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Ascertainment of Energy Consumption Information in the Age of Industrial Big Data

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Abstract

Industrial Big Data and Energy Management have become major strategic topics in manufacturing as they offer possibilities to realize untapped cost and emission saving potentials. The paper discusses the utilization of equipment internal energy-relevant data as part of the Industrial Big Data developments taking place in manufacturing to create energy transparency according to ISO 50001. A classification framework to estimate the required effort of ascertaining information on energy consumption of production equipment is described and the synergy effects with Industrial Big Data related to data acquisition, extraction and infrastructure are discussed. Furthermore, a case study provides insights about the achievable energy transparency in an automotive body shop.

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Keywords: energy transparency, shop floor data, energy monitoring, fields of application

1. Introduction

Industrial Big Data (IBD) [1] and Energy Management [2] have become major strategic topics in manufacturing.

Due to digitalization, most of the production equipment generates data through meters, signal transducers, or digital counters, which are needed for machine control or to observe process execution. Hence, data about process execution, resource consumptions and equipment conditions are consistently available on device level. These data offer many times untapped value for process optimization (e.g. predictive maintenance [3], energy efficiency optimization [4], and quality improvement [5]). Thus for data utilization purposes, it is desirable to gather that data in central data storages. The resulting volume of data from production systems grows at an unprecedented rate leading to IBD [6]. It can be seen in industry that the default collection of this data evolves towards a standard strategy - e.g. at Ford Motors Company [7] - and can be seen in almost every other industry [1, 6, 8].

At the same time, the global energy consumption has been steadily increasing over the past decades and will probably further rise according to studies [9, 27]. Additionally, recent developments show a growing interest in energy related topics of different stakeholders like industry (e.g. strive towards more economic and environmentally sound production), customers (e.g. rising environmental awareness) and legislation (e.g. regulations) [10, 48]. Therefore entrepreneurial execution strategies and regulatory claims often include the introduction of an energy management system according to the ISO 50001 standard or comparable specifications [2].

A key requirement of those is the conscious increase of energy transparency as foundation for energy optimization assessments and the continuous improvement process. The step towards investments into energy data ascertainment faces evident barriers. A common issue is the uncertainty about

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achievable benefits regarding energy and cost savings. This is leading to a difficult perception of efforts, risks and payback time, and results in not acted upon [11, 28].

To overcome this issue, the objective of this paper is to contribute towards the increase of energy transparency in production facilities according to ISO 50001 by the low-cost approach of utilizing equipment internal energy-relevant data in the course of Industrial Big Data. This is leading to the following research questions:

1. How can energy consumption information of production machinery cost efficient be ascertained and how can equipment be classified according to the effort to get energy consumption information?
2. How suitable is the presented approach to holistically increase the energy transparency of one automotive production department?

2. Research Background

2.1. Industrial Big data

IBD is one of the major trends nowadays. The term itself covers more than aspects of data acquisition and extraction, which are only the first steps of the whole Industrial Big Data pipeline. It also stands for the storage and the management of huge amounts of industrial generated data. To make use of the gathered data, techniques originated from the domains of data visualization, data mining, machine learning, and artificial intelligence are applied [12, 13]. These technologies complete the toolset of IBD. Summarized, the term describes a data/ information pipeline from a source – in this case energy meters or production machines – to a sink – in this case either a human or machine –, in which raw data is transformed to valuable knowledge (see fig.1) similar to CRISP DM [14] or KDD [15].

Fig. 2. Big data pipeline [47]

The pipeline has been adopted by the majority of industrial companies to create value from industrial data. Therefore, an infrastructure to source great amounts of data from various data sources has often been already deployed within production facilities. Additionally, data centers with large storage and computing capabilities have been installed e.g. [7, 1, 6, 8]. Because most often not all the required data has been already collected, this infrastructure can be utilized to collect energy data target-driven in the same "pipeline". Doing so reduces the required effort to collect energy data tremendously and leverages synergy effects. Within this paper, the steps "recording/ acquisition" and "extraction/ cleaning/ annotation" in the context of energy data are discussed. The required infrastructure is not further addressed.

