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

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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.

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

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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

- 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].

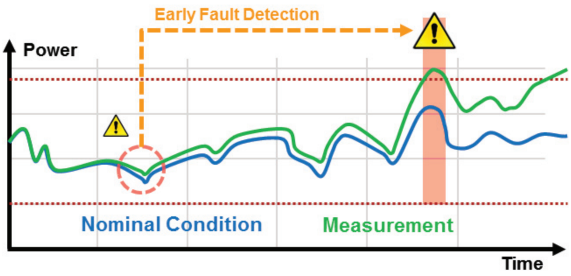

Fig. 1. Condition monitoring exemplary schematic

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