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Electrical Energy Consumption of Beverage Bottling Plants: Analysis, Modeling, and Forecast

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Danke an meine Familie für die jahrelange Unterstützung.
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Content

Preliminary Remarks

The results of the following thesis were mainly produced in the years 2012-2017 on the former Chair of Food Packaging Technology, Prof. Langowski, Technical University Munich. The following publications, related to this work, were published by Isabel Osterroth:

Full Paper (Peer-Reviewed)

Osterroth, I.; Holm, A.; Voigt, T., 2017. Energy demand in beverage-bottling plants, BrewingScience, 70 (May/June 2017), pp. 86–99. DOI: 10.23763/BRSC17-08OSTERROTH

Osterroth, I.; Voigt T., 2021. Energy Consumption of Beverage-Bottling Machines. Sustainability. 13. 9880. DOI: 10.3390/su13179880.

Osterroth, I.; Klein, S.; Nophut, C.; Voigt, T., 2017. Operational-state-related modeling and simulation of the electrical power demand of beverage-bottling plants, Journal of Cleaner Production 162C, pp. 587–600. DOI: 10.1016/j.jclepro.2017.06.006

Dipl.-Ing. Isabel Anna Osterroth is the main author of all the publications listed above that constitute the basis of this thesis. She was responsible for the idea, conception, and execution of the scientific research.

Further Conference Contributions and Oral Presentations (presenter underlined)

<u>Franke, S.;</u> Höfler, J.; Osterroth, I.; Voigt, T.; Langowski, H.-C.; Petermeier, H.: Simulation-based Energy Management Tools for the Food Processing Industry. In: FOODSIM2012, 2012, p. 45-51.

<u>Osterroth, I.,</u> Flad, S.; Voigt, T.; Operational-state-related energy data analysis in bottling plants. 4th International Young Scientist Symposium on malting, brewing, and distilling, Ghent, Belgium, 28.–30.10.2014.

<u>Osterroth, I.;</u> Energy state model for bottling plants. 5th International Young Scientist Symposium on malting, brewing and distilling, Chico, CA, USA 21.–23.04.2016.

<u>Osterroth, I.;</u> Energy consumption of beverage-bottling plants. 36th Congress of the EBC European Brewery Convention, Ljubljana, Slovenia, 14.–18.05.2017.

<u>Osterroth, I.;</u> Zustandsbezogene Stromverbrauchsanalyse im Simulationsmodell, 19. Flaschenkeller-Seminar, Freising, Germany, 04.–05.12.2012.

<u>Osterroth, I.;</u> Stromverbrauchsanalyse in der Abfülllinie, 20. Flaschenkeller-Seminar, Freising, Germany, 03.-04.2013.

<u>Osterroth, I.;</u> Energiedatenerfassung und Auswertung in der Getränkeabfüllung, 21. Flaschenkeller-Seminar, Freising, Germany, 02–03.12.2014.

<u>Osterroth, I.;</u> Einheitliche Spezifikation und Messung von Energie- und Medienverbräuchen. 22. Flaschenkeller-Seminar, Freising, Germany, 08.–09.12.2015.

Poster Presentations (presenter underlined)

Osterroth, I.; Voigt, T.: Energy State Model for Bottling Plants, 6th MSE Colloquium, Garching, Deutschland, 07.06.2016.

Other Publications

Dipl.-Ing. Isabel Anna Osterroth contributed with the results of this thesis (basic models, definitions and data) as a member of the scientific and industrial committee to the publication of *VDMA 8751:2019-03 Packaging machinery (incl. filling machinery)-Specification and measurement of energy and utility consumption.*

Further Research in this field

The results of this thesis were basis for further research projects as e.g., published by Bär et al. in the following publications:

Bär, R.; Voigt, T.; A metamodeling approach for the simulation of energy and media demand for the brewing industry. Journal of Advanced Manufacturing and Processing. 2021, 3; DOI: 10.1002/amp2.10080.

Bär, Raik; Zeilmann, Michael; Nophut, Christoph; Kleinert, Joachim; Beyer, Karsten; Voigt, Tobias; Simulation of Energy and Media Demand of Beverage Bottling Plants by Automatic Model Generation. Sustainability 2021, 13, 10089; DOI: 10.3390/su131810089. Impact Factor: 3.251.

Bär, Raik; Schmid, Sebastian; Zeilmann, Michael; Kleinert, Joachim; Beyer, Karsten; Glas, Karl; Voigt, Tobias; Simulation of Energy and Media Demand of Batch-Oriented Production Systems in the Beverage Industry. Sustainability 2022, 14(3), 1599, DOI: 10.3390/su14031599.

For this thesis empirical data of electricity consumption from industrial beverage-bottling plants were combined with operating state data in order to gain fundamental insights on the electrical consumption behavior. Based on this empirical analysis, generic mathematical models for single machines and an interlinked production line were presented for the first time and implemented in simulation models. While the modeling concept presented here is based on the idea that energy consumption can be described by a limited number of energy demand levels mapped to the occurring operational state of the machine, Bär et al. have later developed a simplified operational state related modeling by omitting the time-dependent variable. The focus of their work is on a more holistic approach. They present first a metamodel for the plant, process, article/recipe, and production plan. The simulation environment is extended by the integration of a production plan and the associated recipe- or article-specific simulation as well as by the simulation of batch-oriented production. As a result, Bär et al. have developed a hybrid simultaneous simulation extending the discrete packaging and bottling area by the batch-oriented production including not only electrical energy but also other consumptions (e.g., thermal energy and compressed air).

Summary of the Dissertation

Megatrends such as sustainability and energy efficiency currently shape the industry worldwide. Modeling and simulation are suitable tools for optimizing complex technical systems. In the beverage industry, bottling and packaging is the final value-adding process step during the production process. This step is realized in modern production lines, which consist of machines interlinked by transport and buffering elements. Each machine within the production line consumes electrical energy and can be considered as an element of an interlinked production system. With an average of 12 % – 35 % of the overall consumption of electrical energy, bottling remains the second-highest electrical energy consumer within a brewery production process besides refrigeration.

The relevant scientific literature presents a variety of models to describe and predict energy consumption of technical systems. Analysis of the available scientific literature and published data indicates that a state- and component-based modeling approach is required for a detailed energy analysis and optimization of an interlinked bottling plant as an example for an interlinked production system. In contrast, common performance indicators are basically related to the amount of product (e.g., kWh/hl produced beer). While no suitable generic models in a high level of detail have been published yet for bottling plants, the general idea of several published models for other production systems for a state-related approach can be adapted. The scientific goal of this thesis is, therefore, to gain fundamental knowledge on the production-related energy consumption behavior of interlinked production systems (here on the example of a beverage-bottling plant) to develop suitable models and to transfer them into validated simulation models as a tool for analysis and optimization on the level of single machines and interconnected systems.

A scientific review of publicly available and scientifically published data on energy and media consumption of bottling plants shows that no detailed data suitable for modeling and validation are currently available. A survey on the German brewing industry was made to collect relevant energy consumption data. The results of this study, published as Publication I, indicated a high demand of energy during standby times and confirmed a high demand for optimization approaches and tools, but the collected database is not yet sufficient for a modeling database. In order to create a reliable database for modeling as well as for the parameterization, verification, and validation of a simulation model, additional empirical data of electricity consumption as well as operating state data (production, lack, tailback, equipment failure, etc.) were collected over continuous time periods up to three months, depending of the availability of the analyzed machine, at several industrial beverage-bottling plants on the level of single machines.

Publication II analyzed the electrical energy consumption on the basis of the collected empirical data in order to gain fundamental knowledge on the electrical consumption behavior and possible influences of the operational behavior of the single system components (machines) as a basis for a generic electrical energy consumption model. Based on this empirical analysis, generic mathematical models for single machines were developed and interlinked to a total production line.

These single model components as well as the interlinked model take the influence of the operating behavior of the single machines on the energy consumption into consideration to enable a detailed and production-related forecast. The modeling concept is based on the idea that energy consumption can be described by a limited number of energy demand levels mapped to the occurring operational state of the machine and that state transitions are described by intermediate levels. The model components are validated by empirical data, which have not been used for modeling before. The generic models were transferred into an experimental simulation model established in the commercial simulation software MATLAB Stateflow.

Publication III presents the generic modeling concept and the basic results of the successful implementation and validation of the energy consumption model for bottling plants using empirical operating state and electrical energy consumption data.

The scientific results of this work were successfully transferred into industrial applications in cooperation with the German Engineering Federation (VDMA Fachverband für Nahrungsmittelmaschinen und Verpackungsmachinen) and a group of industrial representatives. The results were published as *VDMA 8751:2019-03 Packaging machinery (incl. filling machinery)-Specification and measurement of energy and utility consumption.*

For future research, it was found that this modeling concept can be extended by an event-discrete material flow model to a hybrid model instead of using measured operational state data, with an improved set of empirical data for validation. Future research in this field may also focus on the transfer of these results on the heat and media demands (e.g. water or compressed air) of interlinked production systems as well as on the generic development of optimization strategies.

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Zusammenfassung der Dissertation

Nachhaltigkeit und Energieeffizienz sind Megatrends, die die Industrie weltweit prägen. In der Getränkeindustrie ist das Abfüllen und Verpacken der letzte wertschöpfende Produktionsschritt. Dieser Schritt wird in modernen Produktionslinien vollzogen, die aus einer Vielzahl miteinander verketteter Aggregate bestehen. Jede der verwendeten Maschinen verbraucht elektrische Energie. Der elektrische Energieverbrauch der Abfüllung ist, neben dem Verbrauch für Kältesysteme, mit durchschnittlich 12 - 35 % des elektrischen Gesamtverbrauchs der zweithöchste im gesamten Produktionsprozess einer Brauerei. Aufgrund ihrer Zusammenstellung dienen Getränkeabfüllanlagen als klassisches Beispiel für komplex verkettete Produktionssysteme.

Modellierung und Simulation sind geeignete Werkzeuge, um komplexe technische Systeme zu beschreiben und mit veränderlichen Modellen das Verhalten des betrachteten Systems vorherzusagen. Die wissenschaftliche Literatur beschäftigt sich mit einer Vielzahl von Modellen, um den Energieverbrauch technischer Systeme zu beschreiben und vorherzusagen. Die Analyse der verfügbaren wissenschaftlichen Literatur ergab, dass für den dargestellten Anwendungsfall einer verketteten Getränkeabfülllinie ein zustandsbasierter komponentenbezogener Modellierungsansatz geeignet sein kann. Ein geeignetes generisches Modell wurde bis dahin nicht publiziert. Das wissenschaftliche Ziel dieser Arbeit war folglich, ein grundlegendes Verständnis für das Verbrauchsverhalten von Getränkeabfüllanlagen als Beispiel für verkettete Produktionsanlagen zu schaffen, dieses in generische Modelle zu überführen und in experimentierfähige validierte Simulationsmodelle zu implementieren, um so ein Werkzeug zur Optimierung des Energieverbrauchs zur Verfügung zu stellen.

Eine wissenschaftliche Aufarbeitung der öffentlich zugänglichen und wissenschaftlich publizierten Daten zum Energie- und Medienverbrauch ergab, dass keine detaillierten, zur Modellbildung und Validierung geeigneten Daten verfügbar waren. Eine Umfrage in der deutschen Brauindustrie mit dem Ziel, relevante Energieverbrauchsdaten zu erheben, ergab, dass hohe Verbräuche während nicht-produktiver Zeiten anzunehmen sind und großer Bedarf für Optimierungswerkzeuge für den Anwendungsfall besteht. Die Ergebnisse dieser Studie wurden als Publikation I dieser Arbeit veröffentlicht. Für eine Modellierung und Validierung war die erhobene Datenbasis noch nicht detailliert genug. Als Datenbasis für eine weiterführende Modellierung sowie für die Parametrisierung, Verifikation und Validierung eines Simulationsmodells wurden zusätzlich umfangreiche elektrische Verbrauchsdaten und Betriebszustandsdaten an mehreren industriellen Getränkeabfüllanlagen auf Maschinenebene über kontinuierliche Zeiträume bis zu drei Monaten, je nach Verfügbarkeit der untersuchten Einzelmaschinen, erhoben. Abgeleitet aus diesen empirischen Daten wurde ein generisches Verbrauchsmodell entwickelt, das den elektrischen Energieverbrauch einer Abfüllanlage

komponentenbasiert auf Maschinenebene und betriebszustandsbezogen beschreibt. Die Ergebnisse dieser Analyse wurden als Publikation II dieser Arbeit zur Veröffentlichung eingereicht.

Basierend auf diesen Erkenntnissen wurde ein mathematisches Modell zur Beschreibung des elektrischen Energieverbrauchs der Einzelmaschinen unter Berücksichtigung des Betriebszustandes erarbeitet und zu einem Gesamtmodell für die Abfüllanlage verbunden. Grundlage des Modells war die Erkenntnis, dass das elektrische Verbrauchsverhalten über eine definierte Anzahl energetischer Verbrauchsniveaus beschrieben werden kann, die anerkannten Modellen des Betriebsverhaltens zugeordnet werden können. Zustandsübergänge werden über definierte Zwischenstufen beschrieben. Diese Modelle wurden in der kommerziellen Software MATLAB Stateflow in experimentierbare Simulationsmodelle überführt. Publikation III dieser Arbeit präsentiert grundlegende Ergebnisse zur erfolgreichen Umsetzung und Validierung des zustandsbasierten Energiemodells unter Verwendung historischer Betriebszustandsdaten aus der empirischen Datenerhebung.

Die wissenschaftlichen Erkenntnisse dieser Arbeit konnten in Zusammenarbeit mit dem VDMA Fachverband Nahrungsmittelmaschinen und Abfüllmaschinen und einem Arbeitskreis aus Industrievertretern erfolgreich in die industrielle Applikation transferiert werden. Die Ergebnisse wurden als *VDMA Einheitsblatt VDMA 8751:2019-03 Abfüll- und Verpackungsmaschinen-Spezifikation und Messung des Energie- und Medienverbrauchs* veröffentlicht.

Zukünftige Forschungsansätze können den vorgestellten Modellierungsansatz durch eine validierte ereignisdiskrete Materialflusssimulation in seinem Umfang und Anwendungspotential entscheidend erweitern. Hierzu ist es notwendig verbesserte, empirische Daten zu Validierung zu erheben. Ein Datensatz zur Validierung einer Materialflusssimulation sollte vollständige, valide Zustandsdaten nach einem etablierten Zustandsmodell enthalten und auch den Aufbau, sowie das Layout der gesamten Anlage und der zugehörigen Transportstrecken berücksichtigen. Zukünftige wissenschaftliche Ansätze sollten die Anwendbarkeit der präsentierten Modelle auf den Wärme- und Medienverbrauch (z.B. Wasser, Druckluft) prüfen, um ein umfassendes Bild zu Verbräuchen zu liefern, sowie generische Optimierungsstrategien zur Senkung des Energie- und Medienverbrauchs bei der Getränkeabfüllung durch die Anwendung der Modelle zu ermöglichen.

1 Introduction

1.1 Motivation

Sustainability is a megatrend in the packaging industry, which will increasingly shape the industry in the coming years (Olsmats and Kaivo-oja, 2014). Limited resources, a growing public perception of environmental topics, brand image considerations, legal requirements, taxes, as well as direct and indirect cost savings are factors that are forcing the German and international beverage industry to focus on energy efficiency measures. However, the estimated energy-saving potential for industrial plants is still high. The main energy-saving potentials for industrial plants, in general and specifically for food and beverage industry plants, are summarized in Table 1.1-1. The data show that while, for the industry in general, illumination and compressed air are the main energy-saving potential, for the food industry, beside utilization of waste heat nearly half of the estimated saving potential is still made up by optimizations in organizational measures (36 %), optimized plant control (6 %) and load management (5 %). To take advantage of these potentials, detailed process knowledge and suitable tools are required to overview the complex interaction of machines, processes, and peripheries.

Table 1.1-1: Relative energy-saving potentials in industrial processes according each normalized to the related area according to Barckhausen et al. (2016) and Energieagentur NRW (2005).

Industry (general)	
Illumination	70 %
Compressed air	50 %
Pumps	30 %
Refrigeration and cooling water system	30 %
Heat supply	30 %
Ventilation systems	25 %

Food industry	
Utilization of waste heat/heat recovery	50 %
Organizational measures	36 %
Compressed air	25 %
Renewal of steam generation facilities	15 %
Optimized plant/machine control	6 %
Load management	5 %
Thermal insulation	1.5 %

Bottling is the last step in the production of beverages and is important for preserving the product's quality until its consumption, for protection during transport and storage, for sales and marketing reasons, and for legal reasons (e.g., best-before date, declarations). For beverages and beer, the process takes place in modern bottling plants, which consist of individual machines interlinked by buffering transport elements.

A state-of-the-art European brewery (>1 Mio. hl annual capacity, returnable bottles) has a thermal energy consumption of 23 - 33 kWh/hl and an electrical energy consumption of 7.5 – 11.5 kWh/hl (Scheller et al. 2008). Recent sustainability reports of breweries confirm these numbers (e.g. Paulaner Brauerei, Germany 2018: 8.19 kWh/hl electrical and 15.47 kWh/hl thermal for approx. 2 Mio. hl/a (Paulaner Brauerei, 2018)). While more than two thirds of the total energy consumption of a brewery is thermal energy, the one third of electrical energy consumption is responsible for a major share of the energy costs. In Germany, for example, the electrical energy price has nearly doubled from 2012 to 2022 (0.11 €/kWh to 0.19 €/kWh) and the gas price for the same years has increased from 0.035 €/kWh to 0.055 €/kWh (excluding taxes)[1]. Due to the Ukraine war since spring 2022 and the resulting energy crisis prices are volatile, and a further increase of prices is possible.

Using up to 35 % of the total electrical power of a brewery, bottling comes second after refrigeration (40 %) in terms of electrical energy consumption (Fiederer et al., 2001). For the production of bottled water electrical energy is mainly required for the processing of the water (level and type of treatment depends on the water quality) and the bottling (can include the stretch blow molding of the PET bottles) (Gleick and Cooley, 2009). While only some specific machines in a beverage bottling plant consume thermal energy (flash or tunnel pasteurizer, bottle cleaning machine and crate washer), the Sankey diagram of the energy consumption of a brewery by Bär and Voigt shows that all machines consume electrical energy (Bär and Voigt, 2019). Optimizing the electrical energy consumption in bottling can therefore contribute to the reduction of energy consumption in the beverage production. Most modern breweries are already equipped with energy-optimized wort boiling systems, as well as vapor condensers and energy storage systems to recover the waste heat from the energy intensive wort boiling (Scheller et al., 2008). Lately an increasing number of companies are forced by the market to present Life Cycle Assessments (LCA), e.g. following the referenced of the DIN 14040 series for their products, analyzing

[1] Industry price for electricity in Germany in 1st half year 2012: 11.45 euro cent and 1st half year of 2022 19.25 euro cent per kWh for 2000 – 20 000 kWh, . Industry price for gas in Germany 2019: 2.68 cent per kWh (>100 000 Gigajoule). Prices excluding local taxes. (Statistisches Bundesamt (Destatis), 2022)

the carbon emissions during manufacturing of the machines, the operation of the machines (normally 15 years) and the disposal of the machines. These assessments draw additional attention to the energy demand and will increase the need for optimized machines and plants. A recent publication shows a Life Cycle Assessment for a beverage bottling machine:

Stefanini et al. have applied the LCA methodology for an aseptic blowing-filling system. The results show that the main environmental impact (>95 %) is related to the use phase of the machine. Electrical energy was identified as main environmental impact during the use phase of the machine, causing >70 % of the total impact, followed by process steam. The authors therefore concluded that producers should focus on consumption optimization to improve the environmental performance (Stefanini et al., 2022).

The European Commission has published 2020 a Best Available Techniques (BAT) reference document for the food, drink and milk industries, including guidance for energy reduction in the brewing and beverage industry (European Commission, Joint Research Centre, Giner Santonja, et al., 2020). The publication includes mainly practical examples for the brewing process, but the optimization potentials in bottling are not discussed beside low-pressure blowers for PET bottles and optimization examples for the CIP process and reduced water consumption. Examples to optimize the electrical energy consumption in general are limited.

Analyzing production systems is the first important step in identifying energy optimization potentials (May et al., 2015). The analysis of modern production systems can be complex because of the multiple influences and dependencies, which limit the representation of the production systems by mathematical models. In contrast to that, simulation models allow a detailed and dynamic view of the system (Smith, 2003). Thus, alternative production scenarios and decision parameters can be analyzed and optimized (Rebhan, 2002). By saving electrical energy, the production costs as well as environmental pollution can be reduced while simultaneously optimizing productivity (Duflou et al., 2012). Hybrid modeling is particularly suitable for mapping production systems because it takes both discrete and continuous aspects of system behavior into account (Windmann et al., 2013).

Therefore, modeling and simulation are established methods in the scientific literature and industrial applications for analyzing and optimizing complex production systems. In order to exploit the full energy-saving potentials of bottling plants, effective generic analysis methods are required to develop specific optimization strategies for multiple plant variants. As of now, there exists no holistic energy consumption analysis for beverage-bottling plants. Currently, no validated models are available in the scientific literature or industrial applications that optimize the energy consumption of interlinked machine systems for the example of beverage-bottling; only few detailed data have been published. While common energy performance indicators refer to consumption related to a defined production volume (e.g.,., kWh/hl), the operational behavior of the machines suggests the use of an operational-state-related approach to energy optimization.

Scientific research and generic models can provide generic optimization approaches that can be used as industrial tools for optimization and investment decisions, based on reliable data, considering the complex and holistic system structure. The following Venn diagram (Figure 1.1-1) summarizes the main focus topics of the literature presented and discussed in the following chapters. It indicates that there is a demand for simulation-based energy optimization tools for bottling plants considering the operational behavior of the interlinked production plant.

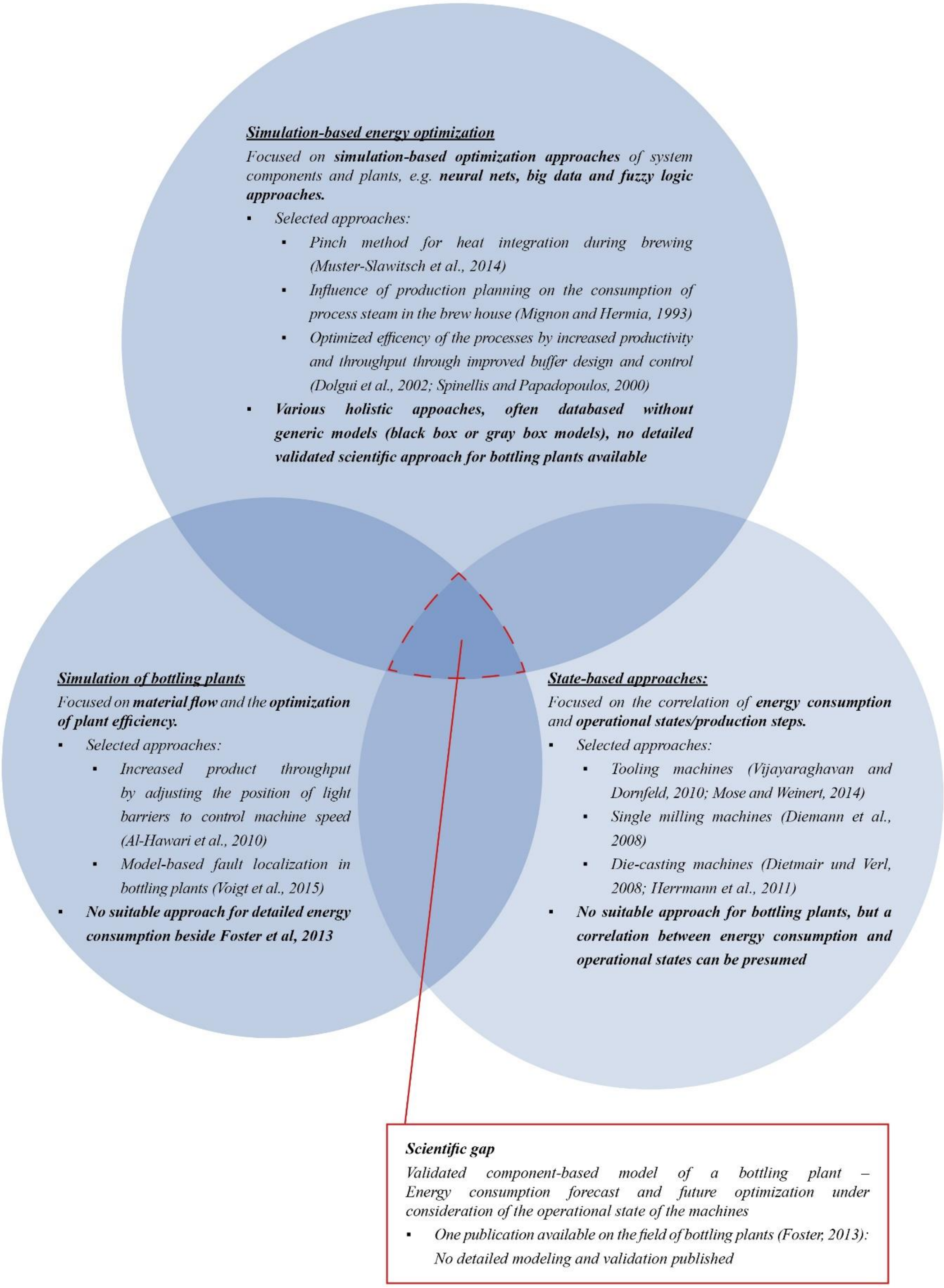

Figure 1.1-1: Venn diagram summarizing an overview about focus areas published in scientific literature concerned with the modeling and simulation of energy consumption in production lines and bottling plants. The relevant literature is discussed in the following chapters.

1.2 Purpose

The purpose of this dissertation is to analyze, model, and forecast the time and operational state related electrical energy consumption of beverage-bottling plants.

While approaches from different industries (e.g. tooling machines) show a state-based energy consumption behavior for machines or systems, for bottling plants there is no fundamental knowledge on the correlation of the energy demand and the machine states available, nor is there a database for modeling or a suitable model for beverage-bottling machines. Therefore, the first aim of this dissertation is to provide basic knowledge regarding the time and state related consumption behavior on the basis of detailed empirical industrial data and to obtain additional background information on the industrial plant structure, consumption structure, as well as current and planned optimization measures of the beverage-bottling industry.

Subsequently based on this analysis the second aim of this work is to develop generic mathematical models for the state-based consumption behavior of single machines within a bottling plant, as well as for the whole plant. These models are supposed to be transferred into verified and validated simulation models to enable the forecasting of the electrical energy consumption under the consideration of the production behavior of the plant. This allows a detailed analysis of beverage-bottling systems as a basis for optimization measures and more energy-efficient future production.

The conceptual idea of the analysis, modeling, and simulation used in this dissertation is presented in Figure 1.2-1. The following is a summary of the scientific goals of this thesis:

- A reliable database to analyze the energy consumption behavior in bottling plants.
- Fundamental knowledge of the consumption behavior of bottling plants under the consideration of the operational state behavior.
- A verified and validated generic consumption model for a bottling plant.
- An implemented simulation model to forecast the electrical energy consumption of a bottling plant.

The specific objectives and selected methods to achieve these goals are summarized in Table 1.7-1 at the end of the introduction, considering the current state of the art, presented in chapter 1. The results are presented as published peer-reviewed scientific paper in the following chapter 2.

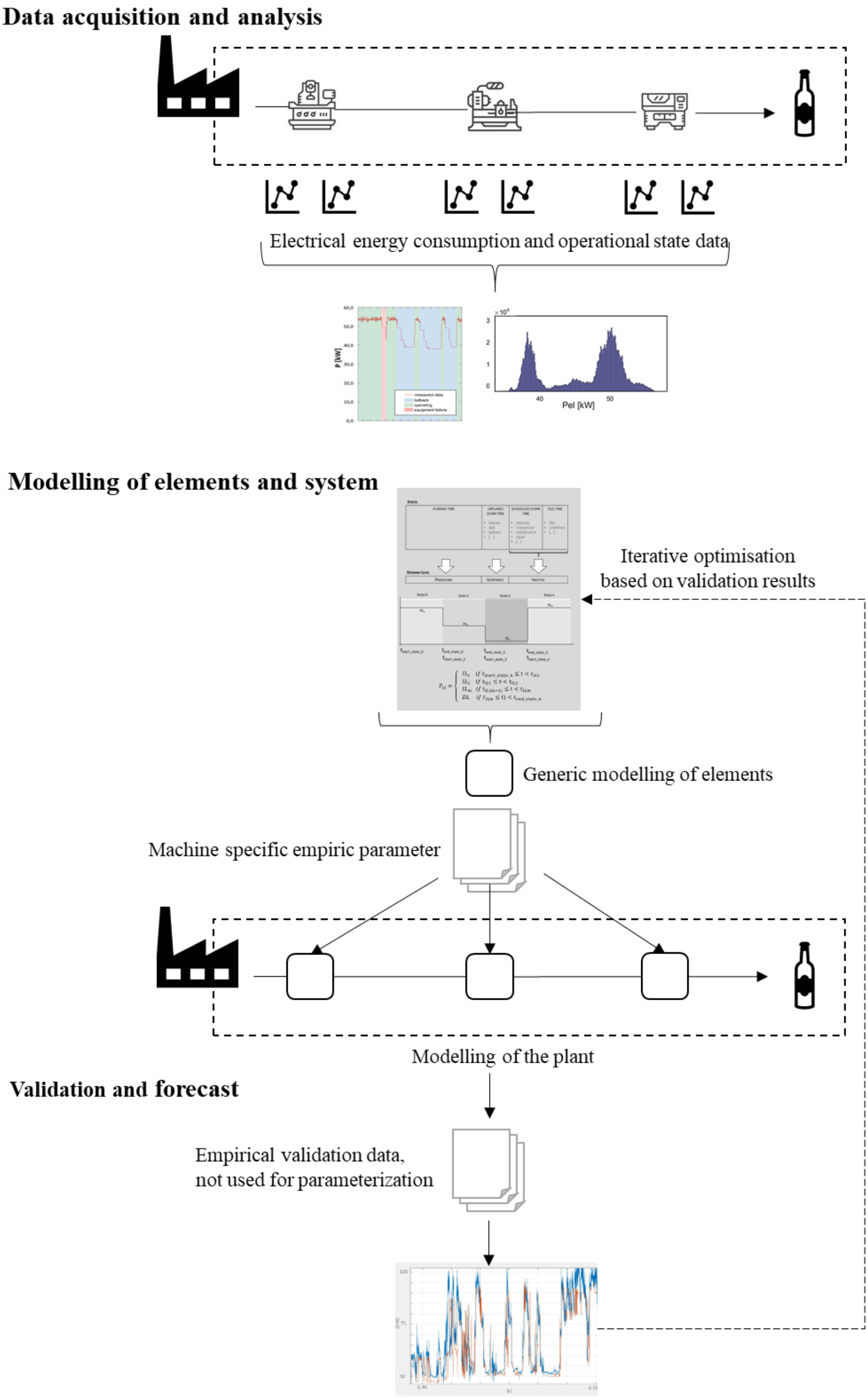

Figure 1.2-1: Electrical energy consumption of beverage-bottling plants: analysis, modeling, and forecast.

1.3 Packaging in the beverage industry: bottling plants

Bottling of beverages is a highly automatized process employed in modern packaging plants, which involves numerous machines interlinked by buffering conveyor systems. Although the products, packaging types (e.g., glass bottles, PET bottles, or cans), and designs of the packages vary, the machine components of bottling plants are virtually the same. The factory design is modular, depending on the specific requirements and functions required for the bottled product (Manger, 2008). Table 1.3-1 summarizes the basic functions of bottling plants and the respective machine types.

Table 1.3-1: Basic functions in the bottling process and required machine equipment (according to Manger, 2008).

Function in bottling process	Machine type	Description
Depalletizing	Depalletizer	Unloading palettes with used or new crates
Depacking	Depacker	Depacking of containers (bottles, cans, etc.)
	New glass slipper	Introduction of new bottles into the system
Cleaning and control	Crate washer	Cleaning of secondary packaging material (e.g. crates)
	Bottle-cleaning machine	Cleaning of primary packaging material (e.g. bottles, removing labels)
Filling and sealing packaging material	Filler and capper (monobloc or as single machines)	Optional: aseptic-filling; Caps depending on the bottle and product type (e.g. bottle cap, twist cap, etc.)
Decor (e.g., labels), labeling (e.g., best-before date), and control of the product	Labeler	Information for consumer and legal requirements
Packaging into an outer packaging	Packer and tray packer	Packaging (e.g.,., bottles) into crates or tray packs, cans into tray packs, and so forth, depending on the application
Palletizing	Palletizer	Palletizing of crates, multipacks, and tray packs on palettes

Function in bottling process	Machine type	Description
Transport	Bottle conveyor and pallet conveyor Air conveyor for PET bottles	Conveyor elements for packages (e.g.,., bottles, crates, and pallets) with a buffer capacity and a dead time
Improvement of shelf life	Flash pasteurizer Tunnel pasteurizer	If necessary (e.g.,., for beer mix beverages or export beer)
Cleaning and disinfection	CIP/SIP systems	Includes heating of the media
Sorting systems for returnable containers	Selective depacking machine	Removes defective and foreign containers
Soft drinks mixing	Beverage mixing and carbonization plants	Mixing of a premix (syrup) with water and gas (CO_2)
Bottle manufacturing	Stretch-blow molder for PET bottles	Usually as monobloc with a filler

Two generally different types of elements describe material flow in bottling plants: aggregates and transport elements. Aggregates can be either assembling units (e.g., putting 20 bottles into one crate), dissembling units (e.g., unloading crates from a pallet), or processing units. Transport elements have a certain capacity to transport objects from one aggregate to another within a certain timeframe. Processing units alter the physical properties of an object processed by a station (e.g., filling an empty bottle). Aggregates can have stochastically occurring, unplanned downtimes, which can be described by distribution functions. Aggregates and transport elements require energy in the processing stage. The relevant scientific literature usually distinguishes between electrical energy and heat consumption and media consumption (e.g. water). As commonly known and stated in, for example, DIN 8743, all machines within a beverage-bottling plant consume electrical energy. For example, the bottle-cleaning machine, the crate washer, and the stretch-blow molder require additional heat or process media (water) (DIN 8743:2014-01, 2014). The state-of-the-art energy consumption behavior in the scientific literature and industrial applications is analyzed in Publication I (page 36 onwards) and complemented by a survey of the German bottling industry.

1.4 Selected approaches to reduce the energy demand of production systems

In order to reduce energy input in production systems, measures are described within three areas: Optimization of machine design, optimization of the production process, and optimization of process control (Duflou et al., 2012). Optimization of machine design is particularly recommended for energy-intensive equipment such as pumps and compressed air systems and their drives (Javied et al., 2016). This can be realized through high-efficiency motors (Abdelaziz et al., 2011), drives with speed regulation (Mecrow and Jack, 2008), or heat recovery (Saidur et al., 2010). Besides machine optimization, maintenance of the production system is an important factor: leaks, for example, in pipes and lines must be strictly avoided (Galitsky, 2008).

Optimization of the process parameters can reduce the energy consumption as described by Rajemi et al. (Rajemi et al., 2010). For example, higher product throughput (process rate) per unit time may result in a lower demand for electrical energy. While most power required is used to maintain the operating state, for some machines the number of product throughput only slightly influences the consumption. At higher product throughput, the constant amount of energy for the operating state is distributed over several products, lowering the specific energy consumption (Apostolos et al., 2013; Gutowski et al., 2006; Li et al., 2014). Preventing product loss within the production process not only influences the resource efficiency but also positively affects the specific energy consumption (Olajire, 2012).

Monitoring the production systems (e.g., according to Lees et al. (2009) and Windmann et al. (2013)) and gaining data for a reliable database to identify specific saving potential of the examined application is a prerequisite for optimization measures (Askounis and Psarras, 1998; Qingchao et al., 2013). Energy-efficient production planning can reduce inactive production times during the production process (see, e.g., by optimizing batch sizes (Duflou et al. (2012) and Gahm et al. (2016), cleaning times (Herrmann et al., 2011; Lees et al., 2009), or maintenance times (Basari et al., 2011; Gharbi and Kenne, 2005; Sachdeva et al., 2008)).

Shutting down unused aggregates can help save energy because, despite their quiescent state, they require large amounts of electrical energy as reported in several publications (Cannata et al., 2009; Giret et al., 2015; Gutowski et al., 2006; Mashaei and Lennartson, 2013; Weinert and Mose, 2014). There is an algorithm for the intelligent shutdown of inactive plants, which reduces the daily energy consumption in production systems by up to 24 % (e.g. (Mouzon et al., 2007; Langer et al., 2014). Programs designed for fault detection and intelligent control save up to 30 % of the electrical energy in the cooling systems of breweries (Olajire, 2012) and improve plant efficiency, and can contribute to a reduction of the energy consumption of a bottling plant (Zhang and Li, 2015). The influence of the operational state on the energy consumption, however, was not considered in the mentioned work.

For analysis tasks, process management systems and energy management systems can be combined (Lee and Cheng, 2016). Swat et al. published an approach for the manufacturing of industrial products, where selected process chains with the lowest energy consumption are used. The paper presents a comparison of two machine generations of a same manufacturer to show the reduced energy consumption on the example of Pulse Electrochemical Machining (Swat et al., 2015). Organizational measures, such as centralizing the peripherals, can increase system availability and decrease the electrical energy consumption through intelligent control (Jovanovic et al., 2014). Studies have shown that the compressor pressure for pressurized air in production systems is usually set higher than necessary. By adjusting the pressure level, up to 6 % of electrical energy could be saved (Kaya et al., 2002).

The scientific literature presents a variety of optimization approaches for energy demand improvement in technical systems. Published data, especially within the beverage industry, indicate that there are still insufficient approaches implemented to use the remaining energy optimization potential. While some optimization approaches such as the use of efficient drives seem simple and obvious and are easy to implement without specific optimization tools, for a more in-depth system analysis, more complex tools are needed. As discussed in Table 1.1-1, nearly half of the estimated optimization potentials are made up by optimizations in organizational measures, optimized plant control, and load management. Table 1.4-1 summarizes the presented approaches of energy optimization measures in production systems and confirms that there are several optimization options, such as the increase of the equipment efficiency, the prevention of product losses, and the total field of process control, which require a deep understanding of the system to be optimized and the appropriate tools, like generic operational state-related models and simulations. Therefore, the following methods are derived for the presented study area of the electrical energy consumption of beverage bottling plants: Analysis of empirical data of the electrical energy consumption and the correlated operational states, identification and mathematical modeling of the operational state based energy states and transferring of the model into a validated simulation model as a tool for future optimization studies.

