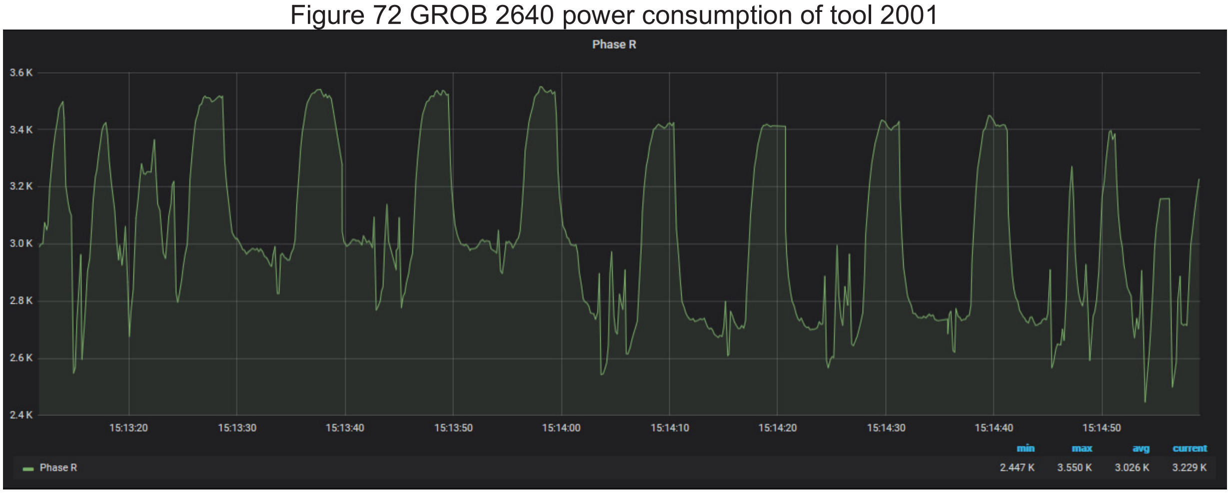
Source: Author (2020)

Figure 71 GROB 2640 power consumption of tool 2040



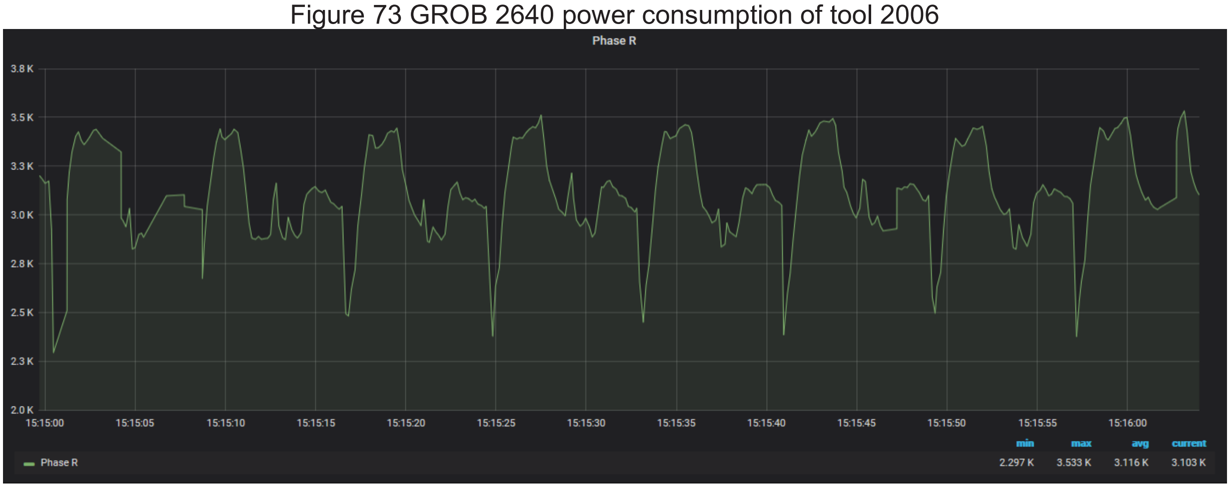
Source: Author (2020)

Figure 72 GROB 2640 power consumption of tool 2001



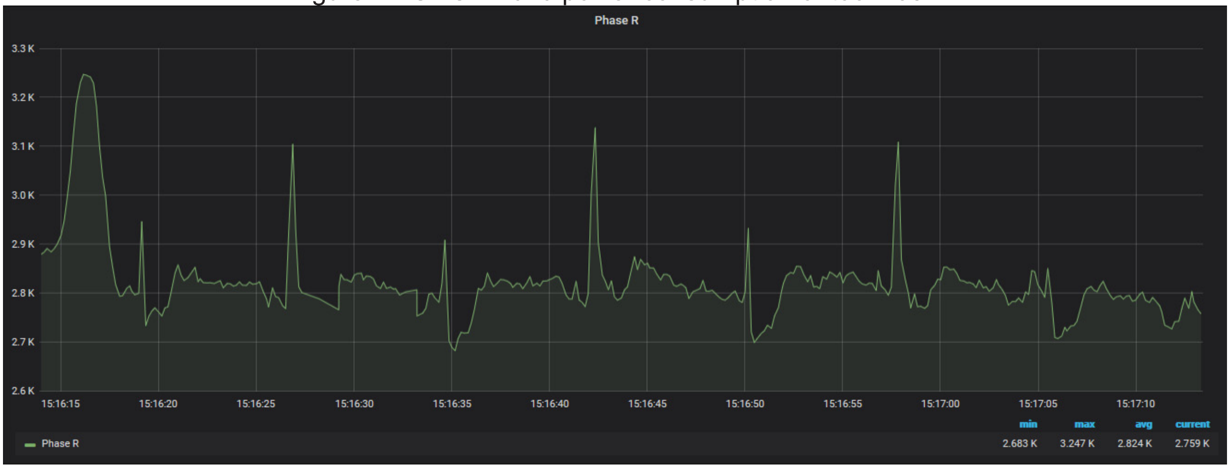
Source: Author (2020)

Figure 73 GROB 2640 power consumption of tool 2006



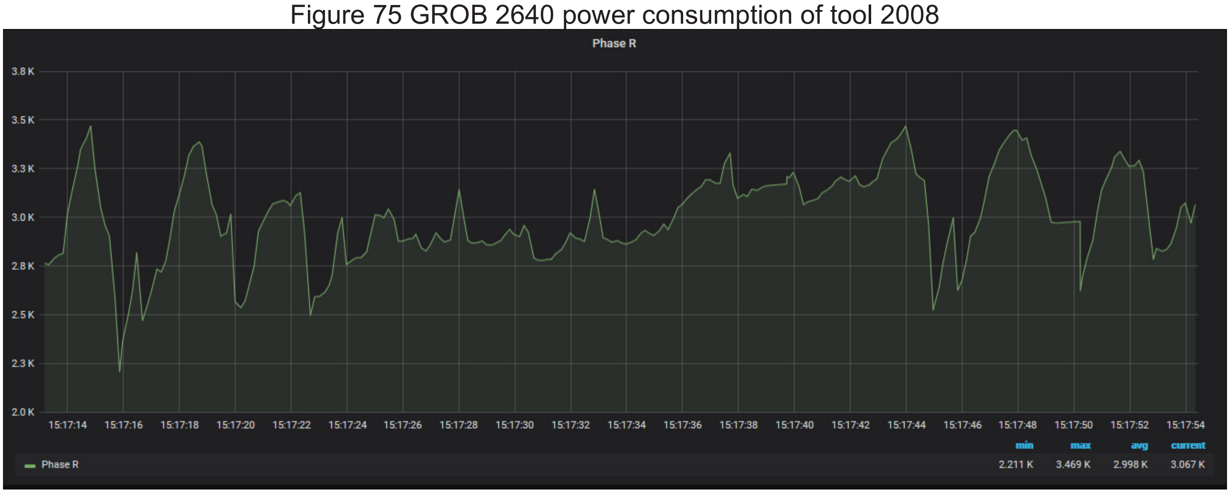
Source: Author (2020)

Figure 74 GROB 2640 power consumption of tool 2032



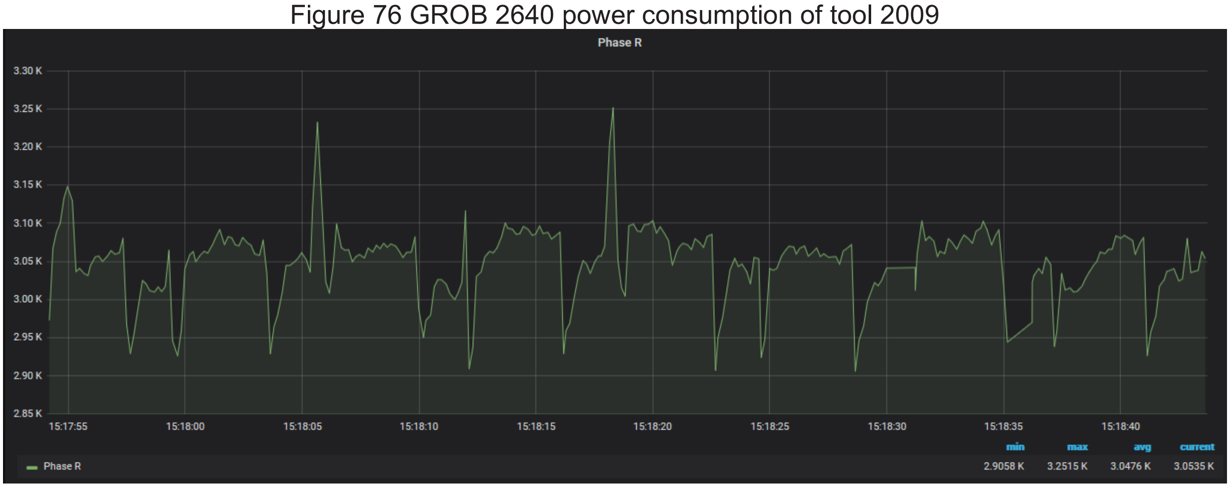
Source: Author (2020)

Figure 75 GROB 2640 power consumption of tool 2008



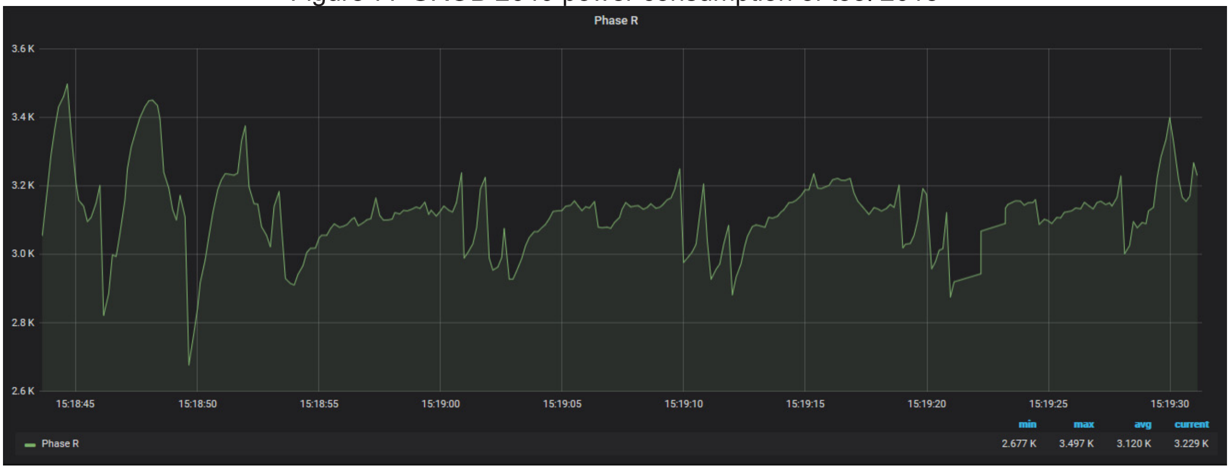
Source: Author (2020)

