Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 48 (2016) 325 – 330

www.elsevier.com/locate/procedia

23rd CIRP Conference on Life Cycle Engineering

# A Power Disaggregation Approach for fine-grained Machine Energy Monitoring by System Identification

Niklas Panten*, Eberhard Abele, Stefano Schweig

*Institute of Production Management, Technology and Machine Tools (PTW), TU Darmstadt, Otto-Berndt-Str. 2, 64287 Darmstadt, Germany*

* Corresponding author. Tel.: +49-6151-16-20-845; fax: +49-6151-16-20-087. *E-mail address:* panten@ptw.tu-darmstadt.de

**Abstract**

Energy monitoring is one major prerequisite for energy efficiency measures. Energy and power data throughout different levels of production allow benchmarking and condition monitoring applications based on insightful energy performance indicators. However, fine-grained measurement concepts for energy and power require high investments with uncertain benefits. This paper presents a low-cost approach to monitor the component-by-component energy consumption with a minimum of sensor technology that can be applied to a variety of production machines. Aggregated energy data combined with components' control signals are the basis for the determination of components' energy consumptions using two system identification algorithms. While one method is realized in an offline-mode after data collection, the second approach utilizes real-time data based on a recursive least squares algorithm. Eventually, the feasibility of the theoretical system identification concepts is shown in a laboratory environment.



Peer-review under responsibility of the scientific committee of the 23rd CIRP Conference on Life Cycle Engineering

*Keywords:* Energy Efficiency; Production Machines; Energy Monitoring; Non-Intrusive Load Monitoring; Power Disaggregation; System Identification

## 1. Introduction

While the worldwide energy demand, greenhouse gas emissions and global average temperatures are increasing [1], the social climate change discussion becomes the focus of attention. As a result of this, within the scope of the 2015 United Nations Climate Change Conference, 196 countries agreed by consensus on 12 December 2015 to the final draft of a global pact (the »*Paris agreement*«) to reduce carbon output and to keep global warming to well below two degrees Celsius [2]. More and more countries enforce the energy transition based on renewable energy sources in order to meet the energy requirements as evidenced by the European Union's goal of obtaining at least 27% of its primary energy from renewable sources by 2030 [3]. Due to the increasing volatility of energy generation a balanced technology mix between renewables, flexible power stations, storages, grid expansion and flexible consumers in »*demand-response*« programs is necessary to ensure the security of supply in a heavily modified electricity system. Another central element of this environmental efforts is to increase overall energy efficiency to reduce the global energy demand. At the EU summit in October 2014, EU countries agreed on a new energy efficiency target of 27% or greater by 2030 compared to projections of future energy consumption based on the current criteria [3].

As a key element of energy efficiency measures as well as demand-response applications, providing appliance-specific energy consumption feedback (*energy monitoring*) can contribute towards systemic energy optimization as it enables better identification and assessment of both energy saving and flexibility potentials [4]. Given a projected share of more than 53% of the total energy use in 2015 [5], the industry sector presents a massive leverage for achieving the mentioned objectives. It would therefore be advisable to achieve a high degree of transparency of energy flows in factories [6].

However, considering the tremendous amount of various energy consumers in the manufacturing industry, measuring the power consumption of individual appliances is extremely


Peer-review under responsibility of the scientific committee of the 23rd CIRP Conference on Life Cycle Engineering
doi:10.1016/j.procir.2016.03.025

costly and tedious [7]. Therefore, a particular research interest concerns methods to gain detailed energy data with reduced measuring equipment. Next to model-based simulation approaches as given in [8,9] a large number of so-called non-intrusive load monitoring (NILM) algorithms have been developed for smart meter applications, which are able to identify specific appliances' load profiles within measured aggregate power data [10–16].

Whereas recent progress in information and communication technology (ICT) has led to cloud-connected machines or equipment that provide data for data-mining applications, the available process data should be integrated in disaggregation algorithms to improve accuracy of disaggregation algorithms. This paper presents a new approach to identify machine components' energy consumption by utilizing aggregate power data and control signals in two system identification algorithms. While one method is realized in an offline-mode with a predefined set of data, the second approach utilizes real-time data based on a recursive least squares algorithm.