Table 1.4-1: Summary of the above discussed selected measures of energy optimization in production processes.

Production process	Machine system	Process control
Increase of equipment efficiency	Highly efficient drives	Deactivation of unused machines and components
Optimized process parameters	Motors with electronic speed control	Failure detection/data acquisition
Prevention of product loss	Heat recovery	Intelligent control
Alternative technologies	Centralization of peripheries	Optimized production planning
Avoidance of leaks, e.g. by proper maintenance		Optimized batch size/production orders

1.5 Modeling and simulation

1.5.1 Methods of modeling and simulation

A system is a set of physical entities that interact and are observable, in which entities can be a specified quantity of matter or a volume in space. A system can be divided into three main components: the input, which influences the values of all the variables occurring in the system; the system itself, which processes elements obtained from the input; and the output, the result of the system's processing (Oberkampf and Roy, 2010). Through simulation methods a model system can be obtained to analyze and optimize a real system.

Simulation imitates a system through dynamic processes. The result, a modifiable and analyzable model, allows one to attain knowledge that can be transferred to reality (VDI 3633-1:2014-12). In order to perform a simulation, generic procedures are established. Several authors described general methods of model finding for simulation studies (e.g., Bungartz et al., 2013; Kühn, 2006; Hedtstück, 2013; März et al., 2011). The first basic steps are to define the system and data acquisition, followed by model design, implementation, validation, and iterative verification, resulting in a reliable simulation. In later steps, experiments can be carried out within the model and the results can be transferred into a real system under investigation, a process known as realization. Model variations are identifiable in different objectives of each simulation study.

The first step of the development of an analyzable simulation model is the analysis of the reference system, in order to create an accurate mathematical model to represent the considered system. Modeling can be performed as structural or pragmatic modeling. In structural modeling, the internal structure of the system is known, but it is abstracted, modified, and reduced, known as the *white box model*. In pragmatic modeling, the internal structure of the system can be unknown and only the behavior or the interaction of the system can be observed and modeled. Not all interactions between subcomponents can be understood; this is called the *gray box model*. When the system behavior is not understood or is only partially understood, this is referred to as the *black box model*. Mixed forms include known and unknown parts of a system and are the most frequent because they are sufficient to map the system due to cost–benefit considerations (Weisberg, 2013).

System analysis can be carried out, for example, by an experimental investigation of the system or by an analytical investigation (e.g., based on system equations). Creating a model, the following steps can be differentiated:

- *Delimitation*: Defining the system boundaries and non-consideration of irrelevant objects.
- *Reduction*: Leaving out object details, in accordance with the model requirements.

- *Decomposition*: Decomposition in single system components.
- *Aggregation*: Connection of single system components to a whole model.
- *Abstraction*: Concept and class formation.

After creating a (mathematical) model, it can be implemented by a programming language into a computer (simulation) model. Often, the simulation results serve as the basis for decision-making if no other suitable analytical means are available or if the consequences of a decision are not apparent. However, system reproduction in an analyzable model can be carried out in various ways with different approaches depending on the initial problem or optimization case (Piehler and Zschiesche, 1990).

Figure 1.5-1 displays a classification of the simulation methods presented by Kühn (Kühn 2006). A stochastic simulation using random stochastically distributed input parameters can be distinguished from a targeted or planned simulation with a strictly predetermined procedure (deterministic simulation, e.g. chemical reactions). For stochastic simulation using random variables, techniques can be further divided into static or dynamic models.

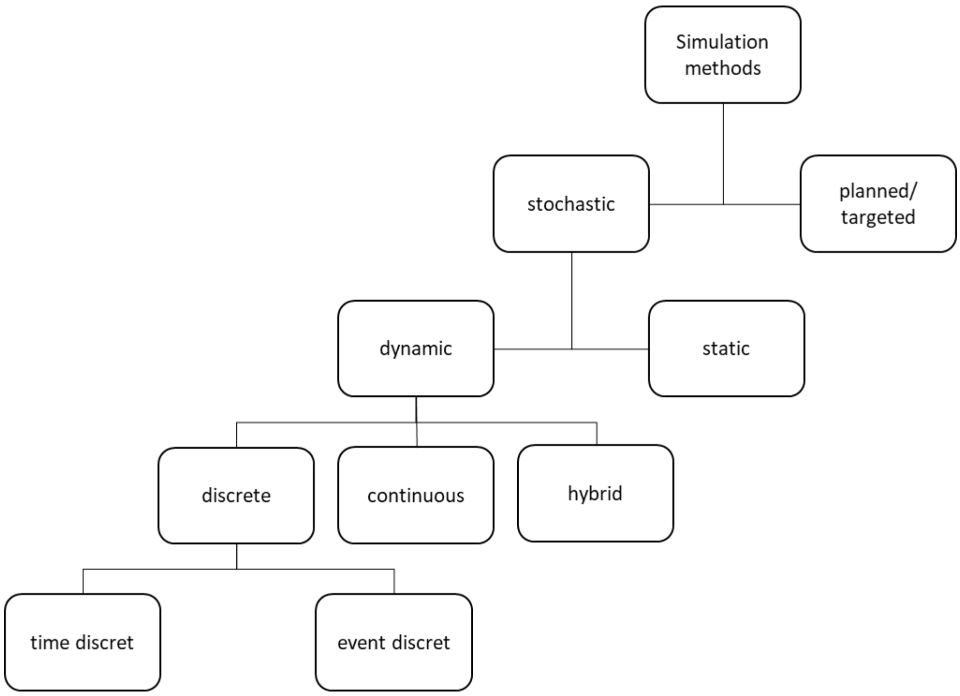

Figure 1.5-1: Classification of simulation techniques according to Kühn (Kühn, 2006)

März et al. generally confirm this classification: The static simulation model considers a system at a particular point in time (e.g. Monte Carlo simulation), while a dynamic simulation model considers the changes over time. The dynamic model behavior can be either discrete (change only at a discrete point, e.g. time-discrete or event-discrete), continuous (continuous changes over time, e.g. based on a differential equation), or a mixture of both (hybrid). Most computer-based simulations in the field of production and logistics are stochastic, use random variables as input parameter and are event driven. This means, those models map the change of the system initiated by the occurrence of an event (e.g. the change of a machine state). This method of simulation is called Discrete Event Simulation (DES) (März et al., 2011).

It is assumed for this work that for the modeling of the electrical energy consumption of bottling plants a hybrid model can be used. While operational state-based changes in the energy consumption are considered as event discrete, the energy consumption over time is taken as continuous.

1.5.2 Methods of model verification and validation

Iterative validation and verification steps are necessary to ensure that a model provides trustworthy results (Sargent, 2011). During verification, the completed model is tested on its intended use in order to examine the general suitability of the model and to detect and debug errors (Carson, 2002). Each individual step of the model is examined and analyzed to determine whether the relevant variables of the real system have been suitably and correctly mapped. The aim of this step is to ensure that the applied simulation technique is correct. Furthermore, this process confirms the conformity with model rules and theories as well as the transfer into the simulation program (Sauerbier, 1999).

Validation is necessary because of the unpredictable system behavioral patterns, simplifications, and small inaccuracies, which create a simulation result that can differ from reality. The following selected methods are found in the literature to verify and validate simulation models.

- Direct validation (see, e.g., Ascione et al., 2012; Struckmeier and Riedel, 2001):

Direct validation provides an indication regarding the fit of the model by directly comparing the deviation of simulated and empirical data. One suitable possible figure for direct validation is the average percent deviation (APD), which can be calculated using the following formula:

$$\mathrm{APD} = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - z_i)}{z_i} \tag{1.1}$$

Here, z_i represents the measured discrete data, y_i is the simulated discrete data, and n is the number of data points.

For a better illustration of the deviations between the simulated and the empirical data, a graphical representation of both datasets is recommended.

- Face validation (see Balci, 1994) and Turing test (see Balci, 1994; Fei and Ming, 2005):

Interviewing experts and future model users is also a common technique that can be used to validate datasets. As a subjective method, a face validation can be utilized as a first assessment to evaluate the suitability of the modeling concept: For the face validation the evaluating person evaluates subjectively whether the model or test is covering the objects of investigation it purports to measure. More reliable than face validation is the Turing test. The Turing test involves experienced experts and consultants who validate the study system. Various previously unknown datasets are presented to professionals to determine which set is simulated and which is empirical. If no difference in the datasets is detected by the professionals, the model is assumed as trustworthy.

- Graphical comparison (see, e.g., Balci 1994; Sargent, 2011; Gabriel und Azanza, 2010):

By overlaying empirical and simulated data, it is possible to obtain differences in the curve properties, such as the slope of the curves, points of inflection, and phase shifts. Although this method is a qualitative consideration, it can be a suitable tool for detecting possible model errors or inaccuracies. Large datasets may be difficult to present in a clear structure.

- Theil's inequality coefficient (see, e.g., Balci, 1994; Fei and Ming, 2005; Hu et al., 2012; Netter et al., 2013; Rowland and Holmes, 1978):

Theil's inequality coefficient (TIC) is an established statistical method used to evaluate a model's forecast accuracy by analyzing the consistency between the simulation and reference (e.g., empirical) output data. This index has its origin in economic sciences and gives a measure of the consistency of a data set of estimated values compared to a corresponding data set of observed values. However, it is now also used in many other fields to validate simulation models.

The TIC is calculated using the following formula:

$$\mathrm{TIC} = \frac{\sqrt{\sum_{i=1}^{n}(y_i - z_i)^2}}{\sqrt{\sum_{i=1}^{n} y_i^2} + \sqrt{\sum_{i=1}^{n} z_i^2}} \tag{1.2}$$

Here, z_i represents the measured discrete data, y_i is the simulated discrete data, and n is the number of data points. The calculated TIC value is between 0 and 1; the smaller the value, the better the simulation result (Netter et al., 2013). This value is considered credible with 0.4 as the maximum for many use cases in simulation published e.g., in the above listed literature.

Since deviations are included quadratically in the calculation, no conclusions on systematic positive or negative deviations of the estimated data from the corresponding observed data are possible, which has to be considered in the evaluation.

Table 1.5-1 and Figure 1.5-2 show an example of a fictive dataset and two fictive simulation runs, where the first run has a good model fit (TIC = 0.05) and the model for the second run is not credible (TIC = 0.41).

Table 1.5-1: Example data of the TIC for a fictive measurement and simulation run.

	i	1	2	3	4	5	6	7	8	9	10	11	TIC
Fictive measured dataset	z	3	3.3	3.3	6	5.3	5	5.3	5.2	4.5	5	3	
Fictive simulated dataset 1	y_1	3	3.2	3.2	3	3.2	3	5.3	5.3	4.4	3	3	**0.05**
Fictive simulated dataset 2	y_2	8	4	4	8	17	10	7	10	7	16	8	**0.41**

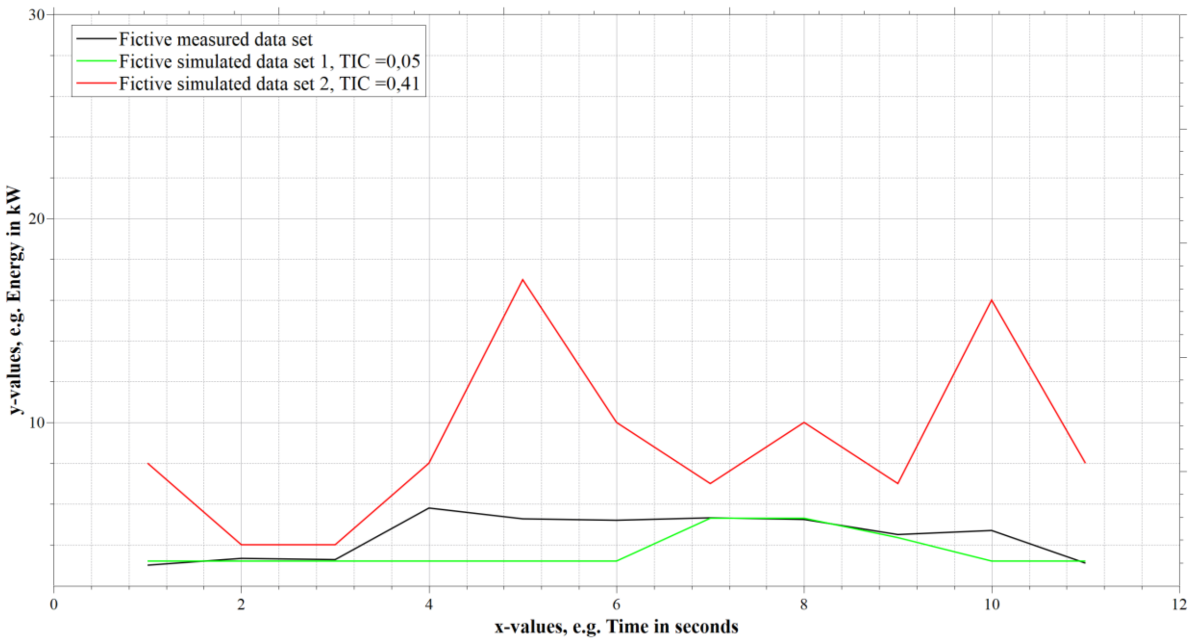

Figure 1.5-2: Example of the TIC for a fictive measurement (black) and simulation run for a credible (green) and noncredible (red) dataset.

1.6 Modeling and simulation of energy consumption in production lines and bottling plants

Modeling and simulation are suitable tools for identifying and quantifying the improvement potential of complex technical systems and, as mentioned above, decision-making (Smith, 2003). Sustainability of production processes, particularly in the packaging industry, is becoming increasingly important (Garetti and Taisch, 2012). Simulated energy data are used as a decision criterion regarding investments in energy efficiency measures as well as for ensuring investment through reliable forecast data (see for example Bewley et al, 2010). Various commercial software tools are suitable for forecasting the energy consumption of production systems (e.g., MATLAB/Simulink by MathWorks with the *Carnot toolbox* for the modeling and simulation of thermal components; *Plant Simulation* by Siemens, a tool for material flow simulation with the option of stationary power levels; *ProSimPlus* for simulating the energy consumption of continuous processes; and *PacSi* by IKA Dresden/SimPlan AG for material flow simulation of packaging machines with the option of stationary power levels). No use case scenarios, which model and simulate the energy consumption of bottling plants using the aforementioned or other commercial simulation tools, have been published. One basic model was published by Forster for packaging and filling based on a discrete event simulation approach, which includes material flow and energy consumption data (Forster, 2013). The model is discussed in the following chapter for hybrid models.

- <u>Neural nets, big data, and fuzzy logic for energy consumption simulation</u>

Neural nets, big data, and fuzzy logic approaches (e.g. Bai et al., 2011; Dash et al., 1997; Lee and Cheng, 2016; Nagel, 2013) provide reliable prognostic results and holistic optimizations but the technical system is considered as a black box. As an example, Nagel developed a holistic model for the energy optimization of a brewery based on reference petri networks. A petri net is a mathematical modeling language based on the concept of a directed bipartite graph, where nodes represent transitions and places. Nagel uses reference petri nets, a subclass of high-level petri nets to represent the causal-logical structure of the system. The dynamic behavior of the system is mapped by markings, also called tokens. The tokens represent the substances, energies or information to be transported or transformed. Nets-within-nets paradigms enable the modeling at different level as the reference from one system-net to another is realized by the tokens. With the described model the energy management system and the steam demand of the brewery could be mapped, analyzed and optimized (Nagel, 2013).

However, the described neuronal nets, big data and fuzzy logic models contain optimization algorithms based on machine learning rather than on generic models that describe the system behavior. Their use is particularly applicable when the results, not the exact structural relationships, are the subject of investigation. The specific learning process may limit the portability of such models from one use case to another.

- Model-based energy optimization

In addition to the mentioned industrial solutions, several recent scientific approaches optimize complex production systems through modeling and simulation approaches. In this context, Muster-Slawitsch et al. developed the SOCO software tool based on the Pinch method to optimize heat integration during the brewing process and showed that a reduction of energy usage of 10 % – 35 % is possible with “intelligent” networks of heat exchangers and storage devices (Muster-Slawitsch et al., 2014). Previously, Tokos et al. proposed a model for thermal integration based on mixed integer linear programming and successfully tested it (Tokos et al., 2010). A simulation model was developed by Mignon and Hermina to investigate the influence of production planning on the consumption of process steam in a brew house (Mignon and Hermia, 1993). Marty et al. developed a model to optimize the use of heat in brew houses (Marty et al., 2016). Many simulation models that optimize productivity or throughput have enhanced the efficiency of several processes through improved buffer design and control (Dolgui et al., 2002; Spinellis and Papadopoulos, 2000), the identification of bottlenecks in plants and processes in the automotive industry and the production of refrigerators (Cao and Ho, 1987; Huang et al., 2003; Silva et al., 2000), or optimized allocation of manpower (Kouikoglou, 2000). Additionally, optimizing the position of light barriers to control machine speed, which is a simulation-based approach, has been shown to increase the product throughput of bottling plants (Al-Hawari et al., 2010).

- State-based approaches

Energy consumption simulation is predominantly used in the manufacturing industry (e.g.,., in welding, turning, and milling processes). Modeled energy consumption is mainly calculated as the specific energy consumption in the production of a single specific product, as reviewed, for example, by Seow et al. (Seow et al., 2013). In addition, alternative process variants have been evaluated for their energy efficiency (Krellner et al., 2011).

Vijayaraghavan and Dornfeld published an approach describing the states of electrical demands (herein also called specific energy pattern) during the in-cycle, idle, start-up, and shutdown stages of metalworking and machining-based manufacturing systems (Vijayaraghavan and Dornfeld, 2010). Furthermore, the influence of the analysed time scale is discussed here. While a scale of days is suitable for optimizing a system on the level of supply chain management or production planning, macro- and microplanning on the level of the manufacturing equipment require an analysis in the scale of minutes or even seconds. For the analysis of control processes, a scale of microseconds might be necessary. It was confirmed that, in order to decrease the energy consumption, the energy data have to be considered in the context of the manufacturing activities. While no validation data for the model are presented in this publication, a case study additionally presented the reason for the occurring state (here mainly a change in the machine speed) and the time and duration of the states.

Weinert and Mose confirmed the model approach of Vijayaraghavan and Dornfeld (Weinert and Mose, 2014). The model of Weinert and Mose for a gas-metal-arc welding application focuses on the energy optimization of process chains on the level of process planning and confirms the necessity of developing a specific, process-dependent normative energy model. This model includes a standby state, a ready-for-operation state, a state of operation under different configurations, a setup state, as well as an out-of-service state and provides the average power demand of every state. No validated forecast is included in this approach.

Dietmair and Verl presented a basic state/transition energy consumption model for a tool machine including nine operational states, which are correlated to the power consumption profiles (Dietmair and Verl, 2008). The results highlight, that the way of operating a machine has an important influence on its actual energy efficiency.

The energy consumption of an injection molding machine was described as correlated to its manufacturing steps (Le et al., 2012). Le and Pang developed a complex decision support system, which identifies five process operational states according to energy measurements for the examples of an injection molding process and a stamping process (Le and Pang, 2013). The model does not focus solely on a state-based energy consumption model. It considers a large number of influences for decision-making, such as raw material prices, operational expenditure, capital expenditure, energy prices, and production sites on different locations. For different machines, different operational states were found, which were correlated to the energy consumption. Start-up, warm-up, idle, and switch-off states were found comparable, whereas pump/heat, stamping, molding, and abnormal states were machine-specific states. The experimental results showed that the presented complex framework achieved an accuracy of 98.52 % and 98.32 % in the case of sufficient training data, as well as 96.55 % and 94.69 % in the case of limited training data. Further scientific investigations in the field of state based energy consumption modeling describe models for single milling machines (Diemann et al., 2008), die-casting machines (Herrmann et al., 2011), and weaving machines (Thiede et al., 2012).

The dependence of energy consumption on the machine's operational state has been used as a simulation approach in several sectors, but none of these models can be directly applied for beverage filling plants. These approaches confirm that the energy consumption of the machines can be described as state-related. The general concept of a state related model seems to be adaptable for bottling plants, even though the state relation is still unknown for this type of production system. The states and the interactions between the state and consumption vary depending on the application. The defined states cannot be adapted directly to bottling machines because of the differences in the functionality (especially the start-up and shutdown behavior). The general approach can be applied to beverage-bottling machines, but there is still a lack of suitable studies on machine conditions that affect the energy consumption. Therefore, a data-based analysis is required as a basis to understand and to model the state-based energy consumption behavior of bottling plants.

- Hybrid modeling and simulation approaches

Hybrid simulation models represent production systems in a particularly realistic manner because they take into account both event-discrete and time-discrete aspects (Windmann et al., 2013). This approach has been applied in the automotive industry by combining the time-discrete concept of state machines with event-driven control processes. A state machine is a device or software application that can be singularly in one state out of a defined number of states, depending on the input parameter. This model was used for decision-making in order to find the lowest resulting energy by varying the following parameters: production time, batch size, and classification (Marzouk et al., 2016).

However, this model does not focus on how single operational states influence the energy consumption. Therefore, process adaptations that affect missing operational states like equipment failure cannot be investigated. A simplified hybrid simulation model was published by Forster for packaging and filling based on a discrete event simulation approach, which includes material flow and continuous energy consumption. Thus, not only energy but also the consumption of media such as compressed air and steam can be simulated (Forster, 2013). The model for a PET plant was implemented in an already existing structure of Plant Simulation, but the publication does neither present a generic state model, nor a mapping of the operational states, nor a statistical validation by empirical plant data.

- Models for the packaging process and the beer and beverage production

The influencing parameters on the energy consumption during the stretch-blow molding process were investigated by varying the design of the PET bottles, which allowed for bottle design optimization according to energy aspects (Daver and Demirel, 2012). The abovementioned published industrial approach by Forster for a PET bottling plant shows limited details and does not present statistical validation results to serve as a generic model for bottling plants.

The energy consumption of the filling equipment does not necessarily depend on the packaging type (Kubule et al., 2016), but rather on the energy consumption caused by the plant (Prabhu and Taisch, 2012). Voigt et al. published an approach for model-based fault localization in bottling plants, showing the dependency between the single interlinked machines of bottling plants and the influence of one machine behavior on the efficiency of a total bottling line (Voigt et al., 2015).

Further approaches to optimize the energy efficiency of beer and beverage production are described in the following publications, but they focus mainly on the process side: Askounis and Psarras, 1998; Campbell and Lees, 2003; Dumbliauskaite et al., 2010; Fadare et al., 2010; Ito et al., 1994; Lees et al., 2009; Lees et al., 2008; Mutua and Kariuki, 2012; Nagel, 2011; Remus et al., 2016; Yang et al., 2013; Zogla et al., 2015. None of these discussed publications presented a detailed component-based modeling approach considering the correlation of the process-specific operational states to the beverage-bottling process.

1.7 Summary of the introduction, scientific aims and methods

Modeling and simulation are established methods for complex energy consumption considerations. A large number of state-based approaches for manufacturing plants have been published. The models, if available, specifically address the production procedures and machine types. For the bottling and packaging industries a lack of models mapping correlations between operational states and the respective energy consumption was found. Nevertheless, some approaches present material flow models for bottling plants and focus on increasing the production efficiency.

The state-based approaches of the automotive industry and tooling machines appear to be a reasonable method of analyzing energy consumption in production lines. However, none of these approaches has been transferred to bottling plants. General knowledge regarding the electrical consumption behavior of beverage factories is lacking as a fundament for generic models and is required to develop a holistic simulation model for energy optimization considerations. Development of methods to analyze, map, and forecast energy consumption in the manufacture of beverages could provide the necessary tools, data, and optimization strategies to reduce the investment risks and get energy reduction measures realized.

Following the aim of this dissertation to find a holistic model to describe the electrical energy consumption of a beverage-bottling plant, it was found that a model is required that considers the operational based influences on the electrical energy demand. A data-based investigation was chosen for system analysis, using empirical data from industrial bottling plants. From the presented literature, a state-based approach was chosen for modeling. As a result of the first data analysis, the input parameters of the system were defined as operational state data and machine-specific energy parameters, whereas the only output parameter was defined as a continuous energy demand over time. The model was defined as a gray box model. It was assumed for this model that it is sufficiently precise to understand only the system reaction (energy demand) on an operational state change, whereas the machine-specific reason (e.g. a signal in the control to shut down a certain consumer at a certain time) does not need to be understood.

As a simplification during the delimitation step of modeling, the conveyors were not considered in the model. The share on the total energy consumption caused by the conveyors is minor and the practical effort for validation is high because of the large number of single drives that must be equipped with active power meters. To fulfill the demand for a generic model, no detailed modeling of the elements in terms of single drives and sub-elements was implemented. Furthermore, no information on the detailed design of the considered machines was available. In the decomposition step, the system of a bottling machine was defined by system elements, which are represented by single machines and can be aggregated to a total plant model. As abstraction of the plant behavior in a later step energy demand level and intermediate level for state transitions were defined, following the results of the system analysis.

With choosing a hybrid model, on the one hand the continuous electrical energy consumption of the system elements can be viewed with a time resolution of one second and, on the other hand, the event-discrete operational state behavior is described by a start and end time of each operational state. While for the published results a targeted or planned simulation run was realized by using historic operational state data, the model was, in general, prepared to operate with stochastically distributed input parameters (e.g., from an additional external material flow simulation). For validation purposes, a targeted simulation run was preferred, as then empirical data (which were not used for modeling) could be used for verification and validation.

The implementation was realized in the established software MATLAB and MATLAB Stateflow. As a database for empirical data, an SQL-based database was chosen. For validation, a variation of different validation methods were chosen on the basis of the presented literature in chapter 1.5.1 to ensure a correct model fit. For direct validation, the average percentage deviation (APD) was calculated. In order to analyze where the deviations occur, a graphical application of both datasets (the simulated and the empirical) was plotted, which also serves as a graphical comparison. The operational state data were set as colored areas in the background, whereas the simulated and measured data were plotted as a graph. To evaluate the model’s forecast accuracy by analyzing the consistency between the simulation and reference, the Teil’s inequality coefficient (TIC) was used.

Table 1.7-1: Summary of the aims and selected methods for this dissertation.

Aim	Method
Reliable database to analyze the energy consumption behavior in bottling plants	Scientific survey in the German beverage industry including a questionnaire with 25 questions about the following: o Structure of the plants o Consumption data o Current and future optimization measures
	Empirical acquisition of machine-based data with a high temporal resolution on representative bottling plants: o Effective electrical input power [kW]: continuous every second/two seconds (as available) o Operational state data: event-discrete (start time, end time, and operational state)
Fundamental knowledge of the electrical energy consumption behavior of bottling plants	Data analysis: o Frequency distributions of discrete measured effective electrical power values to identify peaks o Correlation between measured effective electrical power values and operational states
Generic consumption model of bottling plants	Mathematical modeling of the electrical energy consumption behavior based on the results of the data analysis o Gray hybrid modeling approach ▪ Electrical energy consumption (every second) ▪ Event-discrete operational state o Granularity: machine level
Forecast of the electrical energy consumption of bottling plants	Implementation of the mathematical model to a hybrid simulation model in MATLAB Stateflow: o Data source of operational states: empirically measured industrial data, SQL database o Model connection: Open Database Connectivity (ODBC), SQL database o Model parametrization: empirically measured industrial data o Model validation with empirically measured data, that were independent from the data used for parametrization • Graphical comparison: validation plots • Direct validation: APD • Statistical validation: TIC

1.8 References of the Introduction

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2 Results

2.1 Summary of Publication I: State of the art survey of the energy and media demand of German beverage-bottling plants

This publication analyzes the published data and performance indicators on energy consumption behavior in beverage bottling in order to gain basic insights into the influences on energy consumption and to present the status of consumption figures. In addition, data on the German beverage bottling industry was collected. A questionnaire prepared according to scientific principles and validated with a pretest was made available to companies in the German beverage bottling industry in printed form and online. The questionnaire contained 25 questions about the company, detailed information about the most frequently used bottling line, the energy consumption of the individual machines in the states of operation and, if available, in standby, the company's energy management and energy optimization efforts, and additional data on production planning. During the literature search, it was found that while selected energy and media demand values for filling lines were available, no reliable database with detailed demand data at the machine level could be found. Most of the literature data reviewed was not state of the art, considered only a limited number of machines, and was not related to the process or the operating condition of the machines. The data collected from the survey provided an indication of the installed electrical power of the individual machines used in the bottling plants, consumption during operating and standby times, and heat and fresh water requirements. A slight increase in installed power and electrical energy demand since the 1980s was noted, probably due to a higher degree of automation. A linear relationship between nominal machine speed and electrical energy demand during operation was also found for all machines except bottle washers. It was confirmed that bottle washers have the highest energy demand within interlinked systems. In standby mode, consumption averaged 34% of total consumption, indicating potential for optimization. For most questions, only a limited amount of reliable data could be collected, indicating a need for more detailed, validated data as a basis for future optimization considerations and modeling. More than 80% of the companies surveyed were already investing in measures to reduce energy and media requirements or were planning to do so in the future, which illustrates the relevance of the topic of energy optimization in this industry. Isabel Osterroth was responsible for the study design, the evaluation of the data and results, and the publication of the findings. Alexander Holm supported the work in the creation of the questionnaire and in its implementation and helped in the evaluation of the results as part of his master's thesis. Tobias Voigt was the scientific supervisor and supported this work with professional discussions and advice. The formatting of the text has been adapted to the formatting of this thesis for better readability. The content corresponds to the original print, which was attached to this thesis as an appendix.

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Osterroth, I. A., Holm, A. and Voigt, T.

State of the Art Survey of the Energy and Media Demand of German Beverage-bottling Plants

Sustainability is a megatrend in the packaging industry. Increasing costs, legal requirements and societal trends have put energy optimisation into the focus of the beverage-bottling industry. An essential requirement for profound energy optimisation is a reliable database. The study presented in this paper gathered energy and media demand data from bottling plants at the machine level, as there is a lack of scientific and publicly available data. A detailed questionnaire was provided to German bottling companies. The companies surveyed provided information characterising their bottling plants in terms of nominal speed, age and product range. They also provided data regarding production planning, information on the use of energy management systems and detailed data on machine-related power demand. With an increasing level of detail (e.g. state-based energy demand of machines) the amount of available information decreases. Data were gathered on the installed load of the machines, which could showed a linear correlation to the nominal speed of most machines. Further data for the demand of electrical energy during operation and standby and for the heat and water demand were raised. The electrical energy demand during standby has the highest value for the example of the bottling cleaning machine (median 7.5 kW for n = 10 machines). The heat demand of bottle cleaning machines was found to be 25–80 kJ/bottle. For the fresh water consumption values below 300ml/bottle (arithmetic mean: 220 ml) where found for most machines. The survey shows that more than 80 % of the surveyed companies in the bottling industry are already investing in measures to reduce energy and media demand or plan to do so in the future. The assembled database allows a first benchmark of machines in industrial applications and serves as a reference point for the purchase of new machinery and for further research on optimisation strategies. However, the study shows that there is still insufficient knowledge of the energy demand of bottling plants. Only few companies were able to give detailed information of the energy and media demand at machine level. Further effort are still necessary to increase the database to provide representative values for the bottling industry. General demand models, unified standards for data acquisition and further research on bottling-plant energy demand are necessary to fully exploit the potential energy savings.

Descriptors: energy demand, bottling plants, machine level

1 Introduction

Climate change, resource scarcity, increasing energy costs and a rising level of environmental awareness and a sense of responsibility of consumers are increasingly influencing the beverage-bottling industry. As a result, sustainability has moved increasingly into the focus of the packaging industry [1]. For new investments, energy demand is increasingly important in the cost calculation (capital expenditure vs operational cost) and for total cost of ownership considerations. A study for the German machine supplier sector shows that energy efficiency has a growing impact on sales for machines [2]. Fundamental for optimisation considerations is a reliable database.

Filling and packaging in the beverage industry is one of the main contributors to energy demand in the entire production process with up to 30 % of the total energy and media demand [3, 4]. A number of machines interlinked by buffering transport elements are involved in this process. Beverage-bottling plants are found not only in breweries but also in other industries, such as fruit-juice production, mineral springs and spirits and wine production. The plant technology is similar, but differs in the nominal output [5]. In addition to large breweries, small- and medium-sized companies in the brewing and beverage industry are also aware of the importance of saving energy and maintaining a small ecological footprint [6, 7]. Nevertheless, industry-specific studies found that consumers feel that the brewing industry is putting too little effort into a more rational use of energy [8]. Thus, energy-saving efforts not only provide monetary benefits through reduced energy demand, but also benefit the corporate image by promoting energy efficiency

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2.2 Publication I: State of the art survey of the energy and media demand of German beverage-bottling plants

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Abstract

Sustainability is a megatrend in the packaging industry. Increasing costs, legal requirements and societal trends have put energy optimisation into the focus of the beverage-bottling industry. An essential requirement for profound energy optimisation is a reliable database. The study presented in this paper gathered energy and media demand data from bottling plants at the machine level, as there is a lack of scientific and publicly available data. A detailed questionnaire was provided to German bottling companies. The companies surveyed provided information characterising their bottling plants in terms of nominal speed, age and product range. They also provided data regarding production planning, information on the use of energy management systems and detailed data on machine-related power demand. With an increasing level of detail (e.g. state based energy demand of machines) the amount of available information decreases. Data were gathered on the installed load of the machines, which could showed a linear correlation to the nominal speed of most machines. Further data for the demand of electrical energy during operation and standby and for the heat and water demand were raised. The electrical energy demand during standby has the highest value for the example of the bottling cleaning machine (median 7.5 kW for n=10 machines). The heat demand of bottle cleaning machines was found to be 25-80 kJ/bottle. For the fresh water consumption values below 300 ml/bottle (arithmetic mean: 220 ml) where found for most machines. The survey shows that more than 80 % of the surveyed companies in the bottling industry are already investing in measures to reduce energy and media demand or plan to do so in the future. The assembled database allows a first benchmark of machines in industrial applications and serves as a reference point for the purchase of new machinery and for further research on optimisation strategies. However, the study shows that there is still insufficient knowledge of the energy demand of bottling plants. Only few companies were able to give detailed information of the energy and media demand at machine level. Further effort are still necessary to increase the database to provide representative values for the bottling industry. General demand models, unified standards for data acquisition and further research on bottling-plant energy demand are necessary to fully exploit the potential energy savings. **Descriptors:** energy demand, bottling plants, machine level

1. Introduction

Climate change, resource scarcity, increasing energy costs and a rising level of environmental awareness and a sense of responsibility of consumers are increasingly influencing the beverage-bottling industry. As a result, sustainability has moved increasingly into the focus of the packaging industry (Olsmats and Kaivo-oja, 2014). For new investments, energy demand is increasingly important in the cost calculation (capital expenditure vs operational cost) and for total cost of ownership considerations. A study for the German machine supplier sector shows that energy efficiency has a growing impact on sales for machines (Henzelmann and Büchele, 2009). Fundamental for optimisation considerations is a reliable database.

Filling and packaging in the beverage industry is one of the main contributors to energy demand in the entire production process with up to 30 % of the total energy and media demand (Meißner, 2003; Sattler, 2000). A number of machines interlinked by buffering transport elements are involved in this process. Beverage-bottling plants are found not only in breweries but also in other industries, such as fruit-juice production, mineral springs and spirits and wine production. The plant technology is similar, but differs in the nominal output (Schreiner, 1982). In addition to large breweries, small- and medium-sized companies in the brewing and beverage industry are also aware of the importance of saving energy and maintaining a small ecological footprint (Scheller et al., 2008; Sturm et al., 2013). Nevertheless, industry-specific studies found that consumers feel that the brewing industry is putting too little effort into a more rational use of energy (Rank a Brand e.V., 2015). Thus, energy-saving efforts not only provide monetary benefits through reduced energy demand, but also benefit the corporate image by promoting energy efficiency strategies that go beyond simply fulfilling regulatory requirements, thus demonstrating environmental responsibility.

For breweries, a number of guidelines with recommendations are available, mainly regarding the production process (Brewers Association 2017; Canadian Industry Program for Energy Conservation, 2011; Galitsky et al., 2003; Industrial Energy Efficiency Accelerator, 2011; Scheller et al., 2008). Case studies were made for several applications and were examined in terms of their relevance and effectiveness for the companies involved (Fadare et al., 2010; Muster-Slawitsch et al., 2014; Sturm et al., 2012; Tokos et al., 2010). A comparison of the energy-demand structure and the production process can help to identify specific deficits within the plant and to initiate suitable countermeasures (Heuven and van Beek, 2013; Schu).

Numerous guidelines recommend that individual companies determine their actual energy demand structure—in part using the attached data tables (e.g. ABMI media template (Association of the Beverage Machinery Industry, 2010))—as a first step toward sustainable enterprise management (Beer and Hiller, 1995; Landerer and Mödinger, 2014). The results of comparative investigations, the so-called benchmarks, provide general values, such as water demand in [l/hl] or electricity demand in [kWh/hl] of beer to be sold. However, specific data on the energy or resource demand of company departments or individual machines are not mentioned in these templates. Until now, only a few systematic optimisation approaches have been suggested or introduced for the specific area of beverage filling to reduce the high demand. Collecting and evaluating accurate energy data will help operators, production managers and the management board of breweries to understand the relationship between energy demand and resulting costs. Guidelines recommend the use of energy Key Performance Indicators (KPIs) with monthly and yearly benchmarks. Monitoring and analysis can be the basis of corrective actions, leading to reduced energy costs and a smaller carbon footprint (Brewers Association, 2017). Concrete machine-related demand values for bottling plants, which are fundamental for the development of generic optimisation strategies, are rarely available or are not accessible to the public. Detailed knowledge of the energy and media demand behavior of the machines is the basis for identifying optimisation routes and the development of sustainable energy-saving measures. In addition, publicly available demand values enable a classification of company-owned machines for benchmarking, thus deriving the potential need for modification of individual machines. Detailed knowledge of demand patterns can also form the basis for further simulation studies, which can reduce the risk of investing in inefficient energy-saving approaches. The field of bottling and packaging, with its high demand for electrical energy, should also be the centre of energy-optimisation efforts.