2.2. Shop floor data extraction

Machine and process data acquisition (MDA/PDA) have been established in manufacturing for a long time [16]. The sourcing of this industrial data is physically done through a network, which is – so far – usually hierarchically structured according to the automation pyramid [17]. Latest studies reveal that the classical automation pyramid will gradually be replaced with networked, decentralized organized and (semi-) automated services [18]. Several standards have been developed in this field, with most of them published by the ISO/IEC JTC 1 committees [19].

For the purpose of this paper, the layer structure presented in fig. 2 with level 0, 1 and 2 will be discussed, because these layers affect the effort of shop floor data sourcing the most. Field devices from the lowest level like transmitters, sensors or valves are connected with Level 1 devices like basic control PLCs. The connection is usually done by hardwiring and analog signals or H1 fieldbus. The connection between Level 1 and 2 devices like controllers and supervisory PLCs can be done with H2 fieldbuses and the same protocols like H1 or with industrial Ethernet [20]. More detailed information about protocols, network setups etc. are presented in [21] and within standards from ISO/IEC JTC 1 committees. Once the data has reached the Controller/smart device level, and is for that reason addressable (IP address), it usually can get transferred through industrial Ethernet [22].

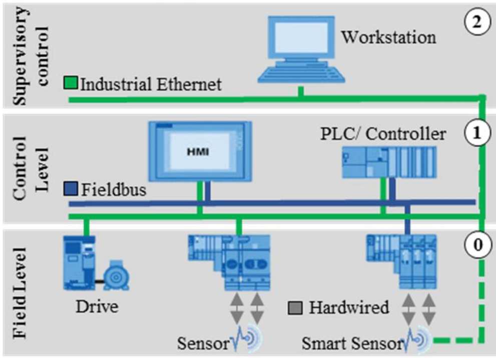

Fig. 1. : Hierarchy in a control system [19]

Afterwards, the so-called ETL (extract, transform, and load) process is performed, which is widely discussed in literature. Data extraction describes the collection of data – in this case from an Ethernet connected equipment. In the second step, data is integrated to a proper format and/or structure to be transferred to a data storage. The "load" process eventually describes the data loading into the final target database. During the ETL process several other/minor steps are done as it is shown in [23].

The collection of energy data from energy metering equipment is similar to common collection flows for process data. Well known standards in this area are published by the ISO/IEC JTC 1/WG 7 committee (e.g. reference architectures in ISO/IEC 29182 [24]). A more modern approach regarding the network infrastructure and the resulting data flow is presented in [25]. In this paper, the use of internet of things technologies (e.g. smart sensors and smart networks) are discussed to improve energy management.

2.3. Methods for ascertaining energy information

According to ISO 50001 chapter 4.4.3 [2], all main consumers have to get evaluated based on measurement of energy consumption and the influencing factors. Due to the cost and saving potentials related to energy transparency, a strategy "where" to measure, "what" medium for "what" reason needs to be developed. This strategy starts in general at the main energy input system points (transformers, distribution boards etc.). Beyond the high level metering points, all "significant" energy users identified in accordance with ISO 50001 should get prioritized and measured [26, 27]. A conceptual framework in order to grasp different levels of energy transparency is developed in [28]. This framework emphasizes a scale to define different levels of measuring data aggregation: Ranging from factory gate energy data (billing data) to total factory energy flow transparency.

In industry, energy transparency is closely connected with the introduction of Energy-Data-Management-Systems (EDMS). The minimal function is mainly ISO 50001 conformity, basic energy data analysis, visualization, reporting, alerting, and system integration [29]. The main data infrastructure requirement is to handle energy data streams with timestamps, and the aggregation of data towards statistical values (e.g. sum, mean, and standard deviation) per time interval (min, h, day). For that reason, information are usually highly aggregated in the direction of time (usually 15min blocks) and local assignment (production department or line). Therefore, apart from condition and process monitoring applications [30], raw data (sampled with high frequencies, split per machine) is usually not required for ISO 50001 conformity.