This paper is structured as follows: Section 2 gives an introduction to energy monitoring, disaggregation concepts and the utilization of detailed energy data. Subsequently, the two system identification disaggregation approaches for energy monitoring are presented in section 3, before a practical case study of the theoretical system identification concepts is presented in chapter 4. Some specific issues of the presented disaggregation strategies are discussed in part 5. Finally, the paper is closed with a conclusion in section 6.

## 2. Background: Energy monitoring and power disaggregation

Energy monitoring and essential metering systems [7] play a significant role for

- providing **information** about energy or power demands, costs, emissions and trends,
- allowing **comparisons** with other plants, departments, assembly lines, machines, components over time,
- setting and tracking realistic **targets** and
- defining adequate **control** measures to react to deviations/inefficiencies at an early stage.

Therefore, it is a crucial part of energy management for evaluating and optimizing the energy use in terms of both energy efficiency [17,18] and energy flexibility [19].

### *2.1. Benefits of continuous fine-grained energy monitoring*

Temporary mobile measurements can be a reasonable method to acquire an energetic status quo of production systems. However for a comprehensive insight of dynamic energy flows in the manufacturing environment, it is highly recommended to achieve a continuous in-depth monitoring of relevant machines, components, production infrastructure and external influences. According to studies energy efficiency projects are less likely pursued without sufficient detail of information to quantify energy distribution or assess implemented efficiency measures [7]. As data on the very detailed unit process level is usually structured according to the value-creation, it offers the highest benefit concerning the technical improvements [20]. Energy performance indicators (EnPIs) on this level are diagnostically conclusive as influence parameters are more obvious which can be corrected in benchmarks and considered in the decision making [21]. In general it is plausible that the more detailed energy data are available the

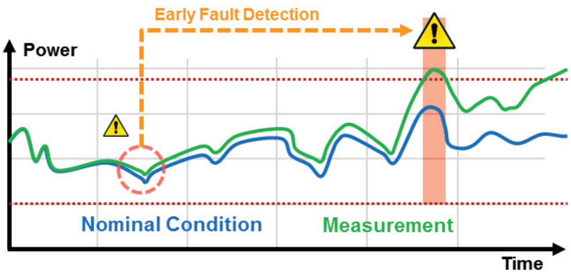


Fig. 1. Condition monitoring exemplary schematic

- more precise energy demands can be associated according to the costs-by-cause principle,
- more informative EnPIs can be calculated,
- more target-oriented sources and causes of inefficiencies can be identified and eliminated,
- better is the awareness of energetic processes in the factory in general.

In order to truly capture and evaluate changes in efficiency it is necessary to have a baseline energy target to compare against, which includes a breakdown of consumption by end use (i.e. space cooling, space heating, lighting, water heating, motors, pumps, etc) instead of aggregate data. Thus, energy efficient factories of the future continuously obtain energy-related rich real-time information down to discrete device level [22].

Properties of physical systems change over time i.e. due to wear or the machining process can be accidently altered such as by utilizing wrong materials. Both incidents usually affect the characteristic energy demand. Continuously monitoring and profiling the power demand in combination with operational data can be an efficient solution for predictive maintenance and process monitoring applications as indicated in Fig. 1 [23,24]. Thus, potential failures can be anticipated so that production availability and product quality improves [25].

However, as failures should be reliably predicted at an early stage and well localized in the production environment, the use of such intelligent predictive technologies also requires energy monitoring on the very component level.