Because of the lack of concrete publicly available data for benchmarks, the aim of the present work is to summarise scientific publications and publicly available knowledge on actual demand data in the field of beverage bottling and to generate further knowledge from an industry-wide survey on energy use in beverage-filling companies.

2. Literature overview

2.1. Bottling technology: Description of study area

Beverages and liquid food are packed in industrial bottling plants. The plant structure and the machines applied depend on the packaging type (bottle, can and keg), the packaging material (glass, polyethylene terephthalate, aluminium, or steel) and packaging concept (single use, returnable). The plant design is modular, and the different requirements of beverage filling can be fulfilled by a variety of machines. According to *Manger* (Manger, 2008), the components of a beverage-filling line are essentially the same (Table 2.2-1).

The plant configuration is influenced by the product requirements, the annual output, the resulting nominal speed of the filler, the product portfolio, the number of bottling plants available in the plant, any spatial conditions and production planning. The machines are laid out according to the nominal machine speed of the lead machine (usually the filler). With buffering conveyers between the upstream and downstream, machines are oversized in terms of machine speed to compensate for downtimes in the up- and downstreaming process and thus keep the lead machine running efficiently (compare to the V-diagram according to Berg (Petersen, 1993)). The machinery used in breweries is similar to that used for bottling mineral water and soft drinks.

Figure 2.2-1 shows a flow chart for the process of filling returnable glass bottles.

Table 2.2-1: General functionalities and machines for bottling. From Ref. (Manger, 2008).

	Function	Machine
Essential	depalletising	depalettiser
	depacking	depacker
	cleaning and control of overpacking (e.g. crates)	crate washer
	cleaning and control of packaging material (e.g. bottles/cans)	bottle-cleaning machine
	filling and sealing of the packaging material	filler and capper
	décor (e.g. labels) and labelling (e.g. best before date) and control of the package	labeler
	packaging into the overpackaging	packer traypacker
	palletising	palletiser
	transport	bottle conveyer palette conveyer
Additional, if required	increase of shelf life	flash pasteuriser tunnel pasteuriser
	cleaning and disinfection	CIP /SIP systems
	sorting systems for returnable containers	selective depacking machine
	machines for the production of soft drinks	beverage mixing and carbonising plants
	machines for bottle manufacturing	stretch blow moulder for PET bottles

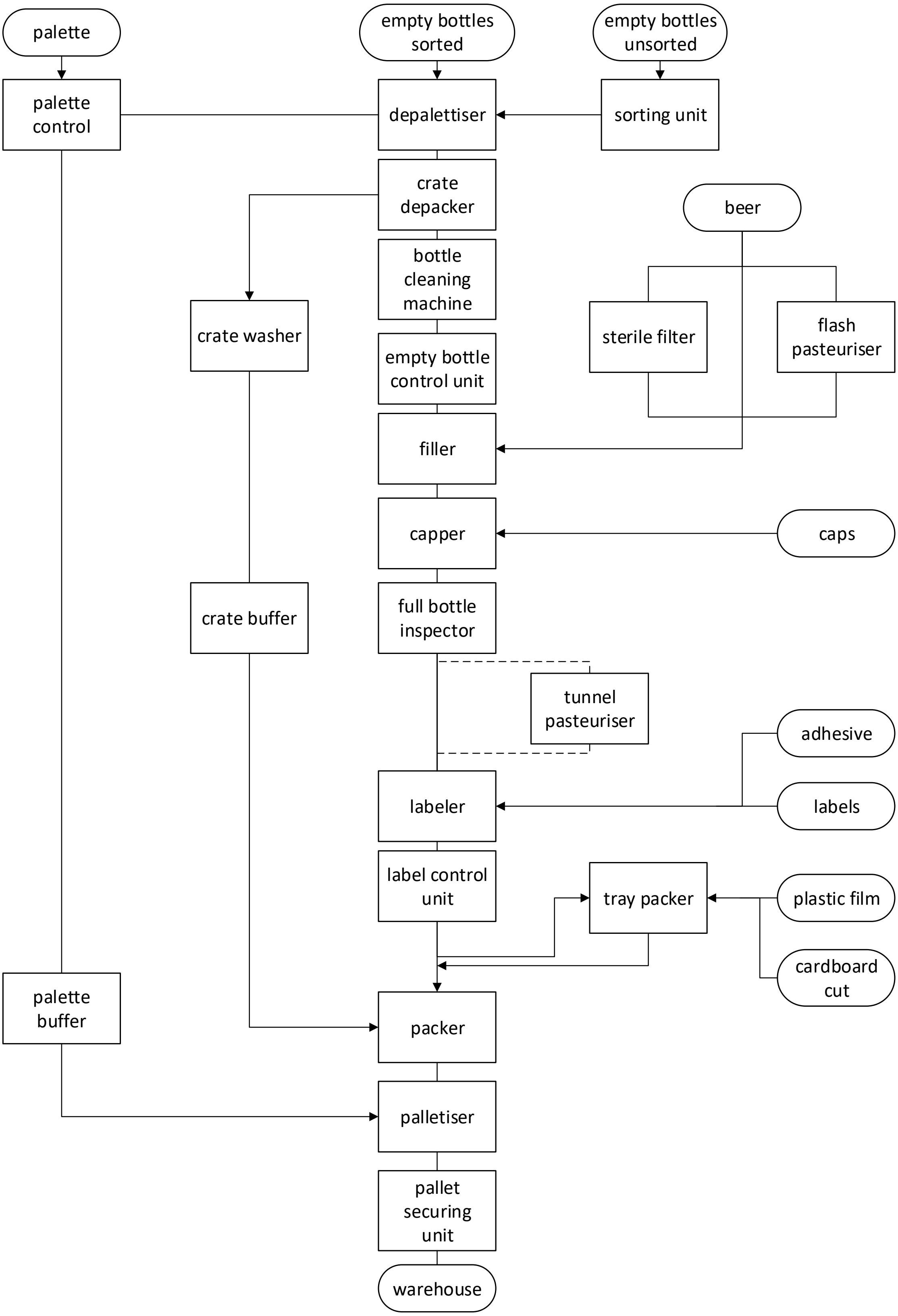

Figure 2.2-1: Flow chart for typical beverage-bottling plant for returnable glass bottles. From Ref. (Manger, 2008).

2.2. Data for characterising energy and media demand of bottling plants

Running a bottling plant requires different types of energy that are clustered into two main forms: electrical power and heat. Most approaches in breweries also deal with water, which is the main media demand. All machines used for bottling require electrical energy. The electrical energy is basically used to drive the machines that perform the basic mechanical functions, for moving the containers through the machine, for driving pumps (e.g. for the filled product or media) and for producing compressed air. Thermal energy is usually needed for heating various media (e.g. cleaning lye) and is mainly used in the cleaning machines (bottle-cleaning machines and crate washers) and pasteurisers (flash and tunnel type). Compressed air is used for beverage filling either as an energy carrier (e.g. stretch blow moulding of PET bottles, transport of empty PET bottles) or for signal transmission (pusher) or cleaning (blow-off, drying). Compressed air is a comparatively energy-intensive energy carrier and can be linked back to demand of electrical power of the compressor (kWh/m^3). Fresh water is used for cleaning the machines and in the bottle-cleaning machine (fresh water spray is used in the final step of cleaning the returnable bottles). Other media, such as lye, belt lubricants and additives, are mainly used in the bottle-cleaning machine and during container transport. The main energy consumers for bottling plants for non-returnable bottles are thus the stretch blow moulder (PET) and the bottle-cleaning machines (glass).

Table 2.2-2: Main energy and media types in bottling plants and common metrics.

Electrical power	Heat	Media
electrical power	steam	hot water
compressed air	fuel (gas/oil)	cold water
cooling	heating media (e.g. water)	treated water
kW installed load	kJ/bottle	ml/bottle
kWh/week	kJ/h	m^3/h
kWh/hl	MJ/week	m^3/week
kWh	MJ/hl	l/l; l/hl
Nm^3/h	kg/week (e.g. steam)	
Nm^3/week and kWh/Nm^3	l/l	

Established energy KPIs for the bottling process are often related to a defined quantity of the product (2.2-1):

$$\text{Specific energy demand} = \frac{\text{Total amount of energy used}}{\text{Total amount of product produced}} \qquad \textbf{(2.2-1)}$$

Other common energy KPIs are related to hectolitres of the corresponding product (see Table 2.2-2).

The following standards give information and recommendations on the energy demand of bottling machines:

- **DIN 8784** stipulates minimum and order related specifications for beverage-filling lines, including the installed load of the machines and machine-specific information (e.g. ml/bottle water) (DIN 8784:2013-09):
  - installed load of all machines [kW];
  - machine-specific: process parameter (e.g. times, temperatures), specific electrical demand [kJ/bottle], compressed air/sterile air [m3/h], gas demand (CO2 or N2) [kg/h], heat demand [kJ/bottle] or [MJ/h], steam [kg/h], specific data for heating processes.
- **Association of the Beverage Machinery Industry (ABMI): Sustainability Templates**: Recommendations for the communication of environmental performance of packaging lines between machinery suppliers and operating or beverage companies including an online availably template (Association of the Beverage Machinery Industry, 2010):
  - scope of supply;
  - general conditions and boundary conditions;
  - sheet for data input and calculations;
  - ecological summary: values for heat, water and electricity summarised for reference parameter: per week/per container/per litre of beverage.

No numerical values are given by the ABMI recommendations or the DIN 8784.

2.3. Publicly available energy data and energy data in scientific literature

Over the last years, some industry associations have published demand values and benchmarks, mainly recorded by consulting companies. The data are related to total production processes or single process areas (e.g. packaging). Most data are published for thermal and electrical energy. The data are mainly in relation to a product volume (e.g. one hectolitre of beer to be sold). In contrast to breweries, for manufacturers of nonalcoholic beverages, few demand data are publicly available. Energy costs for a brewery vary worldwide between 3 % to 10 % of the total budget (Canadian Industry Program for Energy Conservation, 2011; Galitsky et al., 2003; Meißner, 2003). In the last ten years the volume of water required to produce one hectolitre of beer decreased from 5–5.2 hl/hl to 4.2–4.3 hl/hl (Canadian Industry Program for Energy Conservation 2011; Heuven und van Beek 2013, 2013; Donoghue et al. 2012; British Beer & Pub Association 2006). According to the published data the energy required to produce a hectolitre beer is 21.6–90 MJ/hl (electrical power) and 100.8–141.12 MJ (thermal power) or 116.8–271 MJ/hl (total demand) (Canadian Industry Program for Energy Conservation, 2011; Kapusta, 2010). Thermal energy accounts for an average of 70 % of the total energy demand in a brewery, yet results in only 30 % of the energy costs. Therefore, priority should be given to efforts to reduce the electrical energy demand because it represents the greatest potential savings. Data from the U.S. Environmental Protection Agency show that refrigeration, packaging and compressed air consume 70 % of a breweries' electrical energy (Brewers Association, 2017). Bottling accounts for 16.5 %–30 % of the heat and 12 %–35 % of the electrical power (Fiederer et al., 2001; Galitsky et al., 2003; Petersen, 1993; Sattler, 2000).

Table 2.2-3: Selected energy data publicly available and published in scientific literature.

	Country	Sample size	Value	Unit	Year	Source
share of energy cost on total costs	Canada	n.a.	3-8	%	2011	(Canadian Industry Program for Energy Conservation, 2011)
	USA	n.a.	3-8	%	2003	(Galitsky et al., 2003)
	Germany	n.a.	10	%	2003	(Meißner, 2003)
	n.a.	n.a.	30	%	2015	(Michel, 2015)
share of thermal power for bottling	USA	n.a.	20-30	%	2003	(Galitsky et al., 2003)
	UK	n.a.	20-30	%	2000	(Sorrell, 2002)
	Germany	4 breweries	20	%	2001	(Fiederer et al., 2001)
	Austria	14 breweries	25	%	2000	(Sattler, 2000)
	n.a.	n.a.	16.5-25.7	%	1993	(Petersen, 1993)
	USA	n.a.	15-35	%	2003	(Galitsky et al., 2003)
share of electrical power for bottling	UK	n.a.	15-35	%	2000	(Sorrell, 2002)
	Germany	4 breweries	15	%	2001	(Fiederer et al., 2001)
	Austria	14 breweries	18	%	2000	(Sattler, 2000)
	n.a.	n.a.	12	%	1993	(Petersen, 1993)
	USA	n.a.	25	%	2013	(Brewers Association, 2017)
heat demand for bottling	Germany	n.a.	16-26	kWh/hl	2002	(EUROPEAN COMMISSION, 2006)
water demand for bottling	n.a.	n.a.	0.06-0.16	m^3/hl	2002/ 2012	(Olajire, 2012)

	Country	Sample size	Value	Unit	Year	Source
water demand for a specific amount of beer	Europe	n.a.	4.2	hl/hl	2012	(Donoghue et al., 2012)
	worldwide	225 breweries	4.3	hl/hl	2012	(Heuven and van Beek, 2013)
	Canada	n.a.	5	hl/hl	2011	(Canadian Industry Program for Energy Conservation, 2011)
	worldwide	143 breweries	5.2	hl/hl	2008	(Heuven and van Beek, 2013)
	Europe	n.a.	4-10	hl/hl	2006	(EUROPEAN COMMISSION, 2006)
	Finnland	1 brewery	3	hl/hl	2003	(EUROPEAN COMMISSION, 2006)
	Germany	n.a.	3.7-4.7	hl/hl	2002	(EUROPEAN COMMISSION, 2006)
	UK	n.a.	5	hl/hl	2006	(British Beer & Pub Association, 2006)
	Portugal	n.a	4.9	hl/hl	2005	(Olajire, 2012)
	n.a.	n.a.	2.5-4.5	hl/hl	1993	(Petersen, 1993)
electrical power demand for a specific amount of beer	Canada	n.a.	42	kWh/hl	2011	(Canadian Industry Program for Energy Conservation, 2011)
	Latvia	1 (SME)	22,5-25	kWh/hl	2016	(Kubule et al., 2016)
	Austria	13	6.2-35.1	kWh/hl	2010	(Kapusta, 2010)
	Germany	n.a.	7.5-11.5	kWh/hl	2002	(EUROPEAN COMMISSION, 2006)
	Europe	n.a.	8.9-13.7	kWh/hl	2008	(Scheller et al., 2008)
electrical power demand for a specific amount of beer	Portugal	n.a.	12.7	kWh/hl	2005	(Olajire, 2012)
	n.a.	n.a.	8-12	kWh/hl	2012	(Olajire, 2012)
	Germany	n.a.	39	kWh/hl	2010	(Kapusta, 2010)
	n.a.	n.a.	42	kWh/hl	2012	(Olajire, 2012)

	Country	Sample size	Value	Unit	Year	Source
	USA	n.a.	19-35	kWh/hl	2013	(Brewers Association, 2017)
	Austria	n.a.	39	kWh/hl	2010	(Kapusta, 2010)
thermal power demand for a specific amount of beer	Portugal	n.a.	110	M//hl	2005	(Olajire, 2012)
	Canada	n.a.	28.8-43.2	MJ/hl	2011	(Canadian Industry Program for Energy Conservation, 2011)
	Latvia	1 (SME)	219-231	MJ/hl	2016	(Kubule et al., 2016)
	Germany	n.a.	28.6-54	MJ/hl	2010	(Kapusta, 2010)
	Europe	n.a.	85-118	MJ/hl	2008	(Scheller et al., 2008)
	Austria	1 brewery	39.6	MJ/hl	2010	(Kapusta, 2010)
	Austria	n.a.	21.6-90	MJ/hl	2010	(Kapusta, 2010)
	Austria	n.a.	46.08	MJ/hl	2010	(Beer and Hiller, 1995; Kapusta, 2010)
thermal power demand for a specific amount of beer						
total energy demand for a specific amount of beer	Europe	n.a.	116.8	MJ/hl	2012	(Donoghue et al., 2012)
	worldwide	225 breweries	207	MJ/hl	2012	(Heuven and van Beek, 2013)
	worldwide	143 breweries	229	MJ/hl	2008	(Heuven and van Beek, 2013)
	UK	n.a.	161	MJ/hl	2006	(British Beer & Pub Association, 2006)
	worldwide	158 breweries	239	MJ/hl	2004	(Heuven and van Beek, 2013)
	worldwide	86 breweries	271	MJ/hl	2000	(Heuven and van Beek, 2013)

SCHREINER published detailed machine-related energy parameters for bottling plants connected with a cogeneration approach in the early 1980s (Schreiner, 1982). He published detailed machine-related data for the installed load in [kW] and the thermal energy ([kW] and [MJ/h]) required by machines with variable nominal output (from 20 000 up to 100 000 bottles/h).

To summarise the available literature, it can be said that no reliable detailed demand data on machine level are available for industrial bottling. Table 2.2-3 shows selected energy and media demand values for breweries to put the energy and media demand in bottling into perspective. The data available are mostly related to processes (e.g., packaging) as opposed to machines. The data available from SCHREINER are no longer state of the art and consider a limited number of machines. With regard to the optimisation approaches mentioned, a publicly accessible database and detailed measurements in the plants are essential to assess the actual situation and to plan optimisation approaches.

3. Data acquisition

Data acquisition was done by a questionnaire that was designed according to the scientific principles of quantitative-empirical data collection. It contained 25 questions that were customised for every machine type. There are grouped as follows:

- General questions about the company:
  - brewery, mineral springs, or fruit-juice production;
  - number of bottling plants;
  - packaging material, type and size;
  - equipment.

- Detailed information about the most frequently used bottling plant:
  - type of manufacturer;
  - year of construction;
  - nominal speed [bottles/h] or [crates/h];
  - installed load [kW];
  - electrical power demand during operating [kW];
  - electrical power demand during standby [kW];
  - specific energy demand [kJ/bottle];
  - heat (machine specific) [kJ/h];
  - water demand (machine specific) [m^3/h];
  - pressured air demand (machine specific) [m^3/h];
  - gas demand (machine specific) (CO_2) [m^3/h].

- Energy management and optimisation efforts:
    - energy manager/energy management system/DIN ISO 50001;
    - share of energy cost on total production costs;
    - realised energy-optimisation strategies;
    - planed energy-optimisation strategies.

- Data regarding production planning:
    - number of filling days;
    - number of grade chances per week;
    - number of cleaning units per week;
    - detailed information about cleaning (type, duration and energy demand).

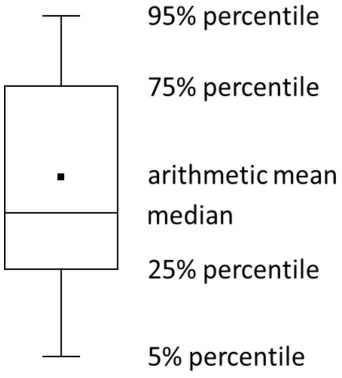

Figure 2.2-2: Boxplot diagram

The machines and the machine-specific parts of the questions were selected according to DIN 8784 (2013). Single parts of the questions were customised for every machine type (e.g. water and heat demand for cleaning machines). The respondents of the questionnaire could choose between different types of bottling lines (PET, glass, returnable, non-returnable) to increase usability. All information was provided voluntarily, and single questions could be omitted. Before publication, the questions were validated by a number of selected companies in a pretest. The survey was available online for 1 year and >550 bottling companies were informed by letter with a written version of the survey. The questions were detailed, leading to an average editing time of >30 minutes. 33 questionnaires were completed to a degree of 15 %–95 %, representing approximately 2 % of the German beverage-bottling industry.

The results of the survey are mainly presented as boxplot diagrams, as recommended in the literature for group studies (Kirchner, 2008). The data are presented in quartiles. Each quartile includes 25 % of the values. For example, the third quartile includes the values of the total nominations that fall between 50 % to 75 % of the maximum. The centre of the boxplot is the median. In contrast with the arithmetic average, the median is not located at the geometric centre of the boxplot but indicates where half of the values have already been mentioned (see schematic drawing in Figure 2.2-2).

4. Results

4.1. Characterisation of participants

All companies provided data for their most frequently used bottling line. Not every question was answered by every company. All companies who entered details for this study use returnable glass bottles, which is characteristic for the German beverage market. Some companies additionally are producing cans (number of companies n = 9) or non-returnable glass bottles (n = 8), PET bottles (n = 6, n = 4 for single use, n = 2 for returnable bottles), or kegs (n = 7). The collected energy and media data were related to returnable glass bottles. The annual output of the companies was between 700 hl/a and 1 900 000 hl/a. The machine speeds varied from 2200 to 72 000 bottles/h and 300 to 4000 crates/h. All companies surveyed provided general data for the filling machine (n = 33) of their bottling plant, most of them for bottle-cleaning machines (n = 31), packers (n = 30) and depackers (n = 31) and crate washers (n = 30), some for palletisers (n = 26), labelers (n = 25), depalettisers (n = 21), pasteurisers (n = 14) and a few for tray packers (n = 7) or stretch blow moulders (n = 1). The machines were mainly younger than 15 years (see Figure 2.2-4).

In this survey, the median nominal speed for the lead machine *filler* is 28 000 bottles/h (see Figure 2.2-5). Questions concerning the detailed demand behavior of the machines were answered by a smaller number of companies. With increasing level of detail, the number of answers decreased (see Figure 2.2-3). Although an average of over 50 % of the companies gave information about the installed load of single machines, only one third of them made an entry in the field of the electrical power demand in operating time and only 25 % for standby times.

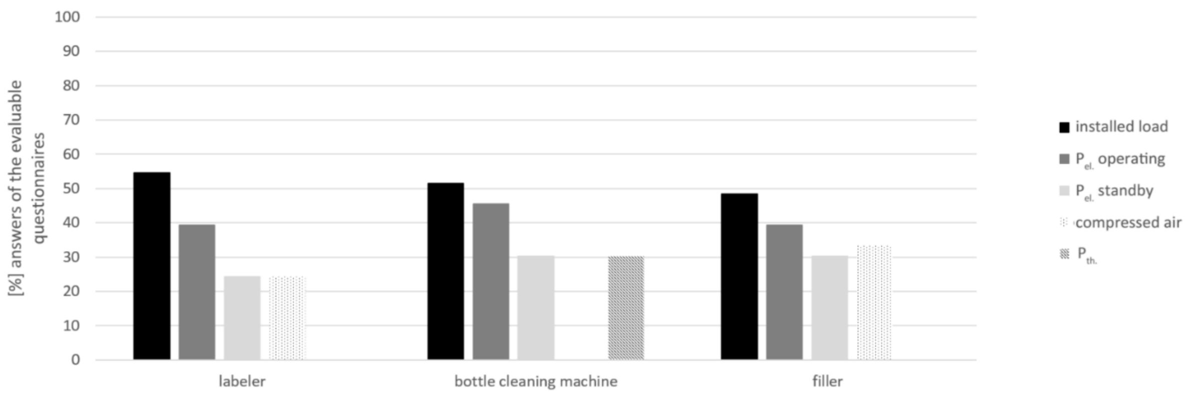

Figure 2.2-3: Percent of detailed answers regarding detailed energy and media demand of machines.

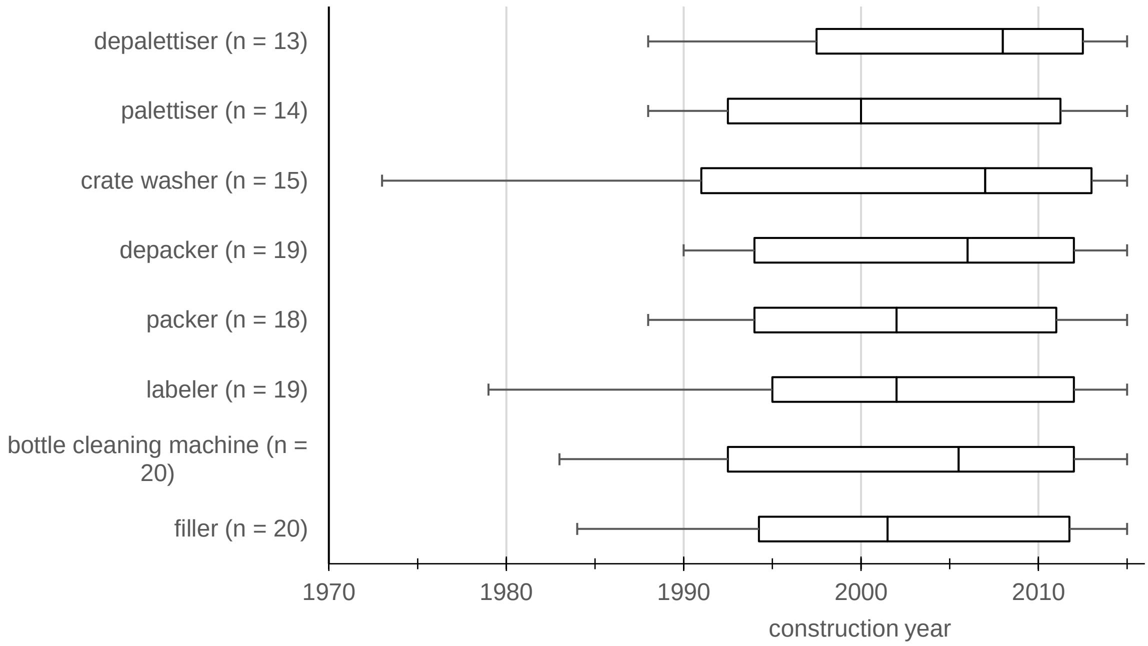

Figure 2.2-4: Characterisation of participants: Boxplot diagram of machine age: approximately 75 % of answers included the year of construction of the machine.

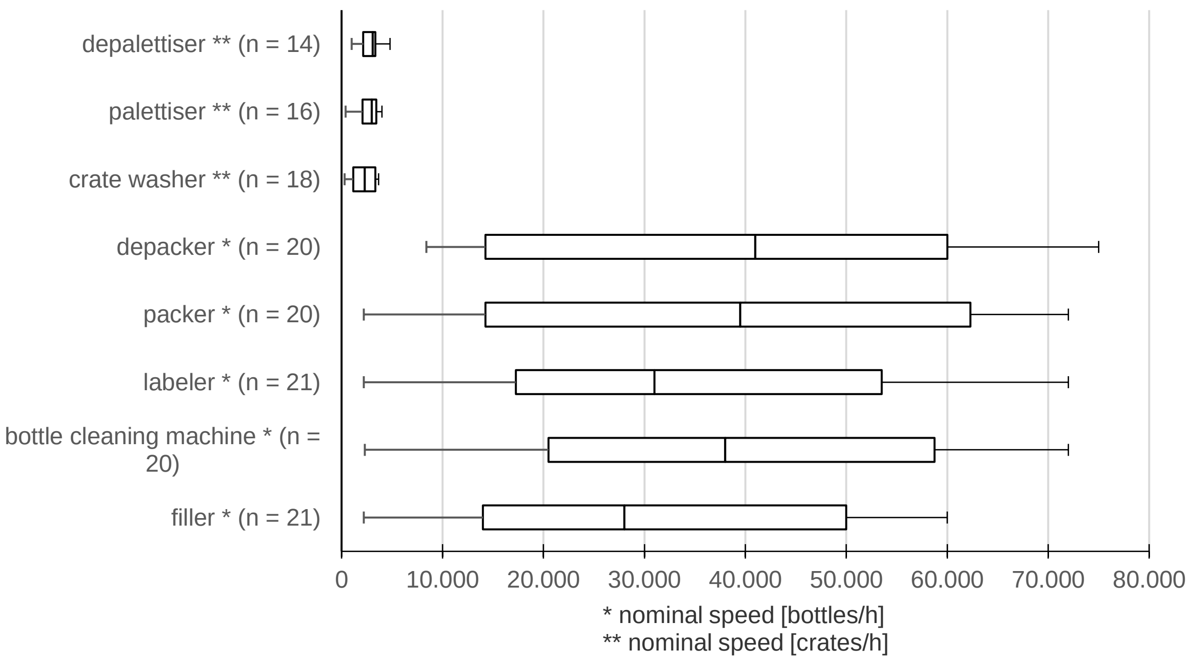

Figure 2.2-5: Characterisation of participants: Boxplot diagram of nominal speed of machines.

4.2. Installed load and electrical energy demand at machine level

The installed load of the individual machines is usually known because it is stated in the machine specification. Nevertheless, only half of the participants provided information on this topic. Figure 2.2-6 shows the installed load for individual machines. More than 50 % of the participants specified a value for the installed load of the individual machines. The bottle-cleaning machines have the highest installed load, followed by the fillers, the palettising machines and the crate washers. A wide range of values were returned for the bottle-cleaning machines. Figure 2.2-7 shows the correlation between the nominal speed of the machines and the installed load of the machines for the example of a labeler, a filler and a bottle-cleaning machine. The installed load increases with increasing machine speed. The plots show a linear correlation between machine speed and installed load.

Only limited data were provided for pasteurisation machines. Machines with a nominal speed of 3200–5000 bottles/h have an installed load of 25–120 kW. The demand during operating is 42–97 kW. A single value of 57 kW was specified for standby (approximately 60 % of the demand during operation). No pertinent information was collected for stretch blow moulders or mixers.

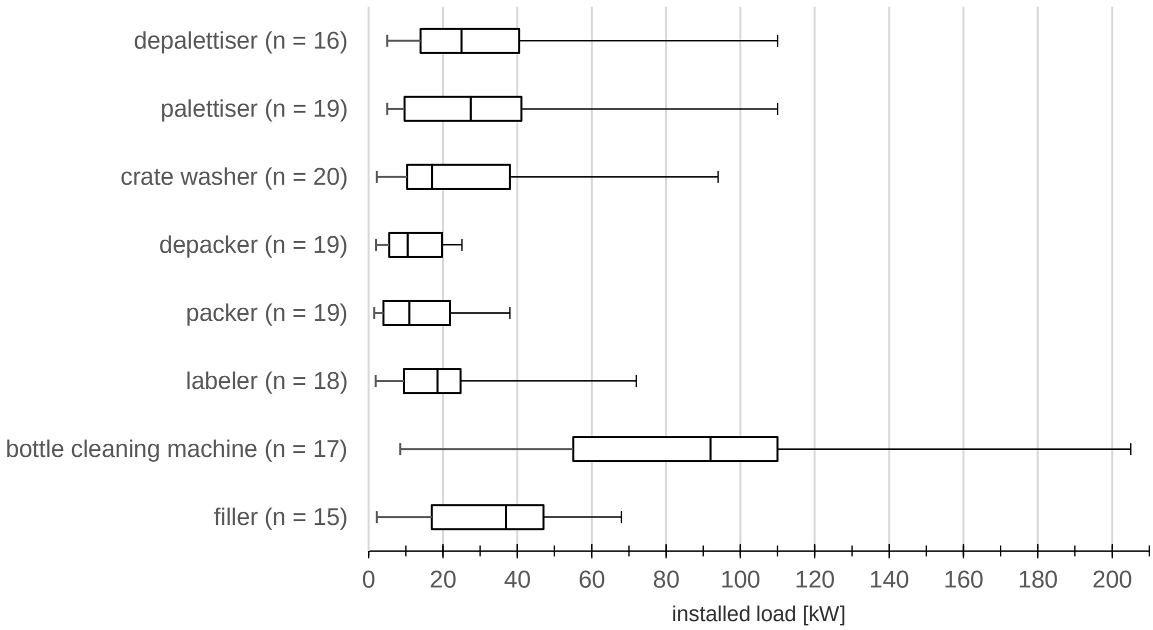

Figure 2.2-6: Installed load on machine level.

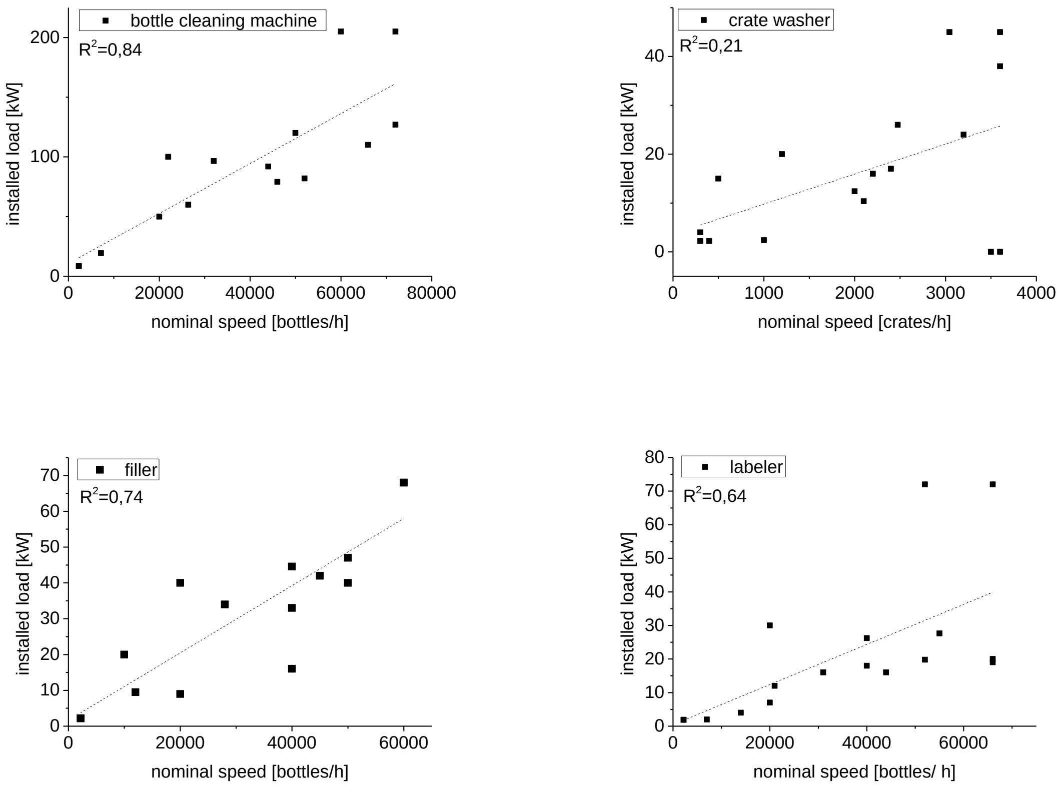

Figure 2.2-7: Correlation between nominal machine speed and installed load.

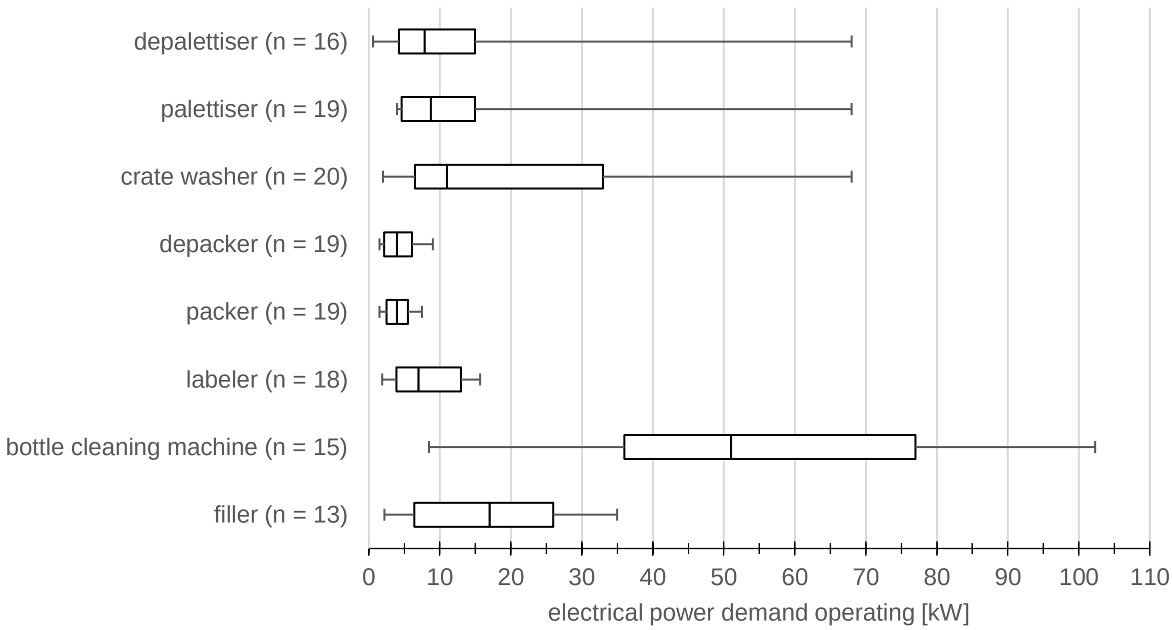

Figure 2.2-8: Electrical power demand during operation.

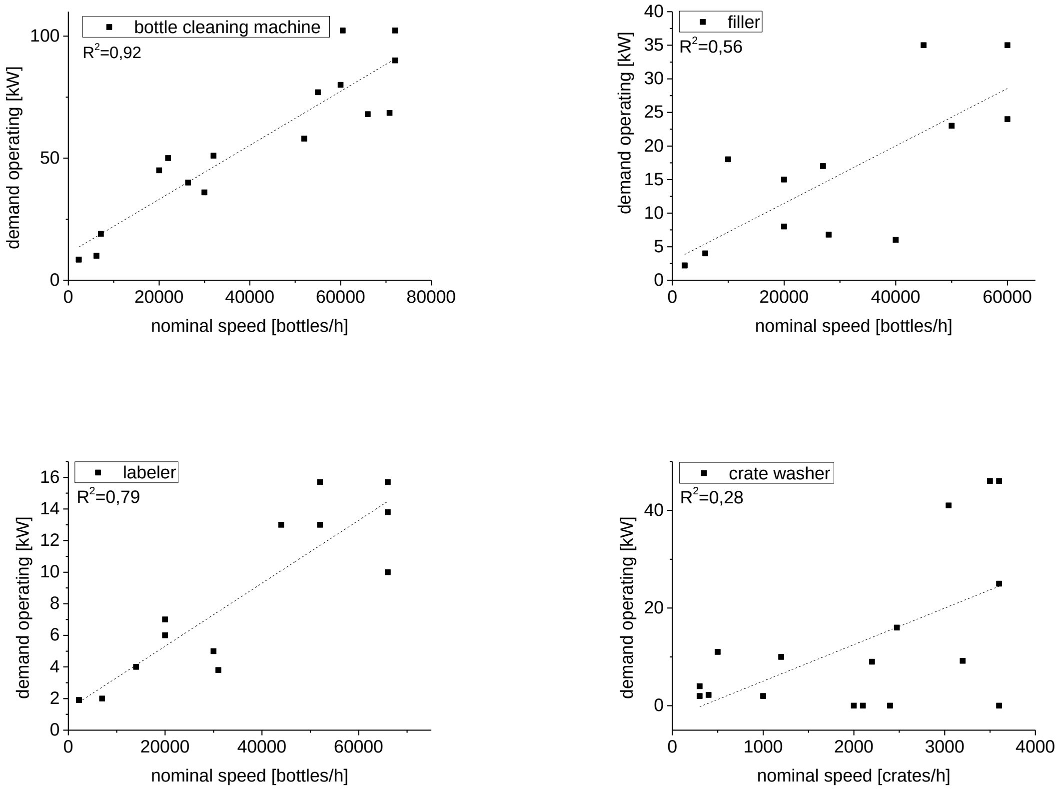

Figure 2.2-9: Power demand during operating depending on the nominal speed of the machines for the main consumer, linear regression and coefficients of determination R^2.