Ascertaining energy consumption information is typically done by measuring with stationary machine external devices or temporary measuring device, according to ISO 50006 [31]. This way of generating energy information is state of the art and can be seen in all ISO 50001 conform factories. This method either requires high investments for stationary measuring equipment or labor costs and less accurate information due to wear etc. at machines in case of mobile measuring. According to [32], installing a continuous measuring point for electric power demand of an existing machine in Europe costs between 1.000 and 3.000 €. In comparison, a typical manufacturing cell of a body shop in Germany consumes electric energy worth around 6.000 € - 8.000 € per year. To reach the level 9 of the framework described in [28], high costs but limited energy/cost saving potentials can be expected. Alternatively, production equipment, especially Machine tools, are sometimes already equipped with an energy input measuring devices. Also, some equipment already provides this energy data in the so-called trace function in the Human Machine Interface (HMI) of the controller. Thus, any temporal characteristic system variables can be collected [33]. The utilization of energy related data can be seen widespread in the area of machine tools [34, 35, 36].

If continuous energy load data is already available, the so called disaggregation approaches could then be used to further break down energy consumption information to subordinated systems based on identification algorithms, which correlate power consumption data with equipment control data (when switching on a machine, the power consumption increase around a certain value) [37].

Hybrid methods that allow a calculation of the consumed energy are another way to gain energy information. They could in generally be differentiated by event simulation and empirical based models. The simulation uses discrete information of different operational states interlinked with the specific energy information per status [38]. The empirical based models utilizing the relationship between process parameters and energy demand [39].

Physical calculation models are typically based on elementary physics and require input of parameter values that are a seldom part of the machinery documentation. Aside from in-depth measurements, basic energy management can also be backed with energy billing information of the energy supplier [28] or using power ratings, estimated utilization times and correlation information [40].

2.4. Classification frameworks for production equipment

Classification frameworks for production equipment are addressed by several research studies. As discussed in 2.3 either in terms of proceeding prioritization or to deal with complexity to develop a measurement and analyze strategy [41]. After defining the relevance of a consumer [27] developed a decision tree for the deriving type of data ascertainment leading to permanent or single measurement. Key decision criteria is the process repeatability, parameter dependencies and opportunities to model the final energy consumption, as alternative acquisition method.

For the purpose of classification according to the contained energy related data, the machine embedded control principle could be used to cluster production equipment. Each control method requires certain input signals from sensors, which can be taken to classify equipment according to the minimal installed sensors. There is a multitude of control methods available [42]. Commonly there are superimposed control methods used (e.g. for speed, torque, power control), which deliver the set points for subordinate voltage or current control. A frequently occurring control method is the field-oriented regulation. Here, mostly currents are measured, and by park transformation divided within a magnetic field and torque forming portion for ideal controlling. In this case, both the output voltage and the currents including the phase angle $\cos(\phi)$ are known in the inverter. For variable speed-drives, frequency converters are providing the drives output voltage (variable within amplitude and frequency). For regenerative drives, even the electrical power to the grid (including inverter losses) can be recorded directly by the inverter data [43].

Besides classification by control method, the way of data transfer could be differentiated [44]. Gathering energy data from production equipment for energy management purposes requires data exchange interfaces. Therefore, production equipment can be classified according to ISO/IEC JTC 1/SC 6 standards, where manufacturing automation networks and data exchange formats of devices are described. Considering this, three groups of supported data exchange interfaces can be identified. In addition, the production equipment can be classified according to the supported data exchange protocol. Due to the large amount of different protocols, only a few are listed: Hardwired (4-20mA, 0-10V); Fieldbus (Modbus/RTU, Profibus-DP, DeviceNet) and Ind. Ethernet (Profinet, EtherNet/IP, OPC UA, MQTT).