### *2.2. Power disaggregation*

In order to obtain fine-grained power feedback, either hardware-based measurements (intrusive) or non-intrusive power monitoring methods can be used. Nonintrusive load monitoring (NILM), or nonintrusive appliance load monitoring (NIALM), can be a cost-efficient solution to gain detailed

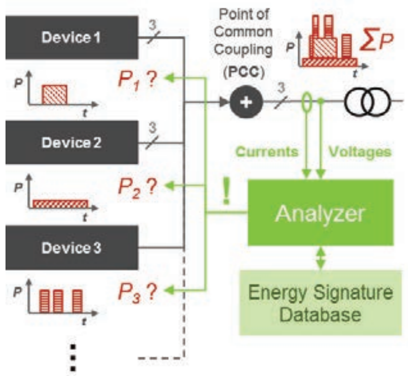


Fig. 2. Disaggregation scheme from single point of aggregate measurement

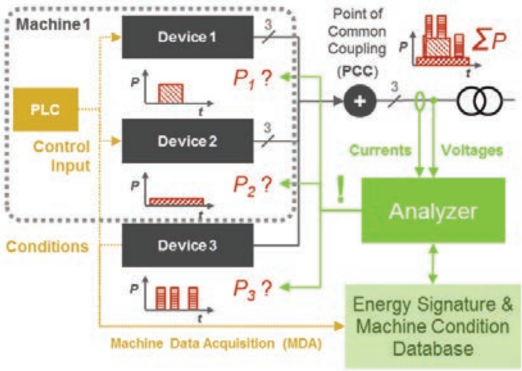


Fig. 3. Proposed disaggregation scheme utilizing aggregate power data correlated with machine data

energy data via power disaggregation instead of attaching individual monitors on each appliance [13]. By analyzing voltages and currents from a single point of measurement, NILM can discern individual devices within the aggregate power data. The approach is based on the fact that individual appliances have different characteristics for steady-state and transition states in both reactive and active power, so called »*energy signatures*«. The appliances' loads are superimposed at the point of common coupling (PCC) and the individual curves can be extracted from the aggregate data by pattern detection algorithms as illustrated in Fig. 2. Before, the systems usually need to be trained to recognize a device on the basis of one or more raw recordings of the single-device power consumption.

A great number of NILM solutions have been developed in the last years especially for residential applications [10–13,16]. They can track energy usage in each home appliance such as television, toaster, lamp, refrigerator, washing machine or vacuum cleaner. Even though the calculated energy data may not be as accurate as measurements, in most cases they can be sufficient for general energy monitoring applications.

However, there is a lack of research results that apply power disaggregation approaches to industrial applications. In typical manufacturing environments, a great number of basic electrical appliances and highly dynamic devices as speed-controlled motors with inverters interfere with NILM systems which may inhibit the deployment of disaggregation systems. [15]

To overcome this drawback and to improve accuracy in industry applications, machine states can be correlated with the aggregate power curves as proposed in [14]. This strategy is particularly advantageous as machine data acquisition (MDA) is state of the art in modern manufacturing facilities in order to track key performance indicators (KPIs), malfunctions or maintenance cycles.

## 3. System identification disaggregation approach

While study [14] breaks the aggregate factory power data down into individual machines by utilizing a regression model, the subsequent proposed disaggregation scheme makes use of an online system identification approach with control data to perceive individual devices power characteristics in real-time (c.f. scheme in Fig. 3).

To identify the dynamic characteristics (in this case power demands) of an unknown physical system, system identification uses statistical methods to estimate parameters of mathematical models from measured data [26]. Therefore, the algorithm adjusts the model parameters to fit the estimated model output $\hat{y}$ and the measured output $y$ with the estimation error $e$ to minimize a predefined cost function (c.f. Fig. 4).