Figure 2.2-8 shows the data for the electrical energy demand at the machine level during operating. The bottle-cleaning machine has the highest electrical energy demand. The order of the other machines is consistent with the data for the installed load. The values for the bottle-cleaning machine, the filler and the labeler for demand during operation range from 18 % to 98 % of the installed load (average is 57 %).

Figure 2.2-9 shows the correlation for the electrical power demand during operating and the nominal machine speed. Beside the crate washers, that show a clear trend to an increasing electrical energy demand with increasing machine speed but a poor linear fit (R^2=0.28), for the other main consumer a linear correlation between the electrical energy demand and the nominal machine speed was found (see Figure 2.2-9).

The electrical power demand during standby is shown in Figure 2.2-10. The demand of the bottle-cleaning machine ranges from 1 % to 78 % (mean: 34 %) of the demand during operation. For the filler the analogous range is 1 %–74 % (mean: 21 %) and for the labeler it is 3 %–70 % (mean: 29 %). For the bottle-cleaning machine, the standby values exceed the values during operation of most of the other machines mentioned.

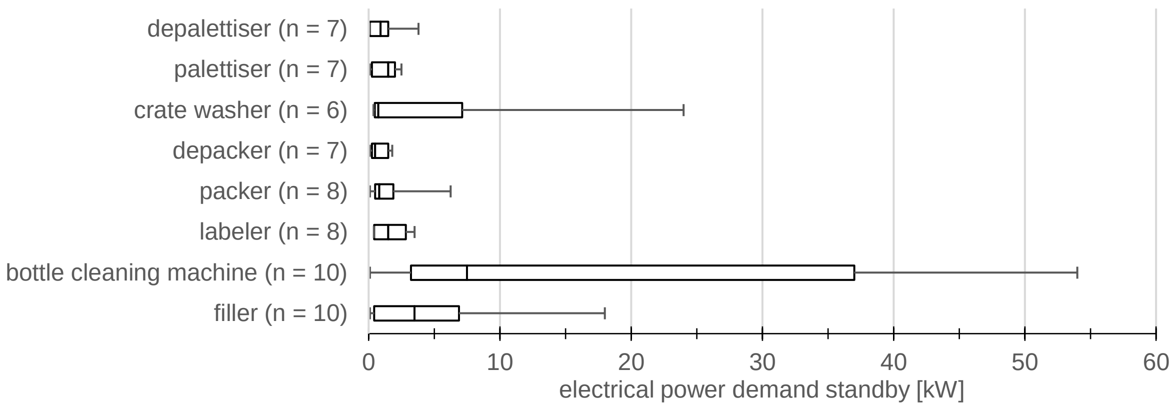

Figure 2.2-10: Electrical power demand during standby.

Figure 2.2-11 shows the demand during standby for the four main consumers. No linear correlation between the machine speed and the energy demand was found for the considered machines (bottle cleaning machine, labeler, crate washer, filler). The figures for all machines show a trend to an increased demand in dependence to an increasing machine speed. The enlarged sample size might bring more information here.

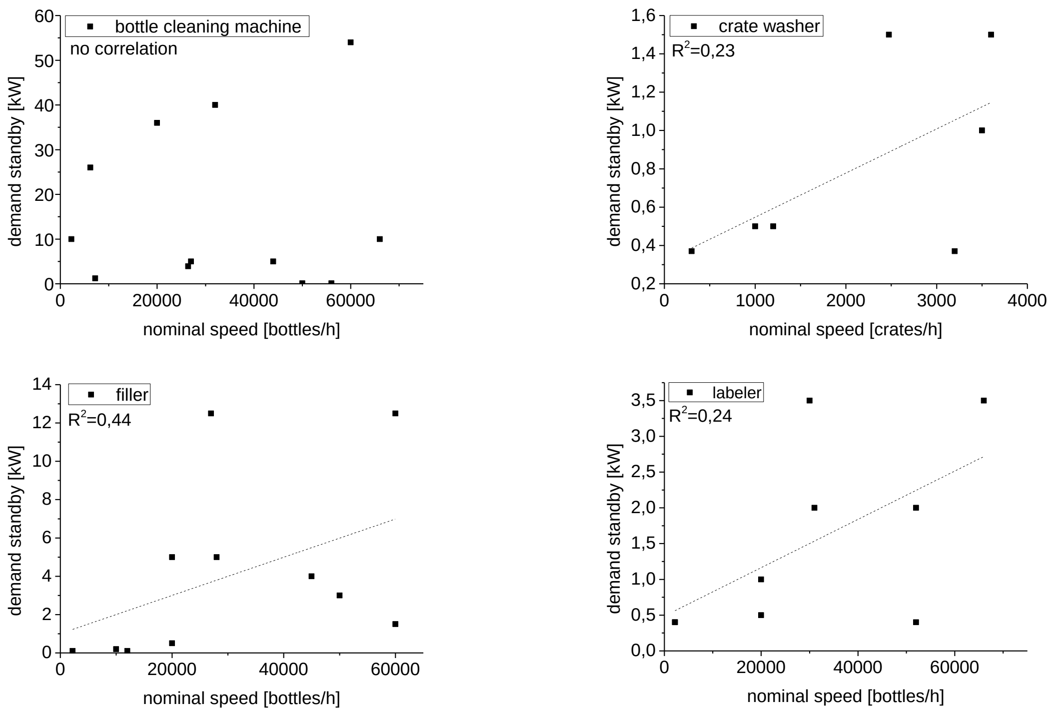

Figure 2.2-11: Power demand during standby depending on the nominal speed of the machines for the main consumer, linear regression and coefficients of determination R^2.

4.3. Heat and media demand at machine level

Concerning the media demand, one third of the companies provided information on the demand of compressed air (see Figure 2.2-12). The values for the labeler and the filler are widely distributed. For the labeler no direct linear correlation appeared between machine speed and demand of compressed air, but there is a tendency that machines with a higher nominal speed consume more compressed air (all demands >50 m^3/h caused by machines with a nominal speed above 45 000 bottles/h).

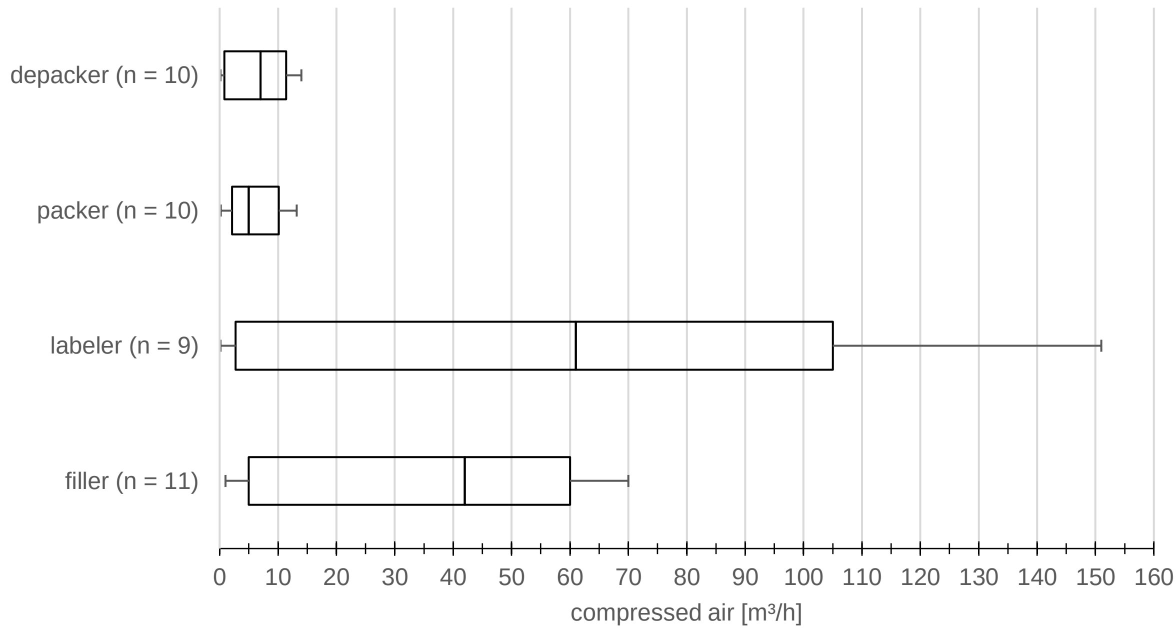

Figure 2.2-12: Compressed-air demand.

Furthermore, data were collected for heat demand of the bottle-cleaning machine and for fresh water demand for the bottle-cleaning machine and the crate washer (see Figure 2.2-13). All data were collected for the bottle size of 0.5l.

Less than 30 % of the companies provided data for heat demand of the bottle-cleaning machine. 75 % of the data fall between 25–80 kJ/bottle. No pertinent data were available for heat demand of the crate washer.

40 % of the companies listed fresh water demand of the bottle-cleaning machine between 140 and 900 ml. The values are spread evenly over the nominal speed of the machines and the age of the machines, except for the highest value, which is related to a machine from the early 1980s with a significantly low machine speed. The water demand of the crate washer is not specified related to single crates but in [m^3/h]. Figure 2.2-14 shows the fresh water demand for the example of the bottle cleaning machine related to the nominal speed and the year of construction. The fresh water demand for this data is not correlated to the construction year nor the nominal speed of the machines. For the linear regression a

poor fit was found for both variables (nominal speed: R^2= 0.12; machine age R^2=0.05, see Figure 2.2-14). For the machine age a trend to a slightly degreasing consumption during the years was found. Therefore, a Q-Q-plot was made to consider the probability of the data. The values follow a nominal probability (not considering the single highest value).

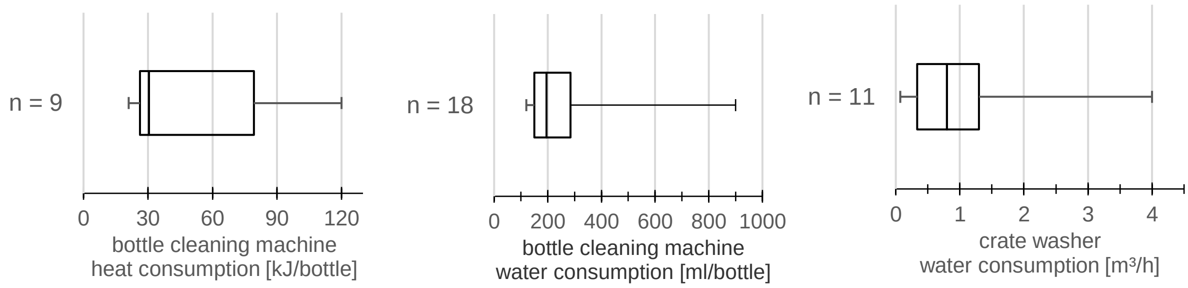

Figure 2.2-13: Heat and fresh water demand of bottle-cleaning machines and crate washer.

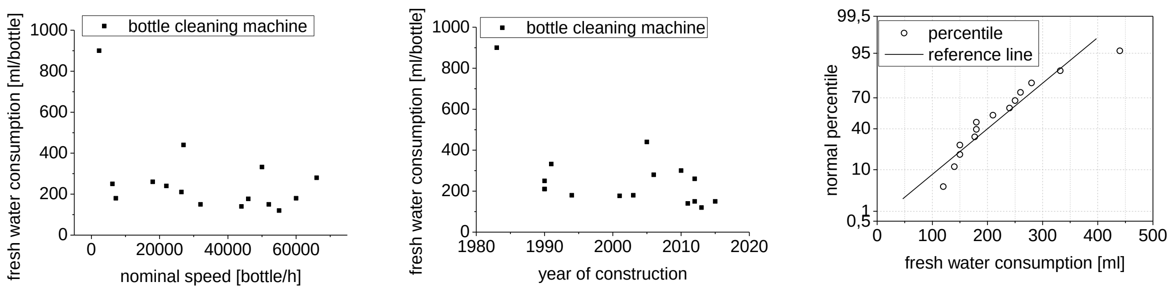

Figure 2.2-14: Fresh water consumption of the bottle cleaning machine related to nominal speed and construction year and Q-Q-plot for normal probability without the single value of 900ml/bottle (μ=222.07; Sigma=87.14).

4.4. Production planning and maintenance

Cleaning and maintenance are periodic processes that consume additional energy. No information about energy demand during cleaning and maintenance was found in the literature. The number of cleaning and maintenance steps is related to technological parameters and to production planning issues (i.e. number of articles per week). Therefore, data were collected specifying the product range and the production plans for a week. Figure 2.2-15 shows the product variety and the proportion of products filled within one production week. For breweries, this study finds a product range between 1 and 85 articles (median is 15 articles). For companies producing mineral water and juice, between 6 and 400 articles (median is 100 articles) were found.

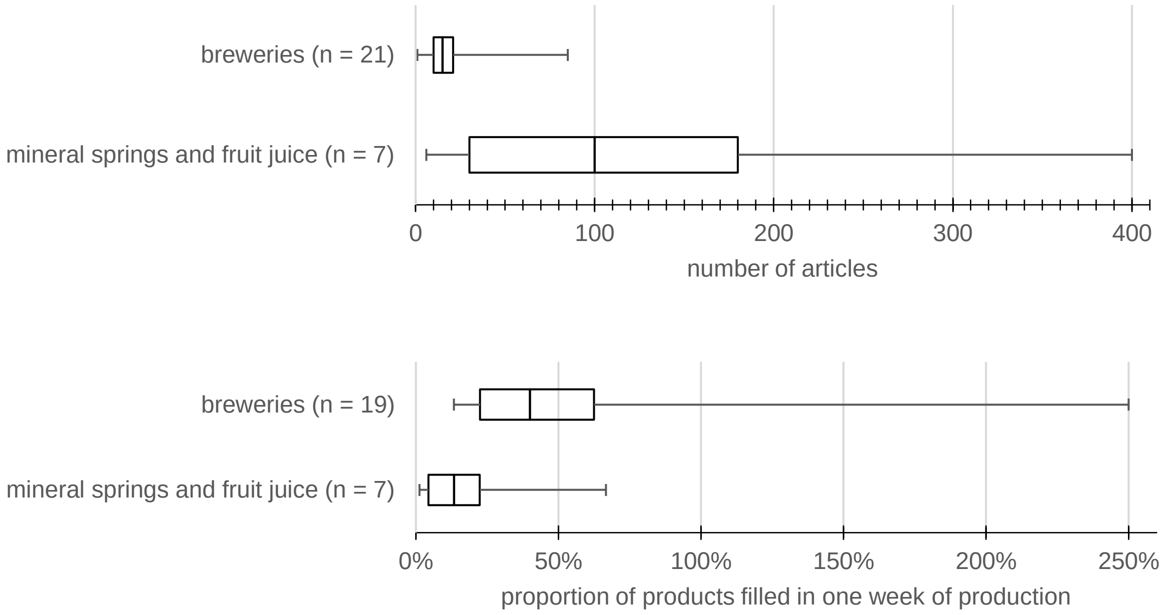

Figure 2.2-15: Ratio of number of total products to products filled in one week of production.

No reliable data regarding the number of cleaning processes per week or the energy demand of single cleaning steps could be obtained from the questionnaires. Data relating to the duration of cleaning processes are summarised in Figure 2.2-16. The data for external cleaning are widely spread because line structures and cleaning standards differ.

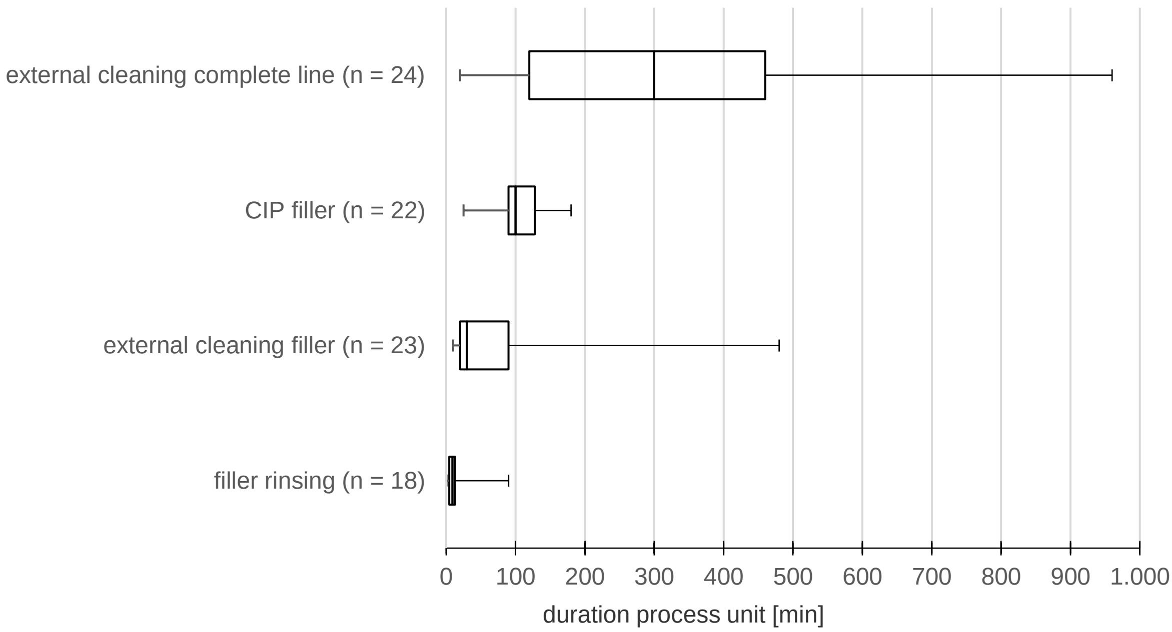

Figure 2.2-16: Duration of various cleaning processes.

4.5. Energy management and present and future optimisation strategies

Of the surveyed companies, 50 % employ an energy manager, and 70 % run an energy management system. Approximately 40 % are certified according to ISO 50001. The year of the certification is predominantly (>90 %) after 2012. More than 50 % were certified in 2014. Approximately half of the responses regarding energy cost as a share of total production cost is 0 % to 20 % (see Figure 2.2-17). More than 80 % of the respondents said they are already investing in energy-optimisation strategies, and over 80 % are planning to invest in energy-saving measures in the future. The companies provided information about current and future optimisation strategies for their bottling plants. The answers could be categorised to the following topics:

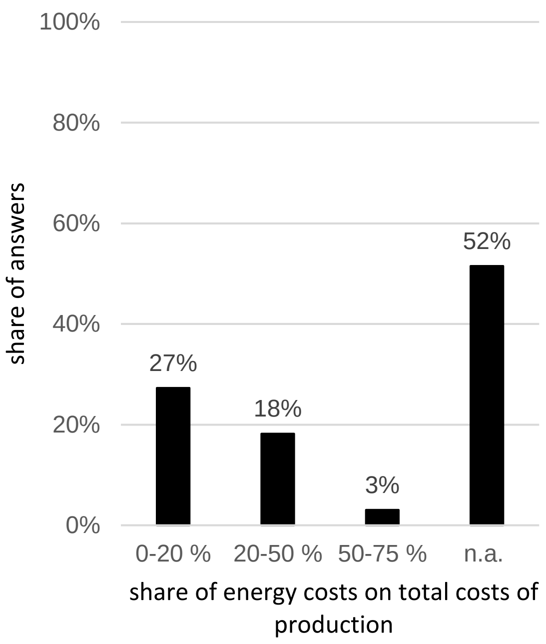

Figure 2.2-17: Share of energy costs on total costs of production.

- Holistic thinking in cycles:
  - heat recovery (mainly bottle-cleaning machine and crate washer, cogeneration unit, product heating);
  - installation of heat exchanger.

- Replacement of equipment (investment in new machines and technology):
  - general replacement of machines and equipment (filler, bottle-cleaning machines);
  - replacement of parts: mainly pumps and electric drives and controls (frequency converter, permanent magnet motors).

- Optimisation of existing equipment and processes:
  - compressed-air supply, leakage management;
  - water and chemical demand (e.g. clocked fresh water spraying for the bottle-cleaning machine);
  - improved insulation of machine parts and pipes and valves;
  - temperature reduction lye at the bottle-cleaning machine.

- Structural measures:
    - data acquisition;
    - production planning;
    - reduction of short term downtimes.

- Building technology:
    - modern lighting (LED).

- Use of renewable energy:
    - photovoltaics;
    - solar thermal energy.

5. Discussion

This study provides information on energy and media demand for bottling plants at the machine level and further information about energy management systems and optimisation considerations. For most questions a limited number of reliable data were collected. The quantity of the collected data must be reviewed critically in terms of further statistical analysis and general statement regarding the demand of bottling machines. This is due to the limited sample size compared to the total numbers of German beverage bottling companies. The data show interesting trends and a demand for more detailed, validated data as a basis for future optimisation considerations.

The values for installed load (electrical power) are usually provided in the specification documents. The low response rate for this question may indicate that the values are not known by the production manager. A gap exists between the installed load and demand during operation times due to peak load demand. Based on the available data, no conclusion can be drawn about whether the machines have a higher installed load than needed. Data from Figure 2.2-7 indicates that a linear correlation exists for most machines between the nominal speed of the machines and their installed load. For the bottle cleaning machine a linear correlation was found between the nominal machine speed and the electrical energy demand during operating and standby times. For all these machines beside the crate washer a linear correlation was found for the electrical energy demand during operating and the nominal machine speed. No correlation was found between the nominal machine speed and the electrical energy demand standby times for the labeler, the crate washer and the filler. The missing linear correlation might indicate optimisation potentials due to different shut down strategies. As the sample size for the standby demand is small, there should be further investigations on the energy consumption behavior during standby times to find saving potentials.

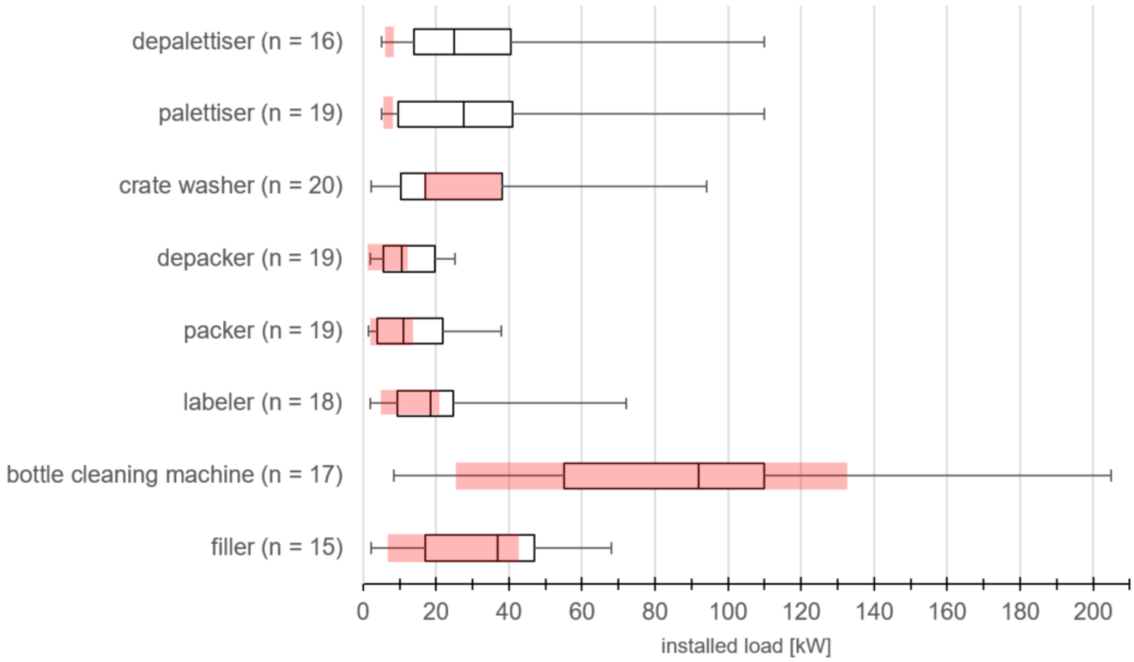

Figure 2.2-18: Comparison of results of present study with published data (Schreiner, 1982) for installed load of bottling machines. The values for installed load the bottle cleaning machines published by Zimmermann (Zimmermann, 2007) are between 11-24 KW for a low nominal speed of the machines (4000-6600 bottles/h) and not included in this figure.

Figure 2.2-18 compares the few data published in the 1980s with the data from the present study. Most data for installed load are in the same range. The data indicate a shift toward a higher installed load, which may be caused by the increased degree of automation since the 1980s.

Data for fresh water demand were provided for bottle-cleaning machines and crate washers. The highest fresh water demand of 900 ml/bottle for a bottle-cleaning machine was from a machine from the early 1980s with a low nominal output. Based on the data a water demand below 300 ml/bottle is state of the art today. The arithmetic average of the data (excluding the single highest demand 900 ml/bottle) is 220 ml/bottle. Four participants specified a fresh water demand significantly above average. It is expected that there is a number of bottling plants remaining with water demand significantly greater than the state of the art. No correlation was found between the fresh water consumption and the machine age or the nominal speed of the machines. It can be assumed, that the fresh water consumption of the older machines might be optimised in the last years resulting in fresh water consumptions comparable to modern machines. The data provided for crate washers are expressed in [m^3/h]. The drawback of this approach is that no possibility exists to draw conclusions on production-related actions that might indicate potential improvements. Few data were provided for heat demand of bottle-cleaning machines. A value of 25–80 kJ/bottle was indicated for 50 % of the machines. No data were available for the heat demand of the crate washer. Modern crate washers are often interlinked with bottle-cleaning machines to reuse the heat.

The data concerning the production planning and the product variety show that several product changes occur per week, resulting in cleaning and change-over processes, which also require energy and media. Therefore, energy demand of the resulting cleaning and change-over processes should be considered for the specific and total energy consideration. No participant gave detailed information about energy demand for the different cleaning units. Although product availability is prioritised, demand should be traced back to the source to include energy and performance considerations into production planning. While specific product-related energy performance indicators (e.g. kW/bottle) are suitable for economic considerations, a cause-related approach (e.g. operation-state based demand) would give more information for optimisation approaches.

Several energy-optimisation approaches are already implemented or planned for industrial applications, as discussed in section 4.5. Given more detailed energy data, it is believed that even more energy savings can be identified.

The focus of this study is on the machine level. Conveyer technology was not included because of its variable structure and to keep the number of questions to a minimum. For future considerations, data for the demand of the conveyer systems would be of interest because several electrical drives (often more than 100) are used for bottle, crate and palette transport.

Although the survey was sent to numerous German bottling companies, the response rate was low due to the high effort of filling out the questionnaire. Furthermore, relatively few companies provided data for the requested level of detail. Nevertheless the data are interesting indicators for energy demands on machine level, showing that detailed measurements might help to identify energy saving potentials. Only a few answers were given to questions concerning the detailed machine demand structure. It is expected that only few companies already measure energy data at this high level of detail. Furthermore, no industry-accepted definition for standby demand exists at the moment. With further knowledge of the production plan, machine efficiency and utilisation factor operational state related energy consumption values can be used for calculation of specific energy waste or specific energy costs. Significant feedback from production managers regarding this question indicted an interest in this type of consideration as a method to identify optimisation potential and to reduce life cycle costs. The available data collected in this study show that the electrical power demand during standby for bottle-cleaning machines are high and exceed the demand of most other machines during operation.

6. Conclusion

The results obtained in this study provide an overview of the energy and media demand of the German bottling industry. General statements regarding the energy demand of bottling machines are missing, due to the limited number of samples. The main consumers are identified and concrete demand data are obtained for a limited number of plants. For some demand values a linear correlation to the nominal speed of the machines were found. Companies running bottling plants can use the data from this study as a basic benchmark against which to compare their existing equipment and as a reference for new machine purchases. The data confirm that optimisation should focus on electrical demand because every machine in a bottling plant uses this expensive type of energy. Optimisations of bottle-cleaning machines should also be given special attention. Because only few, less detailed values are published and because the number of data provided herein is limited, further effort is required to establish a reliable branch database. Although efforts are already underway to improve energy efficiency, significant potential remains to be exploited by further investigations. The results of this study can be used as basic research for future studies on the detailed energy demand behavior, accompanied by further data acquisition, to find generic models describing state-related energy demand for cause-related allocation of demand and detailed optimisation strategies.

7. Acknowledgments

The authors would like to thank all companies who took the time to answer the detailed questionnaire. Furthermore we would like to thank Deutscher Brauer-Bund e.V. and Bayerischer Brauerbund e.V. and the editorial team of BRAUWELT who supported us by promoting the survey among the German beverage-bottling companies. In the end, I would like to express my special thanks to Alexander Holm who realised the execution of the survey in the context of his Master thesis. His motivation and conscientiousness were way above average and it was a pleasure to work with him on the presented research.

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2.3 Summary of Publication II: Energy consumption behavior of food and beverage-packaging machines

The aim of this publication was to gain fundamental knowledge on the consumption behavior of bottling plants on the basis of an improved database. Therefore, empirical operational state and electrical energy consumption data were collected in order to analyze the consumption behavior and potential correlation between the operational state and the energy consumption. Five bottling plants using typical packaging types (returnable glass and PET bottles) and products (water, soft drinks, and beer) were investigated for up to three months with a time resolution of one or two seconds. It was found that bottle-cleaning machines and stretch-blow molders are the most energy-intensive machines. The available guaranteed values for the nominal speed or the values for the installed electrical load was found to be not sufficient for a forecast as there was found a wide deviation to the measured values. The frequency distributions of the measured values showed clearly distinguishable peaks for all machines, indicating a direct correlation between the operational states and the energy consumption. Mapping of the energy consumption data and the operational state data confirmed this. It was found that the energy consumption of food-packaging and bottling machines can be described by a limited number of energy states related to the operational state. The energy states can be mapped to common models describing the operational state behavior. State changes can take place immediately or in time-dependent state transitions, resulting in a constant value after a certain time. The machine speed and product affect the energy performance, but are not appropriate for energy modeling of the machines. The basic concept of operational-state-related energy consumption can be used for future model-based forecasting of the electrical energy consumption of food-packaging and beverage-bottling machines. For a state-based modeling and simulation approach, the model can be simplified to three states (inactive, standby, and production), where each of the states can be presumed as constant.

Isabel Osterroth was responsible for the data acquisition, the development of the analysis methods, and the evaluation and verification of the database and the results of this study. Tobias Voigt was the scientific supervisor and supported the work with professional discussions and advice.

The formatting of the text has been adapted to the formatting of this thesis for better readability. The content corresponds to the original print, which was attached to this thesis as an appendix.

sustainability

MDPI

Article

Energy Consumption of Beverage-Bottling Machines

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Abstract: Sustainability is a megatrend influencing the beverage industry. Knowledge of the consumption behavior and suitable metrics are required for energy optimization strategies. Machine efficiency and energy consumption are intermixed in common parameters, e.g., customary specifications refer to the energy consumption for a specific number of products (e.g., kWh/1000 fillings). This does not reflect the influence that inevitable breakdown times have on the energy consumption (e.g., malfunction, lack, and tailback situations within the material flow). While specific energy performance indicators are useful as a benchmark, it does not provide reliable information to verify plant specifications, or to have a source-related cost allocation as a basis for a weak point analysis. In this work, energy and operational data were analyzed, in order to find a generic description of the operational-state related consumption behavior. Therefore, empirical data on the effective electrical energy and operational state data were collected on machine level of two representative bottling plants and for additional single machines. In the frequency distributions of the discrete values of the measured electrical energy data, three main peaks were found. These can be correlated to operational states such as state-related energy demand level. The change from one demand level to another was found to be reproducible.

Keywords: energy consumption; bottling; energy performance indicators

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1. Introduction

Packaging is the last step in food and beverage production and has an important influence on the product quality, shelf life, and marketing aspects. The packaging of beverages and liquid food is performed by a complex network of machines, which are interlinked with buffering transport units for primary or secondary packages (e.g., bottles and pallets) [1]. The packaging process comprises unpacking and cleaning of the packages, filling them with the product and sealing of the package, examination of the packed product, and packaging in a secondary package or transport package. The legal developments, economic, social, and technical trends, and rising energy costs have shifted the focus of industry to energy. In particular, companies working in the field of the cost-driven beverage and food industry increasingly analyze the energy and media consumption and are looking for optimization strategies. Olajire found, that despite significant technological improvements over the last years, energy consumption, water consumption, and water usage and waste remain major environmental challenges in the brewing industry [2]. The cost of energy is already an important factor in a company's cost structure in the food and beverage industry, which is why monetary considerations have an influence on this development. Recent social and political drivers (e.g., the UN Sustainable Development Goals [3]) accelerate the demand for a more energy efficient production process. The leading worldwide breweries and beverage companies have recently published ambitious targets to become carbon neutral in the nearer future (see e.g., sustainability goals of Anheuser-Busch InBev with 25% reduction in CO_2 emissions across the value chain until 2025 [4], Heineken with 0% CO_2 emission until 2030 [5], and Coca Cola with net-zero carbon emissions by 2050 [6]). Suitable tools and metrics are required to fulfill these targets.

2.4 Publication II: Energy consumption behavior of food- and beverage-packaging machines

Published as:

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Abstract

Sustainability is a megatrend influencing the beverage industry. Knowledge of the consumption behavior and suitable metrics are required for energy optimization strategies. Machine efficiency and energy consumption are intermixed in common parameters, e.g., customary specifications refer to the energy consumption for a specific number of products (e.g., kWh/1000 fillings). This does not reflect the influence that inevitable breakdown times have on the energy consumption e.g., malfunction, lack, and tailback situations within the material flow). While specific energy performance indicators are useful as a benchmark, it does not provide reliable information to verify plant specifications, or to have a source-related cost allocation as a basis for a weak point analysis. In this work, energy and operational data were analyzed, in order to find a generic description of the operational-state related consumption behavior. Therefore, empirical data on the effective electrical energy and operational state data were collected on machine level of two representative bottling plants and for additional single machines. In the frequency distributions of the discrete values of the measured electrical energy data, three main peaks were found. These can be correlated to operational states such as state-related energy demand level. The change from one demand level to another was found to be reproducible.

Keywords

- energy consumption
- bottling
- energy performance indicators
- energy consumption

1. Introduction

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1.1. Beverage-packaging technology: energy consumption of packaging machines

Beverages and liquid foods are packaged in industrial bottling plants consisting of an arbitrary number of cooperating machines and aggregates (manufacturing stations), which depend on the product and packaging type. These are all interlinked with buffering transport elements (mainly conveyors). Various containers, such as bottles (disposable and returnable bottles, PET bottles, and glass bottles), cans, barrels, or kegs, are used for packaging and for transporting different beverages (beer, wine, alcohol-free beverages, etc.). Owing to the modular design of the systems, the different requirements of beverage filling can be met by a variety of machines. According to Manger (Manger, 2008), the components of a beverage filling line are essentially the same:

- Machines unloading and loading pallets, as well as unpacking the reusable containers made of glass and plastic from the transport boxes (e.g., unloading machines, unpacking machines, and new glass slippers).

- Machines ensuring the cleaning and control of the outer packaging (e.g., crate washing machines).
- Machines ensuring the cleaning and inspection of the packaging material (returnable bottles) (e.g., bottle and empty bottle inspectors, bottle-cleaning machines).
- Machines filling and sealing the packaging (e.g., bottle filling machines with a combined capper).
- Machines labeling and checking the packing materials (e.g., labeling machines).
- Packing machines (e.g., shrink packers, palletizers).
- Conveyors for containers, packs, and pallets (e.g., chain conveyors with a drive engine).

In addition, the following are used when needed:

- Machines for bottle manufacturing (e.g., stretch-blow molders for PET bottles).
- Machines improving the biological shelf life (e.g., pasteurizers).
- Machines for cleaning and disinfection (e.g., CIP systems).
- Sorting systems of returnable containers (e.g., selective unpacking machines).
- Machines for producing soft drinks (e.g., beverage mixing and carbonizing plants).

The requirements for individual plant components are related not only to the container type and size and the packaging material (glass, PET, aluminum, or steel), but also to the beverage properties (presence of CO2 and viscosity). During the filling and packaging of the beverages and liquid foods, different media are consumed by different processes. The typical consumption of beverage-bottling, which has a significant commercial effect, includes the following:

- Electrical power and compressed air.
- Thermal power.
- Media such as cold water, lye, additives, and lubricants.

In order to operate a bottling plant, all bottling and packaging machines require electrical power, in addition to cleaning machines (bottle-cleaning machines and crate washers) and pasteurizers requiring thermal energy (see Table 2.4-1). In addition, some machines use compressed air, usually created by electrically driven compressors (mainly packers and palletizers). Water is mainly necessary for the cleaning machines of primary and secondary packaging materials (bottles, crates) and during the pasteurization process. Electrical power is usually used as the main drive for machines moving containers, drive pumps, to perform their basic mechanical functions as well as for the production of compressed air. The consumption of electrical energy is usually linked directly to the function performed. Any interruption of the function or reduction of the output power also leads to reduced consumption in electrically driven motors and pumps. Thermal energy is usually used to heat various media (e.g., heating of products, heating of the lye baths in bottle-cleaning machines, and supply of hot water). The consumption of thermal energy by a machine can be decoupled from its operational state since the media might be heated even in the case of a malfunction in the machine. Compressed air is used during beverage filling either as an energy carrier (stretch-blow molding of PET bottles, transport of empty PET bottles), for signal transmission (pusher), or for cleaning (blow-off, drying). Compressed air is a comparatively energy-intensive energy carrier and is produced using electrical power. Freshwater is usually used to clean machines and is also used in bottle-cleaning machines (cleaning of returnable containers). Other media, such as lye, belt lubricants, and additives, are used mainly in bottle-cleaning machines and during the transportation of containers.