Figure 76 GROB 2640 power consumption of tool 2009



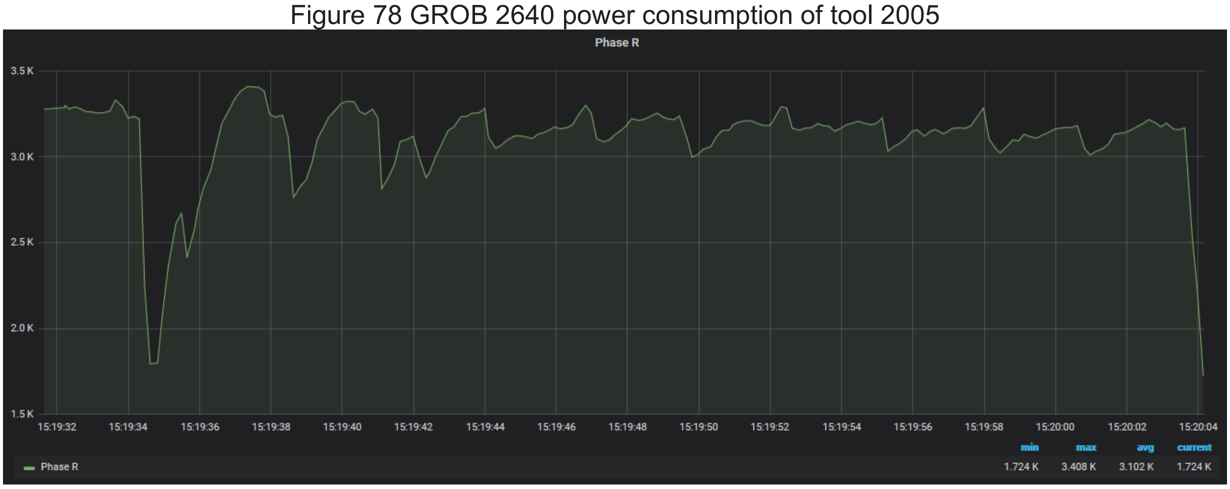
Source: Author (2020)

Figure 77 GROB 2640 power consumption of tool 2015



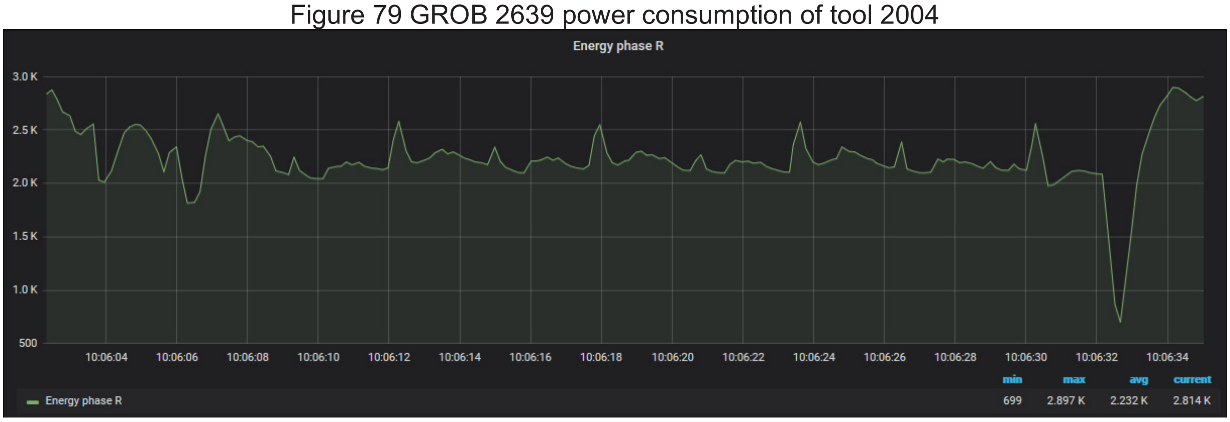
Source: Author (2020)

Figure 78 GROB 2640 power consumption of tool 2005



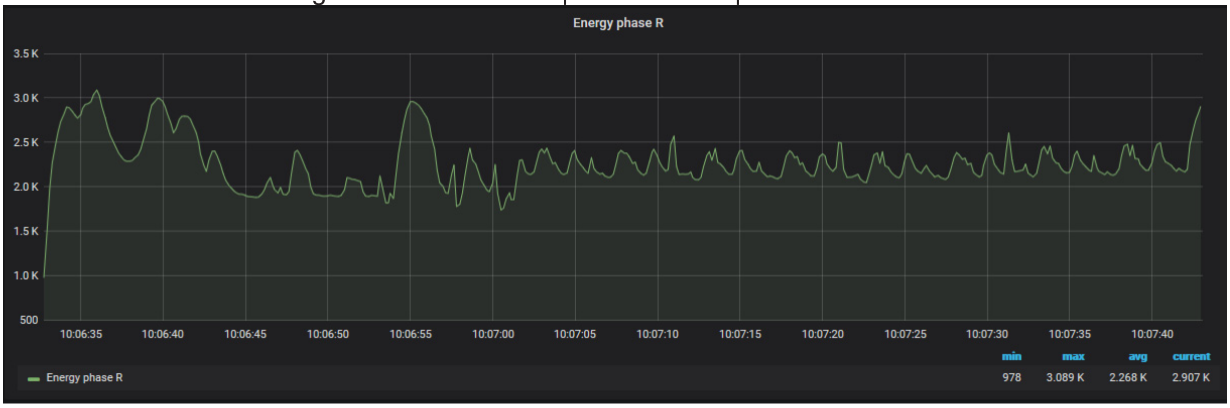
Source: Author (2020)

Figure 79 GROB 2639 power consumption of tool 2004



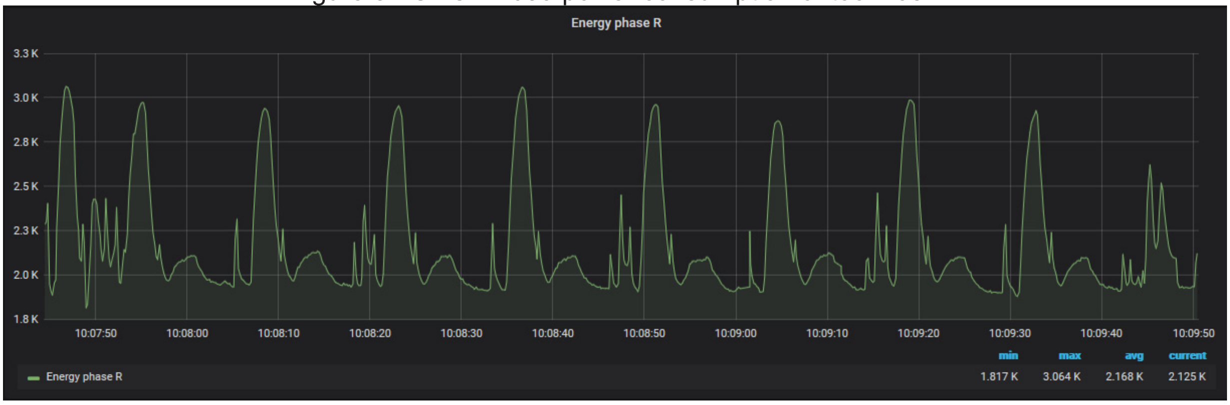
Source: Author (2020)

Figure 80 GROB 2639 power consumption of tool 2030



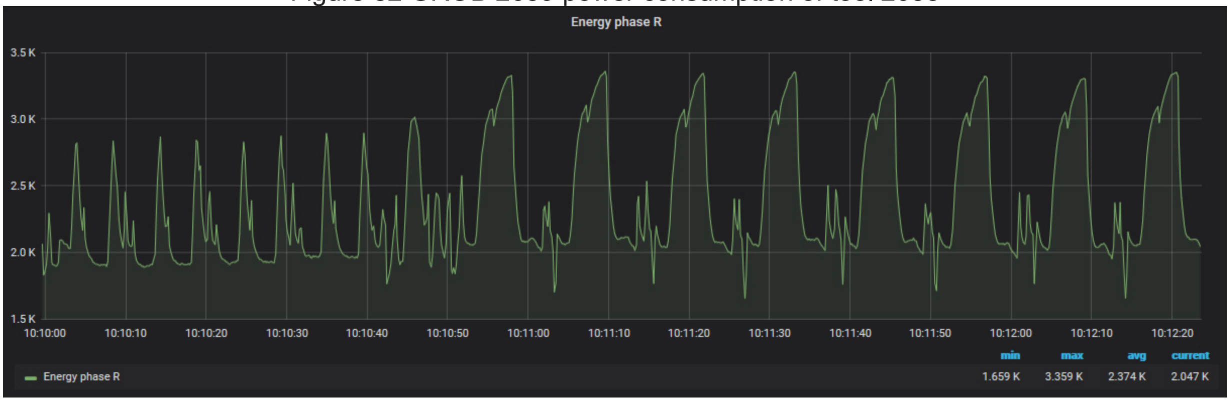
Source: Author (2020)

Figure 81 GROB 2639 power consumption of tool 2031



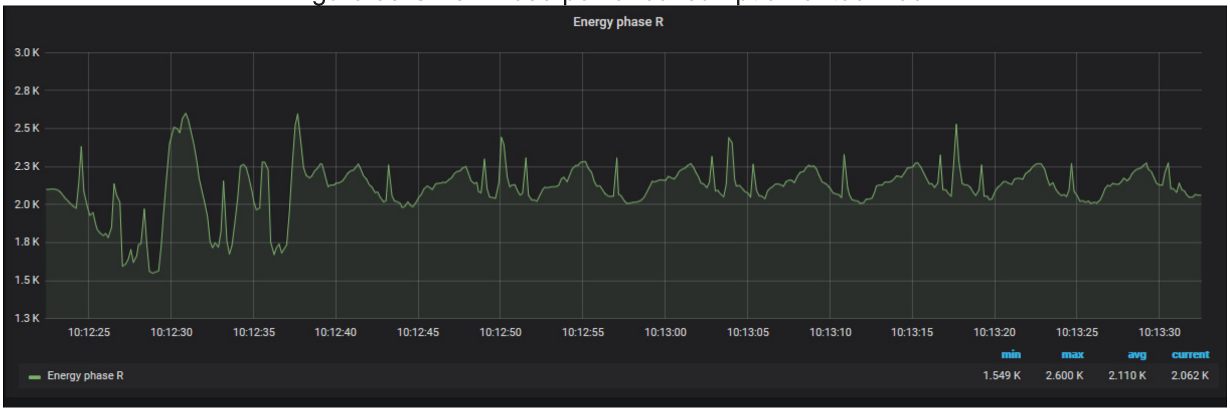
Source: Author (2020)

Figure 82 GROB 2639 power consumption of tool 2035



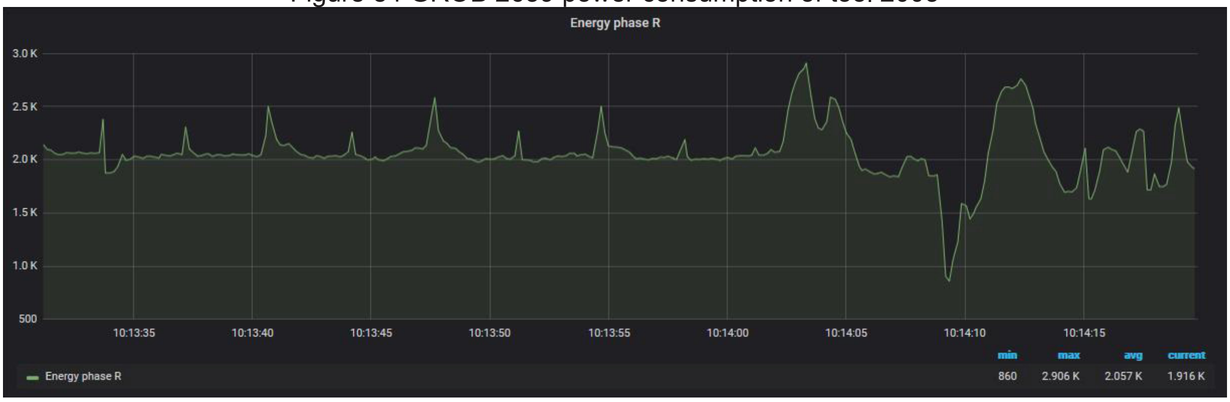
Source: Author (2020)

Figure 83 GROB 2639 power consumption of tool 2002



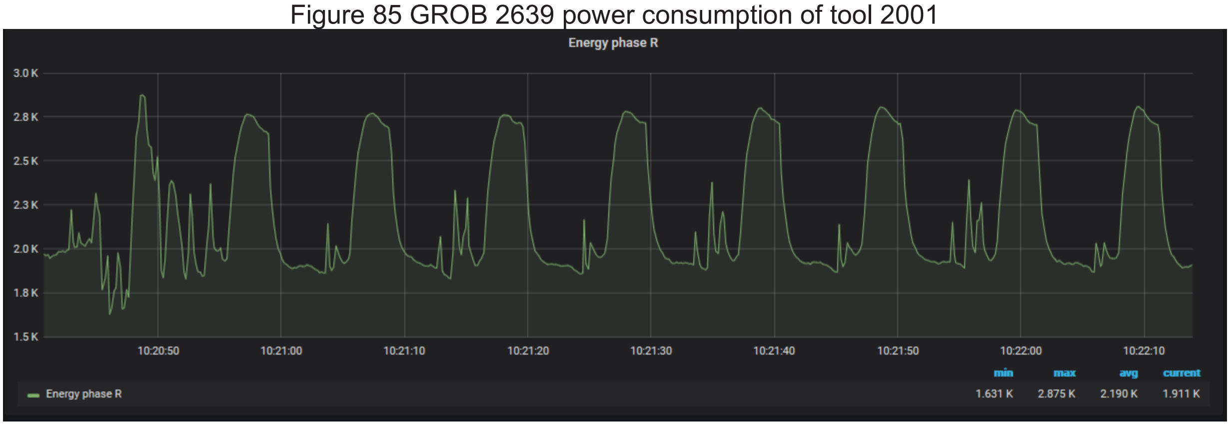
Source: Author (2020)