### 3.1. Mathematical model of the dynamic system

For describing the dynamic energetic behavior of the system a mathematical grey box model in time or frequency domain is used. Considering the equidistant discrete-time sample values obtained by the measurement system, the description is based on a discrete-time model with $k$ as a multiple of the sample time $T_s$ ($kT_s \equiv t$) for proper digital signal processing. A linear system with power output $Y(z)$, control input $U(z)$ and a transfer function $G(z)$ in discrete-time equivalent frequency domain representation is assumed as given in (1) with $m, n \in \mathbb{N}_0$. The model numerator polynomial $B(z)$ and denominator polynomial $A(z)$ correspond to parameters $b_0 \dots b_m$ with order $m$ respectively to $a_0 \dots a_n$ with order $n$ where $m \geq n$.

$$G(z) = \frac{Y(z)}{U(z)} = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_0 + b_1 z^{-1} + \cdots + b_m z^{-m}}{1 + a_1 z^{-1} + \cdots + a_n z^{-n}} \quad (1)$$

On this basis, most physical characteristics e.g. delays or transients with oscillations and damping behavior (PT2 element) can be modelled. However to reduce the complexity of parameter identification in this work, a simple proportional element with transfer function (2) and gain $K$ as parameter $b_0$ is utilized.

$$G_p(z) = \frac{Y(z)}{U(z)} = K \quad ; K \in \mathbb{R} \quad (2)$$

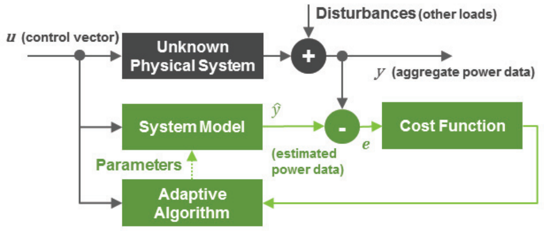


Fig. 4. Principle of system identification

### 3.2. System identification method of Least Squares (LS)

Taking the generalized error $\boldsymbol{e}$ according to (3) into account, the system output for $N \in \mathbb{N}$ samples $\mathbf{y}$ beginning from sample instant time $k$ can be indicated as (4). The $N \times (n+m+1)$ matrix $\mathbf{M}$ incorporates the measured aggregate output power and control data as given in (5). The system model parameters are included in vector $\boldsymbol{p}$ (6) and estimate errors in vector $\boldsymbol{e}$ (7).

$$E(z) = A(z^{-1})Y(z) - B(z^{-1})U(z) \tag{3}$$

$$\boldsymbol{y} = [y_k \quad y_{k+1} \quad \cdots \quad y_{k+N-1}]^T = \underbrace{\boldsymbol{M} \cdot \boldsymbol{p}}_{\hat{y}} + \boldsymbol{e} \tag{4}$$

$$\boldsymbol{M} = \begin{bmatrix} -y_{k-1} & \cdots & -y_{k-n} & u_k & \cdots & u_{k-m} \\ -y_k & \cdots & -y_{k+n-1} & u_{k+1} & \cdots & u_{k-m+1} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ -y_{k+N-2} & \cdots & -y_{k+N-n-1} & u_{k+N-1} & \cdots & u_{k+N-m-1} \end{bmatrix} \tag{5}$$

$$\boldsymbol{p} = [a_1 \quad \cdots \quad a_n \quad b_0 \quad \cdots \quad b_m]^T \tag{6}$$

$$\boldsymbol{e} = [e_k \quad e_{k+1} \quad \cdots \quad e_{k+N-1}]^T \tag{7}$$

For fitting the model, the parameter vector $\boldsymbol{p}$ of the overdetermined system of equations with $N \gg n+m+1$ needs to be determined so that the estimate error $\boldsymbol{y} - \boldsymbol{M} \cdot \boldsymbol{p}$ becomes as small as possible. In the least quare (LS) method $\boldsymbol{e}$ is minimized with respect to a quadratic sum cost function $Q(\boldsymbol{p})$ as given in (8).

$$Q(\boldsymbol{p}) = \sum_{i=k}^{k+N-1} e^2(k) = \boldsymbol{e}^T \boldsymbol{e} = \|\boldsymbol{y} - \boldsymbol{M} \cdot \boldsymbol{p}\|^2 \tag{8}$$

Following this, the fitted parameters $\boldsymbol{p}^*$ with minimum costs can be calculated through (9) for invertible and positive definite matrices $\boldsymbol{M}^T \cdot \boldsymbol{M}$.