Table 2.4-1: Energy and media consumption of bottling machines according to the minimum and order related specifications of beverage filling lines (DIN 8784: 2013-09).

	Electrical power	Compressed air	Heat	Water
Stretch-blow molder	x	x		
Depalletizer	x	x		
Unpacker	x	x		
Crate washer	x		x	x
Bottle-cleaning machine	x		x	x
Labeling machine	x	x		
Pasteurizer	x		x	x
Packing machine/tray packer	x	x		
Palletizer	x	x		

Over the last years, mainly industry associations and consulting companies have published consumption values and benchmarks. The data are predominantly related to the total production processes or single-process units (e.g., packaging). Most of the data are published as total consumption for the production or differentiated into thermal and electrical energy, which is mainly related to the product volume (e.g., 1 hl of sales beer). The cost of supplying energy to a brewery differs worldwide from 3 % to 10 % of the total budget (Canadian Industry Program for Energy Conservation, 2011; Galitsky et al., 2003; Meißner, 2003). Over the last 10 years, the required volume of water to produce 1 hl of beer decreased from 5.0–5.2 hl to 4.2–4.3 hl (Canadian Industry Program for Energy Conservation, 2011; Heuven and van Beek, 2013; Donoghue et al., 2012; British Beer & Pub Association, 2006). 16.5 %-30 % of the total heat and 12 %–35 % of the total electrical power are needed for the bottling process (Fiederer et al., 2001; Galitsky et al., 2003; Petersen, 1993b; Sattler, 2000). Hauser and Shellhammer analyzed the sustainability challenges in beer production and found, that packaging has a large share on the environmental impact of beer production (Heuser and Shellhammer, 2019). In contrast to breweries, only a limited amount of consumption data has been published for manufacturers of nonalcoholic beverages. No detailed machine-based consumption data and analyses of beverage-packaging machines have been published in the scientific literature, with the exception of one report (Schreiner, 1982) in the early 1980s. No energy data correlated to the operational state of single machines have been published either.

For in-depth analyses and optimization measures, a detailed consideration of the energy consumption on the machine level is lacking. Measurements on bottling and packaging machines in industrial applications related to this research indicated, that there is a significant difference between the installed load and the average measured consumption, which indicates a saving potential. The influence of the machine efficiency on the energy consumption is not considered in commonly used key performance indicators. This does not consider e.g., the influence of breakdown times, which, because of equipment failure, lack, and tailback situations, inevitably occur during the production. While considering the energy consumption of a defined amount of product is useful for comparison of the performance of two plants, and management decisions, it does not provide reliable information to verify specified machine-based consumption data or for a source-related cost allocation as a basis for a weak point analysis and machine, process and automation optimization. Some manufacturers started to specify a consumption level related to the nominal speed. However, consumption values for planned or unplanned stops of machines were missing in the past. With VDMA 8751:2019-03 Packaging machinery (incl. filling machinery)-Specification and measurement of energy and utility consumption (VDMA 8751:2019-03) recently a normative directive was published to close this gap.

Osterroth et al. have published a summary of bottling related energy KPIs and a survey for the German beverage bottling industry. It was found in this publication, that the available and published data are not yet detailed enough for a modeling approach (Osterroth et al., 2017a), that could be used as a tool for energy optimization of bottling plants. The available data are not suitable for any comparison, as the survey approaches and system boundaries vary a lot. No correlation between the current machine or process state and the energy consumption has been investigated, and considerations to reduce the energy and media consumption have been limited locally to individual system components or to a high-level view so far. With detailed knowledge regarding the consumption behavior and with a generic model mapping this behavior, the main consumers can be detected, identifying optimization potential in the production process, the machines and the plant automation.

1.2. Models describing the energy consumption in industrial manufacturing lines

Some models that describe the energy consumption of machines in manufacturing lines can be found in the scientific literature: Dietmair and Verl published a generic energy consumption model for decision-making and energy efficiency optimization in manufacturing for plants, machines, and components based on a statistical discrete event formulation (Dietmair and Verl, 2009). Lees et al. described a utility consumption model for real-time load identification in a brewery (Lees et al., 2009). Several fuzzy and neuronal net models have been developed for electrical load forecasting (e.g.,., Dash et al., 1998; Lertpalangsunti and Chan, 1998). One example of the use of mathematic modeling is the energy optimization of refrigeration systems in breweries. Xu et al. developed a case-based reasoning (CBR) energy consumption model for cutting periods in CNC lathes (Xu et al., 2016). Cataldo et al. worked on the modeling, simulation, and evaluation of energy consumption for a manufacturing production line (Cataldo et al., 2013). For tooling machines, a calculation method was developed by Kuhrke using "energy blocks," which are consumption patterns based on functional changes in the machine operations, comparable to operational states. For those machine tools, for mass production, a state-based model was defined, describing the detailed single phases of the production process, based on energy blocks (Kuhrke, 2011). This model was published in VDMA 34179 as a measurement instruction determining the energy and resource demand of machine tools for mass production (VDMA 34179:2015-03) and was updated in 2019 (VDMA 34179:2019-04). Braun et al. discussed a state-based energy consumption modeling approach for the example of wireless sensors and wireless local area networks, considering the consumption patterns for single states and state transitions (Braun et al., 2015). No operational-state-related consumption model has been yet published for the application of food-packaging and beverage-bottling industry. Owing to their high interlinking level and high output (up to 120,000 packages per hour), packaging and bottling machines differ from other manufacturing plants. It was found that state models from other industries cannot be transferred to bottling plants directly. Customary specifications refer to the energy consumption for a specific number of products (e.g., kWh/1,000 fillings). Osterroth et al. published a state related simulation model for bottling plants to close this scientific gap [Osterroth et al., 2017b], which is completed by the here presented data analysis. As part of this work, the energy behavior of food- and beverage packaging machines were analyzed systematically, considering the recent operational state of the machines for the first time.

1.3. Purpose

The data presented in this paper were unpublished by now, extend the existing non-sufficient database, complete the normative direction VDMA 8751:2019 and the published simulation approach and give additional insights in the state related energy consumption behavior for a larger number of considered machines. It is assumed that a detailed generic model, can be used as the basis for in-depth analysis of the consumption behavior, for identifying inefficient production times, and for conducting further research on modeling and simulation of energy consumption of food and packaging plants. The purpose of this study is to gain fundamental knowledge regarding the operational state related consumption behavior of packaging and bottling machines based on detailed empirical data from industrial plants. Detailed empirical electrical energy data on machine level shall be analyzed to identify main consumer and to provide generic statements for future modeling and forecasting approaches and optimization measures.

2. Data Acquisition

Owing to the lack of reliable data, electrical energy consumption data and operational state data of 20 machines in industrial applications were considered to characterize the consumption behavior of bottling and packaging machines in the food and beverage industry.

2.1. Acquisition of energy data

The electrical power consumption was recorded with active power meters of the highest available sample rate (1 or 2 s) as effective electrical power (kW). Depending on the technical possibilities, integrated (Janitza UMG 96RM-PN, measurement accuracy: ±0.2 %) or mobile measuring instruments (Fluke 435 II, measurement accuracy: ±1 %) were used. All active power meters were state of the art and calibrated. The measured discrete values were recorded in a MS SQL database with a timestamp.

2.2. Acquisition of operational state data

Physical machine state changes of production machines and lines can be described by established state models mainly used for machine control and automatization. Beverage bottling plants and packaging machines are generally described by some state models in scientific research and industrial application:

The American National Standards Institute (ANSI) and the Instrumentation, Systems and Automation Society (ISA) published the international standard ANSI/ISA-S 88 (ANSI/ISA 88.00.01-2010), addressing batch process control. In which models, terminology modes and states of single process unites or machines are defined. These definitions are not part of the standard but are generally defined. The model describes operating modes (automatic, semi-automatic, and manual) and operating conditions (idle, running, complete, paused, holding / held, restating, stopping /stopped, aborting /aborted). In the operating state model a focus is placed on the transitions between the final states. For the application to packaging machines a technical report is published (TR88.00.02-2015, 2015).

The “Weihenstephan Standard” defines a communication protocol, data tags to acquire relevant production data and procedures for efficiency analysis (e.g. OEE indicators, cost transparency), tracking

& tracing of batches, transport units and orders and the monitoring of production processes and the product quality . It includes a state model, describing the physical machine states with its operating mode (off, automatic, semi-automatic, manual), its program (e.g., production, start up, clean) and its operational state. The “Weihenstephan Standard” state definitions are harmonized with the definitions of the OMAC Packaging Machine Language Working Group, which has also published a uniform state model to describe the different operation states and user actions with packaging machines.

For the analysis of the production and performance of packaging and beverage bottling lines a time model is established in accordance to DIN 8743 (DIN 8743:2014-01) The machine working time t_m is defined as the theoretically available time (24 h/ 7 days a week). Deducting the idle time (e.g., weekend, holidays) the machine work time is defined. The operating time is defined as the machine working time reduced by scheduled downtimes (e.g., cleaning/ maintenance). During the machine working time breakdowns will occur due to internal and external failures. The machine running time is the working time reduced by the breakdown time. The time model is correlated with the physical machine state (see Figure 2.4-1).

<table>
<tr><td colspan="6">theoretical available time (24 hours, 7 days a week) t_T</td></tr>
<tr><td colspan="5">machine working time t_W</td><td rowspan="4">idle time
▪ idle
▪ undefined</td></tr>
<tr><td colspan="4">operating time t_O</td><td rowspan="3">scheduled down time t_D
▪ cleaning
▪ chanceover
▪ maintenance
▪ repair</td></tr>
<tr><td colspan="3">running time t_R</td><td rowspan="2">unplaned down time t_F
▪ failures
▪ lack
▪ tailback</td></tr>
<tr><td>quality time t_Q</td><td>scrape time t_{LQ}</td><td>performance loss time t_{LP}</td></tr>
</table>

Figure 2.4-1: Time model according to DIN 8743 (DIN 8743:2014-01) and example states (grey).

The state data was collected time discrete every second or every two seconds by the manufacturing execution systems (MES) in accordance with the industrial “Weihenstephan Standard” based on the time model according to DIN 8743 (DIN 8743:2014-01). If no MES was available the data was collected by the Weihenstephan Test Tool, collecting the state information directly on the PLC of the machine or manually (handwritten notes). The state data was recorded event discrete with a start time and an end time of the state. The state information is based on a state model and indicates whether a machine is producing (operating state “operating”) or waiting to produce in a suspended state due to an internal cause (“failure”, “held”, “emergency stop”) or external cause (“lack”, “tailback”, “idle”, “prepared”). There was no data available for the machine mode (on/ off) and program (e.g., “Production”, “Maintenance”, “Cleaning”). The state information can be assigned to time intervals in accordance with the time model of DIN 8743 (DIN 8743:2014-01). Before analyzing the state data, the correct acquisition of the machine states was verified at least three times for each state by checking the state information in the recording database in parallel with the actual machine behavior. The data acquisition system does not record information about the states of the bottle, crate and pallet conveying systems and the inspection machines. It is for this reason, that they were not considered in this work.

2.3. Considered bottling plants and data

To get representative data five bottling plants using typical packaging types (returnable glass and PET bottles) and products (water, soft drinks and beer) were considered for the data analysis. All machines of two bottling plants were analyzed, for the other ones only the main consumer (bottle cleaning machine or stretch-blow moulder) were taken into account. Additionally, a packaging machine for tray packs was analyzed having a control machine from a different packaging application. The following Table 2.4-2 shows a summary of the bottling plants.

Table 2.4-2: Summary of data acquisition on the considered packaging machines.

	Electrical consumption data	Sample rate	State data	Number of machines	Packaging type	Product
Bottling plant 1	active power meter, integrated	2 s	MES	10	Returnable glass bottle	water, soft drinks
Bottling plant 2	active power meter, integrated	2 s	WS Test Tool	9	PET bottle (single use)	water, soft drinks
Bottling plant 3	Active power meter, mobile	1 s	MES	1	Returnable glass bottle	beer
Bottling plant 4	Active power meter, mobile	1 s	manually	1	Returnable glass bottle	water, soft drinks
Bottling plant 5	Active power meter, mobile	10 s	manually	1	PET bottle (single use)	water, soft drinks
Packaging machine A	Active power meter, mobile	1 s	manually	1	Tray packs	Various

3. Results

3.1. Development of analysis methods

For the in-depth analysis of the measured energy consumption data of packaging and bottling machines the frequency distribution of the measured discrete effective electrical power values was plotted as histograms for every single machine (see Figure 2.4-2). The class width of the histogram was defined depending on the number of the single values and the distribution. It was assumed, that peaks represent a so-called energetic demand level. As the height of the peaks is assumed to be the result of the ma-chine use (occurring operation states) during the measurements, the peaks were qualitatively evaluated.

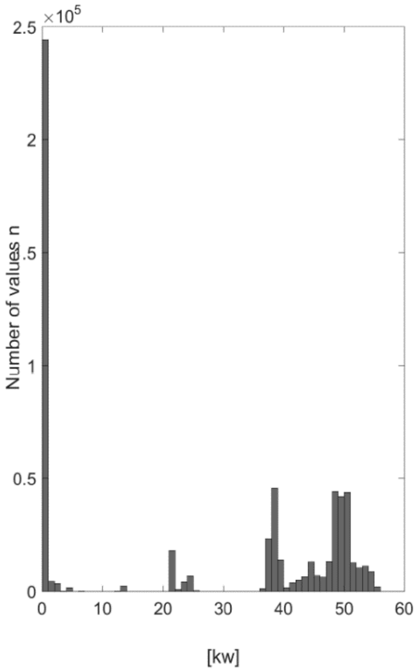

Figure 2.4-2: Example of frequency distribution of the measured discrete effective power values.

The first analysis results plotting the electrical energy and the occurring operational states indicated a correlation between the consumption and the operational states (see Figure 2.4-3).

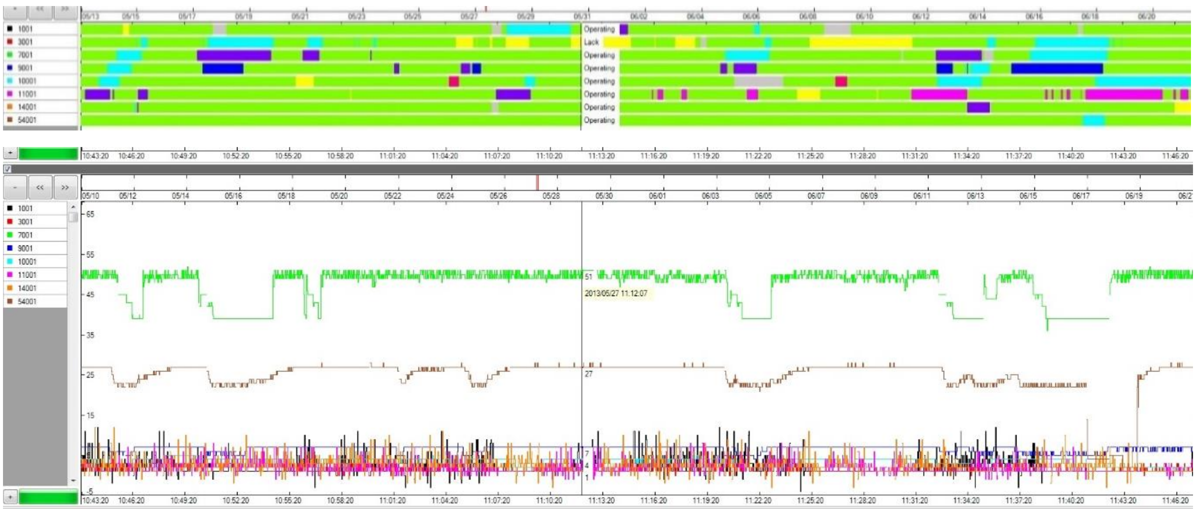

Figure 2.4-3: Example of the measured effective electrical energy raw data and empirical operational state raw data plotted over time for different machines (Machine ID: 1001, 3001, etc.).

For the purpose of illustration and analyzing the correlation between the energy consumption and operational states, a diagram was developed, showing the measured effective electrical power plotted as a time-discrete 2D line plot with colored event-discrete intervals (areas) in a background layer representing the occurring operational states. The boundaries of the intervals are described by the start time and end time of the operational state ([start_time$_{\text{state n}}$; end_time$_{\text{state n}}$], see Figure 2.4-4). Therefore, every defined operational state was assigned a color (see Table 2.4-3). Similar operational states were summarized to one color, for example, *lack* and *lack in branch line*.

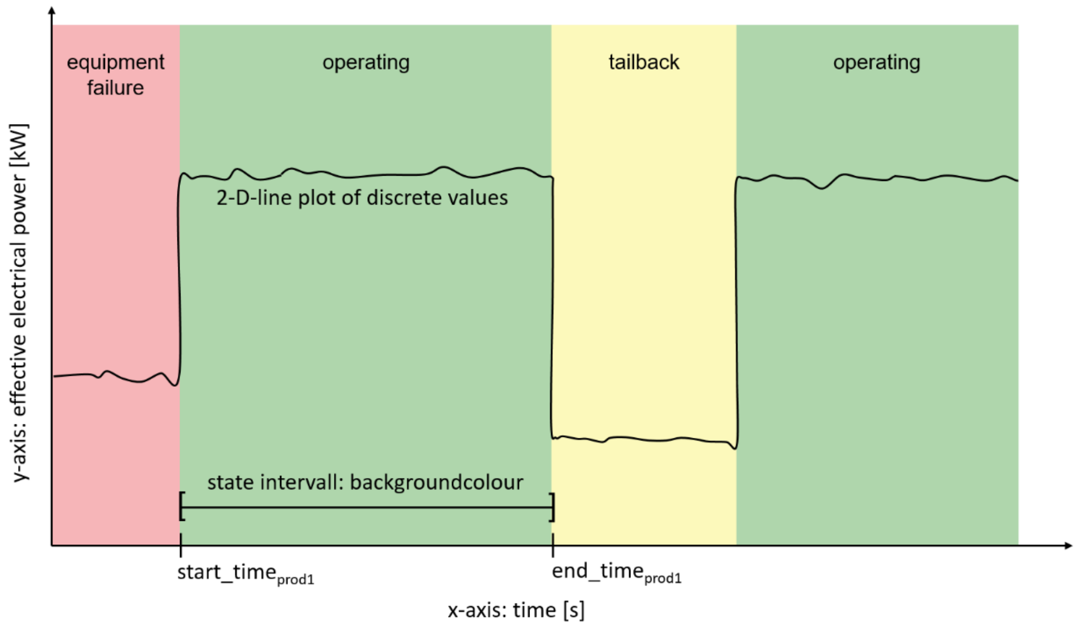

Figure 2.4-4: Example plot for evaluating the correlation between the operational state and energy consumption.

Table 2.4-3: Operational states and related background colors in the plot.

Operational state	Color coding
Prepared	Orange
Lack	Blue
Tailback	Yellow
Lacking branch line	Blue
Tailback branch line	Yellow
Operating	Green
Equipment failure	Red
External failure	Dark orange
Held	Grey
Idle	Grey

3.2. Electrical energy consumption of packaging and bottling machines

For the considered bottling plants, the average consumption for single machines was calculated. Owing to the limitations in the available measurement instruments, no data on the conveyor system of the returnable glass bottling plant were available. For the PET bottling plant, the total value of the bottle conveyor and the total value of the pallet transport were available.

3.2.1. Selected absolute consumption values on the example of a PET bottling plant (Plant 2)

Table 2.4-4 shows the selected measured electrical energy consumption for all considered machines on the example of the PET bottling plant (Plant 2) for three time periods of 24 h each during a production phase. The stretch-blow molder was identified as the main consumer with an average consumption of 157 kW, which is more than 50 % of the total consumption of the line (245 kW on average). The conveyor systems had an average consumption of 6 % of the total consumption (4 % for the bottle conveyor and 2.2 % for the pallet conveyor).

Table 2.4-4: Measured electrical energy consumption for the example of a PET bottling plant for three time periods of 24 h each, sorted by main consumers.

	$\sum t_1$ [kWh]	$\sum t_1$ [kWh]	$\sum t_1$ [kWh]	Avg. Consumpt. [kW]	Standard deviation [kW]	Share [%]
Stretch-blow molder A	3,019.0	4,281.0	3,998.6	156.9	22.5	64
Labeler A	343.6	449.7	513.2	18.1	2.9	7.4
Shrink packer A	326.1	448.5	446.6	17.0	2.4	6.9
Cooler A (stretch-blow molder) A	267.6	385.9	373.6	14.3	2.2	5.8
Palletizer A	259.2	365.8	356.3	13.6	2.0	5.6
Conveyor (bottles) A	189.2	258.8	254.4	9.8	1.3	4.0
Filler A	157.8	203.7	200.2	7.8	0.9	3.2
Conveyor (pallets) A	107.0	141.9	135.5	5.3	0.6	2.2
Handle application A	46.9	62.2	61.2	2.4	0.3	1.0
Conveyor belt lubrication A	1.2	1.3	1.3	0.1	<1	<1
Preform feed A (stretch-blow molder) A	1.2	1.2	1.2	0.1	<1	<1
Total consumption, 24 h	4,718.8	6,600.0	6,342.0	245.3		

Figure 2.4-5 shows a comparison of the installed load and the specified consumption for nominal speed as well as the measured average consumption and the consumption during production times for the example of the selected machines of bottling plant 2. The figure shows a wide range between the specified values and measured values. For the stretch-blow molder and filler block including the cooler and preform feed, less than 50 % of the installed load was measured. Peak loads were not found with this interval of measurement (one value per second).

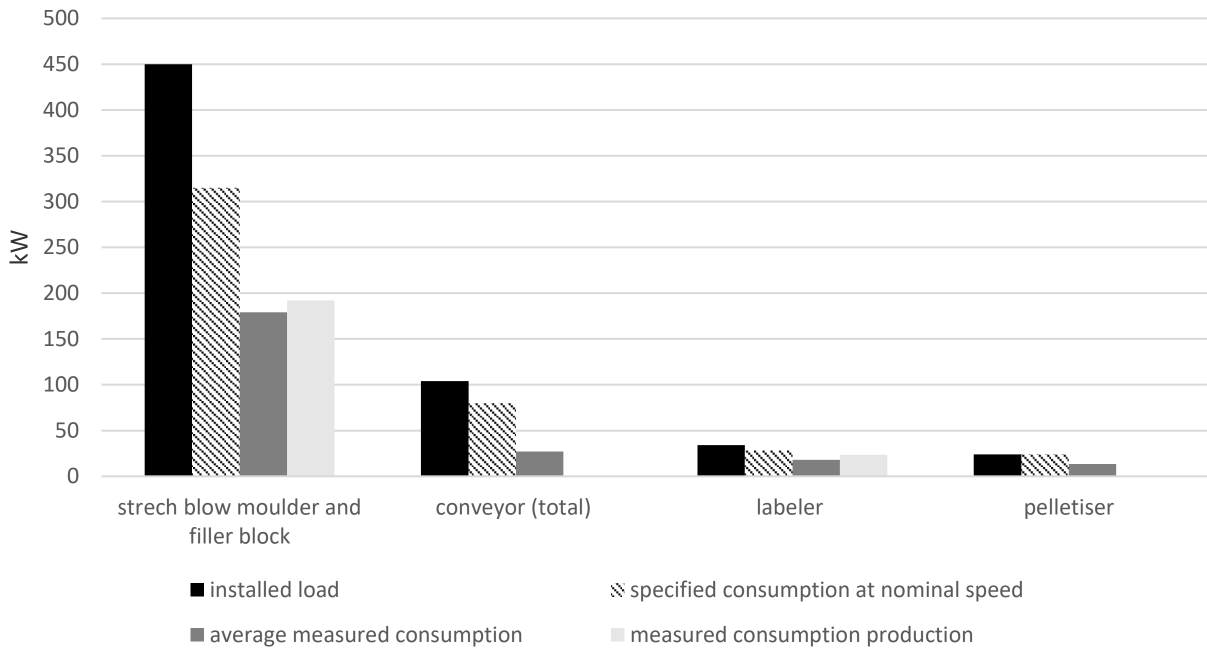

Figure 2.4-5: Installed load, consumption nominal speed, measured average consumption, and measured consumption during production.

Additionally, the energy consumption during longer unproductive times (e.g., weekends) was analyzed. Table 2.4-5 shows a summary of the average measured consumption during a time period of >24 h as well as the percentage of consumption compared to the average value. While the main consumer, stretch-blow molder, has a low percentage of consumption during these times, the labeler and the filler have a higher percentage of consumption during these times. For the stretch-blow molder, the filler's and the labeler's detailed operational state data were available.

Table 2.4-6 summarizes the specific energy consumption for those machines for a time period of one production week and specifies the occurring operational states as well as the consumption during these times.

Table 2.4-5: Measured average power consumption during an unproductive time period of >24 h.

	Average consumption [W]	Standard deviation [W]	[%] of average consumption
Labeler	4,112	2,341	33
Filler	2,020	385.1	16
Stretch-blow molder	1,715	62.4	14
Conveyor (pallets)	1,082	25.4	9
Conveyor (bottles)	1,058	465.7	9
Handle application	1,024	836.4	8
Palletizer	581	2.7	5
Handle application	407	3.4	3
Cooler (stretch-blow molder)	231	4.8	2
Preform feed (stretch-blow molder)	49	1	<1
Conveyor belt lubrication	48	1.6	<1
Total consumption	12,327		

Table 2.4-6: Specific energy consumption of the main consumer for a time period of one week and an analysis of the consumption related to the operational behavior of the machines. No state data are available for the shrink packer and palletizer.

	Stretch-blow molder		Filler		Labeler	
	[h]	[Wh/ 1000 bottles]		[Wh/ 1000 bottles]		[Wh/ 1000 bottles]
Production	119	4,290.2	117	212.8	121	581.6
Prepared	4.6	12.4	5.2	8.1	3.5	3.3
Lack	0.1	1.3	0.0	0.0	4.6	4.4
Tailback	6.8	145.8	7.8	9.9	4.8	4.6
Equipment failure	8.1	195.6	4.9	6.5	2.5	2.2
Held	29.2	48.7	33	37.4	31.7	25.2
Total		4,694.0		274.8		621.2
Availability of the machine		71.0 %		69.8 %		72.0 %

Figure 2.4-6 shows the typical consumption structures for a PET bottling plant (A) for single-use bottles and a glass bottling plant (B) for returnable glass bottles. The main consumers of these types of bottling plants are the stretch-blow molders (PET) and the bottle-cleaning machines (glass).

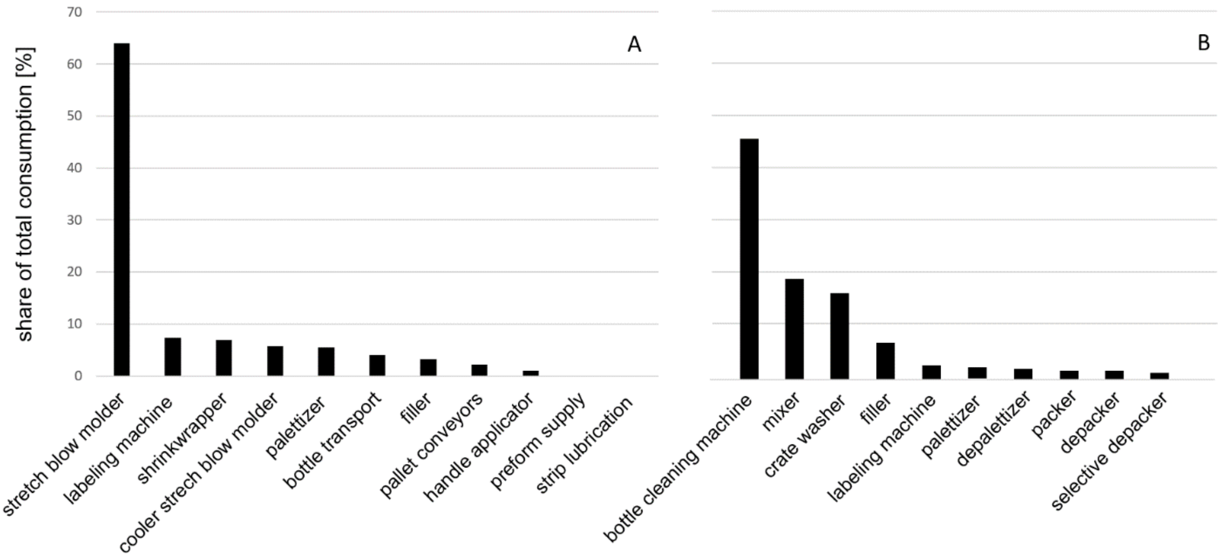

Figure 2.4-6: Consumption structure of a PET bottling plant (A) and a glass bottling plant (B). Own measurements for *n* = 1 production line of each type, showing the main consumers: stretch-blow molders and bottle-cleaning machines. The average consumption of the stretch-blow molder is 157 kW, whereas that of the bottle-cleaning machine is 49 kW.

3.2.2. Discussion of the absolute consumption values

Both considered lines have a main consumer, which has a significant share on the total consumption of the total bottling plant (stretch-blow molder: >60 % for PET bottles; bottle-cleaning machine: >45 %), which should be the focus of optimization considerations.

The installed load and the specified consumption differ from the measured consumption during production times by up to 60 %. The common considerations using these values for an estimation of the energy consumption will have a limited accuracy. For optimization purposes and business decision criteria, these values should be verified by measurements of the actual consumption. For modeling and forecasting of the energy consumption, the implemented parameter should be verified at least by single measurements on the considered plant.

It was found that there is a correlation between the consumption behavior (see, e.g., Table 2.4-6) and the occurring operational states. A simple consideration of the specified consumption values will not result in an accurate forecast, as measurements have proved a deviation to the actual consumption value. The availability of the machine, defined as the share of production time to the total time, and the resulting differing consumption during the occurring operational states will influence the specific energy consumption. Therefore, in the following chapter, the operational-state-related energy consumption behavior will be analyzed in order to provide a reliable analysis of the influence of the operational state and the detailed characterization of the consumption behavior.

The energy consumption of the conveyor elements was measured to be 6.2 % of the total consumption for the PET bottling plant and should ideally be considered in future measurements. Owing to the large number of single drives, the measurement requires some effort. If possible, the measurement can be summarized to one or two areas. Because of the limited number of devices for measurement, no values are available for the returnable glass bottling plant in this work.

3.3. Operational-state-related energy consumption behavior

3.3.1. Analysis of empirical energy consumption data in correlation to operational state data

For all machines, the frequency distributions of the measured discrete effective electrical power values (kW), plotted as histograms, were analyzed. The following figures show an example of a bottle-cleaning machine, which is one of the main consumers in the bottling process for returnable glass bottles according to the measurement shown in Figure 2.4-6.

Figure 2.4-7 shows the measured discrete effective electrical power values, plotted as a histogram, for 42 days of measurement. Three main peaks were identified. Peak 1 indicates low consumption, which is significantly larger than Peaks 2 and 3. This is the result of the longer idle times (weekends, nights) during the measurement. Peak 2 shows reduced consumption and Peak 3 shows the highest consumption in kilowatt. The peaks are not all clearly delineated, but they are merged into each other (Peaks 2 and 3).

While comparing the consumption patterns of the machines shown in the 2D line plots of the effective power data with colored state information in the background and a detailed frequency distribution histogram (right part of Figure 2.4-8), a correlation between the identified peaks and the operational states can be proven. Figure 2.4-8 shows the details of the 2D line plot mapping the electrical energy consumption pattern of production time interrupted by a tailback, lack, or equipment failure situation for a bottle-cleaning machine (Machine A). The effective electrical power value changes with the operational state changes of the machine.

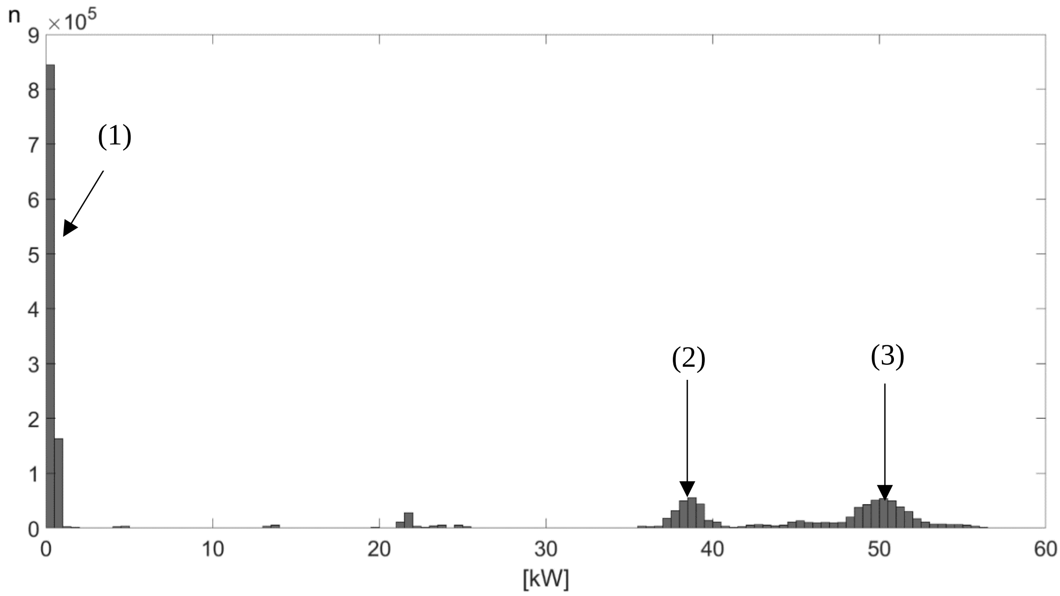

Figure 2.4-7: Histogram of the measured effective electrical power data of bottle-cleaning machine A over a period of 42 days: three main peaks (Peaks 1, 2, and 3).

The two peaks in the histogram (Figure 2.4-7 and Figure 2.4-8, left) fit the value of the almost constant performance level that the machine reaches after a state change. Different types of peaks related to the running times (see the time model in Figure 2.4-1) were found for the machines. The peaks of the machines with a steady operational behavior (bottle filling machines, bottle-cleaning machines, thermoforming machines, etc.) were high and narrow, whereas they were flat and extended for cycling and intermittently operating machines (packer, palletizer) (see the example of the unpacker in Figure 2.4-9).

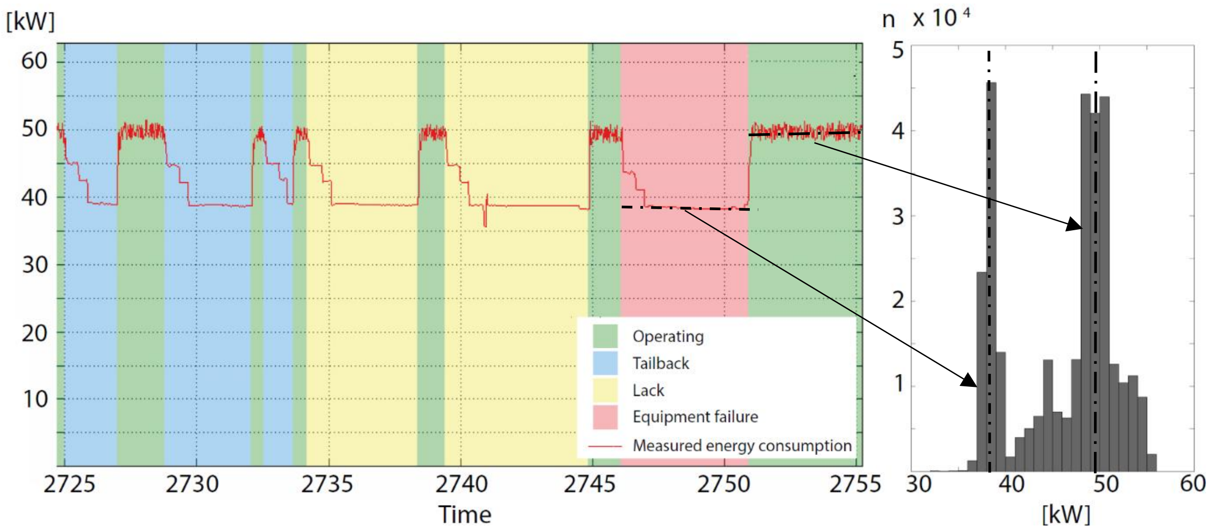

Figure 2.4-8: Bottle-cleaning machine A. Details of a typical consumption pattern and related operational states (left) and a histogram of the measured values for the operating time (a time period of 14 days, right in the figure) adapted from (Osterroth et. al, 2017b).

Figure 2.4-9 shows the frequency distribution histogram for an unpacking machine. Figure 2.4-10 shows the correlation between the histograms and 2D line plots for the unpacker. The alternating values for the effective electrical power during the operational state operating resulted in a flat and extended peak.

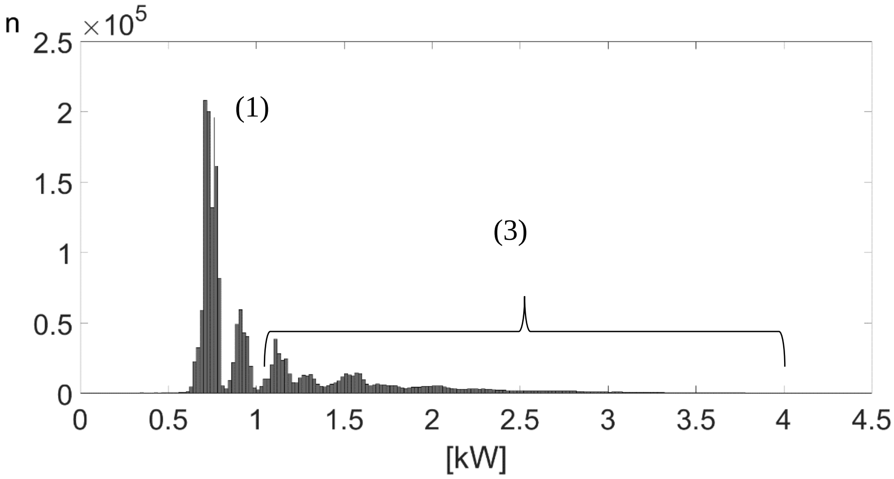

Figure 2.4-9: Histogram of the effective electrical power data of the intermittently operating machine (unpacker) over a period of 14 days: three main peaks with one flat and extended peak (Peak 3) between 1 and 4 kW.