Figure 84 GROB 2639 power consumption of tool 2003



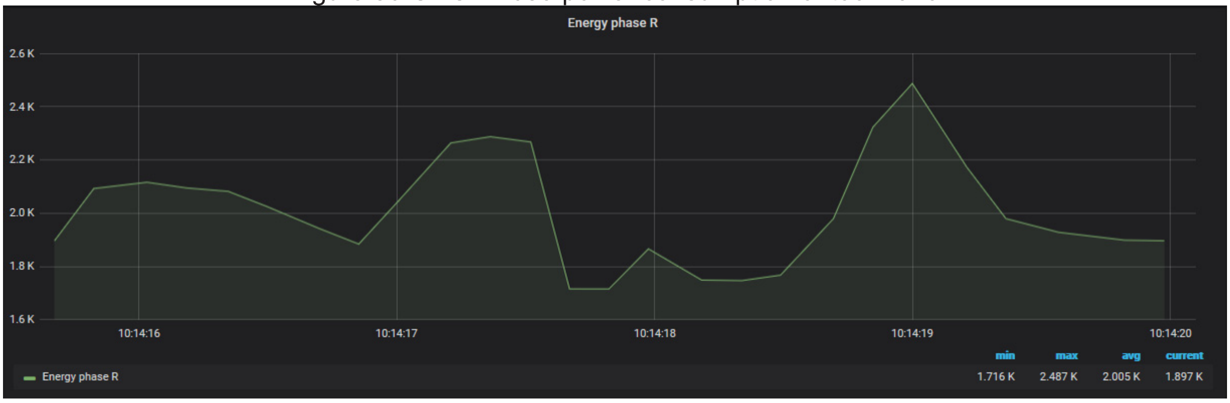
Source: Author (2020)

Figure 85 GROB 2639 power consumption of tool 2001



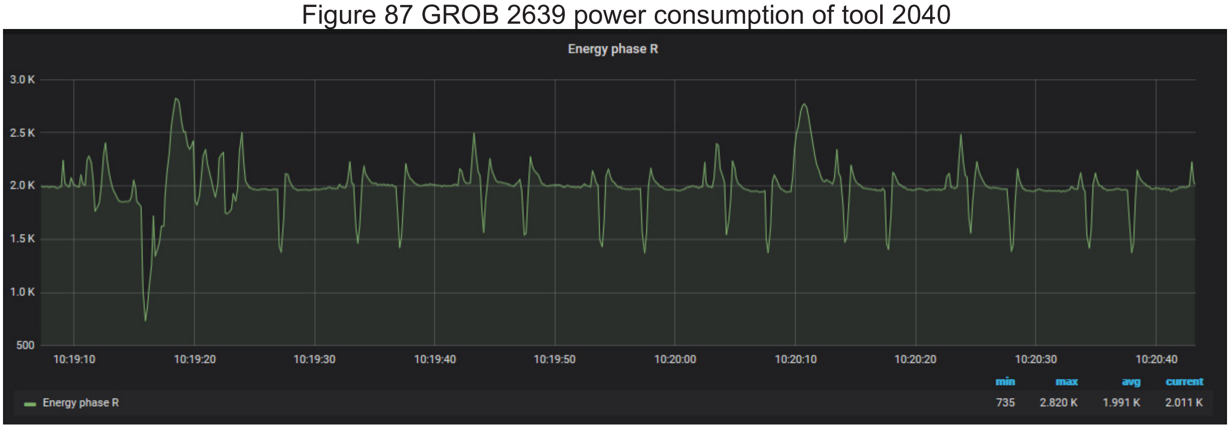
Source: Author (2020)

Figure 86 GROB 2639 power consumption of tool 2026



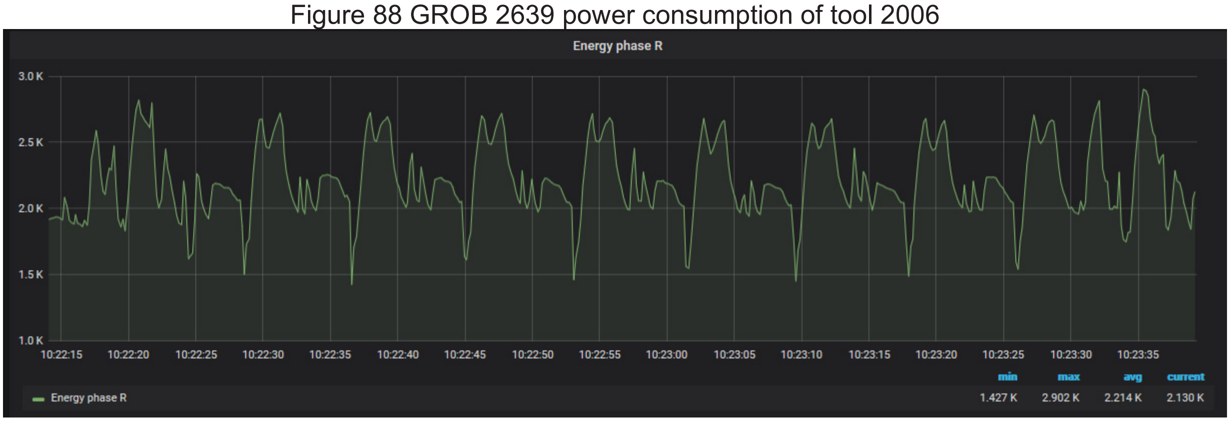
Source: Author (2020)

Figure 87 GROB 2639 power consumption of tool 2040



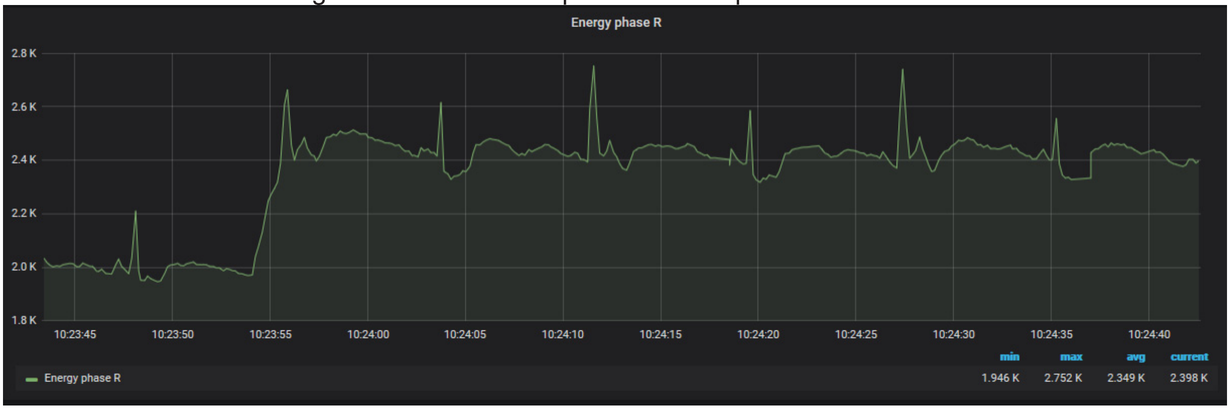
Source: Author (2020)

Figure 88 GROB 2639 power consumption of tool 2006



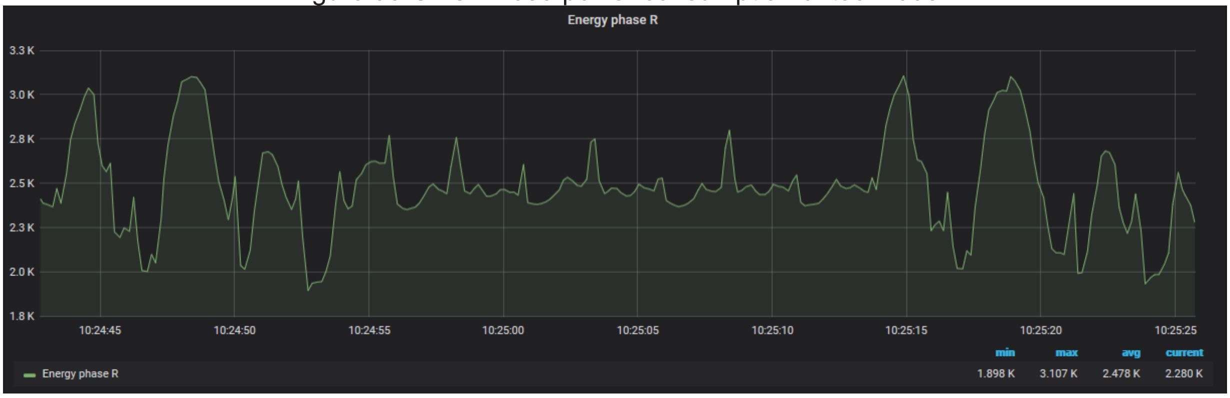
Source: Author (2020)

Figure 89 GROB 2639 power consumption of tool 2032



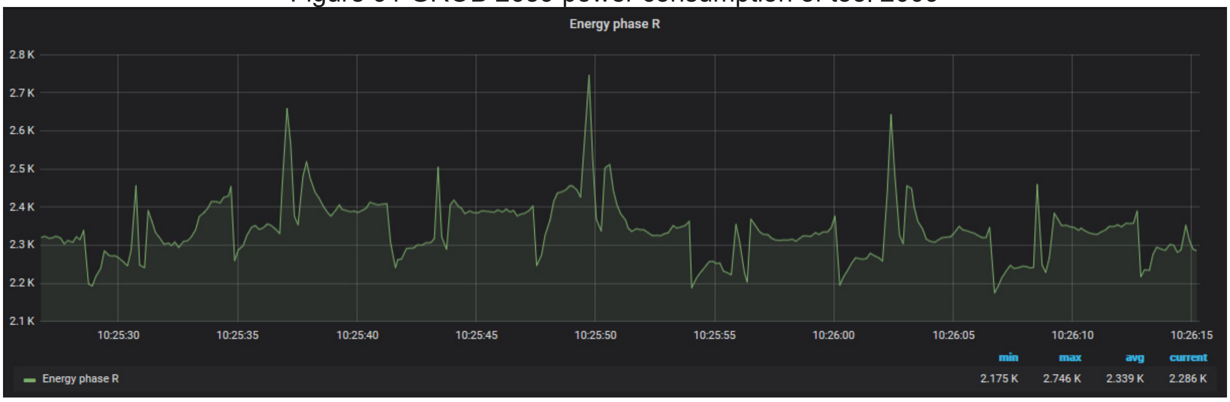
Source: Author (2020)

Figure 90 GROB 2639 power consumption of tool 2008



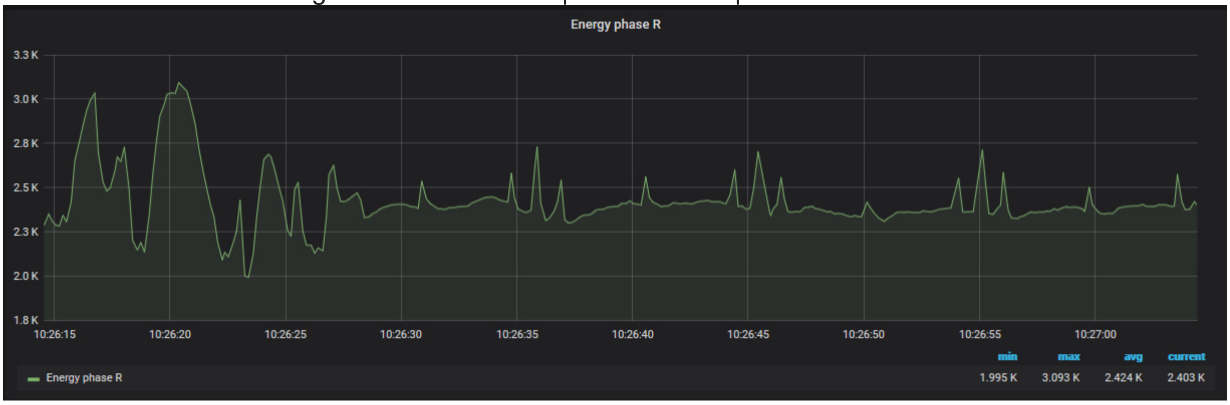
Source: Author (2020)