2.4. Key takeaway on the state of research

Current research regarding energy data collection from production equipment shows that Industrial Big Data infrastructure provides all key features, needed to extract data from production equipment (2.1). Due to the developments in course of Industrial Big Data, more and more data from production equipment will be captured by default and stored in central data storages. The above mentioned review shows different methods to ascertaining energy data. The widest spread approach – the installation of external metering devices - usually covers only main consumers due to the related costs of measuring equipment. The opportunity to utilize machine-embedded energy data is addressed in several research studies. Requirement for those is the availability of either continuous aggregated energy data (disaggregation approach) or energy conditional data (hybrid model approach). The physical calculation approach of different machine embedded input parameters as energy data source is not state of the art.

Classification frameworks are addressed by several research papers, mainly in terms of measurement prioritization, complexity and type of data ascertainment. Less scientific research is found in the direction of classifying equipment and efforts according to its capability to hold valuable data for energy management purposes and to exchange this data. Therefore an application framework summarizing the previous energy data sourcing methods and referring to the cost optimum utilization of industrial big data infrastructure will get developed.

3. Methodical approach

3.1. Classification Framework

In the following, the developed classification framework for production equipment according to its applicability to provide information for energy monitoring is described. The framework is presenting paths of energy information ascertainment and the related effort. Each path targets to provide normalized and aggregated energy data in the form of average power per time unit as information for superior information and control systems. For evaluation, seven main data sources (DS) will be distinguished. The qualitative effort point assessment is shown in {}, starting from {0} with very low effort to {6} indicating a high hassle to acquire the data:

(DS-0) Nominal values for low relevance of consumer {0}
(DS-A) Stationary, permanent external measurement {6}
(DS-B) Mobile, temporary external measurement {5}
(DS-C) Internal direct usable energy data {1}
(DS-D) Disaggregation approach based on permanent aggregated energy and process or machine-status data {2}
(DS-E) Hybrid modeling based on conditional energy data interlinked with either permanent machine-status data or process data for empirical data models {3}
(DS-F) Physical Calculation of energy data based on available process data {2}

For virtual metering point calculation (methods D to F) either edge computing or central computing approaches can be used as the data preprocessing unit (DPU):

(DPU-a) Machine embedded controller {1}
(DPU-b) Existing ext. processing unit (workstation, PLC) {2}
(DPU-c) New ext. processing unit {3}
(DPU-d) Superior existing information & control system {2}

The overall framework in figure 4 is in generally based on the allocation of the above mentioned elements (DS A till F and DPU a till d), by considering the increasing implementation effort from the left to the right and the control system hierarchy until the supervisory control level at the top. Starting at the left-bottom on the field-level with a relevant consumer which has no output signal available the decision tree in [27] will help to decide between the necessity of permanent (DS-A) or temporary (DS-B) measurement. To ascertain energy data without additional energy metering the main requirement is that the machine calculates output signals from sensor input signals to control the process. In addition, the machine has to be connected to a network (addressable) or is at least be ready to get connected with such a network. If the device is connected through industrial Ethernet, the data needs to be accessible. If the device is connected to a fieldbus, data need to lay on an output channel, which is connected with a control device (e.g. PLC). Once available on an industrial Ethernet-connected control device, the data can be collected from there. Due to the limited amount of output channels of the fieldbus this will not always be possible. If all output ports are allocated for other signals an external metering equipment needs to get installed in order to acquire energy data.

In the next step, it is necessary to identify whether the control unit provides any energy relevant data. In the best case, the control unit data already includes the average power consumption. This information can be found in the data sheet of the machine or directly through the manufacturer. Also, frequency converter controlled equipment could typically provide the necessary energy data. If further data is required for component consumption breakdown, the disaggregation approach could be used to deliver the requested information (DS-D) [37].