$$\boldsymbol{p}^* = arg\,min\, Q(\boldsymbol{p}) = (\boldsymbol{M}^T \cdot \boldsymbol{M})^{-1} \boldsymbol{M}^T y \tag{9}$$

### 3.3. Recursive method of Least Squares (RLS)

As can be seen in (9), the inversion of a $(n+m+1) \times (n+m+1)$ matrix is necessary to identify the parameters. This calculation burden is a considerable limitation for online system identification where changes of the system parameters are supposed to be tracked in real-time. In case of the supposed power disaggregation application, the online feature is essential for condition monitoring systems as described in chapter 2.

However, by applying the *recursive* least square algorithm (RLS) new data can be integrated with reduced complexity in each recursion step. According to [27] the updated parameter vector $\mathbf{p}_{k+1}^*$ can be calculated based on the old parameters $\mathbf{p}_k^*$ with the updated data matrix $\mathbf{M}_{k+1}$, output $\mathbf{y}_{k+1}$ and the auxiliary matrix $\boldsymbol{H}_k = \left(\mathbf{M}_k^T \cdot \mathbf{M}_k\right)^{-1}$ as given in (10). Furthermore, the matrix $\boldsymbol{H}$ is determined in a recursive way in (11).

$$\boldsymbol{p}_{k+1}^* = \boldsymbol{p}_k^* + \underbrace{\frac{\boldsymbol{H}_k \boldsymbol{M}_{k+1}}{1 + \boldsymbol{M}_{k+1}^T \boldsymbol{H}_k \boldsymbol{M}_{k+1}}}_{\gamma} (\boldsymbol{y}_{k+1} - \boldsymbol{M}_{k+1}^T \boldsymbol{p}_k^*) \tag{10}$$

$$\boldsymbol{H}_{k+1} = \boldsymbol{H}_k - \boldsymbol{\gamma} \boldsymbol{M}_{k+1}^T \boldsymbol{H}_k \tag{11}$$

### 3.4. Enhancement for Multiple Input – Single Output (MISO)

Considering a multiple input single output (MISO) system, $j$ sub-systems (electrical devices) correspond to the control signals $u_k^{(1)} \dots u_k^{(j)}$ and the gain parameters $K^{(1)} \dots K^{(j)}$ of the proportional models. According to that, the data matrix and parameter vector turn into (12) and (13).

$$\boldsymbol{M} = \begin{bmatrix} u_k^{(1)} & \cdots & u_k^{(j)} \\ u_{k+1}^{(1)} & \cdots & u_{k+1}^{(j)} \\ \vdots & \ddots & \vdots \\ u_{k+N-1}^{(1)} & \cdots & u_{k+N-1}^{(j)} \end{bmatrix} \tag{12}$$

$$\boldsymbol{p} = [K^{(1)} \quad \cdots \quad K^{(j)}]^T \tag{13}$$

By incorporating more devices in the model, the disturbance loads get smaller which improves the accuracy of the proposed disaggregation approach.