Figure 91 GROB 2639 power consumption of tool 2009



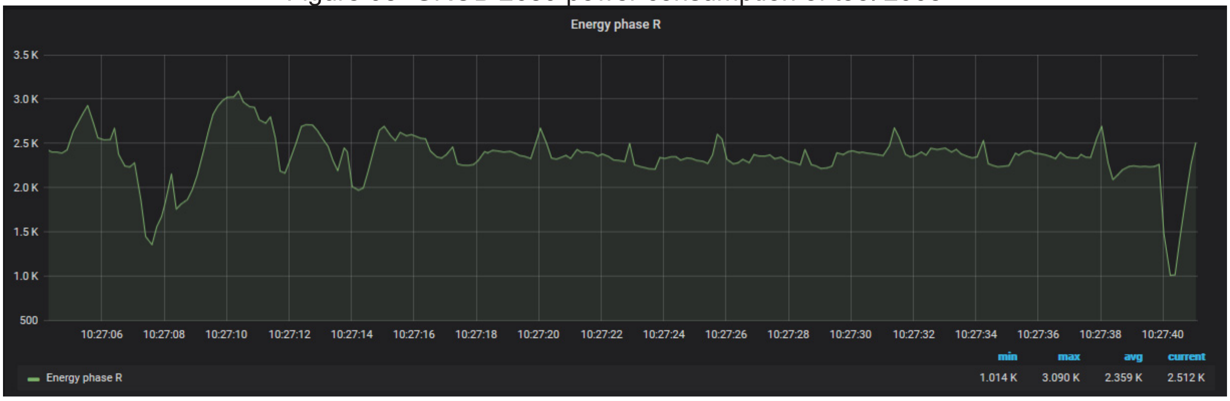
Source: Author (2020)

Figure 92 GROB 2639 power consumption of tool 2015



Source: Author (2020)

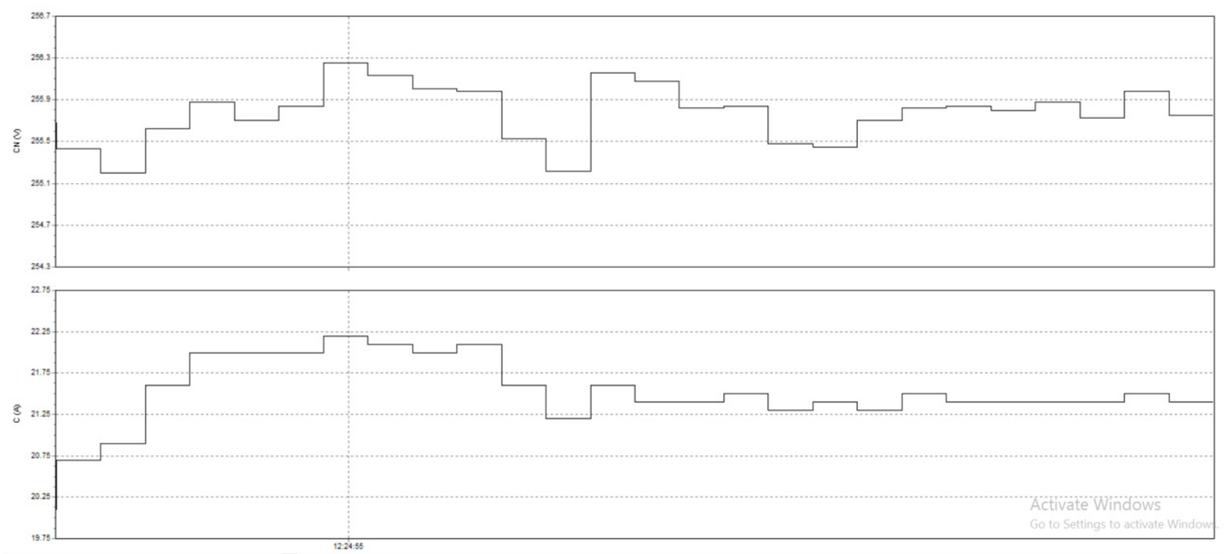
Figure 93 GROB 2639 power consumption of tool 2005



Source: Author (2020)

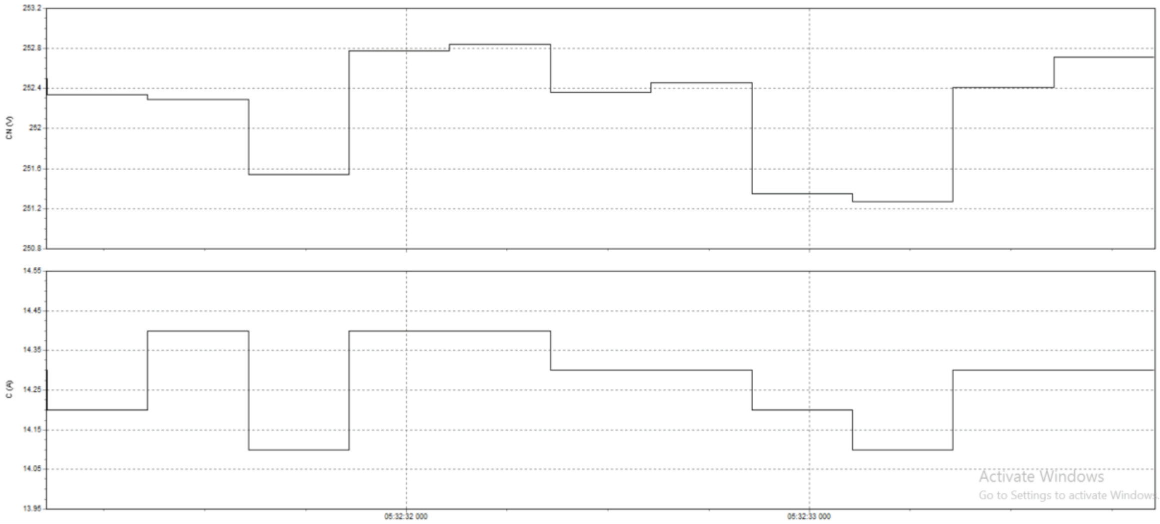
Annex 4

Figure 94 LATHE EMAG 14720 power consumption working



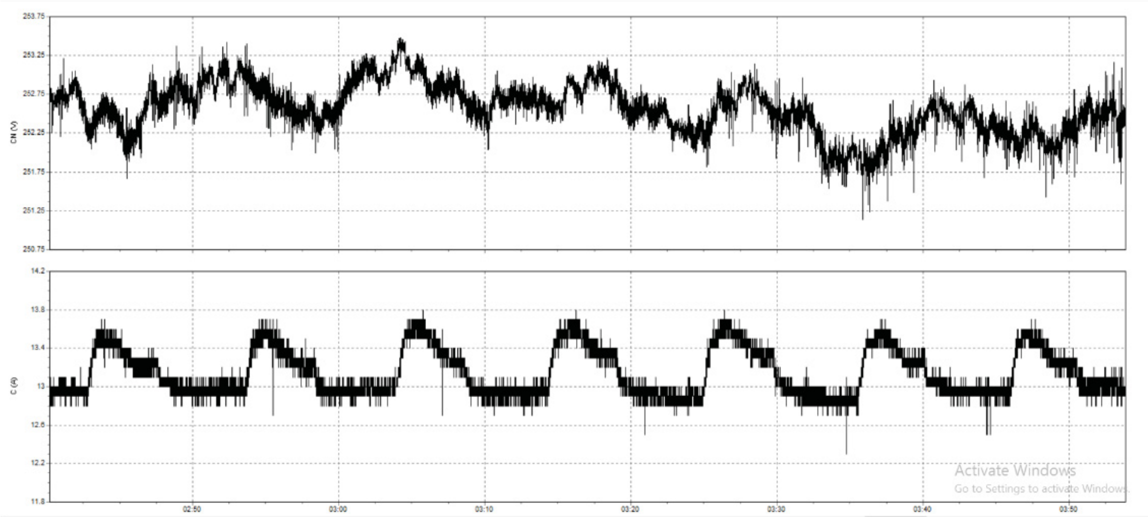
Source: Author (2020)

Figure 95 LATHE EMAG 14720 power consumption at standby mode



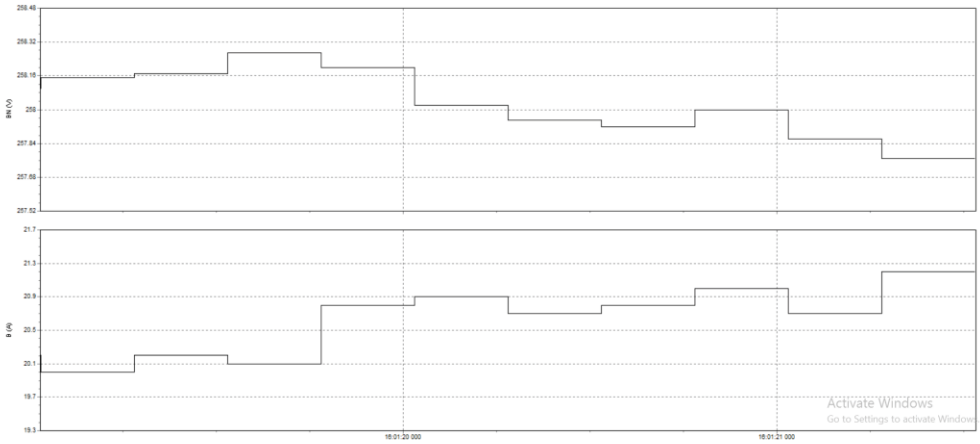
Source: Author (2020)

Figure 96 LATHE EMAG 14720 power consumption off



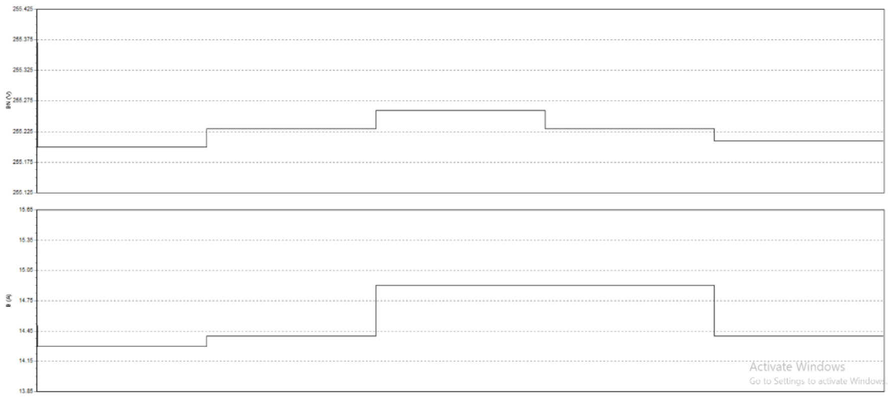
Source: Author (2020)

Figure 97 LATHE EMAG 3217 power consumption working



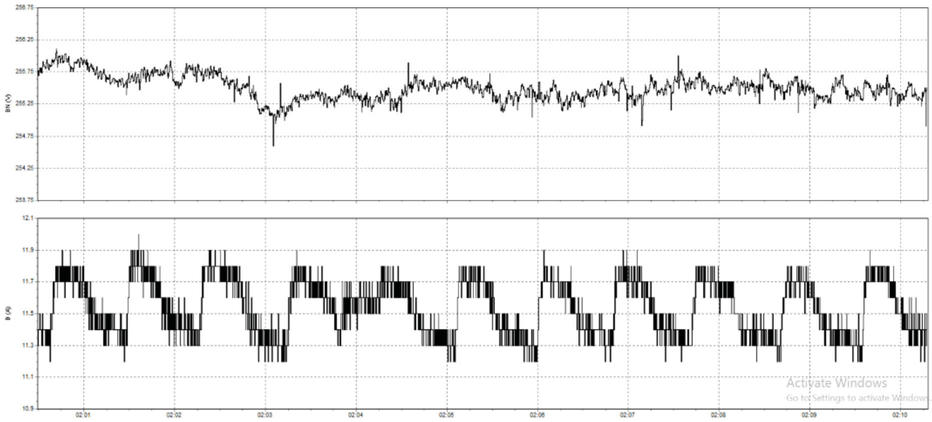
Source: Author (2020)

Figure 98 LATHE EMAG 3217 power consumption at standby mode



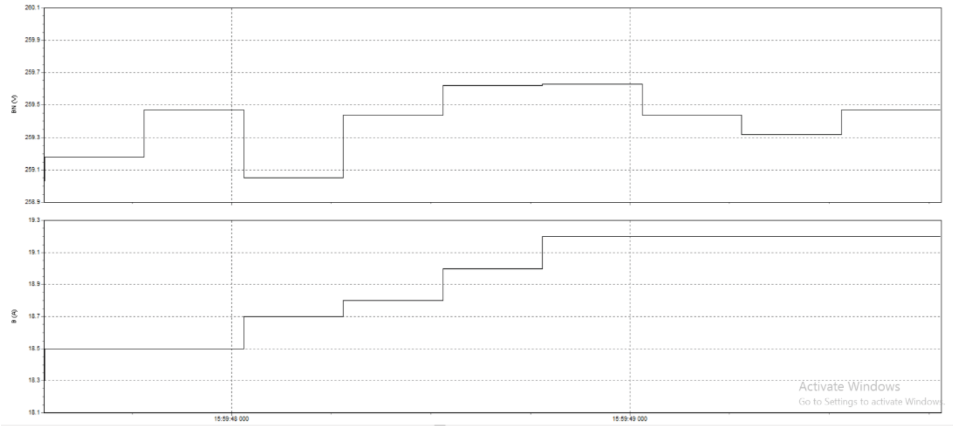
Source: Author (2020)