In case the control unit does not provide the power consumption directly, it could get calculated based on hybrid (DS-E) or physical (DS-F) models and process or machine data. By requesting the manufacturer or analyzing the machine control methods and feedback variables it is possible to identify which equations are needed to calculate the energy consumption. Some possible principles for control can be found in 2.3.

One example for the physical modeling approach (DS-F) could be based on the mechanical power P_{mech} of a speed controlled electric motor with the rotational speed n and the motor torque M. By dividing the mechanical power with the motor efficiency $\eta\ (n, M)$, which is usually supplied as a set-point specific characteristic map, the electric power can be calculated using equation (1) [45].

$$P_{el} = \frac{P_{mech}}{\eta(n, M)} = \frac{2 * \pi * n * M}{\eta(n, M)} \quad (1)$$

Another example are modern variable-speed pumps utilize current converters to adjust the pump power according to the demand in an energy efficient way. The electrical energy demand of the pump is often calculated on the control unit based on the converter feedback data. Besides that, many pumps include internal sensors to measure the medium temperature, pressure and they often provide inputs to add external sensor signals (e.g. remote flow temperature, pressure, volume flow) for control purposes. When a volume flow sensor

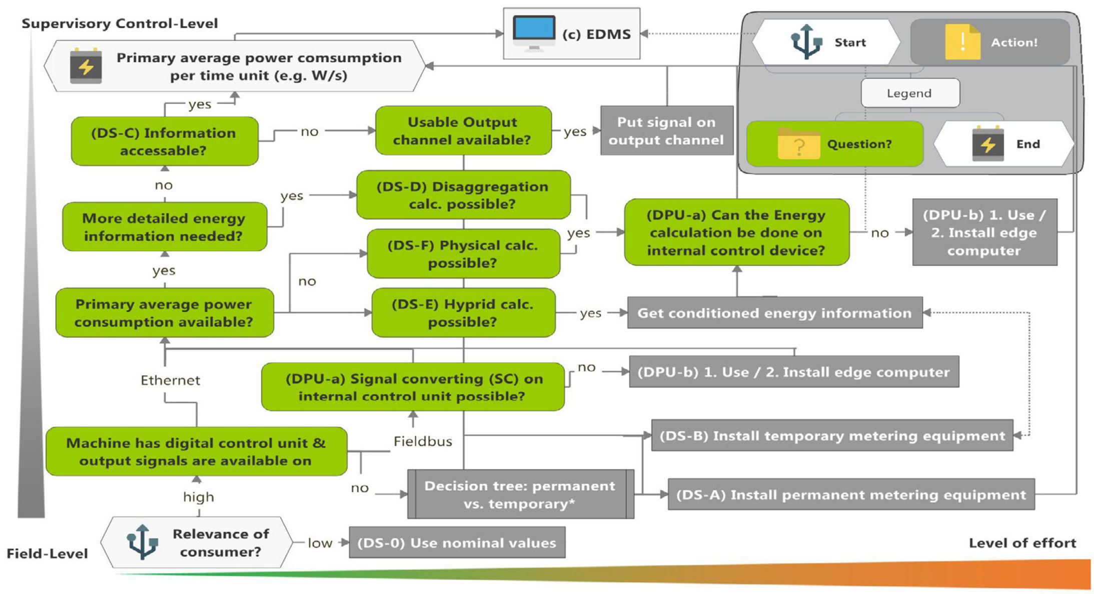

Figure 4: Classification framework

and remote flow temperature sensor are embedded, the heat flow $\dot{Q}$ can be calculated according to equation 3. In this case, the mediums thermal capacity c, density ρ, volume flow $\dot{V}$ as well as forerun temperature T_{fr} and return flow temperature T_{rt} need to be given as process data.

$$\dot{Q} = c \cdot \rho \cdot \dot{V} \cdot (T_{fr} - T_{rt}) \tag{3}$$

While temperature sensors are available at low costs and both the thermal capacity and density can be obtained from literature, volume flow sensors might add additional costs. Volume flow can usually approximate utilizing the pump characteristic map provided by the manufacturer. Therefore, assuming the electrical power, relative set point (and pressure) is given, the volume flow can be extracted from a look-up table.