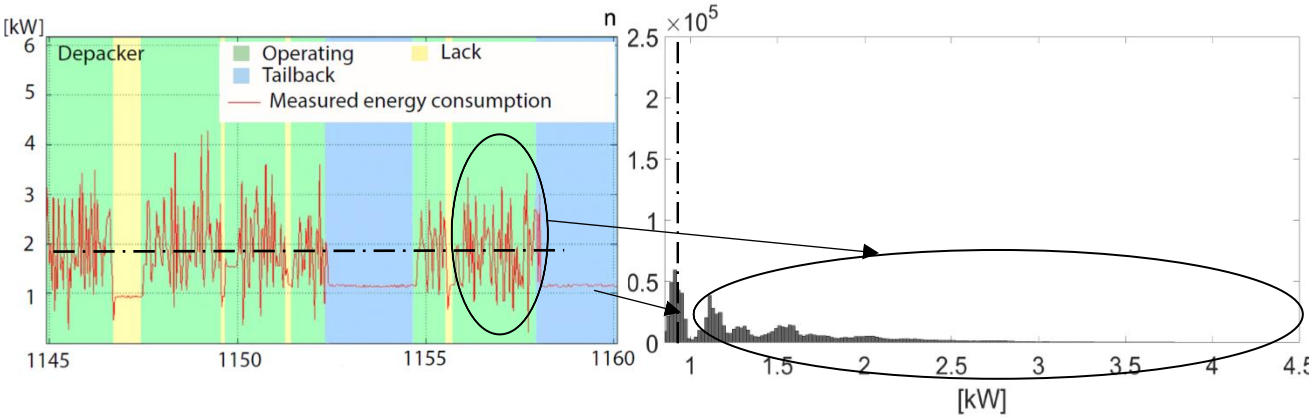

Figure 2.4-10: Unpacker A. Details of a typical consumption pattern and related operational states (left) and a histogram of the measured values for the operating time (right).

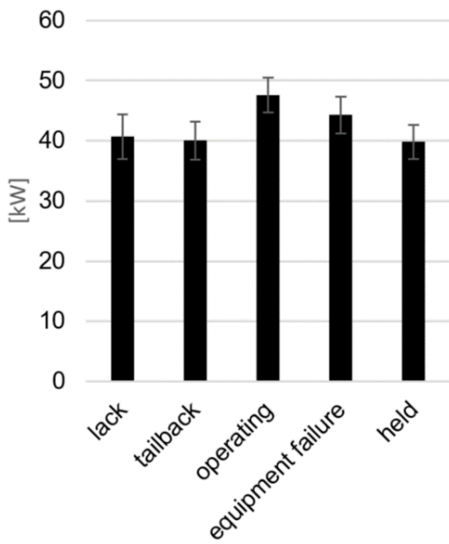

Figure 2.4-11: Average effective power (kW) and standard deviation (kW) for occurring operational states for bottle-cleaning machine A over an example time period of *t* = 4 h.

"Lack," "tailback," "equipment failure," and "held" show similar values in the consumption pattern. This could be verified in a more detailed analysis of the consumption behavior during the single states. Figure 2.4-11 shows the average values of the effective power of single states for an example time period of 4 h. No significant difference between the total consumption values of "lack" and "tailback" was found. The occurring equipment failures were shorter than any lack and tailback situation in this time period. As illustrated in Figure 2.4-8, the value of effective power decreases depending on the time of the chance until a constant value is reached. Owing to the short duration of the state equipment failure, the lower constant value of effective power was not reached. This resulted in a higher average effective power value. Any differences were due to the fact that equipment failure is shorter than lack/tailback events. For all other investigated machines, besides the mixer, clearly definable peaks were found. The number of peaks identified and the description of the peaks for all machines are summarized in Table 2.4-7. A minimum of two peaks were found for all machines. For most machines, three main peaks were found.

Table 2.4-7: Analysis of the consumption peaks of the considered machines.

Plant	Machine	Main peaks	Correlation to the operational state
Bottling plant 1	Depalletizer	3	(1) Related to inactive times (2) Related to downtime, multimodal peak (3) Extended peak, related to running time
	Unpacker	3	(1) Related to inactive times (2) Related to downtime, multimodal peak (3) Extended multimodal peak, related to running time, not clearly defined (see the example in Figure 2.4-19 and Figure 2.4-110)
	Selective depacker	3	(1) Related to inactive times (2) Multimodal peak, related to downtime (highest peak due to extended downtimes) (3) Related to running time, extended peak
	Bottle-cleaning machine	3	(1) Related to inactive times (2) Minor peak related to heating-up processes, main peak related to running time (3) Related to operation
	Filler	(3)	(1) Multimodal peak, related to inactive times (2) Related to downtime, multimodal peak (3) Related to running time *Note*. The speed of the machine was reduced resulting in a reduced energy consumption for >1 min after the beginning of a downtime due to technological reasons (emptying of the machine). This results in a multimodal peak (2)
	Labeler	3	(1) Multimodal peak, related to inactive times (2) Multimodal peak, related to downtime (3) Related to running time, extended peak
	Packer	3	(1) Related to inactive times (2) Related to downtime (3) Related to running time, extended peak
	Mixer	3	No direct correlation found

Plant	Machine	Main peaks	Correlation to the operational state
Bottling plant 1	Palletizer	3	(1) Related to inactive times
	Palletizer		(2) Related to downtime
			(3) Related to running time, extended peak
	Crate washer	2	(1) Related to inactive times/downtime
			(2) Related to running time
Bottling plant 2	Stretch-blow molder	3	(1) Related to inactive times
			(2) Related to downtime
			(3) Related to running time
	Labeler	3	(1) Related to inactive times
			(2) Related to downtime
			(3) Related to running time
	Shrink packer	4	(1) Related to inactive times
Bottling plant 2	Shrink packer		(2) Related to downtime
			(3) Related to downtime
			(4) Related to running time
	Packer	3	(1) Related to inactive times
			(2) Related to downtimes
			(3) Related to running time
	Filler	(3)	(1) Related to inactive times, multimodal peak
			(2) Related to downtime, multimodal, not clearly defined
			(3) (a, b, c) Three main peaks all related to running time, different products with different machine speeds produced on the machine during the measurement time.
	Handle application	3	(1) Related to inactive times
			(2) Related to downtime, multimodal peak
			(3) Related to running time
Bottling plant 3	Bottle-cleaning machine	3	(1) Related to inactive times
			(2) Minor peak related to heating-up processes, major peak related to downtime
			(3) Related to running time

Plant	Machine	Main peaks	Correlation to the operational state
Bottling plant 4	Bottle-cleaning machine	3	(1) Related to inactive times (2) Minor peak related to heating-up processes, major peak related to downtime (3) Related to running time
Bottling plant 5	Stretch-blow molder	2	(1) Related to downtime (2) Related to running time *Note*. The measurement time was only 8 h; no inactive times were considered.
Packaging machine A		2	(1) Related to inactive times, related to downtime (2) Related to running time *Note*. The measurement time was only 8 h; no inactive times were considered. There was no significant change in consumption owing to the variation of materials/production parameters.

3.3.2. Consumption behavior during state transitions

Evaluating the frequency distributions of the packaging and bottling machines, it should be noted that the observed peaks are not clearly distinguished, but rather they merge into each other. The measured data shows some machine state changes taking place immediately (e.g., packer). On the other hand, in fillers or bottle-cleaning machines, the states change stepwise by state transitions according to the machine's function (e.g., bringing the product out of the machine, stepwise switching of the pumps for technological reasons; see Figure 2.4-12). State transitions are reproducible, as shown in the example in Figure 2.4-12 for two machines and 20 state transitions (change from *operating* to *equipment failure*). No significant correlation was found between the duration of a downtime (0–180 s) and the energy consumption within the first 60 s of the following running time (see Figure 2.4-13). The measurement methods have been shown to be unsuitable for short-term peak loads resulting from the powering up.

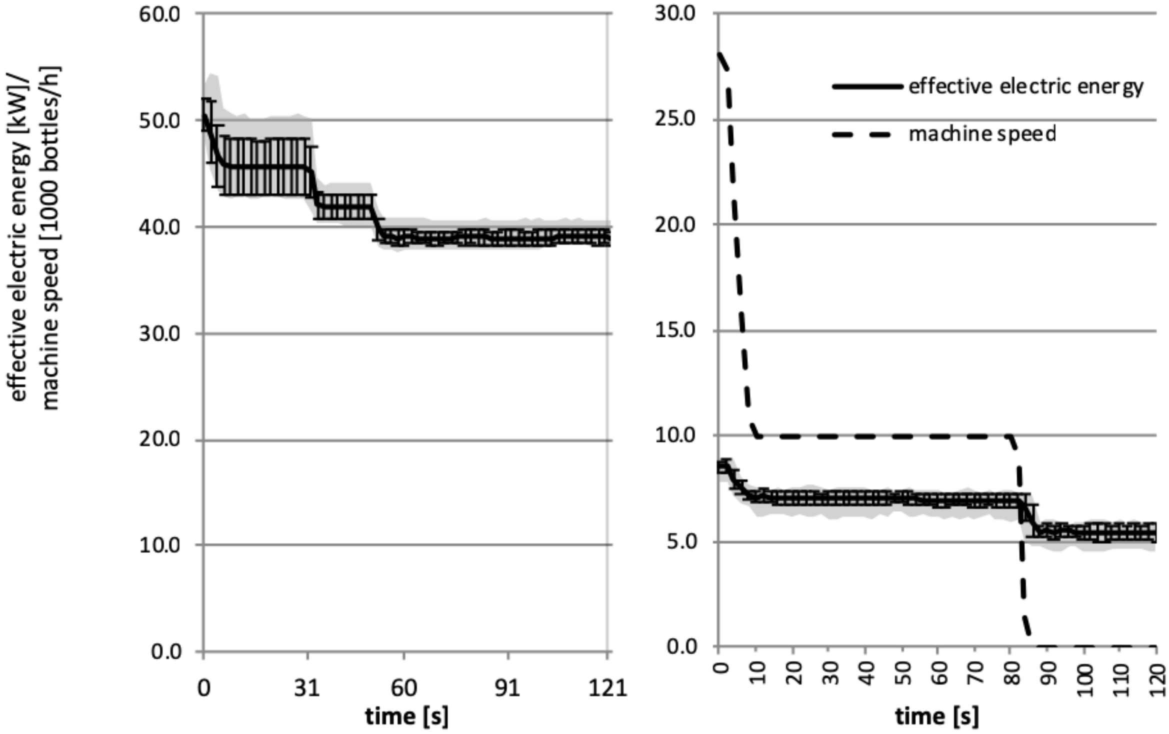

Figure 2.4-12: Reproducible state transition from operating to equipment failure for *n* = 20 chances: average of the effective electrical energy, standard deviation, and maxima and minima (gray) of the measured values for a bottle filling machine (right) and a bottle-cleaning machine (left).

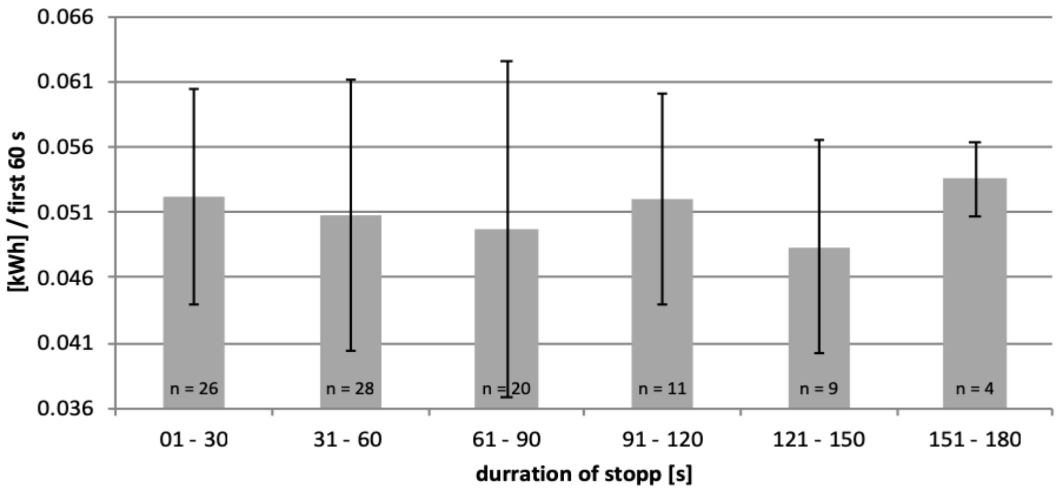

Figure 2.4-13: Average effective consumption (kWh) over the first 60 s of production, as well as the standard deviation (kWh) sorted by the duration of the downtime before the measurement of a labeling machine. No significant correlation between the duration of the stop and the energy consumption within the first 60 s of production was found.

Figure 2.4-14 shows the influence of the machine speed on the energy consumption. While the machine speed was reduced by more than 60 % in the first step of state transition, the energy consumption only reduced by 17.5 %. In the second step, the machine speed was further reduced to zero, but still more than 60 % of the initial energy was consumed by the machine. The influence of the machine speed on the electrical energy consumption is machine-specific, as it depends on the type of consumer within the machine (e.g., electrical drives, pumps, or compressed air), which is not necessarily correlated to the machine speed.

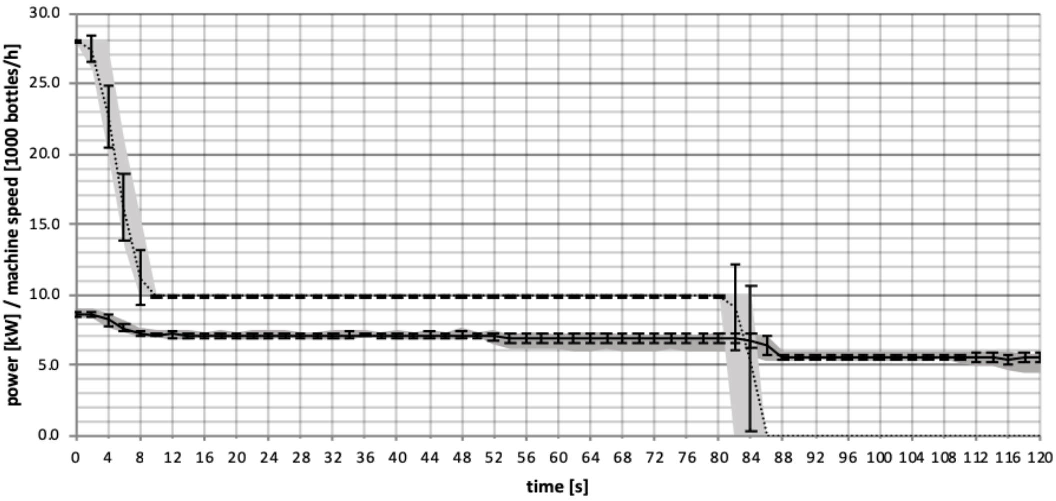

Figure 2.4-14: Bottle filling machine 1. Reproducible machine speed and influence on the consumption behavior after state transitions from production to equipment failure (*n* = 20 state transitions). A machine speed reduction of −64 % results in a reduction of effective electrical power of −17.5 %.

3.3.3. Discussion of the operational-state-related energy consumption behavior

The measured effective electrical energy data proves a correlation between the consumption behavior and the machine's operating state. An operational-state-related approach to modeling suits all machines well, except for mixers. A mixer, showing defined peaks in the frequency distribution not directly matching the operational states, is a process machine influenced by the upstream production process and cannot be described by the same models as processing packaging and bottling machines. All other machines analyzed showcased a limited number of peaks in the frequency distribution of the measured consumption values. Correlating the frequency distributions with the colored 2D line plots showed an energy demand level matching the changing operational states. Some machines show multimodal peaks, which can be related to single states (mainly to downtimes). The multimodal frequency distribution peak indicates a machine-specific shutdown behavior. In order to create a detailed description of the machine consumption behavior, state changes in accordance with the elapsed time can be utilized. State changes take place as state transitions. They can be described as reproducible. The time after a state change also influences the level of effective electrical power and can be used to describe the behavior during state changes. For extended modeling (e.g., for simulation cases), the duration of transitions can be determined by data analysis or from the PLC.

The measurements show the operational state being a major influence on the energy consumption of packaging and bottling machines in contrast to the machine speed. Machine speed is directly correlated to the operational state but is not suitable for the modeling of the consumption behavior, as shown in Figure 2.4-14. This is the result of machine-specific components requiring electrical power, and this is not directly linked to the machine speed. The number of peaks is similar no matter what product was used; however, their position shifts (in kilowatt). Therefore, the product and process conditions do not influence the state dependency, but only the value of the energy level. In order to characterize the energy consumption behavior, the system boundaries, including the nominal speed of the machine, have to be defined, as well as the reference product and process.

4. Summary and Outlook

PET and returnable glass bottling plants both have a main consumer significantly influencing the total consumption (bottle-cleaning machines and stretch-blow molders). Based on the results, it can be said that the energy consumption of food-packaging and bottling machines is described by a limited discrete number of energy states related to the operational state. The product type produced by the machine might influence the discrete value of the described energy states and can be considered as a parameter in modeling approaches. The observed energy states can be mapped to common models describing the operational state behavior and are comparable for all the considered machines. State changes can take place immediately or in time-dependent state transitions, resulting in a constant value after a certain time. The machine speed is not directly correlated to the energy consumption and therefore not suitable for energy modeling of the machines. The basic concept of operational-state-related energy consumption can be used for future model-based forecasting of the electrical energy consumption of food-packaging and beverage-bottling machines. The consumption values during non-productive times are still high and should be analyzed in more detail for optimization purposes in future research. Potential technical and technological changes, as well as changes in the plant automation might lead to reduced energy demand during down times, supporting the ambitious industry targets on sustainability. For a state-based modeling and simulation approach, it is assumed, that for most machines a model can be simplified to three main consumption states (inactive, standby, and production). The described energy demand level can be regarded as nearly constant. Furthermore, a state-related model can be used for cause-related energy analyses (e.g. to find energy optimization potentials related to downtimes) and future specifications of machines (e.g. decision criteria for improved total cost of ownership considerations). Future research can focus on operational-state-related modeling and forecasting in order to develop complex optimization strategies taking both into account, the operational state behavior of the interlinked plants and the specific energy behavior of the single machines in the system.

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2.5 Summary of Publication III: Operational-state-related modeling and simulation of the electrical power demand of beverage-bottling plants

This publication presents a generic machine and state-based consumption model of interlinked production lines on the example of a beverage-bottling plant in order to forecast the electrical energy consumption under consideration of its operational behavior. A mathematical model was developed for the consumption behavior considering the results of an empirical data analysis. The energy consumption is described by a defined energy demand level (DL) correlated to the operational states of a machine and state transitions taking place with a limited number of constant intermediate levels (ILs). The generic model was implemented in computational models using the simulation software MATLAB Stateflow. A model was parametrized for the example of a beverage-bottling plant using parameters calculated from an empirically measured industrial energy consumption dataset. Additional operational state data in a high level of detail (one value per second) from the same plant were provided by a historical record via a standardized Open Database Connectivity (ODBC) interface from an MS SQL database. Model validation was performed as a statistical validation and visual validation based on empirically measured data not used for parametrization. The Theil's index was found to be below a critical value of 0.4 for all the considered machines of a bottling plant. A total deviation of [0.3, 4.3] % for a 95 % confidence interval ($\alpha = 0.05$) for three validation runs of 14 days each for the total line was calculated, showing the validity of the model.

Isabel Osterroth was responsible for the data acquisition, evaluation, the modeling concept, the simulation model, and the validation concept of the model. Severin Klein supported this work during his master's thesis with simulation architecture and validation studies. Christoph Nophut supported this work with simulation tools and professional discussions. Tobias Voigt was the scientific supervisor of this work, with his role as a leader of the research team "Plant Engineering and Information Technology". He supported this work with professional discussions and advice.

The formatting of the text has been adapted to the formatting of this thesis for better readability. The content corresponds to the original print, which was attached to this thesis as an appendix.

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Operational state related modelling and simulation of the electrical power demand of beverage bottling plants

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ABSTRACT

Modern food companies focus on green value. While modelling and simulation methods for the prognosis and optimisation of the production efficiency of bottling plants are well-established and published, applicable state based models for the energy demand are missing. To close this gap this study presents an enhanced modelling and simulation approach for the electrical energy demand of food packaging machines and plants. It follows the hypothesis, that the electrical energy demand of bottling machines may be represented by a limited number of discrete energy demand levels correlating to their current operating states. A generic model was found defining energy demand level (DL), state transitions taking place through a finite number of constant intermediate level (IL) and a generic mapping to the operational states. Constant demand levels were parameterised empirically using operational state and active power data collected during a three month period in industrial bottling plants. For plants in the food and beverage industry electrical energy saving potentials up to 35% are expected. The presented simulation model was validated using industrial plant state data and measured power demand values. As Theil's index was found to be below a critical value of 0.4 for all machines and the total line and the total deviation for the total line with a 95%-confidence interval [0,3; 4,38] for $\alpha = 0{,}05$ for three validation runs of each fourteen days the simulation was found satisfactory for analysing electrical energy optimisation strategies in a future application.

1. Introduction

The food and beverage industries have been characterised by high demand and steady international growth over recent years. The global beverage market in particular is expected to expand further (see Fig. 1). According to a recent study, the global bottled water market alone was valued at approximately 170 billion USD in 2014 and this is expected to rise to approximately 280 billion USD by 2020 (MarketResearchStore, 2015).

The low profit margins in most sectors of the international beverage industry, the need for highly efficient processes, energy price increases and the growing awareness of environment issues have resulted a drive for SUSTAINABILITY in food and beverage production: recycling technologies (especially PET-recycling), reduced weight packaging, intelligent and innovative processes, reduced usage of energy and resources, innovative plant control and demand-optimized systems are increasingly the focus of R&D activities and industry (Olsmats and Kaivo-oja, 2014).

1.1. Packaging plants

The packaging process is the last highly automated step of modern food and beverage production. It is performed in high-performance packaging lines which involve various machines interlinked with buffering transport elements. For beverages, bottling lines are used for different types of containers: returnable, non-returnable glass bottles, polyethylene terephthalate (PET) bottles and cans. Depending on the type of container, machines for depalletising, depacking, cleaning and control of the containers, filling/capping/labelling of the containers, packing, palletizing and transporting are required (Manger, 2008). The design of a typical bottling plant for returnable glass bottles is shown in Fig. 2. For PET bottle production, a stretch blow moulder for producing the bottles directly before filling and optionally a shrink packer are also necessary.

Depending on the machines being used, different types of energy are consumed, as Table 1 shows for a returnable glass bottling plant. All the machines in a bottling plant require electrical power. In addition, a supply of heat for the cleaning machines and, if

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2.6 Publication III: Operational state related modeling and simulation of the electrical power consumption of food packaging plants

Published as:

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Keywords

energy demand forecast; beverage bottling; energy state modeling; simulation; electrical demand

Highlights

- Energy states related to operational states
- Validated simulation model for bottling plants
- Forecast of the electrical energy demand in bottling machines

1. Introduction

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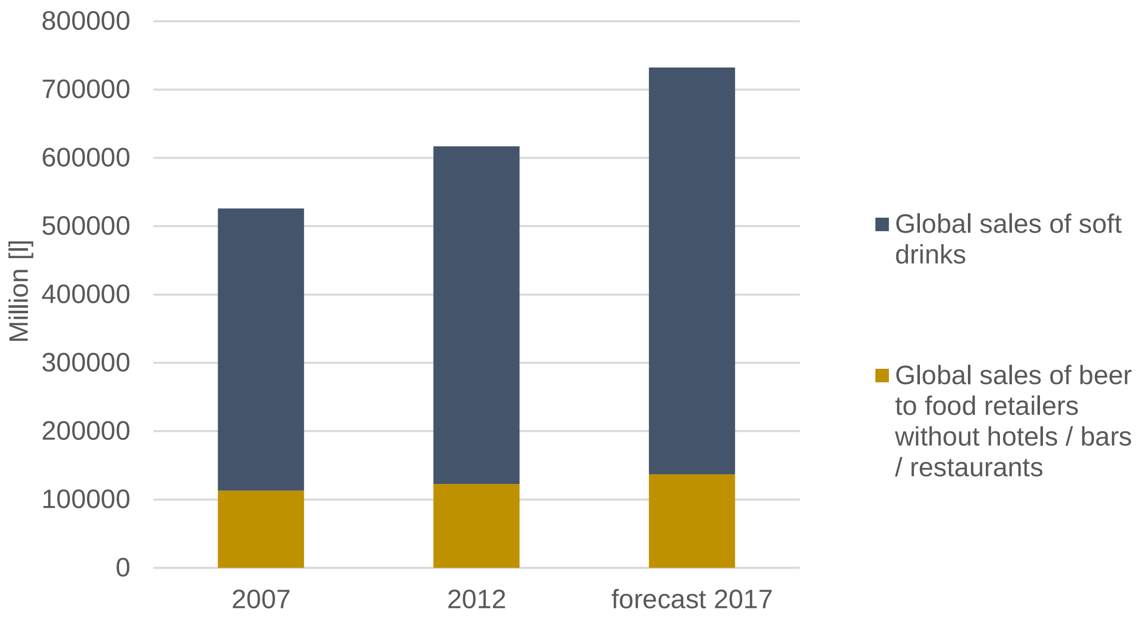

Figure 2.6-1: Growth of the global beverage industry 2012-2017 (Fritsche, 2013).

The low profit margins in most sectors of the international beverage industry, the need for highly efficient processes, energy price increases and the growing awareness of environment issues have resulted a drive for sustainability in food and beverage production: recycling technologies (especially PET-recycling), reduced weight packaging, intelligent and innovative processes, reduced usage of energy and resources, innovative plant control and demand-optimised systems are increasingly the focus of R&D activities and industry (Olsmats and Kaivo-oja, 2014).

1.1. Packaging plants

The packaging process is the last highly automated step of modern food and beverage production. It is performed in high-performance packaging lines which involve various machines interlinked with buffering transport elements. For beverages, bottling lines are used for different types of containers: returnable, non-returnable glass bottles, polyethylene terephthalate (PET) bottles and cans. Depending on the type of container, machines for depalletising, depacking, cleaning and control of the containers, filling/capping/labelling of the containers, packing, palletizing and transporting are required (Manger, 2008). The design of a typical bottling plant for returnable glass bottles is shown in Figure 2. For PET bottle production, a stretch blow moulder for producing the bottles directly before filling and optionally a shrink packer are also necessary.

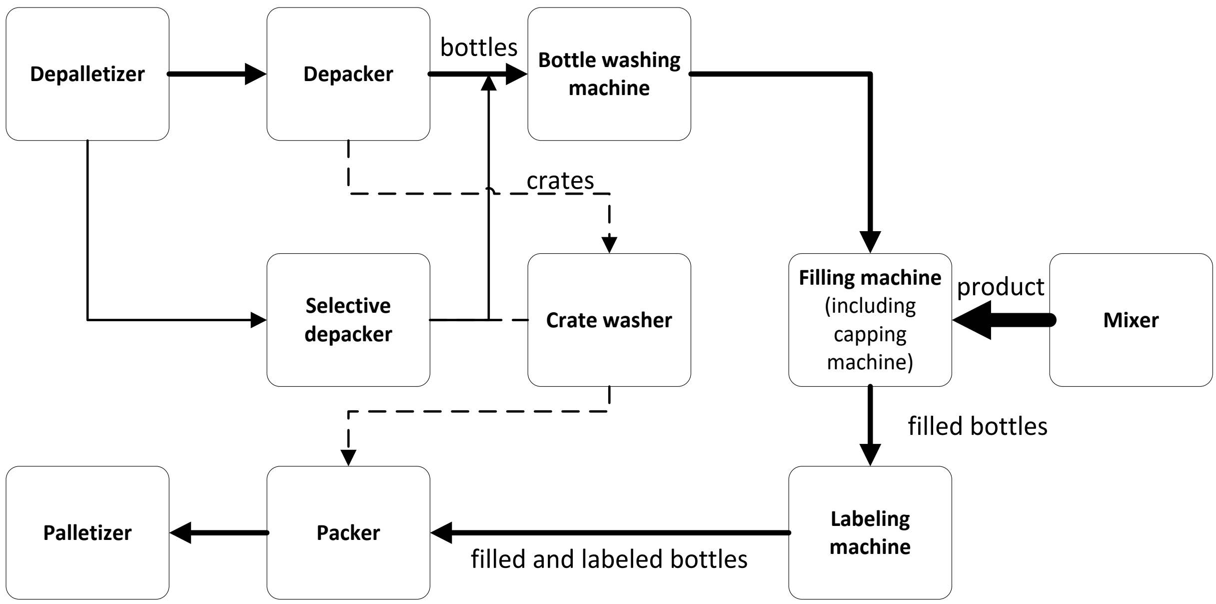

Figure 2.6-2: Design of a bottling plant for returnable glass bottles.

Depending on the machines being used, different types of energy are consumed, as Table 2.6-1 shows for a returnable glass bottling plant. All the machines in a bottling plant require electrical power. In addition, a supply of heat for the cleaning machines and, if present, the pasteurizer is necessary. For some machines (filling and capping machine, labelling machine, packer, palletizer), compressed air is necessary which is usually generated by electrical energy. Filling machines need air for proper technological operation (e.g. pure sterile air or high pressure air blast). Water is required for cleaning bottles and crates as well as for cleaning the plant itself.

Table 2.6-1: Energy and media demand of bottling machines according to EN DIN 8784 (DIN 8784:2013-09, 2013)

	Electrical power	Air	Heat	Water
Depalletizer	X	X		
Depacker	X	X		
Crate Washer	X		X	X
Bottle washing machine	X		X	X
Filling and capping machine	X	X		
Labelling machine	X	X		
Packer	X	X		
Palletizer	X	X		

The electrical energy demand for the bottling step is 12-35 % of the total electrical energy demand for beer production (Galitsky et al., 2003; Petersen, 1993). For the production of soft drinks and bottled water, electrical energy is usually only required for the pumping and bottling step as the thermal cooking and heating steps are not required. The total energy demand for bottling does not significantly differ for the different types of containers (see Figure 3). Apart from one publication in the 1980s (Schreiner, 1982) no detailed machine based energy data are available for industrial bottling plants.

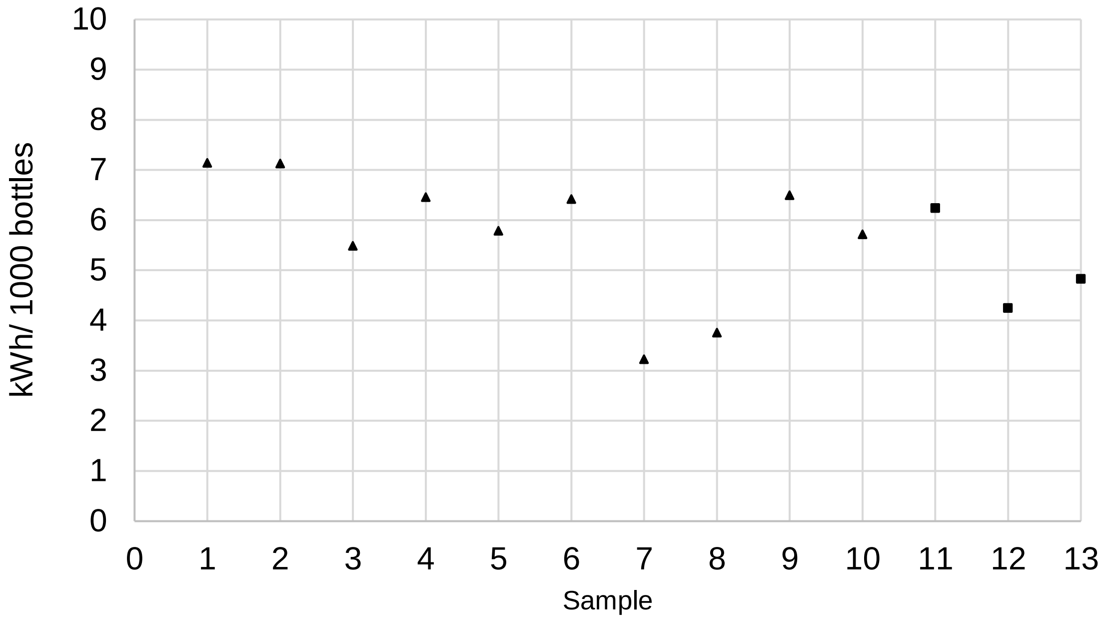

Figure 2.6-3: Electrical energy demand for bottling (empirical data, 2012-2014 (Osterroth, 2014)); samples 1-9 are from returnable glass bottling plants (▲), samples 11-13 are from PET bottling plants (■).

For in-depth analyses and effective optimization strategies, it is necessary to correlate the operational states and the energy demand in order to differentiate between performance and energy performance indicators. Established industrial indicators [kWh/ 1000 fillings or hl] provide no indication of the demand of the individual production steps (e.g. times for which a machine is not in use, which can be readily optimized). Also, published energy data for bottling plants are not linked to operational states or machine actions and cannot be used for operational state related models, as presented in our approach.

1.2. Modeling and simulation of the energy demand

Following the energy crises of the 1970s, individual optimization activities were undertaken in the whole of the food and beverage industries (for examples see (Galitsky et al., 2003; Gibson, 1980; Ito et al., 1994; Lees et al., 2009; Mignon and Hermia, 1993, 1993; Muster-Slawitsch et al., 2014a; Muster-Slawitsch et al., 2014b; Mutua and Kariuki, 2012), including for bottling (Gleick and Cooley, 2009). Overviews of the state of the art in energy and resource efficient methods and techniques as well as the electrical energy requirements of discrete manufacturing steps have been published (Apostolos et al., 2013); (Duflou et al., 2012); (Gutowski et al., 2006). Modeling and simulation methods for the prognosis and optimisation of production efficiency are well-established. In recent years much research work has been done to develop simulation models for forecasting the energy demand of manufacturing lines. Approaches are known for modeling, simulation and evaluation of energy demand in manufacturing processes (Cataldo et al., 2013). Cataldo et al. present an interesting model for a simple serial engine assembly line including four machines. The model describes the mechanical behavior of the machines, the control functions and the energy demand behavior. The control functionalities are modelled using Finite State Machines (FSMs). For the energy demand approximately constant power profiles were defined. No generic definition of energy states and no generic mapping is described. The described machine application differs (e.g. milling, welding, screwing, drilling) from bottling machines in concerns of machine function, complexity (>10 machines for bottling) and high nominal speed. Anyway basic ideas of this approach, like the general concept of describing the machine functions (operating states) and the energetic behavior (energy states) can be adopted for forecasting approaches of bottling machines. The presented research in this paper focuses on the development of a generic model describing energy states for bottling machines, the behavior during state changes and a mapping to the operational states.

For cutting machines a calculation method was developed by (Kuhrke, 2011) using "energy blocks", which are demand patterns based on functional changes to the machine operations, comparable to operational states. The model of Kuhrke shows an interesting approach of state based energy forecasting using demand pattern but lacks a generic energy state model with defined energy states and a mapping of energy states and operational states. The model is specific for one machine type with specialised machine functions and cannot be adapted for packaging and bottling machines. The complex connection of various machines, influencing the material flow has not been a subject of this investigation. Muster-Slawitsch et al. (Muster-Slawitsch et al., 2014a) developed a software tool based on the pinch point method for optimising heat integration in brewing processes. Based on this model, energy savings of up to 10–35 % could be realised using an intelligent network of heat exchanger and heat accumulators. Tokos et al. (Tokos et al., 2010) presented a valid model for heat integration based on a mixed integer linear program. Mignon and Hermia (Mignon and Hermia, 1993) developed an optimisation tool for batches in order to influence the production planning and reduce steam demand. Those models are specific for thermal energy and not valid for electrical energy demand related to mechanical machine functions. Meyer et al. (Meyer et al., 2013) presented automated energy management using a manufacturing execution system (MES) based on a hybrid modeling approach. Although this approach is focused on MES functions, using static energy parameters for a forecast, the hybrid modeling idea might although be interesting for bottling machines. Daver and Demirel (Daver and Demirel, 2012) presented a modeling and simulation approach for improving the energy demand in the stretched blow process for PET bottles for carbonated soft drinks. The model is valid for a detailed machine specific optimisation but does not include an energy state model and is not generally valid for bottling machines. It can be integrated in future optimisation considerations as a basis for advanced studies on the energy optimisation for PET bottling plants. Cannata et al. (Cannata et al., 2009) presented an approach for energy efficiency driven process analysis and optimisation in discrete manufacturing focused on using constant static values for defined machine functions for analysis, management and control of discrete manufacturing systems in a near-real time environment with a cross layer-structure. Even if the focus and the machine functions of this approach are different, the consideration on machine level should be used in a new approach for bottling machines. No adaptable energy state model is presented in this approach.

Discrete-event models are used for mapping the operational states of production lines, such as a bottling plant in this case, with the main intention being to increase plant efficiency. In these models the change of a value or state is performed by a discrete event at any given time. Discrete-event models are often used to represent production processes such as packaging a food product. A typical mathematical consideration is the queuing theory (Papadopoulos and Heavey, 1996; Sauerwein, 2013). The interlinked production line is abstracted to a line of failure prone individual machines, in which the product is transported in a predetermined sequence from machine to machine. Interruptions to the production flow due to single machine stops are compensated by intermediate buffer systems. Analytical approaches are known for this, for example Markov chains, that enable the approximate prediction of the availability of buffers (Dolgui et al., 2002); (Spinellis and Papadopoulos, 2000). These simulation approaches are based on stochastic models which describe the state transitions of the machines in systems of differential equations. Forecasting the plant efficiency can be done with similar approaches (Han and Park, 2002); (Kouikoglou, 2000). Other approaches have also been published (Al-Hawari et al., 2010; Apostolos et al., 2013); (Bottani et al., 2006); (Windmann et al., 2013). Kadachi introduced a discrete-time simulation of a bottling plant, which is a simulation-based tool for planning and analysis of bottling plants (Kadachi, 2001).

Applicable solutions regarding the operational state related energy demand of food packaging plants were not considered in any of the aforementioned approaches. None of the mentioned approaches presents a generic energy state model enabling a cause-related, operational state based forecast of the energy demand. Approaches using fuzzy logic or energy pattern can provide accurate forecast results but with missing empirical models no cause-related development of optimisation scenarios is possible.