Figure 99 LATHE EMAG 3217 power consumption off



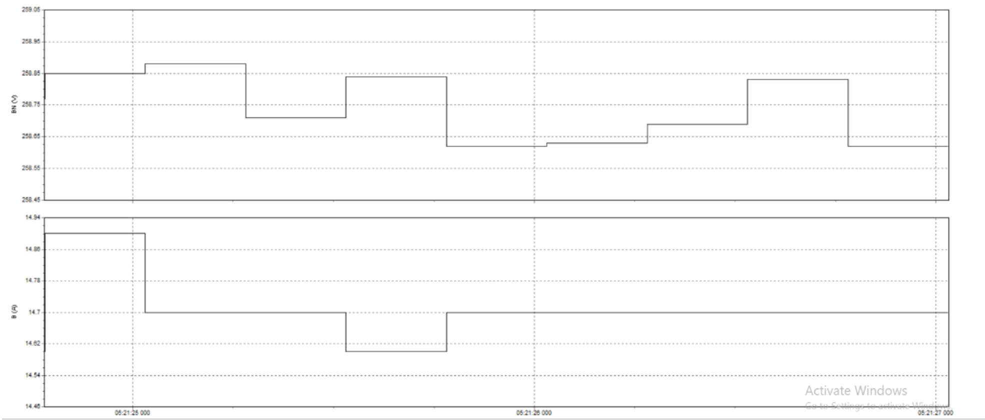
Source: Author (2020)

Figure 100 LATHE EMAG 3219 power consumption working



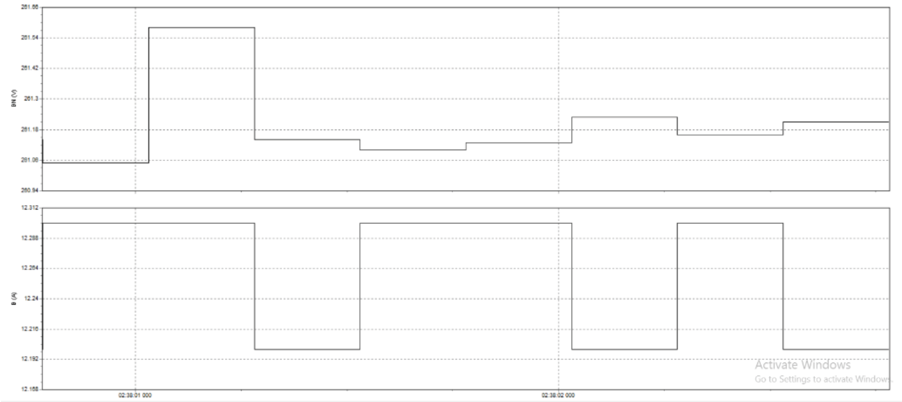
Source: Author (2020)

Figure 101 LATHE EMAG 3219 power consumption at operational mode



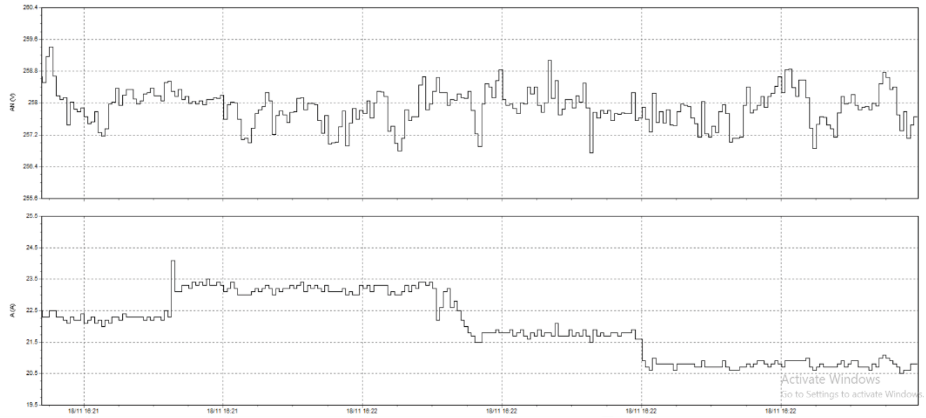
Source: Author (2020)

Figure 102 LATHE EMAG 3219 power consumption standby



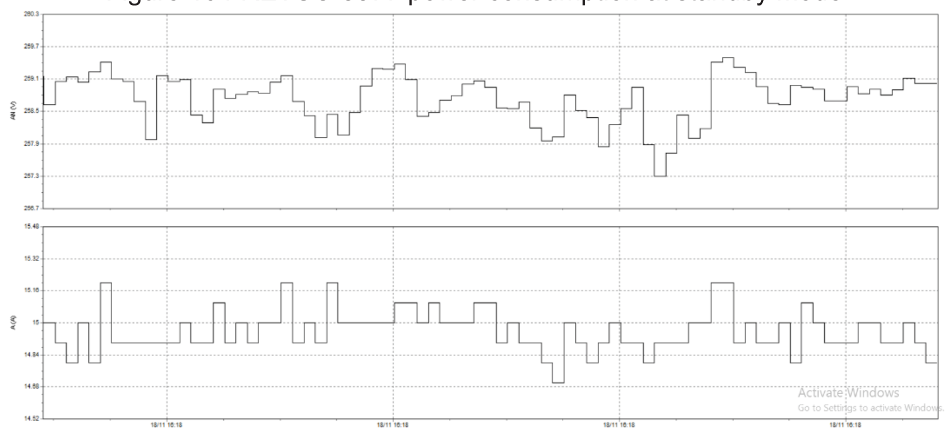
Source: Author (2020)

Figure 103 RETCO 3377 power consumption working



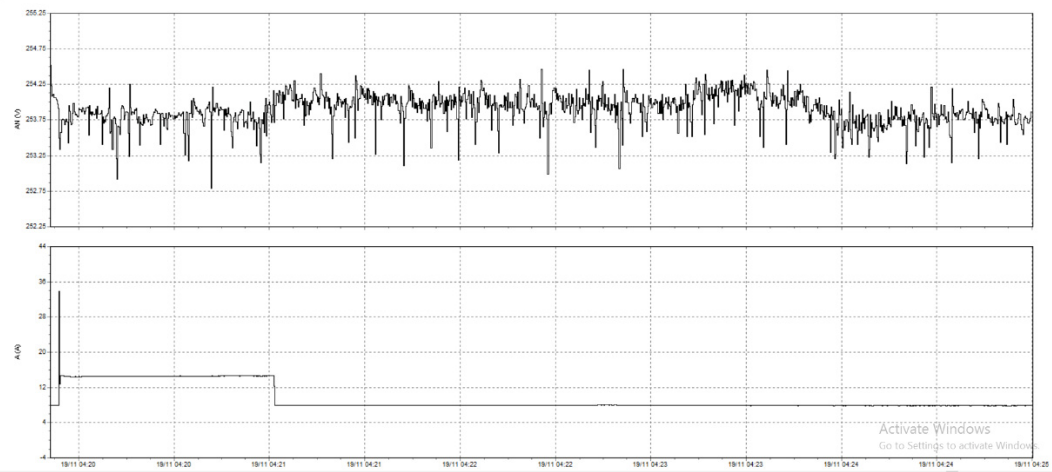
Source: Author (2020)

Figure 104 RETCO 3377 power consumption at standby mode



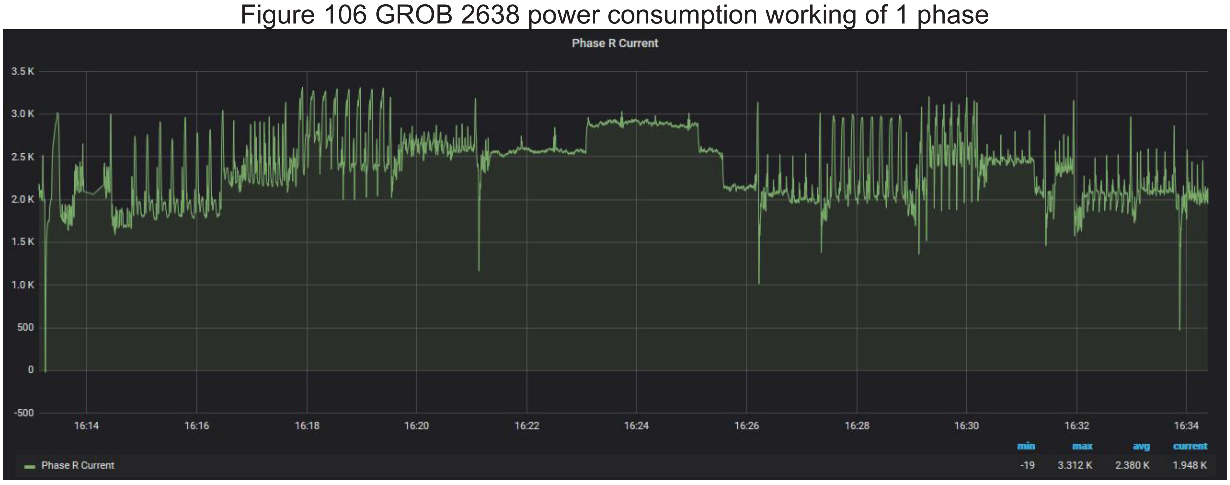
Source: Author (2020)

Figure 105 RETCO 3377 power consumption off



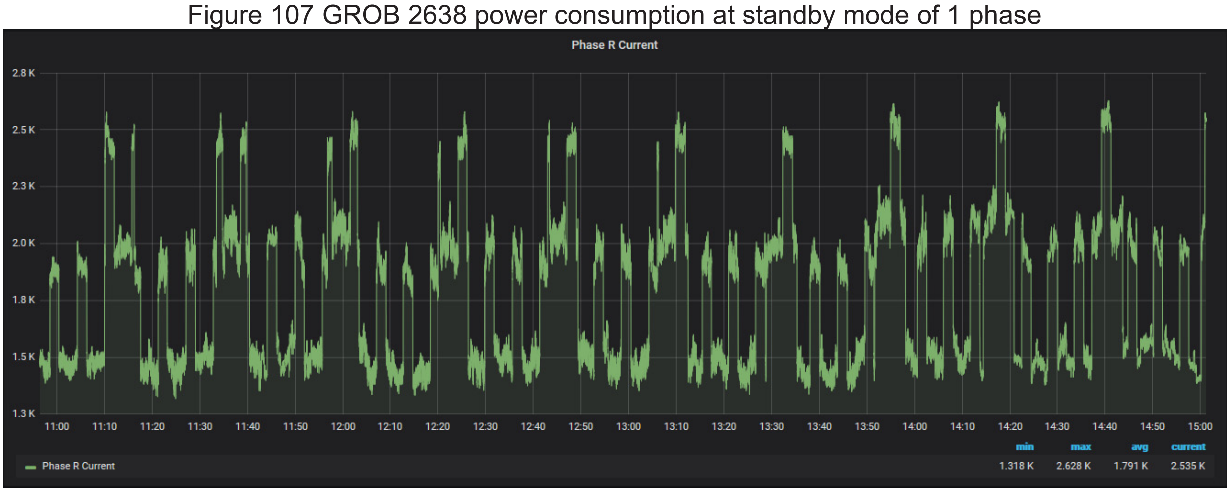
Source: Author (2020)