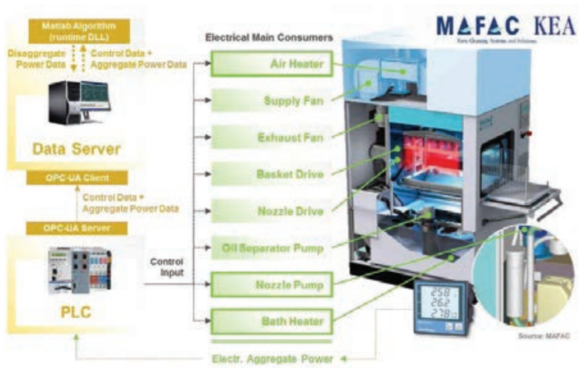


Fig. 5. Setup and functional schematic of the test system

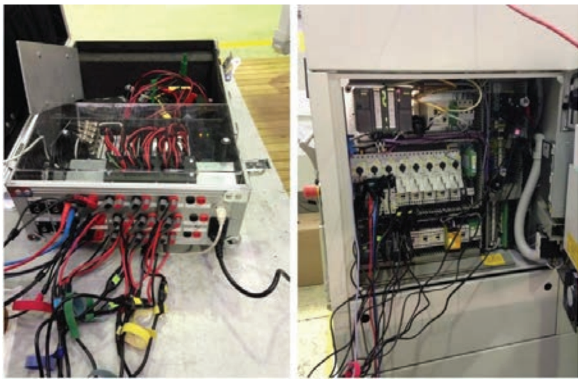

Fig. 6. Measurement setup within the test bench

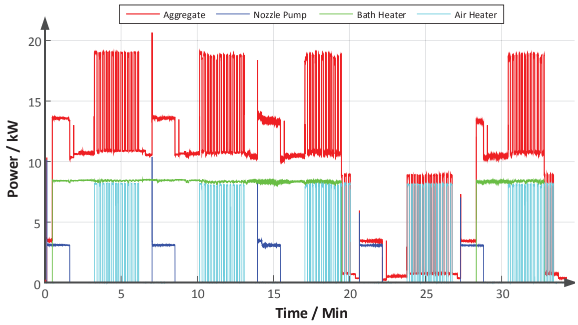


Fig. 7. Measured aggregate and component power curves

## 4. Case Study

A case study is carried out to examine the power disaggregation application based on the MISO RLS system identification approach under laboratory conditions. A »*KEA*« cleaning machine from MAFAC with a Bosch Rexroth PLC served as the basis for the analysis. The aggregate power measurement is realized by a Janitza 96 RM-P universal measurement device which is connected to the PLC by ProfiBus. The aggregate power data and the control variables of the electrical main consumers like heaters, pumps drives and fans are shared via OPC-UA communication protocol. Subsequently, the data are gathered by a Bosch Rexroth *General Data Server* (GDS) which executes the algorithm based on a Matlab runtime DLL [24]. The setup and the functional schematic is further visualized in Fig. 5. For analysis purposes the individual power curves of three devices (bath heater, air heater and nozzle pump) are recorded with external measurement equipment as can be seen in Fig. 6.

The algorithm and measurements are executed with a sample rate of $f_s = 1\,\text{Hz}$. The measured aggregate and component power curves are plotted in Fig. 7. As can be seen in Fig. 8, the RLS disaggregation algorithm is able to identify the power characteristics of the individual loads. The zero start parameter vector continuously adjusts to the actual average power value over time. However due to very rapid state transitions, the settling time for identifying the air heater power demand is quite high in this setup.

## 5. Discussion

The power disaggregation performance of the presented system identification algorithms is presented by practical analysis. However, there are some limitations and open issues of the proposed disaggregation approaches that are discussed in this section.

First, it is assumed that the power demand can be described as a linear system in reference to the control signal. Even though this is applicable for most cases, non-linear models can be necessary for selected appliances which might require a non-linear system identification approach.

Furthermore, the presented algorithm might fail to identify high dynamic devices with variable operating points like speed-controlled motors. However, most of those converter-based embedded systems offer built-in feedback of current power consumption which can be incorporated into the model for disturbance rejection.

Aside from that, the current algorithm inevitably needs persistent control signals of the devices available. This is likely to cause difficulties if control embedded systems do not offer status feedback which then cannot be acquired and used for further calculations. For cases like that, a hybrid disaggregation approach could be favorable that combine 'classical' NILM algorithms based on machine-learning and pattern recognition with the proposed control-data-based system identification strategy.

Further work will focus on improving this disaggregation strategy for industrial applications as well as on studying more complex machines and components as described above.