Once it is determined whether it is possible to calculate the energy demand of a machine, it is necessary to identify, if the control unit can do the necessary calculations itself (DPU-a). If the control unit cannot do the calculations, they have to be computed outside the machine in an additional step. Depending on the available infrastructure, it might be necessary to install and use a peripheral edge computer (e.g. workstation) to do the calculations (DPU-c). Alternatively, the calculation can also be centrally performed in a superior information & control system (DPU-d: e.g. EDMS). The proposed framework is showing the different methods to gain normalized aggregated energy information and can be applied to machines or components in order to estimate the effort to gain energy information.

4. Industrial Case Study

Due to the high automatization degree and network connected devices, the proposed framework was applied in an automotive body shop, with the main equipment components: robots, turntables, spot welding, stud welding and sealing machines.

4.1. Stud welding and adhesive sealing

Both, stud welding and adhesive sealing are standalone applications and according to the framework therefore either need to get connected to the plant network or need to get measured with fixed or mobile devices (DS-A or DS-B). As stud welding could be classified as a repeatable process, with no dependencies on machine and product parameter temporary metering would be sufficient (DS-B). Whereas adhesive sealing is dependent also in terms of ambient conditions, permanent measuring is necessary (DS-A) [27].

4.2. Resistance spot welding

The resistance spot welding devices have a control system, which usually does not deliver energy consumption figures. However, they deliver data, which allow to calculate the energy consumption, based on physical formula (DS-E). Using the constant supply voltage U, constant proportional factor FN and the constant transmission ratio of the transformer U_T together with the real time data of the control unit (welding current I_s, welding time t and the real time phase angel Pha_{Value}) the energy consumption of every spot weld can be calculated according to equation 4.

$$E_{SW} = \frac{I_s}{U_T} * FN * \sqrt{\frac{Pha_{Value}}{100}} * U * t \tag{4}$$

4.3. Turntables

The control unit of the analyzed turntables provides a range of parameters as the rotational speed or the motor current. As described in [45] the electric power can be calculated through the mechanical power and the motor efficiency (equation 5), which is provided in the datasheets of the motor. The mechanical power can be calculated as given in equation 6 with the torque M_{motor} and the rotational speed n. The rotational speed is provided in real time by the control unit. The torque can be calculated according to equation 7 through the engine constant k_T provided in the data sheet and the real time engine current I.

$$P_{el} = \frac{P_{mech}}{\eta} \tag{5}$$

$$P_{mech} = 2\,\pi * M_{motor} * n \tag{6}$$

$$M_{motor} = k_T * I \tag{7}$$

4.4. Robots

The robots achieve the best rating according to the presented framework, because they provide energy consumption figures per cycle (Wh/cycle, DS-E) and the actual power (W, DS-C). The information could than directly be passed to the EDMS.

4.5. Effort evaluation and data validation

The framework got applied to identify opportunities to utilize machine embedded data for energy transparency purposes and evaluated the efforts to do so. Finally mobile measurements proving the data accuracy for a defined test setup:

Table 1. Effort evaluation & method accuracy for main body-shop equipment

Equipment	SC	DS	DPU	Effort point	Accuracy
sealing	No/0	DS-A / 6	None / 0	{6}	n.a.
stud welding	No/0	DS-B / 5	None / 0	{5}	n.a.
spot welding	No/0	DS-F / 2	DPU-b / 2	{4}	95 %
turntables	No/0	DS-F / 2	DPU-b / 2	{4}	96 %
robots	No/0	DS-C / 1	DPU-b / 2	{3}	98 %

For all equipment, no signal converting (SC) was necessary, but in case of possible data-source (DS) high differences in effort can be shown. From sealing with the highest effort points to the robots which already providing the requested information. The required calculations were all performed on the available workstations (DPU-b), where the data was initially collected and from where it was send to the EDMS. The calculated energy consumption through real time control unit data was compared to mobile energy measurements, to validate the virtual metering points. The results in table 1, column "accuracy" finally approved the presented approach with high reliability.