Figure 106 GROB 2638 power consumption working of 1 phase



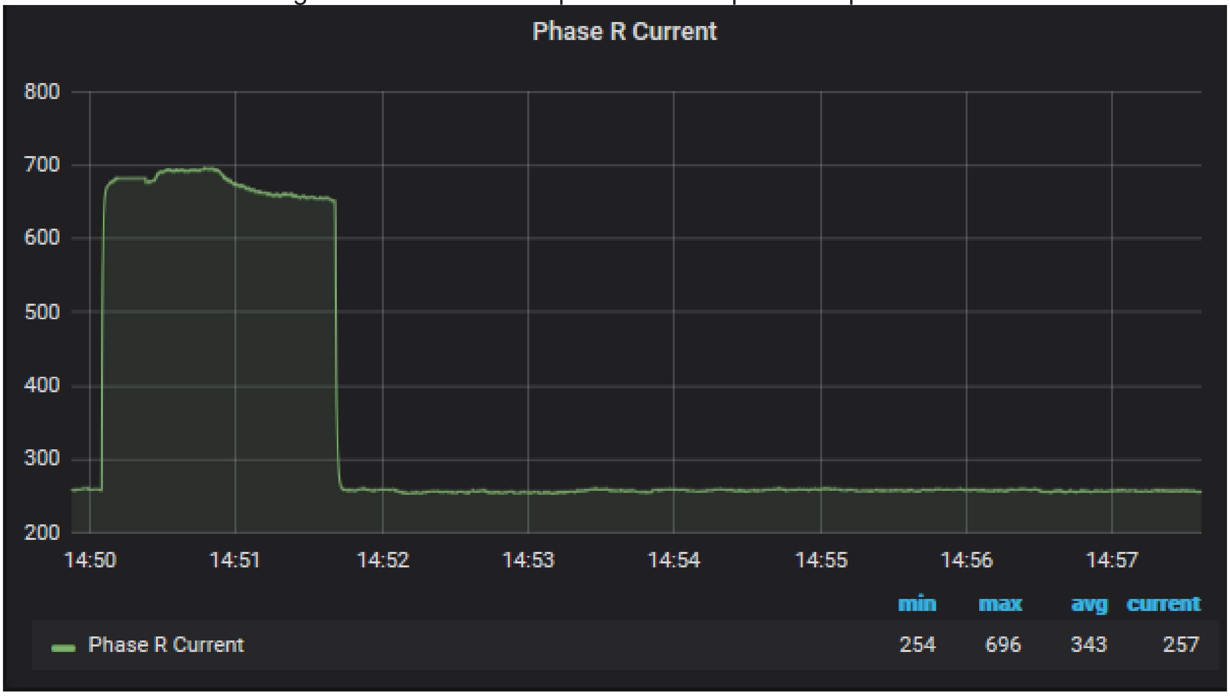
Source: Author (2020)

Figure 107 GROB 2638 power consumption at standby mode of 1 phase



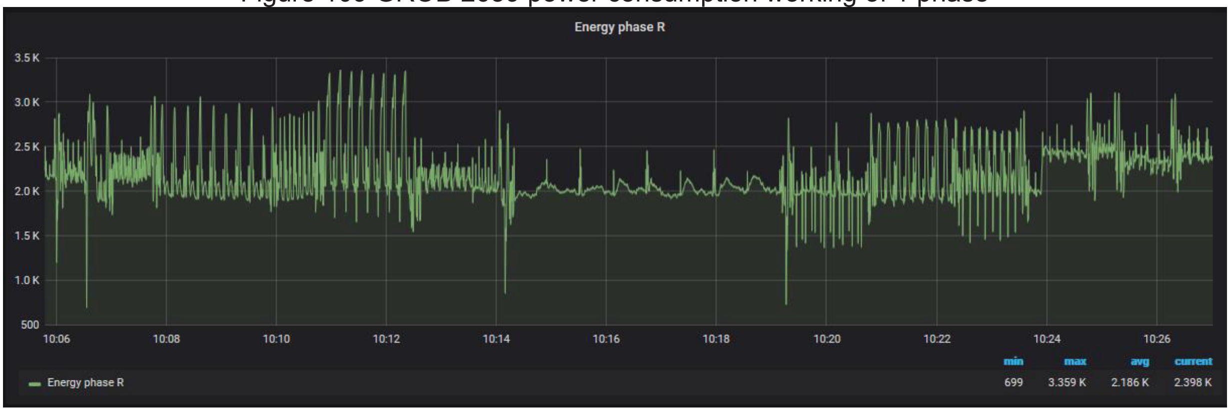
Source: Author (2020)

Figure 108 GROB 2638 power consumption of 1 phase off



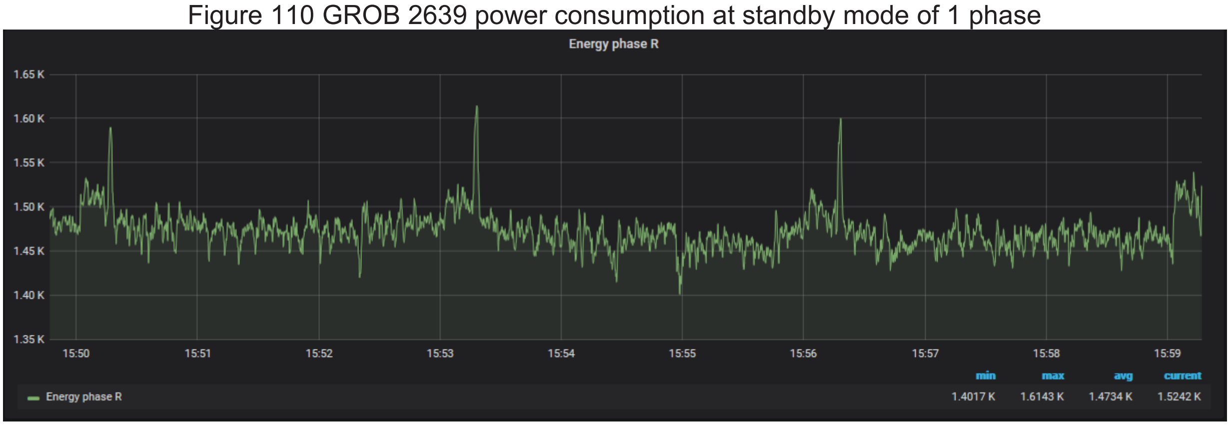
Source: Author (2020)

Figure 109 GROB 2639 power consumption working of 1 phase



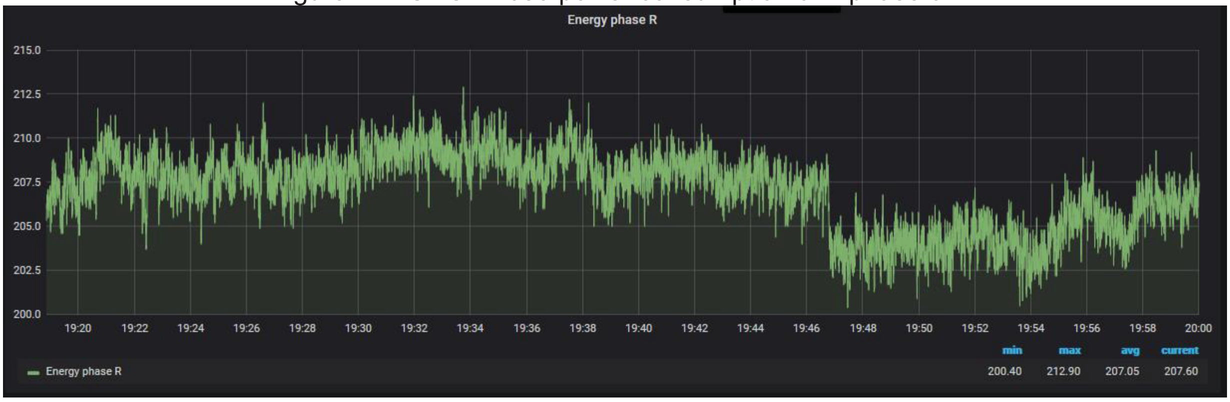
Source: Author (2020)

Figure 110 GROB 2639 power consumption at standby mode of 1 phase



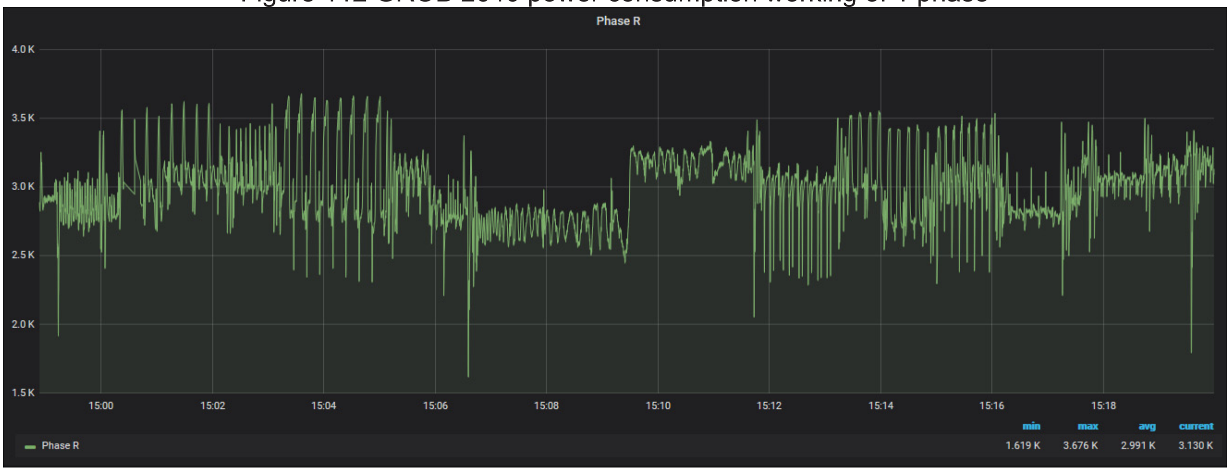
Source: Author (2020)

Figure 111 GROB 2639 power consumption of 1 phase off



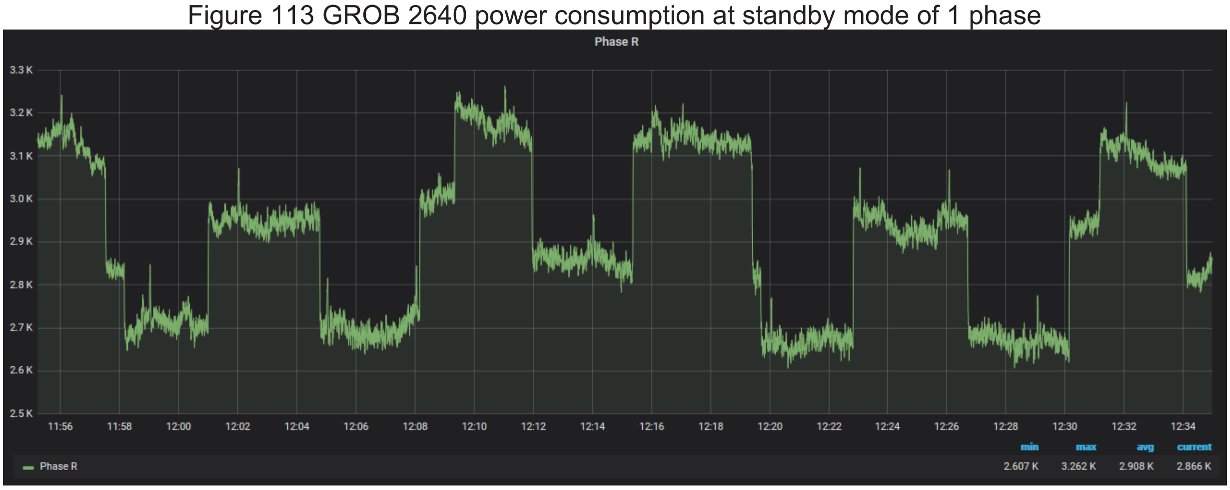
Source: Author (2020)

Figure 112 GROB 2640 power consumption working of 1 phase



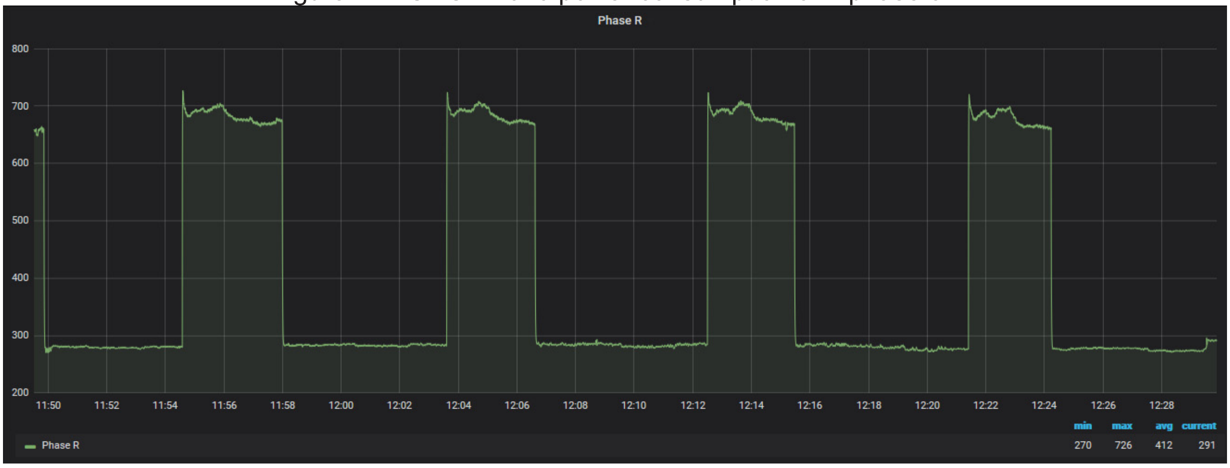
Source: Author (2020)