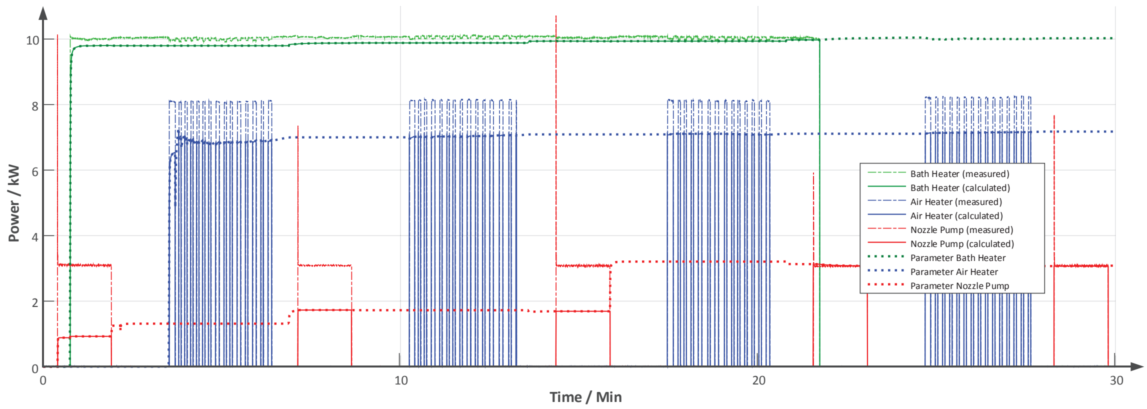


Fig. 8. Transient response of online power disaggregation results compared to the actual measured power curves

## 6. Conclusion

In this paper, a new power disaggregation approach based on a system identification algorithm utilizing aggregate power and control data is presented. By applying this monitoring concept on machine PLCs or on a machine data acquisition (MDA) server, individual device power demands can be extracted from aggregate power data. To reduce the computation burden, the proposed linear least square fitting algorithm is modified for recursive online calculation with real-time data input. Furthermore, the noise rejection and accuracy is improved by extending the system model for multiple appliances into a multiple input single output (MISO) formulation.

Finally, the MISO RLS algorithm is validated with a test bench based on a cleaning machine connected to a data server. The results reveal that the power demand of the individual machine components can be estimated by utilizing the developed disaggregation strategy. To increase accuracy as well as applicability for various machines and components, further research is needed in this field.

However as MDA is increasingly available in manufacturing environments, the approach of using aggregate power data correlated to machine and process data may be a cost-efficient solution for fine-grained continuous energy monitoring in industrial applications. Thus, the proposed strategy can contribute to increase energy transparency in factories as the general basis of further energy efficiency, energy flexibility and energy-based condition monitoring measures.

## Acknowledgements

The authors are grateful to the German Federal Ministry for Economic Affairs and Energy (BMWi) and the federal state of Hesse for funding the presented work in the project *ETA-Fabrik*.