For the food and beverage industry a saving potential for electrical energy up to 36 % is expected (Barckhausen et al., 2016). This paper introduces a novel operational state related modeling and simulation approach for forecasting the electrical energy demand of complex bottling and food packaging lines. A generic energy state model, a modeling of the transitions and a mapping to the occurring operational states, based on established operational state models are presented in this paper. The model was implemented in the established environment of Matlab Stateflow. As no operational state related energy data were available for validation, state based electrical energy data were collected for validation (see section 2). The operational state basis of this approach enables detailed differentiation of electrical energy demand, identification of possible energy savings and realisation of an energy efficient operational mode.

2. Data acquisition

The present study considered an industrial bottling and packaging plant for returnable glass bottles of a medium-sized German beverage company producing mineral water and soft drinks. The plant is designed for a nominal output of 28,000 bottles/h and its main use is for filling returnable 0.75 l bottles. The material flow and the machines involved are shown in Figure 2.6-2. The line is equipped with an automatic production data acquisition system which acquires and records state and mode information about the individual machines every second in accordance with the industrial “Weihenstephan Standard” (Voigt et al., 2010). This state information is based on a state model and indicates whether a machine is producing (operating state “operating”), or waiting to produce in a suspended state due to an internal cause (“failure”, “held”, “emergency stop”) or external cause (“lack”, “tailback”, “idle”, “prepared”). No data for the machine mode and program were available. The state information can be assigned to time intervals in accordance with the time model of DIN 8743 (DIN 8743:2014-01, 2014) (see Figure 2.6-4).

<table>
<tr><td colspan="6">theoretical available time (24 hours, 7 days a week) t_T</td></tr>
<tr><td colspan="5">machine working time t_W</td><td rowspan="4">idle time
▪ idle
▪ undefined</td></tr>
<tr><td colspan="4">operating time t_O</td><td rowspan="3">scheduled down time t_D
▪ cleaning
▪ changeover
▪ maintenance
▪ repair</td></tr>
<tr><td colspan="3">running time t_R</td><td rowspan="2">unplaned down time t_F
▪ failures
▪ lack
▪ tailback</td></tr>
<tr><td>quality time t_Q</td><td>scrape time t_{LQ}</td><td>performance loss time t_{LP}</td></tr>
</table>

Figure 2.6-4: Time model according to DIN 8743 and examples of operational states (grey) (DIN 8743:2014-01).

Before analysing the state data, correct acquisition of the machine states was verified at least three times for each state by checking the state information in the recording database in parallel with the actual machine behavior. The data acquisition system does not record information about the states of the bottle, crate and pallet conveying systems and the inspection machines. For this reason, they were not considered in this work.

Additionally, devices were used to record the electrical power demand (active power) of each individual machine. All active power meters were calibrated and the discrete values were recorded in a database every two seconds (maximum sampling rate of the active power meters) for all the machines except the conveying systems and inspection machines. The electrical power demand data and operational state data for all the machines described above were collected for a period of 10 weeks.

3. Energy demand behavior of bottling machines

Data analysis found, that there is a correlation between the operational state of machines and the current energy demand for all considered bottling machines. Figure 2.6-5 shows a 2-D-lineplot of the electrical energy demand with the occurring operational states according to Weihenstephan Standard in the background. The right part of the figure shows the frequency distribution of the measured discrete energy demand values with two main peak, correlating to the operational states. The demand value for different types of stops, e.g. lack, tailback and equipment failure was found to be equal.

Figure 2.6-5: Example of the correlation between operational states and electrical energy demand, showing two of three occurring main demand level for the example of a bottle cleaning machine.

Further data analysis showed, that after an operational state change the energy demand is not inevitable chancing immediately from one constant value or a constant demand behavior to another value/ behavior. Some operational state changes result in a characteristic repeatable cascade behavior. Figure 6 shows a typical example of a reproducible and stepwise reduction of the electrical power demand. It shows an operational state change from operating to equipment failure for a bottle cleaning machine.

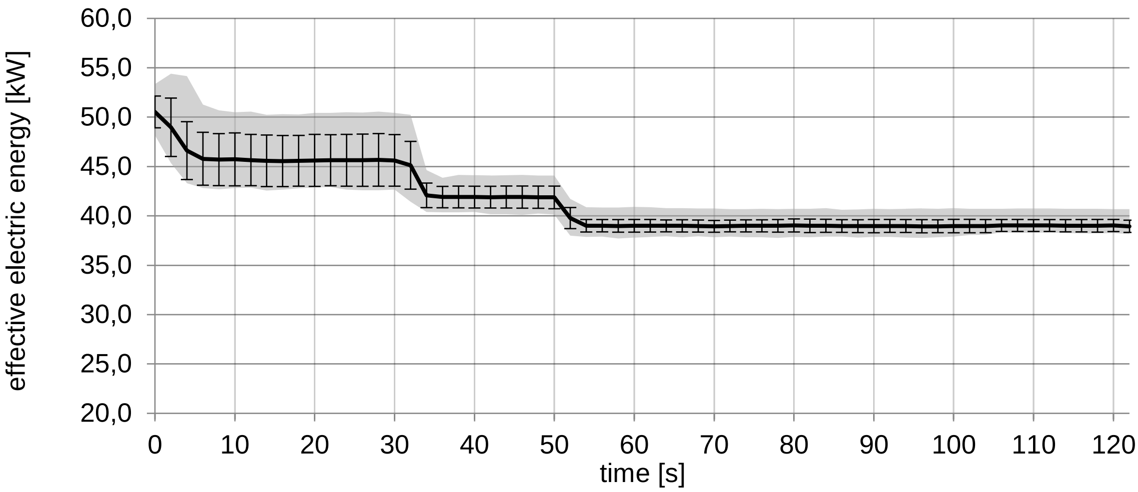

Figure 2.6-6: Reproducible energy demand behavior after an operational state change from operating to equipment failure for n=20 changes: Average of the effective electrical energy, standard deviation and maxima and minima (grey) of the measured values for a bottle filling machine.

No energy state model was defined yet, describing energy states and state transitions for bottling machines. No mapping is known of the energy demand behavior of bottling machines and occurring machine operations or operational states.

4. Modeling approach: generic energy demand model

For the modeling it was assumed that the energy demand of a machine correlates with its operational state. During non-productive times (e.g. tailback, lack in the material flow, failures) machines shut down components such as pumps, resulting in reduced power demand. Initial analysis of the electrical power and operation state data enabled three main power conditions (demand levels DL) to be identified for all the machines used in bottling lines. Based on this idea a generic model was developed to describe the operational state related electrical power demand, including three main power conditions (demand levels DL), a modeling of state transitions and a mapping of the operational states to the resulting energy demand level. The three main DL describing the energy demand behavior of machines used for bottling were defined as follows:

- **Inactive**

  When not in use (documented by its related operating mode *off*) the demand level of the machine is minimal. Individual components that are not switched off for technical or technological reasons may remain switched on during this time (e.g. network components, lighting, remote access services, control, media) and cause a constant demand level.

- **Suspended**

During downtimes (e.g. due to *tailback, lack, equipment failure*) the machine is not producing and rests in a standby level. The machine stays switched on and ready for production without or with minimal delay.

- **Producing**

The machine is running at its planned operating speed and fulfilling the process steps it was designed for without technical or organisational disturbances. This demand level can be directly mapped to the operating state *operating*.

The defined demand levels **DL** can be mapped to the operational states, based on the classification of time definitions for packaging machines and packaging installations documented in DIN 8743 (DIN 8743:2014-01, 2014). Figure 2.6-7 shows the mapping of the operational states to the resulting power conditions (demand levels **DL**).

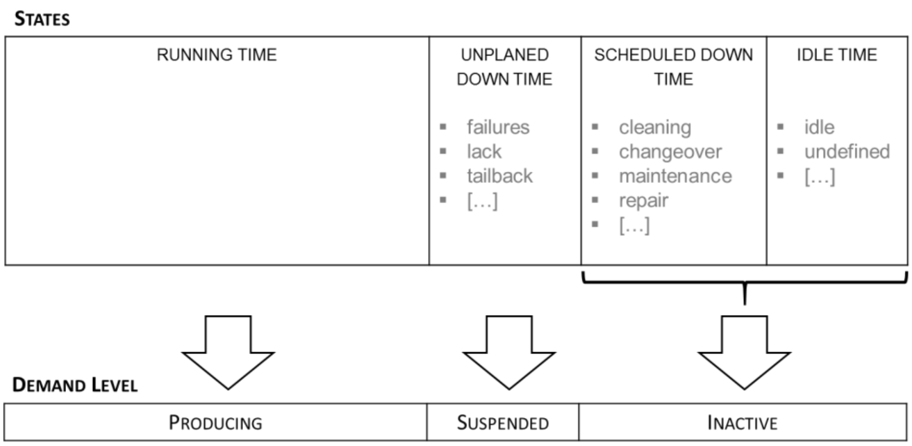

Figure 2.6-7: Mapping of the operational states and the resulting electrical demand level (DL).

Therefore the electrical power demand P_{el} depends on the current operational state (state (2.6.2)) as presented in (1) and Figure 8.

The operational states are described by the start time (tstart_state_n) and end time (tend_state_n). As the time intervals overlap, the start time of a new operational state is the end time of the prior operational state.

$$DL = \{Producing, Suspended, Inactive\} \tag{2.6.1}$$

$$state = \{running\ time, unplaned\ downtime, scheduled\ downtime, idle\ time\} \tag{2.6.2}$$

$$P_{el}(state) = DL \tag{2.6.3}$$

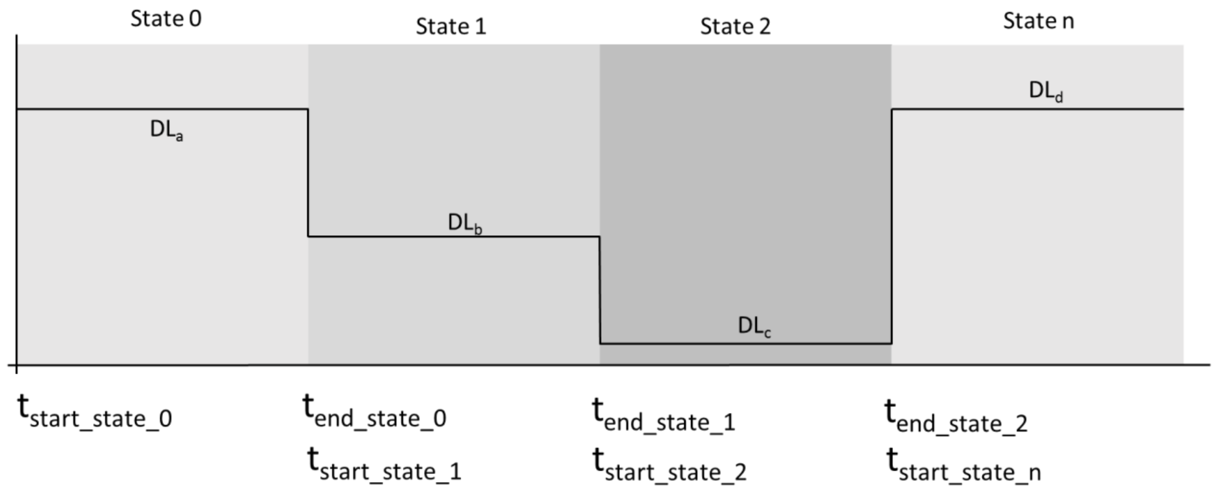

Figure 2.6-8: Demand level (DL) of the machines is correlated to the operational state (state). The operational state is characterised by a start time start time ($t_{start\_state\_n}$), an end time ($t_{end\_state\_n}$) and a characteristic value indicating the type of the state (here generically described as: 0, 1, 2).

In-depth analysis of the power behavior after changing from one of these demand level to another showed that transitions take place in steps due to physical machine functions, for example the controlled shutdown of machine components (Koch et al., 2015; Osterroth et al., 2014; Osterroth and Voigt, 2016). This transition can be described as a finite number of constant intermediate level IL (e.g. switching off pumps after different waiting periods). After reaching the new demand level DL the value remains constant until the next state change (steady phase).

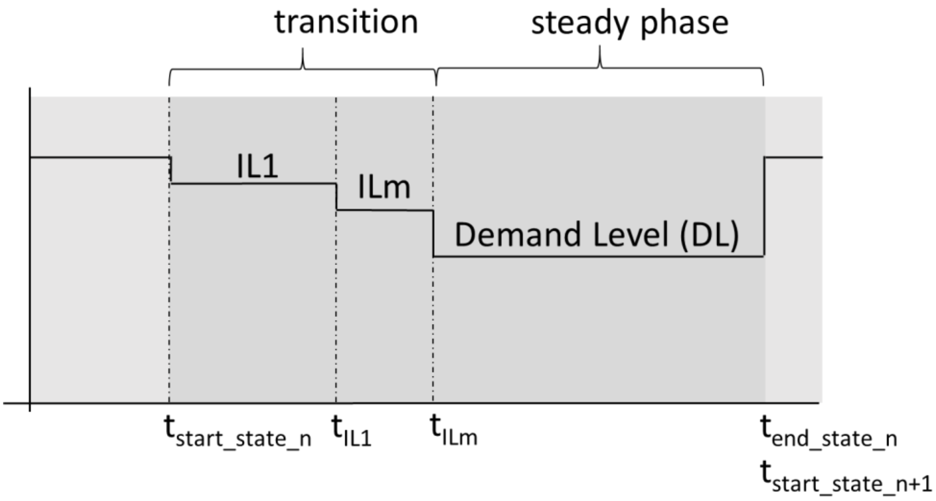

Figure 2.6-9: The energy demand within a state is described with a transition phase and a steady phase. The transition from one DL to another with a finite number of intermediate level IL.

To represent this discrete behavior, these steps of the state transition were modelled by their average intermediate demand levels **IL** and the end times $\mathbf{t_{IL}}$ (determined from the end time of the last demand level **DL**) of the respective levels, which are specific for each of the machines. A new intermediate level was defined if the two subsequent values (measuring cycle of 2 seconds) were significantly different from the previous value. The modeling of the demand level changes for n intermediate levels was as follows (2.6.4.):

$$P_{el} = \begin{cases} IL_1 & if\ t_{start\_state\_n} \leq \mathrm{t} < t_{IL1} \\ IL_2 & if\ t_{IL1} \leq \mathrm{t} < t_{IL2} \\ IL_m & if\ t_{IL(\mathrm{m}-1)} \leq \mathrm{t} < t_{ILm} \\ DL & if\ t_{IL\mathrm{m}} \leq \mathrm{t}) < t_{end\_state\_n} \end{cases} \tag{2.6.4}$$

5. Model Implementation

Based on the modeling approach, a generic component was developed in order to model the power demand behavior of a bottling or packaging machine and implemented in the environment of Stateflow (MATLAB R2015a). The simulation environment was chosen as it is a well-established environment with open interfaced to other simulation environments and databases, allowing to expand the model and to enable a transfer to a future industrial application. The developed generic environment allows the setting up of models for individual machines as well as for whole packaging lines with any number of machines. The model requires operational state data and energetic parameters as input variables. The conceptual design of the simulation environment is depicted in Figure 2.6-10.

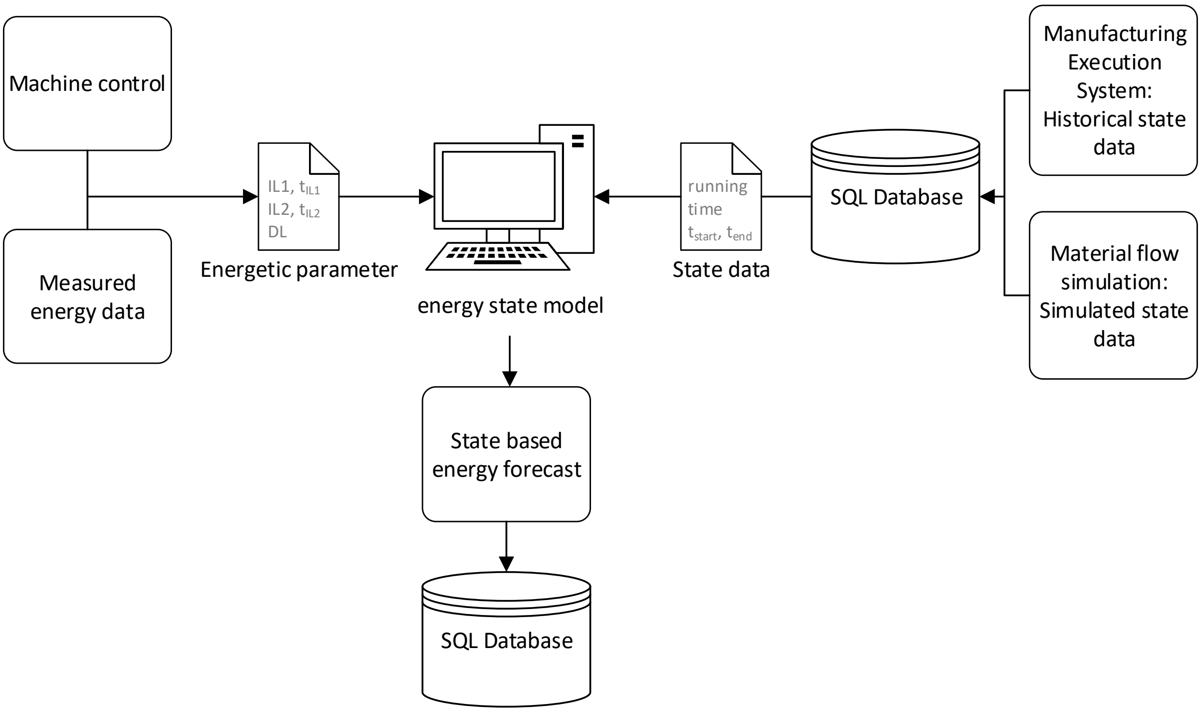

Figure 2.6-10: Conceptual design of the simulation environment.

The operational state data can be either extracted from a historical record (e.g. from a manufacturing execution system) or, for future applications and optimisation runs, from a material flow simulation representing the production behavior of the individual machines as components of an interlinked production line. State data are provided to the MATLAB model via an ODBC interface using standardised entity–relationship model (ER model) in SQL. The model processes program, mode and state information for further optimisation.

For parameterisation of the model components, energetic parameters are needed which describe the actual electrical demand [in kW] for the relative demand level and state transition as described in the modeling approach. These energetic parameters can be obtained by analysing measured energy data for the described machine or by using parameters based on machine control parameters (time, chronological order and type of the machine components shut down during non-productive times).

6. Model parameterisation using historical energy data

In this work, historical energy demand data were used from ten machines in the relevant industrial bottling line (see 2. Data acquisition). The values of the energy parameter representing the DL, which was kept constant in the model, were calculated by taking the arithmetic mean of the measured electrical power during the relevant operational state based on the presented modeling approach (example shown in Figure 2.6-11).

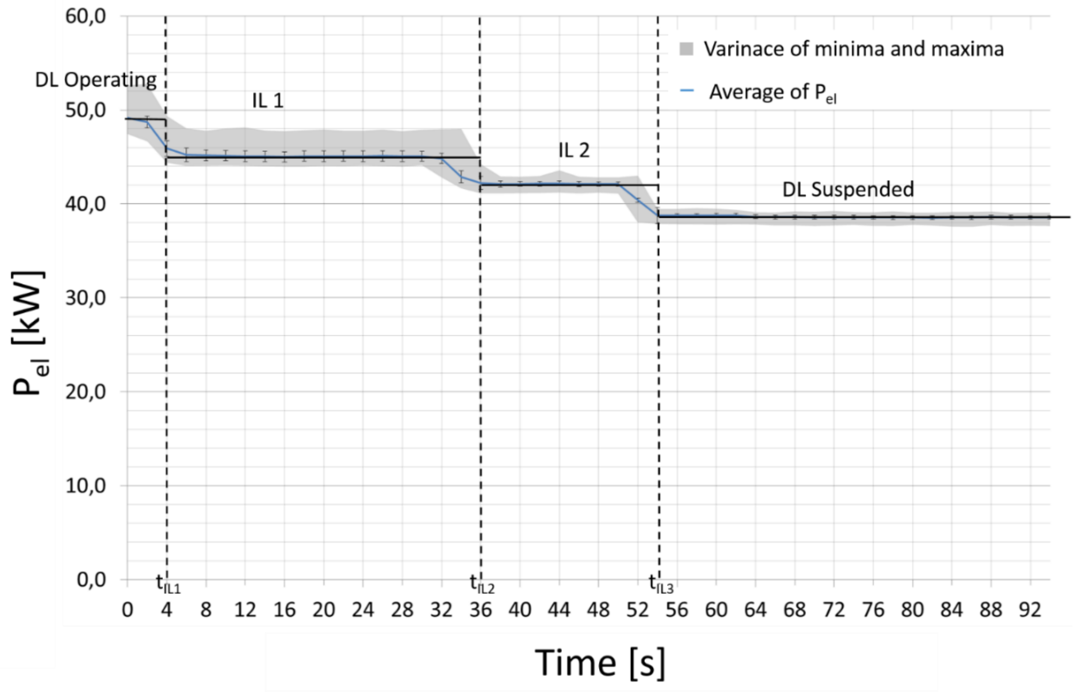

Figure 2.6-11: Stepwise change of the demand level of the bottle cleaning machine (maximum variation, average value and confidence interval (α=0.05) of 20 measurements).

The values were calculated for time periods of one day for each machine, using time periods not used for validation. IL values were calculated from the same time period. For identification of a new IL and the relevant time for the transition, confidence intervals were used. A new intermediate level was defined if the two subsequent values (measuring cycle of 2 seconds) were significantly different from the previous value. The automatic production data acquisition system was not able to give information about planned downtimes. It was therefore assumed that if a state other than production exists for a longer time than the calculated double mean downtime of the machine it is shut down (e.g. for a weekend). For the example of the filling machine, on average more than 95 % (95.3 %, 97.2 % and 97.2 % for the validation periods) of the downtimes are below the double mean downtime (see Figure 2.6-12).

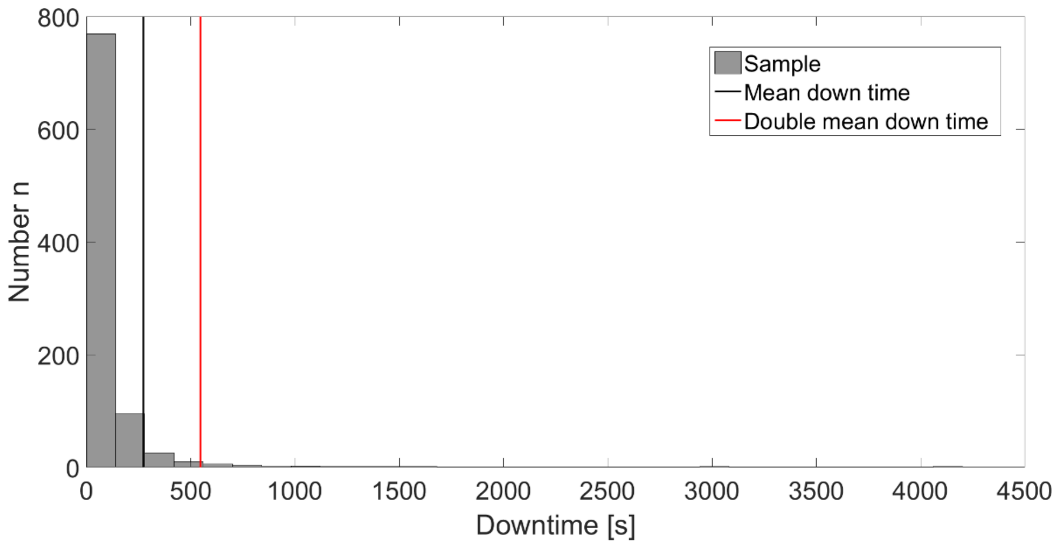

Figure 2.6-12: Mean downtime and double mean downtime for the example of the filling machine. 97.2 % of the downtimes are below the double mean downtime.

As a consequence, the modelled DL was switched to INACTIVE for times longer than the double mean downtime. The energetic parameters (DL, $IL_{1\text{-}n}$, $t_{1\text{-}n}$) for each machine were derived from the measured energy data, evaluating one day of machine energy data with a significant number of changes for each state. The required state data for the individual machines of the production line were used from a historic record of the relevant MES.

7. Model validation

The following criteria were used for validation:

- Industrial plant data
- Visual-validation plots to evaluate the consistency of the simulated and the measured data in terms of the operational state correlation
- Established statistical methods for model validation:
  - Average percentage deviation (APD)
  - Theil's inequality coefficient (TIC)

Model validation was performed using measured energy data and operational state data from the described bottling line in industrial application, at time intervals not used for parameterisation. Three different time periods, each of fourteen days, were used to represent a usual production process. The measured operational state data for the validation periods were entered into the model as input values. The simulated energy demand was compared to the measured energy demand over this time period. The acceptability of the model was evaluated for individual machines and the whole line using direct visual estimation with a validation plot. In the validation plots the intervals of the relevant operational states (start time to end time of the state) are visualised as coloured areas in the background of the plots of the measured and simulated energy demand data. Figure 2.6-13 shows an example validation plot for an individual machine. Breakdown times according to Figure 2.6-4 are coloured red. Running time is coloured green and downtimes are coloured grey (not shown in this example).

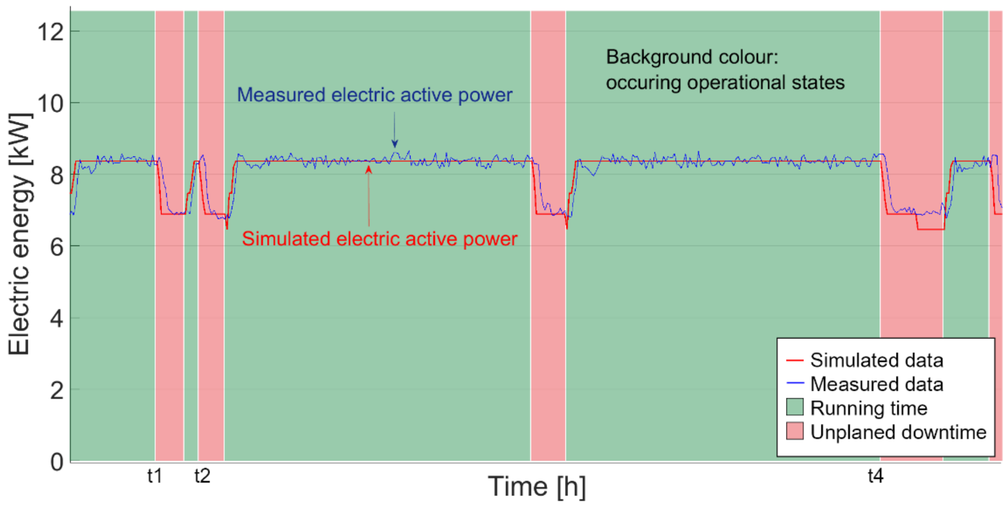

Figure 2.6-13: Example of a validation plot (filling machine).

Statistical evaluation was performed using the average percentage deviation (APD (2.6.5)). The creditability of the model was validated using Theil's inequality coefficient by analysing the consistency between the simulated energy data and the reference measured energy data. Theil's Inequality Coefficient (TIC (2.6.6)) and the resulting credibility (Θ (2.6.7)) are widely used for model validation in the scientific literature (Chen, 2011), (Hu et al., 2012), (Jiao and Li Wei, 2013), (Netter et al., 2013).

$$\mathbf{APD} = \frac{1}{n}\sum_{i=1}^{n}\frac{(y_i - z_i)}{z_i} \tag{2.6.5}$$

$$TIC = \frac{\sqrt{\sum_{i=1}^{n}(y_i - z_i)^2}}{\sqrt{\sum_{i=1}^{n} {y_i}^2} + \sqrt{\sum_{i=1}^{n} {z_i}^2}} \tag{2.6.6}$$

where: z_i: measured discrete data, y_i: simulated discrete data

$$\theta = \frac{0{,}40 - TIC}{0{,}40} \tag{2.6.7}$$

The value of TIC is between 0 and 1. The smaller the value, the more accurate the simulated result. This value applies credible up to a limit of 0.4 (Theil, 1965). For the validation plots a MATLAB script was developed to create automated plots of the simulated and measured energy data in order to identify deviations between the measured and simulated data. The operational states were plotted as coloured areas in the background of the plots.

8. Results

8.1. Calculated empirical parameters

For all the machines, energy parameters were calculated based on statistical analysis of the empirical energy and state data described in section 6. The calculated parameters are summarised in Table 2.6-2.

Table 2.6-2: Calculated energy parameters for the relevant machines.

Machine	Level	Production		Suspended		Inactive
		P [kW]	t [s]	P [kW]	t [s]	P [kW]
Depalletizer	IL1	2,25	2	1,55	3	-
	IL2	2,17	1	1,32	10	-
	IL3	2,07	2	1,08	34	-
	DL	2,44	-	0,99	-	1,04
Depacker	IL1	1,53	1	1,49	2	-
	IL2	1,71	1	1,23	66	-
	IL3	1,90	2	1,22	31	-
	DL	1,69	-	1,17	-	0,89
Selective depacker	IL1	1,63	2	1,41	4	-
	IL2	2,24	1	-	-	-
	IL3	1,89	1	-	-	-
	DL	1,55	-	1,20	-	0,76
Washing machine	IL1	49,21	2	45,58	17	-
	IL2	50,21	1	42,78	10	-
	IL3	50,90	175	38,92	185	-

Machine	Level	Production		Suspended		Inactive
		P [kW]	t [s]	P [kW]	t [s]	P [kW]
Washing machine	DL	51,37	-	37,75	-	0,44
Filler	IL1	7,47	2	7,87	3	-
	IL2	7,88	1	7,27	2	-
	IL3	8,22	1	6,89	29	-
	DL	8,37	-	6,46	-	3,18
Labeller	IL1	2,05	7	-	-	-
	IL2	2,47	2	-	-	-
	IL3	2,73	1	-	-	-
	DL	3,35	-	1,91	-	0,43
Packer	IL1	1,36	1	1,61	2	-
	IL2	1,74	9	1,32	44	-
	IL3	2,07	2	-	-	-
	DL	1,94	-	1,38	-	1,10
Mixer	IL1	9,80	163	4,00	2	-
	IL2	19,09	347	1,75	59	-
	IL3	-	-	1,29	10	-
	DL	20,41	-	0,99	-	0,00
Palletizer	IL1	1,75	3	1,77	9	-
	IL2	2,10	7	1,44	70	-
	IL3	2,57	18	-	-	-
	DL	2,49	-	1,41	-	1,05
Crate Washer*	IL1	18,26	1	18,40	2	-
	IL2	18,40	1	18,20	2	-
	IL3	18,48	12	-	-	-
	DL	18,39	-	18,01	-	0,00

8.2. Model validation results

The Stateflow model was parameterised for validation with the values presented in section 7.1. Validation was performed for three different time periods of fourteen days for each machine (except the crate washer due to problems with the data record) and provided reproducible results for all the validation periods. The results of the statistical analysis for the validation period of fourteen days for all individual machines and the whole line are presented in Table 2.6-3.

Table 2.6-3: Summary of the validation results.

	TIC	APD [%]	Measured	Simulated	Tot. deviation [|%|]	Credi-bility	Accepta-bility
Depalletizer	0,34	50 %	410 kWh	457 kWh	11 %	0,15	
	0,29	47 %	418 kWh	492kWh	18 %	0,28	partially
	0,34	41 %	555 kWh	468 kWh	16 %	0,15	
Depacker	0,19	28 %	333 kWh	359 kWh	8%	0,53	
	0,18	28 %	356 kWh	378 kWh	6%	0,55	partially
	0,20	27 %	432 kWh	413 kWh	4%	0,50	
Selective depacker	0,12	8 %	298 kWh	307 kWh	3%	0,70	
	0,12	8 %	305 kWh	312 kWh	2%	0,70	yes
	-	-	-	-	-		
Bottle cleaning machine	0,18	65 %	4785 kWh	4639 kWh	3 %	0,55	
	0,16	31 %	6007 kWh	6009 kWh	0 %	0,60	yes
	0,13	52 %	8624 kWh	8271 kWh	4 %	0,68	
Filling machine	0,12	19 %	1373 kWh	1466 kWh	7 %	0,70	
	0,11	16 %	1541 kWh	1543 kWh	0 %	0,73	yes
	0,09	15 %	1836 kWh	1775 kWh	3 %	0,78	
Labelling machine	0,19	37 %	352 kWh	356 kWh	1 %	0,53	
	0,18	40 %	392 kWh	398 kWh	1 %	0,55	yes
	0,15	29 %	539 kWh	523 kWh	3 %	0,63	

	TIC	APD [%]	Measured	Simulated	Tot. deviation [|%|]	Credi-bility	Accepta-bility
Packer	0,26	51 %	394 kWh	428 kWh	9 %	0,35	partially
	0,22	45 %	403 kWh	438 kWh	9 %	0,45	
	0,25	57 %	497 kWh	468 kWh	6 %	0,38	
Mixer	0,25	85 %	1869 kWh	1356 kWh	27 %	0,38	
	0,27	148 %	1692 kWh	1458 kWh	14 %	0,33	no
	0,19	69 %	3117 kWh	2549 kWh	18 %	0,53	
Palletizer	0,28	38 %	430 kWh	464 kWh	8 %	0,30	
	0,26	33 %	449 kWh	491 kWh	9 %	0,35	partially
	0,29	37 %	600 kWh	531 kWh	11 %	0,28	
Crate Washer*	-	-	-	-	-		
	-	-	-	-	-		partially
	0,24	19 %	2670 kWh	3295 kWh	23 %	0,40	
Complete line	0,13	29 %	10244 kWh	9832 kWh	4 %	0,68	
	0,12	26 %	11563 kWh	11522 kWh	0 %	0,70	yes
	0,10	21 %	18871 kWh	18293 kWh	3 %	0,75	

The validation plots for all machines beside the mixer confirmed, that both the measured data and the simulated data depend on the operational state changes. The 2-D line plot of the simulated data follows the 2-D-lineplot of the measured data.

The models parameterised for the washing machine and the filling machine showed the lowest average percentage deviation (APD), as confirmed by the good correlation between the simulated and measured energy data shown in the validation plots (see the validation plots in Figure 2.6-14 for the bottle washing machine, in Figure 2.6-15 for the filling machine and in Figure 2.6-16 for the labelling machine) and by the total deviation of the fourteen day validation period of on average below 3 %. All the TIC values for this machine model are significantly below 0.4 (0.09-0.12 for the filling machine and 0.13-0.18 for the bottle washing machine). The credibility of the model for these machines is high (0.55-0.68 for the washing machine and 0.70-0.78 for the filling machine).

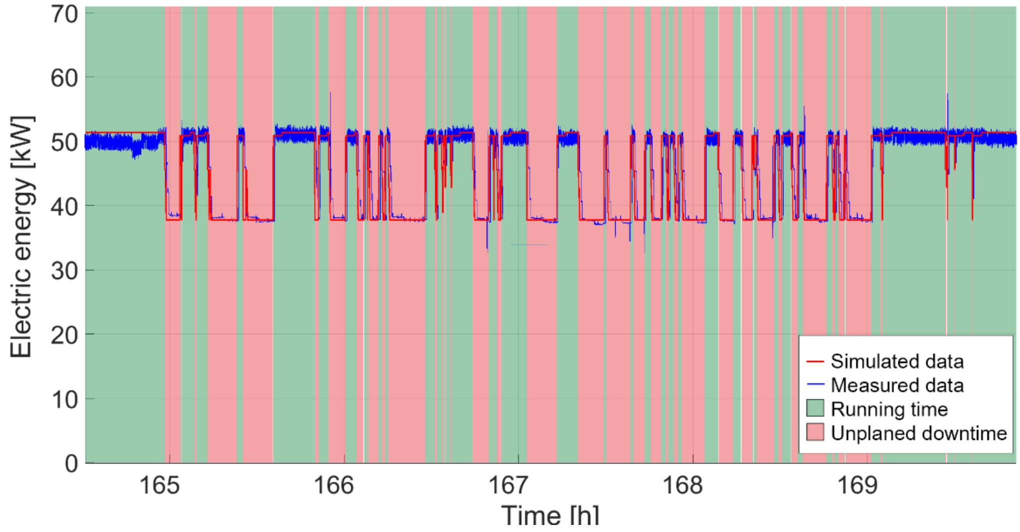

Figure 2.6-14: Validation plot for a bottle washing machine (total experimental time: 20160 min; measured total demand: 6007 kWh; simulated total energy demand: 6012 kWh).

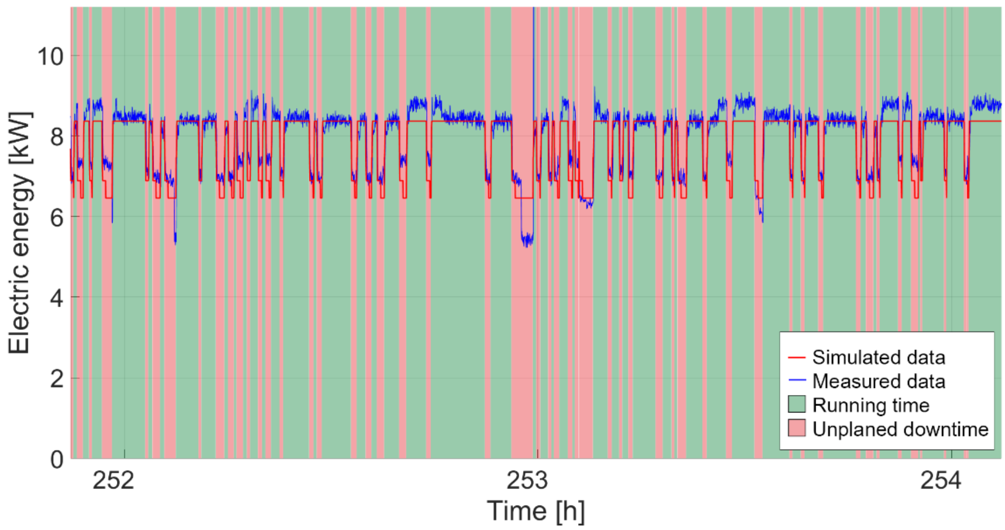

Figure 2.6-15: Validation plot for a filling machine (total experimental time: 20160 min; measured total demand: 1836 kWh; simulated total energy demand: 1775 kWh).