Figure 113 GROB 2640 power consumption at standby mode of 1 phase



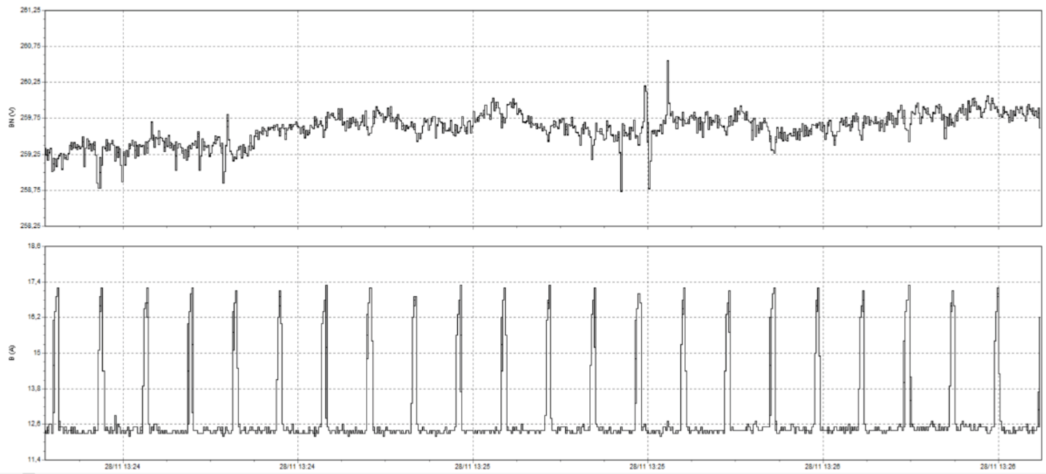
Source: Author (2020)

Figure 114 GROB 2640 power consumption of 1 phase off



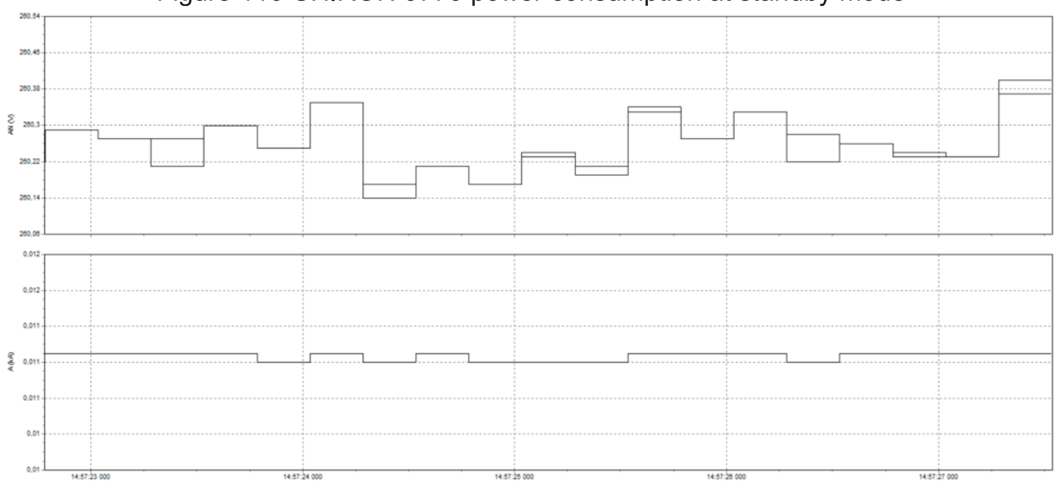
Source: Author (2020)

Figure 115 CHIRON 9770 power consumption working



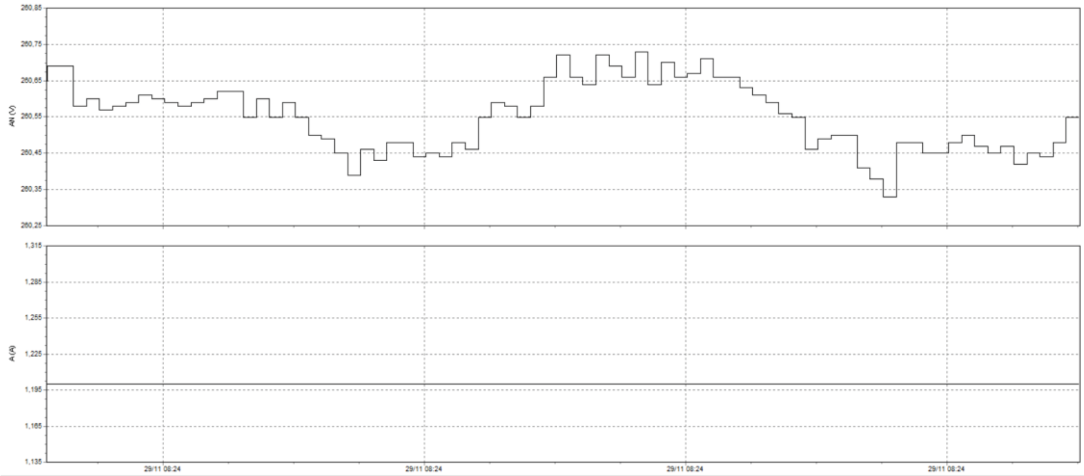
Source: Author (2020)

Figure 116 CHIRON 9770 power consumption at standby mode



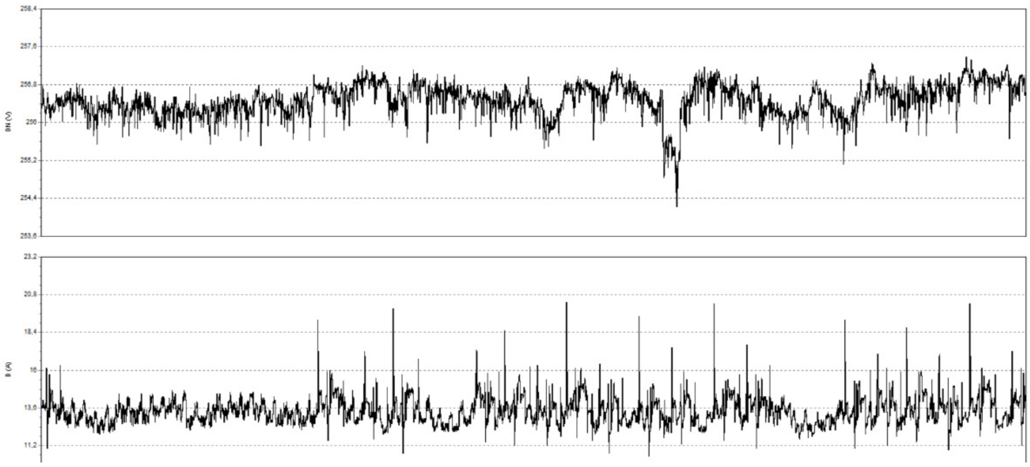
Source: Author (2020)

Figure 117 CHIRON 9770 power consumption off



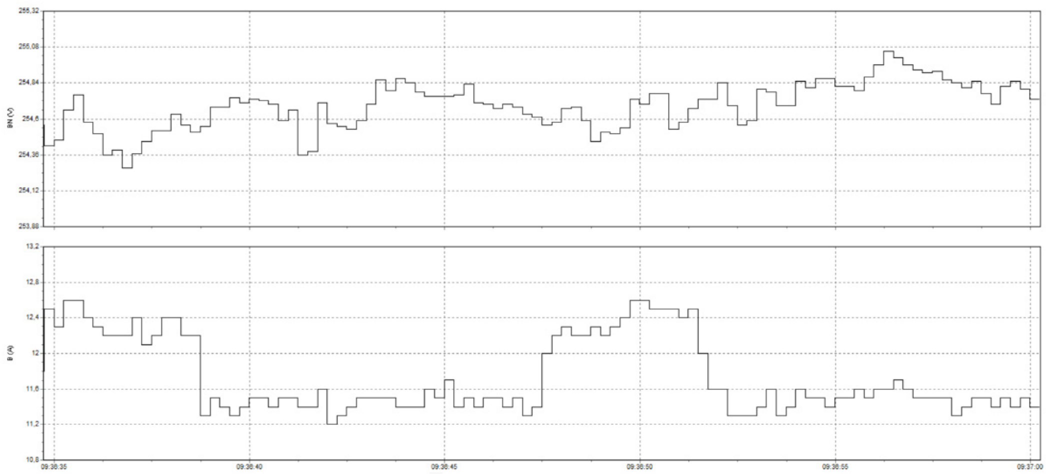
Source: Author (2020)

Figure 118 RETCO 4672 power consumption working



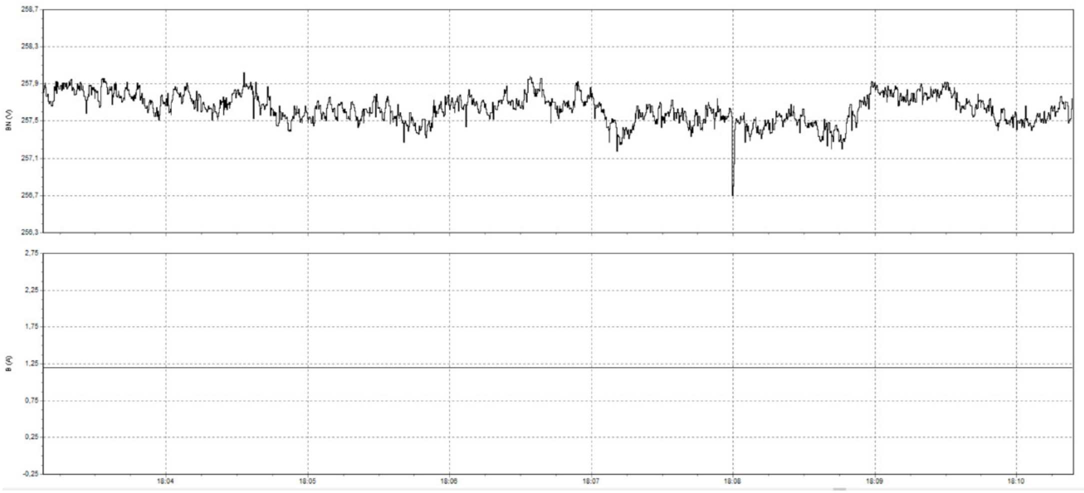
Source: Author (2020)

Figure 119 RETCO 4672 power consumption at standby mode



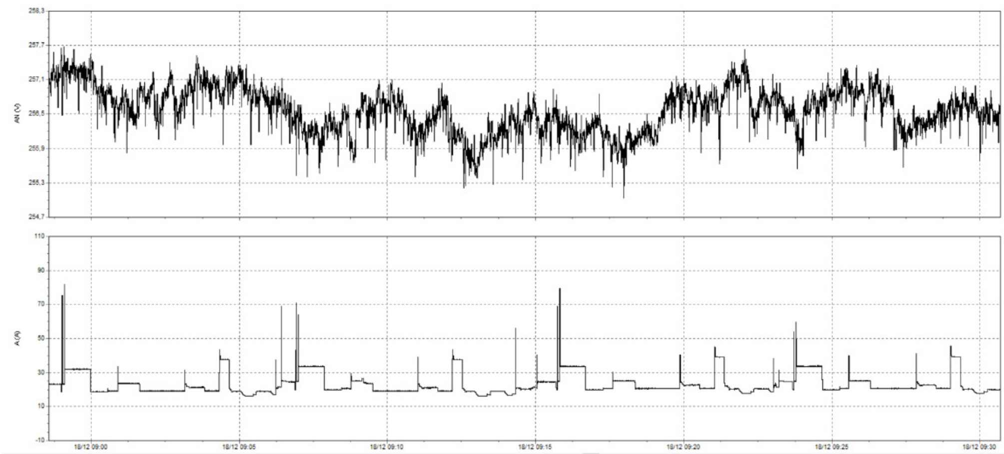
Source: Author (2020)

Figure 120 RETCO 4672 power consumption off



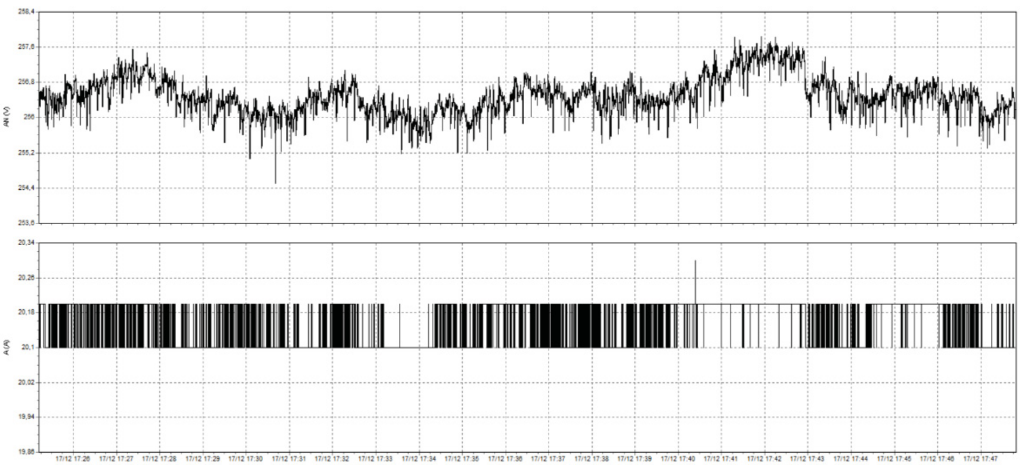
Source: Author (2020)