## References

[1] International Energy Agency. World Energy Outlook 2014. Paris: IEA Publications; 2014.
[2] UNFCCC. Conference of the Parties. Adoption of the Paris Agreement. Proposal by the President. Geneva (Switzerland); 2015.
[3] European Council. Conclusions of the European Council (23-24 October 2014) on the 2013 climate and energy policy framework; 2014.
[4] Ehrhardt-Martinez K, Donnelly KA, Laitner S. Advanced metering initiatives and residential feedback programs: A meta-review for household electricity-saving opportunities. Washington, D.C.: American Council for an Energy-Efficient Economy; 2010.
[5] Energy Information Administration. International energy outlook 2013 with projections to 2040. [Place of publication not identified]: Energy Information Admini; 2013.
[6] O'Rielly K, Jeswiet J. The Need for Better Energy Monitoring within Industry. Procedia CIRP 2015:74–9.
[7] Kara S, Bogdanski G, Li W. Electricity Metering and Monitoring in Manufacturing Systems. In: Hesselbach J, Herrmann C, editors. Glocalized Solutions for Sustainability in Manufacturing. Berlin, Heidelberg: Springer Berlin Heidelberg; 2011, p. 1–10.
[8] Eberspächer P, Schraml P, Schlechtendahl J, Verl A, Abele E. A Model- and Signal-based Power Consumption Monitoring Concept for Energetic Optimization of Machine Tools. Procedia CIRP 2014:44–9.
[9] Verl A, Abele E, Heisel U, Dietmair A, Eberspächer P, Rahäuser R et al. Modular Modeling of Energy Consumption for Monitoring and Control. In: Hesselbach J, Herrmann C, editors. Glocalized Solutions for Sustainability in Manufacturing. Berlin, Heidelberg: Springer; 2011, p. 341–346.
[10] Froehlich J, Larson E, Gupta S, Cohn G, Reynolds MS, Patel SN. Disaggregated End-Use Energy Sensing for the Smart Grid. Pervasive Computing, IEEE 2011;10:28–39.
[11] Iyer SR, Sankar M, Venkata Ramakrishna P, Sarangan V, Vasan A, Sivasubramaniam A. Energy disaggregation analysis of a supermarket chain using a facility-model. Energy and Buildings 2015:65–76.
[12] Sankara A. Energy disaggregation in NIALM using hidden Markov models. Rolla, Missouri: Missouri University of Science and Technology; 2015.
[13] Hart GW. Nonintrusive appliance load monitoring. Proc. IEEE 1992;80:1870–91.
[14] Gebbe C, Klemm F, Zhai S, Reinhart G. Estimating Machine Power Consumptions through Aggregated Measurements and Machine Data Acquisition. AMM 2014;655:61–6.
[15] Kien Nguyen Trung, Zammit O, Dekneuvel E, Nicolle B, Cuong Nguyen Van, Jacquemod G. An innovative non-intrusive load monitoring system for commercial and industrial application. In: 2012 International Conference on Advanced Technologies for Communications (ATC 2012), p. 23–27.
[16] Zoha A, Gluhak A, Imran MA, Rajasegarar S. Non-intrusive load monitoring approaches for disaggregated energy sensing: a survey. Sensors (Basel, Switzerland) 2012;12:16838–66.
[17] Beck M, Sielaff T. Linked energy systems of production sites of the future. Advanced Materials Research, Publisher Trans Tech Publications, Switzerland 2013;769:319–26.
[18] Abele E, Sielaff T, Beck M. Konfiguration energieeffizienter Werkzeugmaschinen. wt Werkstattstechnik online, Springer VDI Verlag, Düsseldorf 2012;102:292–8.
[19] Graßl M, Reinhart G. Evaluating Measures for Adapting the Energy Demand of a Production System to Volatile Energy Prices. Procedia CIRP 2014;15:129–34.
[20] Spiering T, Kohlitz S, Sundmaeker H. Advanced Product and Process Design Through Methodological Analysis and Forecasting of Energy Consumption in Manufacturing. In: Azevedo A, editor. Advances in Sustainable and Competitive Manufacturing Systems. Heidelberg: Springer International Publishing; 2013, p. 29–43.
[21] Kuhrke K, Schrems S, Eisele C, Abele E. Methodology to Assess the Energy Consumption of Cutting Machine tools. In: Proceedings of the 17th CIRP International Conference on Life Cycle Engineering, p. 76–82.
[22] Karnouskos S, Colombo AW, Martinez Lastra JL, Popescu C. Towards the energy efficient future factory. In: 2009 7th IEEE International Conference on Industrial Informatics (INDIN), p. 367–371.
[23] British Institute of Non-Destructive Testing, 10th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies 2013 (CM 2013 and MFPT 2013): Krakow, Poland, 18 - 20 June 2013. Red Hook, NY: Curran; 2014.
[24] Abele E, Panten N, Menz B. Data Collection for Energy Monitoring Purposes and Energy Control of Production Machines. Procedia CIRP 2015;29:299–304.
[25] Mobley RK. An introduction to predictive maintenance. 2nd ed. Amsterdam, New York: Butterworth-Heinemann; 2002.
[26] Landau YD, Zito G. Digital control systems: Design, identification and implementation. 1st ed. London, New York, NY: Springer; 2006.
[27] Keesman KJ. System identification: An introduction. London, New York: Springer; 2011.