The model parameterized for the labelling machine showed an APD between 29 and 37 % caused by irregular demand, especially during production times (see the validation plot in Figure 2.6-16), due to the variable machine speed during production. The total deviation for the validation periods is low (-3 % to 1 %). The TIC is between 0.15 and 0.19 indicating a credible model (credibility 0.53-0.63).

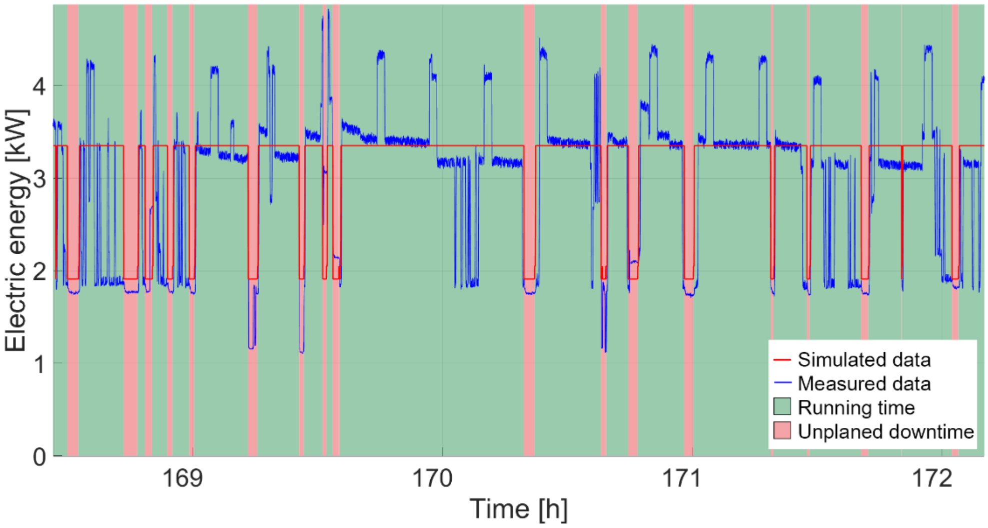

Figure 2.6-16: Validation plot for a labelling machine with variable machine speed (total experimental time: 20160 min; measured total demand: 392 kWh; simulated total energy demand: 398 kWh).

The model parameterised for the selective depacker showed accurate validation results. Due to data record problems for this machine, there are only two validation periods. The APD (8 % for both periods) and TIC (0.12 for both periods) for this model are low and the total deviation of the model is 2-3 %. The credibility of the model is high (0.70 for both periods).

The machine models parameterised for the packing machines (depacker and packer) have a TIC between 0.19 and 0.26. The ADP for the depacker is 27-28 %, for the packer the ADP is higher (45-57 %). The total deviation of the forecasted demand for both machines is between 4-11 %. The credibility is 0.50-0.53 for the depacker and 0.35-0.45 for the packer.

The machine model parameterised for the depalletizer has the lowest credibility (0.15-0.28) and a TIC close to 0.4 (0.29-0.34). The APD is between 41-50%. The total deviation, disregarding the mixer and the crate washer, was the highest (11-18 %). The model parameterized for the palletizer shows better results than the depalletizer with a TIC of 0.28-0.29, a total deviation of 33-37 % and a credibility of 0.28-0.35.

For the crate washer, validation data for only one period were available due to data record problems. The TIC is 0.24 and the credibility is 0.40. The machine model parameterised for the mixer has the highest total deviation and the highest ADP (up to 148 %). Validation plots showed only partial correlation between the operational state and the energy demand.

In summary, the validation results show that for all machines the TIC is below the published critical value of 0.4 proofing a satisfactory model fit. The TIC for the total line is low (0.10-0.13) and the credibility of the whole line model is high (0.68-0.75). The total deviation of the forecasted energy demand in the validation period has a 95 % confidence interval of [0.3; 4.8] for α=0.05. As optimisation potentials up to 35 % are expected the validation is satisfactory for future research on state based electrical energy consumption. The data published in this paper show, that the bottle cleaning machine has a major influence on the energy demand of the total line. The packers have a minor influence. The state based approach shows, that the demand of the machines during downtime is high (see results for bottle cleaning machine). Based on this validation, the model can be used to analyse optimisation consideration related to changes in energetic parameter (e.g. for suspended due to intelligent shut-down behavior) and organisational changes (e.g. changes in the shift system resulting in a reduced idle time).

The dynamic validation plots show very good correlation between the simulated and measured electrical energy data (see complete validation period and detail in Figure 2.6-17).

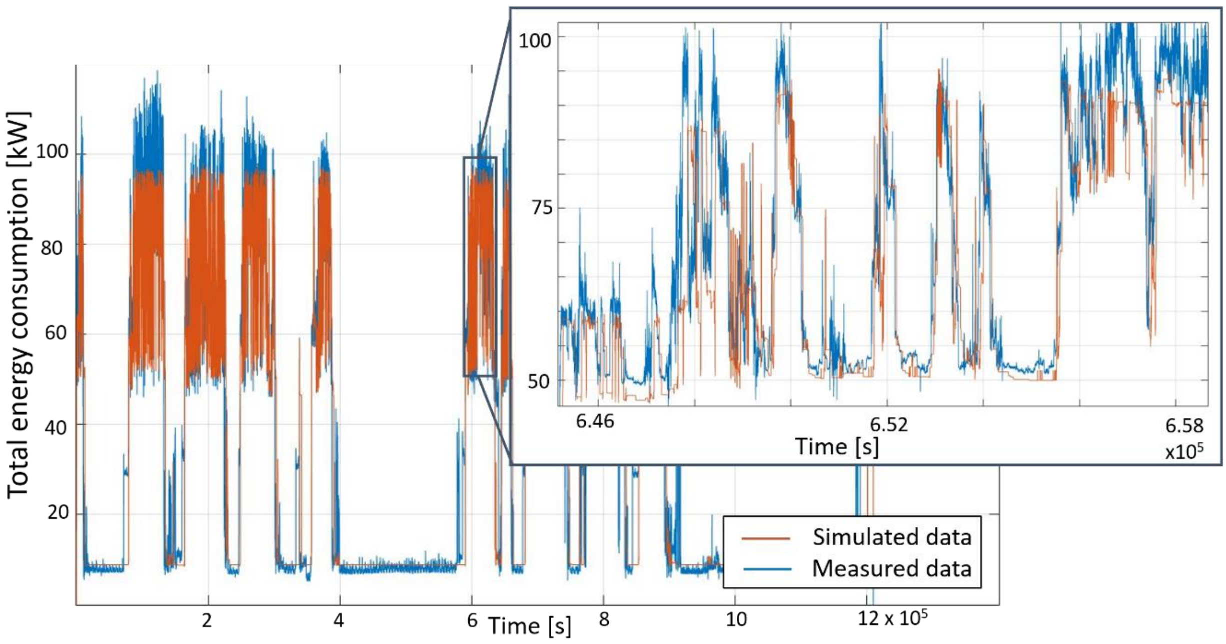

Figure 2.6-17: Validation plot and detail for the whole packaging line (experimental time: 14 days (12.096 x 105 s)).

9. Discussion of the results

The model was validated using visual and statistical criteria (validation plot and ADP/ TIC/ credibility). In the first validation step all the validation plots showed a clear difference between the energy demand during the production time, mapped as DL PRODUCTION, and the machine downtime, mapped as DL SUSPENDED. For all machines the DL INACTIVE was clearly identifiable as expected due to the mechanical machine behavior. For some machines the DL values are averages of the alternating values caused by machine behavior (e.g. labelling machine) but these are nevertheless sufficiently precise. The validation plots for all machines beside the mixer confirmed, that both the measured data and the simulated data depend on the operational state changes. The 2-D line plot of the simulated data follows the the 2-D-lineplot of the measured data.

For all machines the TIC was below the published critical value of 0.4. Validation plots for all the machines showed that some parts of deviations, as indicated by the TIC and the APD values, were caused by minor time shifts of the energy pattern in the validation data relative to the measured operational state data, due to technical reasons in the data acquisition. The individual machine models of all the continuously operating machines (washing machine, filling machine, labelling machine and crate washer) describe the real electrical power demand with acceptable deviations and show good correlation in the validation plots. For the selective depacker, washing machine, filler and labeller the credibility is high and the models can be accepted as valid for development and optimisation.

For the palletizer and packer the value of the credibility was low. The validation plots showed highly fluctuating power demand due to the cyclic functioning of these machines. The machines which operate in cycles have a high APD due to their alternating demand caused by the single cycles, which are not considered during the production time due to the availability of the state data. The models are not yet able to adequately map the exact machine demand behavior based on standard operational state data. This type of modeling approach therefore has limitations, although the TIC is above the critical value. For such machines the model should be extended to consider cyclic operation to better map the exact machine behavior. Further optimisation of the forecasting result could possibly be achieved by using an extended time period for parameter acquisition in order to balance the variation of the actual demand.

The validation results for the mixer are ambiguous. Some simulated machine operation periods were correctly reproduced whilst others showed unrealistic behavior. For the mixer, the model could not simulate unexpected switching operations (such as the irregular switching on of pumps during production). This resulted in a high APD value. The model should be improved for the respective operation periods.

The power demand forecast for the whole line had a deviation of only 3-4 %. Thus the model parameterised for the whole bottling plant is valid for forecasting the total electrical energy demand. Figure 2.6-17 illustrates that there is good correlation between the forecasted and measured values. The forecasted behavior reproduces the real trend of the electrical power demand. The peak load behavior was not mapped due to the averaging of the energy parameters. The influence of the poor forecasts for the machines which operate in cycles is low due to their low power contribution to the total demand in the whole line. The high average percentage deviation of their models had only minor relevance to the overall result.

The model, showing the main consumer “bottle cleaning machine”, can be used to show the influence and effectiveness of single energy reduction efforts (e.g. a reduction of the energy demand during unplanned downtimes by an optimised pump management) on the total energy demand of the line.

As discussed, the values of the statistical and visual validation show a high correlation between the simulated and the measured data. Therefore, the model can be evaluated as valid and satisfactory. The state based energy demand model with newly defined energy demand level for bottling machines, the generic description of the transitions with intermediate level and the mapping of operational states and the energy levels enables detailed state based future optimisation considerations for bottling plants:

The model can be used to evaluate the effectiveness of single optimisation strategies for bottling plants. For the considered plant the bottle cleaning machine has the highest influence on the total line demand. During downtimes the demand is still significant higher that for example the demand of the bottle filling machine. The demand during downtime is mainly caused by pumps circulating the lye. Optimisation efforts should focus on the reduction of these demands. The model can be used to show the effect of a optimisation measure by using a new set of parameters (e.g. 30 KW instead of 37 kW during the DL SUSPENDED due to more efficient pumps or the additional shut down of a pump). With the modelled and parameterised INTERMEDIATE LEVEL the influence of optimised shut down cascades of single machines on the total demand of the line can be assessed. The simulation results can be used to calculate the resulting savings depending on the plant specific production plan represented by the given operational states. With this information potential optimisation strategies can be compared and the most suitable specific for the considered plant can be chosen. By now the model can only be used with given operational state parameters. Further research on a validated material flow simulation will enable flexible changes in the production plan to investigate structural optimisation strategies and to use additional optimisation potentials.

10. Conclusion and outlook

The basis of this modeling approach was that the electrical energy is correlated to the operational states. This was verified by assigning valid parameters for all machines, apart from the mixer. The model allowed simulation of the electrical power demand of the individual machines and the whole bottling and packaging plant for beer, soft drinks and mineral water. There was good agreement between the simulated and real data, with acceptable deviations. The operational state based model allows detailed analysis of the power demand based on actual production behavior. Demand can be related to production phases. For palletizing machines, packers and mixers the approach needs to be extended. For a more detailed model, additional energy demand levels can be defined in the unused production times (e.g. for heating up, cleaning) based on the same modeling approach. Furthermore, there should be consideration of the demand behavior of transport modules. For future applications the existing models could also be parameterised using program data from machine control systems. This would directly provide information about the shutdown behavior of the machine without the effort and cost of taking measurements. By using simulation data from a material flow simulation environment, comparison of various scenarios would be possible. The interlink between the dynamic demand behavior model and the discrete material flow model will enable the analysis of the influence of production plans and the mode of operation of individual machines and the whole interlinked line. Aspects of production research, such as life cycle costing of new and existing production lines for beverage production, can be estimated based on this model. The model can be used for further research on optimisation options and for identification of the most energy efficient operational scenarios. The basic idea of a generic state based energy demand model for bottling machines can be adapted for packaging machines and be used as a basis for future specifications purchasing new machines, energy measurements in existing bottling and packaging lines and cause-related analysis of demands.

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3 Summary of the Results

The scientific goal of this thesis was to gain fundamental knowledge on the production-related electrical energy consumption behavior on the example of a beverage-bottling plant, to develop suitable generic models and to transfer them into validated simulation models as a tool for analysis and optimization on the level of single machines and total plants as interconnected systems.

The electrical energy consumption of bottling plants has been analyzed in a high level of detail in order to provide a reliable base for the modeling and forecast of the energy consumption in bottling plants. In a first step a literature research was performed that found a lack of published and industrial available electrical energy consumption data, suitable for modeling and forecasts. A survey in the German beverage industry was used to improve the database. The result of this survey were basic data of the plant structure, machines and a limited quantity of energy consumption data on machine level. A high energy demand in standby times indicated optimization potential, the surveyed companies confirmed a need of energy consumption optimization measures and tools.

The obtained data-base on this survey was not detailed enough for modeling. Therefore, it was enhanced by empiric data collected on industrial bottling plants (>20 machines in total) over continuous time periods of up to three months: Operational state data were collected based on the *Weihenstephan Standard* state model every second and electrical energy was measured in kW every two seconds, using state of the art effective power meter on every main machine of the plant. To gain fundamental knowledge from the empiric data for modeling, the correlation of the electrical energy consumption data and the operational states of the machines were analyzed. For this frequency distributions of discretely measured effective electrical power values were plotted and abundant states (peaks) of the frequency distributions were identified as electrical demand levels (DLs). A correlation between these abundant states or peaks of the frequency distributions and the event-discrete operational state behavior of the single machines was confirmed by plotting the empiric electrical energy data in a 2-D line plot together with the current operational state of the machine, represented by colored areas in the background of the plot (see example of the validation plot in Figure 2.4-4). For the modeling of this behavior generic electrical demand levels and transitions between these DL where defined and mapped to the operational state model and described by a step function (see equation 2.6.1 to 2.6.4).

For the forecast of the electrical energy consumption in bottling plants, the modeling was transferred into a MATLAB Stateflow model. For parametrization of the demand level and state transitions empirical data were used. Operational states for the forecast were provided from empirical data in a SQL database, connected to the model via an ODBC interface. For model validation empirically measured data were used from measurements not used for parametrization before. The model was considered as valid by using statistical and visual validation methods. Based on the Theil's inequality coefficient (TIC) below 0.2 for a majority of the machines and below 0.4 for all considered machines, the model was considered as valid. The total deviation between simulated and measured energy consumption for a complete bottling plant was [0.4, 4.8] % with a 95 % confidence interval (α=0.05). Additional visual validation plots confirmed a correlation between the measured data and the forecasted data. Table 2.6-1 summarizes the main findings:

Table 2.6-1: Summary of the aims and results of the presented work.

Aim	Method	Result
Reliable database to analyze the energy consumption behavior in bottling plants	Literature research	○ Lack of published data ○ Lack of reliable industrial data for modeling
	Scientific survey in the German beverage industry	○ Basic data of plant structure and energy consumption for the German beverage bottling industry ○ High energy demand in standby times indicating an optimization potential ○ Database not sufficient for modeling/validation ○ High demand on optimization tools
	Empirical acquisition of machine-based data on representative bottling plants: ○ Effective electrical power (kW) ○ Operational state data (start time, end time, and operational state)	○ Reliable database data for two representative bottling plants (returnable glass and PET) and selected machines: • >20 machines • Effective electrical power [kW] every two seconds • Operational state changes (every second) • >10^8 discrete values

Aim	Method	Result
Fundamental knowledge regarding the electrical energy consumption behavior in beverage-bottling plants	Data analysis: ○ Frequency distribution of discretely measured effective electrical power values ○ Correlation between measured effective electrical power values and operational states	○ Peaks in frequency distributions of the discrete values of measured effective electrical power: electrical demand levels (DLs) ○ Correlation between quasi-continuous consumption behavior and event-discrete operational state behavior
Generic consumption model	Mathematical modeling of consumption behavior based on the results of the data analysis	○ Definition of the electrical DL ○ Section-wise defined function to describe the electrical DL and transitions ○ Mapping of the DL and operational states
Forecast of electrical energy consumption	Implementation of the mathematical model into a hybrid simulation model ○ Energy consumption: MATLAB Stateflow ○ Operational states: empirical data in an SQL database ○ Model connection: ODBC, SQL database ○ Model parametrization: empirically measured data ○ Model validation: empirically measured data independent of those used for parametrization	○ Successfully parameterized, validated simulation model for electrical energy consumption ○ Correlation of simulated and measured consumption in visual validation plots ○ TIC below 0.2 for most machines and below 0.4 for all considered machines ○ Total deviation between simulated and measured energy consumption for a complete bottling plant of [0.4, 4.8] % with an 95 % confidence interval (α=0.05)

4 Discussion of the Results and Conclusion

4.1 Energy consumption in bottling plants

A summary of the publicly available data and scientific literature in Publication I, Chapter 2.2, shows that only a limited database of published machine- or operational-state-related energy consumption data for beverage-bottling plants is available. Most data are published for thermal and electrical energy. The majority of the published data are related to total production processes or single-process areas (e.g.,., packaging in total), and only few are available on the machine level. Machine specific data published by Schreiner were not considered as state of the art anymore due to the age of the data and the increasing degree of automation over the last 30 years (Schreiner, 1982). Common key performance indicators (KPIs) are often related to a production volume (e.g.,., [kWh/hl]) and do not allow conclusions on optimization potentials of single production steps for the considered plant.

The literature summarized in Publication I showed that the energy costs for a brewery varies worldwide between 3 % and 10 % of the total production cost. The share of the electrical energy demand of the total energy demand of a brewery is on average approximately only 30 %, yet this demand results in approximately 70 % of the energy cost. Therefore, priority should be given to the efforts to reduce the electrical energy demand because it represents the greatest saving potential. Bottling accounts for 16.5 % – 30 % of the heat and 12 % – 35 % of the electrical energy demand and should therefore be one of the focus areas for energy analyzes and optimization.

The survey conducted on the German bottling industry, and published in Publication I, showed that many companies demonstrate interest in energy efficiency topics but have limited access to detailed consumption data. The companies surveyed provided general data for filling machines (n = 33) in their bottling plants, most of them for bottle-cleaning machines (n = 31), packers (n = 30), depackers (n = 31), and crate washers (n = 30); some for palletizers (n = 26), labelers (n = 25), depalletizers (n = 21), and pasteurizers (n = 14); and a few for tray packers (n = 7) or stretch-blow molders (n = 1). The results of this study in general provide a good overview of the machines used in the German bottling industry, as well as their energy consumption and energy optimization measures, but have to be reviewed critically in terms of further statistical analyses, as the quantity of the collected data is limited. Additionally, high interest in energy optimization strategies was confirmed in the survey, as 50 % of the surveyed companies already have an energy manager, 70 % run an energy management system, and 40 % have recently been certified according to DIN ISO 50001, which states requirements and guidance for use of energy management systems. More than 80 % already invest in energy optimization strategies, and over 80 % are planning to invest in energy-saving measures in the future and are looking for suitable tools.

Today, all global players on the brewery market and an increasing number of small and midsize breweries have published ambitious targets to reduce energy consumption and their carbon footprint, confirming the results of this study also on an international level (e.g. “Together towards zero” initiative by Carlsberg: Double the global rate of improvement in energy efficiency until 2030 (Carlsberg, 2020)).

The age of the bottling machines considered in the study was found to be mainly less than 15 years, which was considered as representative for the German beverage industry. Most answers given in this study were related to returnable glass bottles, and the median nominal speed for the lead machine filler was 28,000 bottles per hour, which are characteristic of the German beverage market. Some companies included in this survey additionally produce cans ($n = 9$), non-returnable glass bottles ($n = 8$), PET bottles ($n = 6$: $n = 4$ single-use bottles, $n = 2$ returnable bottles), and kegs ($n = 7$). Only data related to returnable glass bottles were considered, due to the limited number of data for the other packaging forms.

The data indicated a slight increase in the energy demand of single machines during the last 30 years related to the nominal machine speed due to an increased degree of automatization and complex machines, compared to the data published by Schreiner in the late 80s (Schreiner, 1982), which could in general be confirmed by the data of this study (see Figure 2.2-18 in Publication I). Bottle-cleaning machines had the highest value for the installed power and the electrical energy demand during operation. For most main consumers within a bottling plant, a linear correlation between the nominal speed of the machine and the installed power was found. As an example, a linear correlation between the installed power and the nominal machine speed for a main consumer, a bottle-cleaning machine, was found with $R^2 = 0.84$ for n = 14, and a linear correlation was also found for the energy demand during operation and the installed power with $R^2 = 0.92$ for n = 15. During standby times, a high energy demand of up to 78 % (mean: 34 %) of the energy demand during operating times was found for the main consumer, a bottle-cleaning machine, as well as for the filler (up to 74 %, mean: 21 %) and the labeler (up to 70 %, mean: 29 %). For standby times, no linear correlation was found between the nominal machine speed and the energy demand. Even if the machine speed is zero, the machines consume energy. These results indicate a high optimization potential, especially during standby times, and a demand for a detailed model. Only machine speed was found as not suitable as input parameter for the modeling of the energy consumption considering the influence of the machine down times on the total energy consumption, which do not necessarily correlate to the machine speed.

In addition to the survey, for Publication II and later Publication III individual measurements on industrial bottling plants were performed to gain a more reliable database for modeling and parametrization and validation of forecast models. High density operational state data and electrical energy data (a data point every second for the operational state and a data point every two seconds for the electrical energy consumption for all available machines) were collected on industrial bottling plants over continuous time periods up to three months. The data of the measurement were verified by an onsite comparison of the observed machine state and the automatically recorded operational state. A correct record was confirmed. For the energy measurements, state of the art effective power meters were used. The resulting extensive database of electrical energy and state data for a consistent time period was considered as suitable for in-depth analyses. The analysis in this work focuses on the production time, as only data for the machine state and not for the machine program (e.g. production, cleaning, maintenance, etc.) and machine mode (e.g. automatic, semiautomatic, off, etc.) of the machine were available for data acquisition. In future data acquisitions and analyses, the program and mode should be considered to further increase the accuracy of the forecast models.

4.2 Electrical energy consumption behavior of bottling plants

Publication II analyzes the electrical energy consumption behavior on the basis of the collected empirical data. Plotting the discrete measured values for the effective electrical power of single machines as a frequency distribution resulted in defined abundant states (peaks) of consumption values, which were identified and later defined as energy demand levels (DLs). The observed peaks or abundant values in the frequency distribution cannot be clearly distinguished from each other, because of the transitions from one level to another and the resulting intermediate values. By comparing the consumption pattern of the machines represented as 2-D line plots of the effective power data with colored state information in the background and a detailed frequency distribution histogram, a correlation between the assigned peaks to an operational state was identified (see Figure 2.4-8 in Publication II). The first peak of energy consumption in the frequency distribution for all considered machines corresponded to a low consumption level and was correlated to longer idle times (weekends, nights). The second abundant state that was found in the frequency distribution showed a reduced energy demand, compared to the maximum values of the distribution, and was correlated to downtimes. The third peak of values in the frequency distribution was assigned to operating/running times. Three resulting main machine operations correlated to consumption peaks were summarized: inactive times, downtimes, and running times. No clear differentiation in the electrical energy demand during the different types of downtime (tailback, equipment failure, and lack) was found. The energy behavior of the single machines was, therefore, simplified as a limited number of constant demand levels, which were defined based on the observed peaks or abundant values in the frequency distribution.

Operational state transitions lead to a reproducible energy behavior (e.g. reducing of the demand in a stepwise manner) for specific machines, such as bottle cleaners. Others reduce or increase the consumption value in a minimum time after a state change. The measured data show some machine state changes taking place immediately (e.g.,., for packers), whereas others (e.g.,., fillers or bottle-cleaning machines) are realized in a stepwise manner according to the machine’s function. State transitions are reproducible, which was proven in the example of two specific machines and n = 20 state transitions (change from *operating* to *equipment failure* for a bottle-cleaning machine and a bottle washing machine). No significant correlation between the duration of the stop and the energy consumption within the first 60 s of production was found. The influence of the machine speed on the electrical energy consumption was found to be machine-specific, as it depends on the type of consumer within the machine (e.g.,., electrical drives, pumps, or compressed air), which is not necessarily correlated to the machine speed. The product and process conditions do not influence the state dependency in general but affect the value of the energy level.

Comparing these results with the models of Vijayaraghavan and Dornfeld and Weinert and Mose, it was found that the general approach of a correlation between electrical energy consumption and the operational state could be confirmed. Nevertheless, the observed operational states and resulting the resulting energy consumption behavior for bottling plants vary from the published states (Vijayaraghavan and Dornfeld, 2010, Weinert and Mose, 2014). For bottling machines for example no set-up or configuration states were found. Dietmair and Verl (Dietmair and Verl, 2008) presented a basic state/transition energy consumption model for a tool machine including nine operational states, which are correlated to the power consumption profiles, while for bottling plants it was assumed, that only three main consumption level are necessary. The models are application specific and therefore not transferable to bottling plants.

4.3 Generic modeling of the electrical energy consumption of a bottling plant

Based on the results of the empirical data analysis, a model was developed describing the energy behavior of a bottling machine by three main demand levels (DLs): inactive DL, suspended DL, and production DL. These DLs were assigned to the operational states, described by a start time ($t_{\text{start\_state\_n}}$) and an end time ($t_{\text{end\_state\_n}}$). When the time intervals overlap, the start time of a new operational state represents the end time of the prior operational state. In the model, the DL value is held constant over time. State transitions were modeled using finite number of constant intermediate levels (ILs) as well as end times t_{IL} (determined by the end time of the last DL) of the respective levels, which are specific to each machine. A step function describes the electrical energy demand over time (see section 4. in Publication III, page 112).

Modeling was successfully verified by graphical verification for running times and planned downtimes, which are described by the DL “Inactive” in the model. No verification or validation data were available for the machine program mode, as they could not be recorded for the considered plant. In future applications, it might be necessary to extend the model with further DLs (e.g.,., cleaning or other machine-specific DLs), which is possible in the presented model, as the DL are defined as finite number of defined states and parametrized with specific values. The model was found to be valid for single bottling machines, beside the mixer. The mixer is part of the bottling plant and directly connected with the filler, yet it is a process aggregate not showing the same operational state characteristics as the other considered machines. There was no correlation between the energy demand and operational states identified for the mixer. While the contribution of the mixer to the total electrical energy demand is low in this consideration, a different model for the mixer should be considered for the future.

4.4 Forecast of the electrical energy consumption

The mathematical model of the DL and state transition was implemented in the established environment of MATLAB Stateflow (MATLAB R2015a). A generic component parametrized for different single machines was developed. Single generic components can be interlinked to a total bottling plant and parametrized for the consumption behavior of a specific machine (e.g., bottling machine, filler). The model requires values for the DL, IL, and the times of the IL as an input parameter, as well as operational state data. The energy parameters (value in kW) for the defined DL were calculated using the collected empirical energy data. For future simulation studies specific figures from the equipment supplier can also be used, if available. For some machines, the DLs are averages of an alternating machine behavior (e.g., a labeling machine with a variable machine speed based on the nominal speed of the lead machine filler), but these average values were later found to be sufficiently precise during validation. Historical records of operational state data (e.g., from the MES) or operational state data as an output of a material flow simulation can be used as an operational state input of the presented model. In Publication III, historically recorded state data were used.

The energy consumption model was successfully validated by visual validation plots evaluating the consistency of the simulated and measured data in terms of the operational state correlation. For all validation methods, the measured energy and operational state data from industrial plants were used at time intervals independent from the data used for parametrization. The measured operational state data were provided to the model as an input parameter. The correlated measured energy data were compared with the simulated energy data over this time period. Additionally to the visual validation, established statistical indicators were used to prove the model fit for individual machines and the whole line: Theil's inequality coefficient (TIC) evaluates a model's forecast accuracy by analyzing the consistency between the simulation and reference (e.g., empirical) output data. Additionally, for three reference periods of 14 days each, the average percentage deviation (APD) of the simulated and the measured discrete values and the total deviation in percent of the accumulated total demand were calculated.

The validation plots for all machines besides the mixer confirmed the correlation between the operational states and the simulated and measured electrical energy consumption, for all considered machines. The models parametrized for the bottle-cleaning machine and the filling machine showed the best model fit and the lowest total deviation over the three validation runs (with a mean of 2 % for the bottling machine and 3 % for the filling machine). As these two machines are the main consumer, this supports a good model fit of the model for a total line. For the main consumer the TIC was below 0.2.

The credibility of the models parameterized for the palletizer and the packer was lower. The validation plots show a highly fluctuating energy demand as these machines operate in cycles. Within operating the machine performs a number of repeated cycles, which can vary in their speed, to align with the design speed of the lead machine. The calculated mean value for the operating DL was considered to be suitable for packers and depackers (below 10 % total deviation, considering the total deviation during the validation period of 14 days). For the palletizer, the deviation was higher (>10 %) and the model was considered as only partially acceptable, because of the cycle-wise operational mode. As the total share of consumption from the total energy consumption of the plant is low for these machines, it was considered that the model is sufficiently accurate for this use case.

For the total production line, a low TIC (0.10–0.13) was found, which indicates a good model fit, and the resulting credibility of the model was high (0.68–0.75). The total deviation within the validation period of 14 days had a 95 % confidence interval with [0.4, 4.8] % for $\alpha = 0.05$. As a comparison, the energy data-driven decision support system for by Le and Pang has an accuracy between 94.7 % and 98.5 %, depending on the quality of the training data (Le and Peng, 2013). Taking into consideration a possible optimization potential of approximately 35 % for bottling plants, it can be assumed that the model is suitable as an optimization tool for bottling plants.

For the first time, the validated hybrid forecasting model enables a detailed forecast of the electrical energy consumption for bottling plants on a machine level, considering the complex interactions of the machines by the material flow. The generic model component was confirmed to be valid for single machines and a total plant. The model concept allows the forecast of the impact of energy parameter changes on the total consumption of the plant, based on a realistic operational behavior of the plant. As example, the influence of a reduced demand resulting from a machine optimization for the operational state “suspended” (e.g. by optimized machine control or reduced shutdown times) on a total production period can be analyzed in the model. For this the optimization can be evaluated using a variation of parameter for IL and t_{IL} in the model comparing the resulting current consumption of the total plant. Additionally the influence of structural changes in the factory layout (e.g.,., by implementing an additional or more energy-efficient machine) or organizational changes (e.g.,., shift model, changes in running or downtimes) on the electrical energy demand of the plant can be analyzed and evaluated.

5 Outlook

As presented and discussed in this thesis, an operational-state-related forecast model was found to be valid for bottling plants. The presented model now enables extensive simulation studies, including various parameters of the material flow and energy consumption. In order to further increase the flexibility and accuracy of the model, a number of parameters can be subject of future research. Furthermore, the basic modeling results could successfully be transferred into an industrial application and shall support the bottling industry by defining correct energy consumption guarantees for new machines, and to evaluate the electrical energy consumption of existing machines.

5.1 Future scientific research

- **Simulation studies**

Referring to the optimization potentials presented in section 1.6 of the Introduction, simulation studies should be performed to generate reliable data to optimize bottling plants. Generic scientific procedure models for energy optimization as well as plant-specific optimization strategies can be developed on the basis of the model presented.

- **Model extension by a material flow simulation model**

While, for the presented model, operational state data were provided from a historical record, a model extension by a material flow simulation would allow providing operational state data by a variable event-discrete material flow simulation. Event-discrete material flow models are focused on mapping the plant structure and all the parameters, which influence the operating behavior of the system and the system components. As output, the model extension could provide operational state data in a high level of detail (e.g. every second). For the development of a material flow model, to map the operating behavior of the individual components of a system, stochastic errors of the elements should be considered, as well as the influences of the upstream and downstream machines. Further analyses and model development can also focus on including conveyors into the model.

- **Model transfer to other energy and media types**

First measurements in the environment of this thesis indicated that the idea of operational-state-related modeling and simulation of electrical energy consumption seems to be transferable to other energy and media types of a bottling plant. This was also already confirmed for single machines in the industrial application (see 5.2. Industrial Transfer). In a single measurement, the freshwater consumption of a bottle-cleaning machine was measured and a positive correlation was found between the freshwater consumption and operational states, similar to the electrical energy. Further measurements should verify the transferability of the result to other energy and media types like thermal energy, freshwater, and pressured air consumption.

Bär et. al have continued the research in this field and could confirm and extend the presented model. They used the here presented modeling approach for the electrical energy demand of machines and could simplify it by omitting the time-dependent variable. They developed a metamodel as a standardized and generic framework for the modeling of production systems, divided into the models: plant, process, article/recipe and production plan. He uses a generic and standardized data structure as well as tools for the automatic determination of the required simulation parameters (Bär and Voigt, 2021).

Furthermore, they extended the modeling idea to a holistic approach. The simulation environment is extended by the integration of a production plan and the associated recipe- or article-specific simulation as well as by the simulation of batch-oriented production. As a final result, he has developed a hybrid simultaneous simulation extending the discrete bottling plant by the batch-oriented production method in the batch area (e.g. brewhouse) including not only electrical energy but also other consumptions (e.g. thermal energy, compressed air) (Bär et al., 2021; Bär et al.. 2022).

5.2 Industrial transfer of the results

The German Engineering Federation *Verband Deutscher Maschinen- und Anlagenbau (VDMA)* has formed a network with several member companies of the German food machine suppliers and bottling and packaging industry to discuss different technological challenges (*Fachverband Nahrungsmittelmaschinen und Verpackungsmaschinen*). The basic modeling results and state definitions of this thesis and further work in cooperation with an industrial consortium were summarized to the normative fundament *VDMA 8751:2019-03: Abfüll- und Verpackungsmaschinen- Spezifikation und Messung des Energie- und Medienverbrauchs* for the specification and measurement of energy and media consumption in bottling and packaging machines (VDMA 8751:2019-03).

While the published model only focuses on three main demand levels (inactive DL, suspended DL, and production DL) for industrial application, a further division of the suspended level into *High Level Standby* and *Low-Level Standby* was decided to enable the differentiation of the availability of the machine after standby times (see Figure 4.-2.1). The DLs are called “power level” in the English translation of the normative fundament and are defined as shown in Figure 5.2-1.

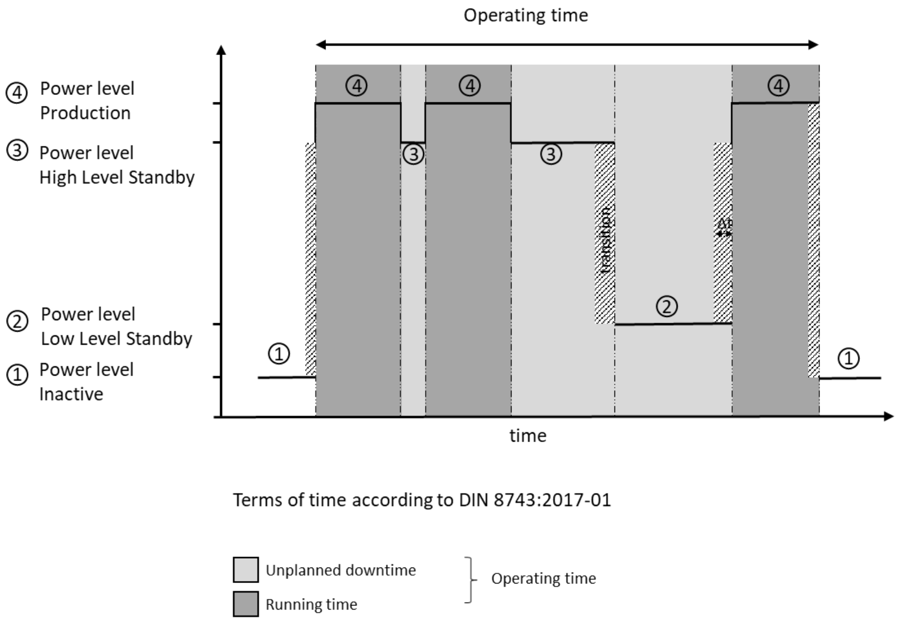

Figure 5.2-1: Descriptive model of energy performance level in packaging and bottling machines (own figure, published in VDMA 8751:2019-03).

The published VDMA specification defines key figures and machine performance levels, for which average energy and media consumption values can be specified related to defined system boundary conditions. Based on these specifications the expected energy- and media consumption can be calculated for a given production pattern, comparable to the modeling in the presented work. The calculated consumption can be verified in a defined measurement of energy and media consumption in an acceptance run of the machine system.

This published normative fundament is therefore intended to support the bottling industry in achieving their sustainability goals by providing them with a method of specifying the energy demand of new machines, having transparency between different available options and verifying them in a defined acceptance run. Additionally, a method is provided for evaluating the energy demand of existing machines and bottling plants.

5.3 References of Discussion and Outlook

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Abbreviations

ANSI	**A**merican **N**ational **S**tandards **I**nstitute
APD	**A**verage **P**ercent **D**eviation
DIN	**D**eutsche **I**nstitut für **N**ormung e. V.
DL	(Energy) **D**emand **L**evel
DT	**D**own **T**ime
e.g.	**e**xempli **g**ratia (for example)
IL	**I**ntermediate **L**evel
ISA	**I**nternational **S**ociety of **A**utomation
KPI	**K**ey **P**erformance **I**ndicator
LED	**L**ight-**E**mitting **D**iode
MDT	**M**ean **D**own **T**ime
MES	**M**anufacturing **E**xecution **S**ystem
MTBF	**M**ean **T**ime **B**etween **F**ailure
NTP	**N**etwork **T**ime **P**rotocol
n	**n**umber
ODBC	**O**pen **D**ata**b**ase **C**onnectivity
OEE	**O**verall **E**quipment **E**ffectiveness
PET	**P**oly**e**thylene **t**erephthalate
SQL	**S**tructured **Q**uery **L**anguage
TBF	**T**ime **B**etween **F**ailure
TIC	**T**eil's **I**nequality **C**oefficent
VDMA	**V**erband **D**eutscher **M**aschinen- und **A**nlagenbau e.V.
WS	**W**eihenstephan **S**tandards

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