Figure 121 TECNOFIRMA 66461 power consumption working



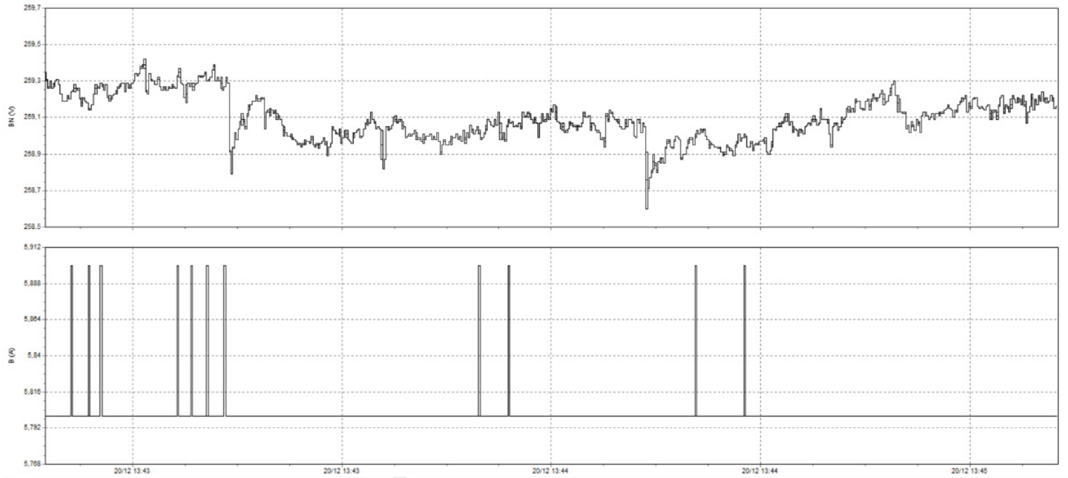
Source: Author (2020)

Figure 122 TECNOFIRMA 66461 power consumption at standby mode



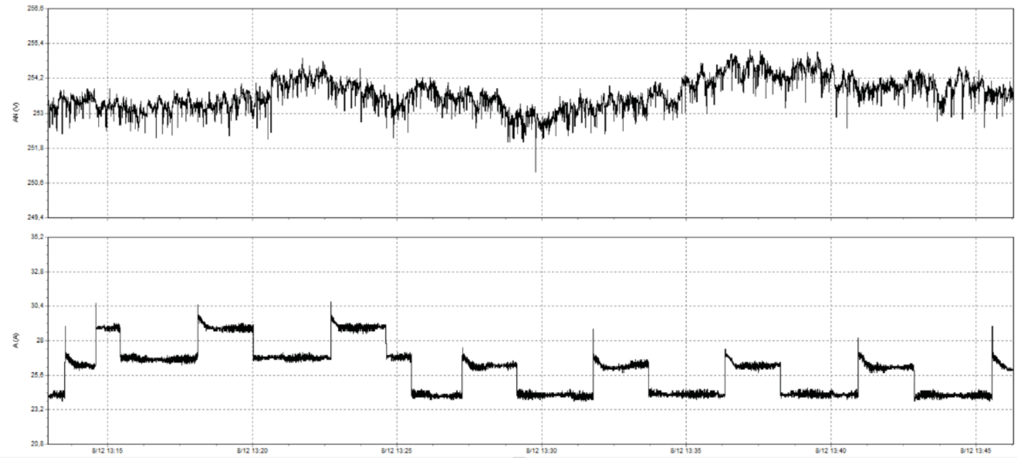
Source: Author (2020)

Figure 123 TECNOFIRMA 66461 power consumption off



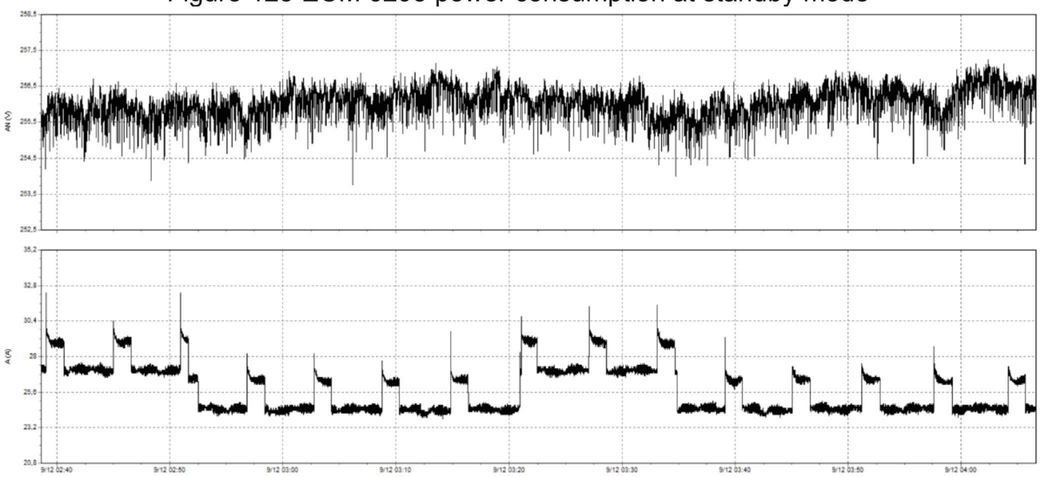
Source: Author (2020)

Figure 124 ECM 6293 power consumption working



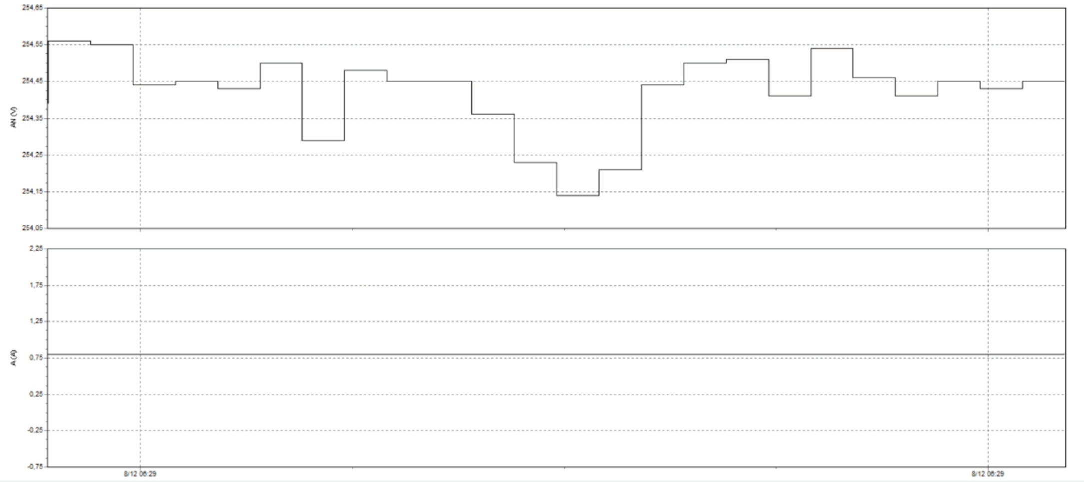
Source: Author (2020)

Figure 125 ECM 6293 power consumption at standby mode



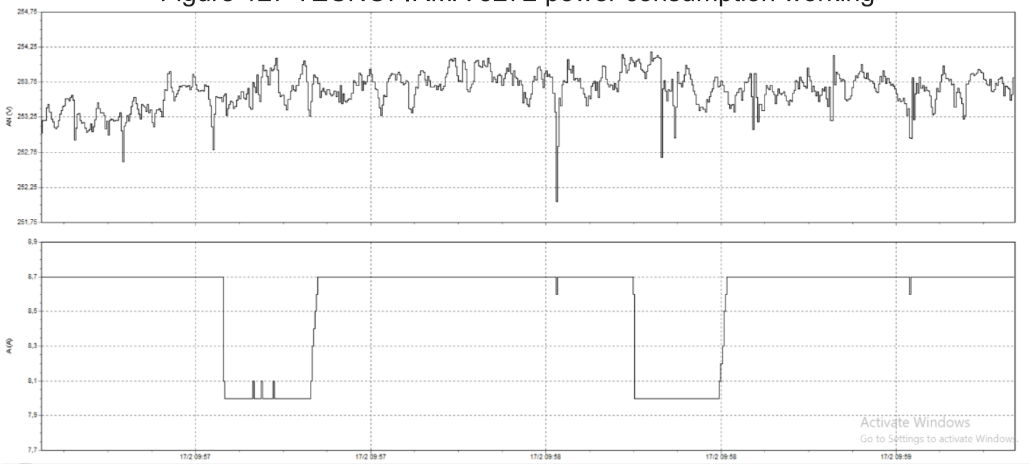
Source: Author (2020)

Figure 126 ECM 6293 power consumption off



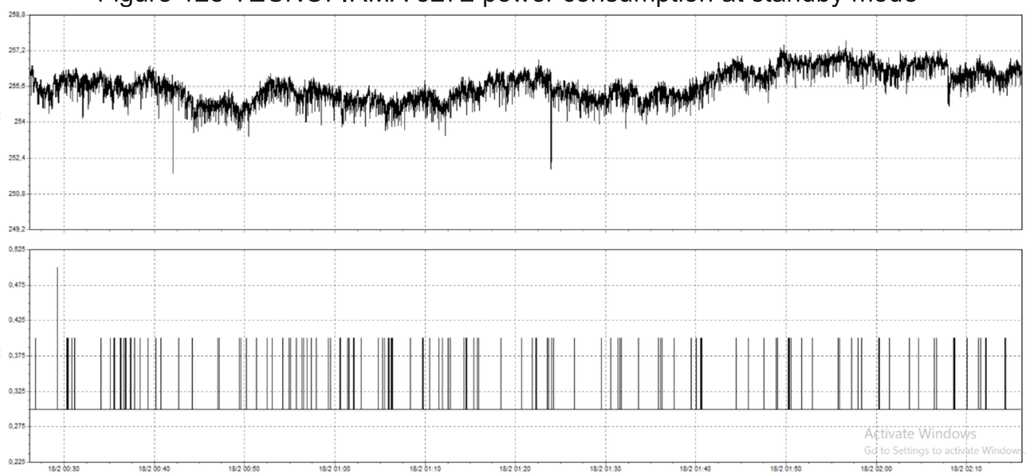
Source: Author (2020)

Figure 127 TECNOFIRMA 5272 power consumption working



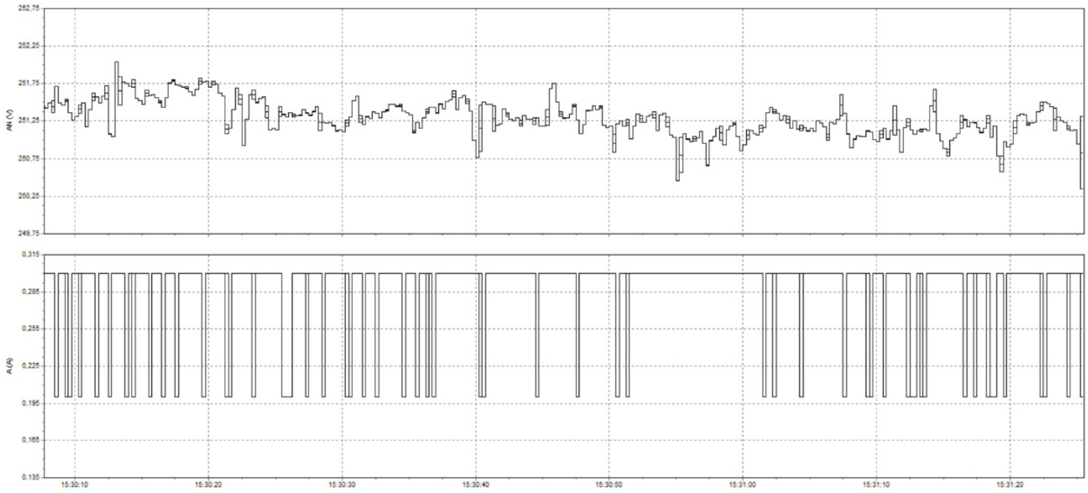
Source: Author (2020)

Figure 128 TECNOFIRMA 5272 power consumption at standby mode



Source: Author (2020)

Figure 129 TECNOFIRMA 5272 power consumption off



Source: Author (2020)