5. Summary and Outlook

5.1. Summary of results

In this paper, a classification framework for the effort estimation of energy data extraction from production equipment is presented and successfully validated within an automotive body-shop. Besides temporary and stationary measurement and approaches of disaggregated energy data, the paper also described the utilization of either already existing machine embedded energy data or the physical calculation based on process data.

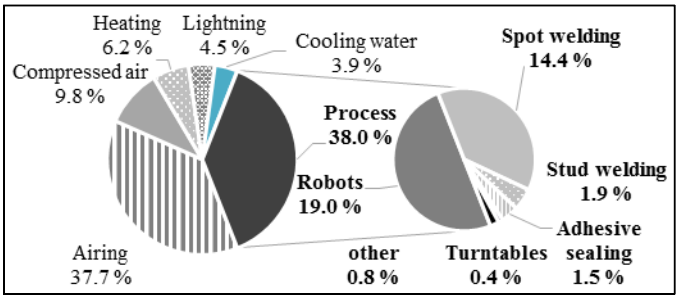

Fig. 5. Electrical energy consumption share in body shop

The case study shows that using the presented framework has the potential to reduce the costs of energy transparency tremendously. Without installing any external metering device, by using the available IBD data extraction infrastructure (data extraction methods, data processing tools and data storage), and by utilizing machine embedded data, reliable information about energy can be retrieved and used for energy management purposes. Figure 5 shows the final energy consumption of robots, spot welding devices and turntables, which make up 89 % of the energy consumption on the process level and can be continuously measured and monitored by this method. This means, regarding the whole body shop, it is possible to monitor at least 33.8 % of the total energy consumption without installing any additional energy metering device.

5.2. Outlook and challenges

The presented approach mainly focusses in the application on electrical energy information. The expansion of the framework to other types of energy like thermal or pneumatic energy offers to leverage the same effects and so, to provide a cost-efficient energy transparency gain in these areas.

This leads to the idea of going a few steps further on the Big Data pipeline (cf. fig. 1) towards data analysis and modelling. In this paper, the gathered data has been used within physical models for electric energy. The combination of different energy forms on the one hand might require new ways of integrating these models for a holistic view. This view bases on the application of methods originated in the field of IBD, e.g. Machine Learning based models that are able to learn physical models in combination with the ability to detect anomalies within the data.

This perspective of predictive analysis can be enhanced by looking for the causes of anomalies within the data. As a so-called root causes analysis, this extends the presented approach by detecting systemic irregularities or errors within the energy management. The insights gained from such analysis allow the human – whether as operator or on a higher aggregated perspective – to derive necessary actions for the prevention of errors or irregularities. If the detected irregularities could be prevented, a systematic analysis of the lowest possible energy operating level at which the desired product quality and quantity be reached, becomes possible. Hence, this enables further reductions of energy costs at a large scale.

The enhancement of the available IBD infrastructure with new tools/techniques needs to be reviewed. As the amount of data is increasing steadily, smart data annotation is becoming crucial, as it is the basis to find and link information and so, to realize the full potential of IBD. Due to the amount of data, data handling is facing more and more performances issues. Especially cloud, distributed storage and wireless technology promise to hold significant potential to improve data management performance and to connect isolated areas.

Additionally, within highly connected manufacturing environments with plenty legacy equipment there is a large potential of benchmarking different components with similar or same usage to evaluate technical efficiency. The utilization of machine embedded energy consumption data enables to leverage this potential due to the low costs compared to the implementation of external measuring devices. Furthermore, deeper analysis can be done based on the available low granular component data instead of today's highly aggregated consumption figures e.g. within the production line to identify the best operating model and support approaches for target process control parameters like total cost per hour [48].

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