Chapter 9
Non-intrusive Load Monitoring on Component Level of a Machine Tool Using a Kalman Filter-Based Disaggregation Approach

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9.1 Introduction and Motivation

Today's society is increasingly concerned with ecological awareness in order to protect the environment. The political and social discussions focus on greenhouse gas emissions and rising global average temperatures. Furthermore, the total world consumption of primary energy is estimated to increase by 28% between 2015 and 2040 [1]. For that reason, the EU climate strategy aims to gradually reduce greenhouse gas emissions and increase the share of renewable energies, combined with improvements in energy efficiency [2].

As almost half of the global primary energy demand in 2017 will be caused by the industrial sector [3], there is considerable room for action to achieve the mentioned EU climate goals [2]. Progressive digitalization plays a major role here, as it offers the potential to make production processes more energy efficient. Furthermore, optimization approaches can be identified by transparent energy flows [4]. Within the

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Twin-Control project, which develops new concepts for simulating machine tools and the machining processes, the presented work was developed. These models, which are developed within this project, show both, the possibilities of making production processes more energy efficient and also take other life cycle characteristics such as the optimization of maintenance into account [5].

Measuring energy[1] values is an essential prerequisite for implementing energy efficiency measures through

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

One way to obtain measured values is by applying temporary mobile measurements. Mobile measurements give an overview of the energetic status quo of a machine tool. Nevertheless, for comprehensive analyses of the machine's components, the use of stationary, permanent in-depth monitoring is better suited. In order to obtain performance data for the individual components, a distinction can be made between two methods:

(1) Hardware-based measurements (intrusive)
(2) Non-intrusive measurement techniques.

Hardware-based measurements of power and energy at component level require high investments in sensors and the associated devices. Non-intrusive measurement methods such as non-intrusive load monitoring (NILM) or non-intrusive appliance load monitoring (NIALM) [6] can be a cost-effective solution for obtaining detailed energy data using a power disaggregation. The NILM measurement method can detect individual devices within the performance data by analysing voltages and currents from a higher-level single point of measurement. Since the individual devices have different properties for steady-state and transition states in both reactive and active power, these so-called *energy signatures* can be used to assign the measured power to an individual component. At the point of common coupling (PCC), the loads of the devices are superimposed and then the individual curves are extracted from the aggregated data by pattern detection algorithms. In addition, control data of inferior components can be used to estimate the individual load using system identification approaches [7]. In this way, the Kalman filter-based disaggregation approach presented in this chapter allows a continuous energy monitoring at component level of machine tools with only one sensor needed at the machine tool's electric PCC.

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[1]In this chapter, the electrical energy and electrical power are meant, when energy and power are mentioned.

9.2 Related Work

Several NILM solutions have already been developed in recent years within the residential sector [6, 8–11]. They are used to derive the energy demand of home applications such as refrigerators, lamps, vacuum cleaners, televisions and toasters. The energy data calculated by the NILM method may not be as accurate as the measured data, but it is sufficient in most cases for energy monitoring applications. For industrial applications, there are no comparable approaches of energy disaggregation and only few publications exist [7, 12–14]. Furthermore, in typical production environments, there are many sources of interference for NILM systems, such as basic electrical appliances and highly dynamic devices. One example is a speed-controlled motor with inverters, which may inhibit the deployment of disaggregation systems [12]. To minimize disturbances in industrial applications and to improve the accuracy of the algorithm, the machine states can be correlated to the aggregated power curves as proposed in [7, 13]. Since machine data acquisition (MDA) in modern production manufacturing facilities is already frequently used to calculate key performance indicators (KPIs) or to plan maintenance cycles, this strategy is particularly helpful. Thus, available industrial big data helps to provide better insight into the machine's energetic performance by applying power disaggregation algorithms.

9.3 Kalman Filter-Based Disaggregation Approach

The goal of the Kalman filter is to determine system states as accurately as possible, which can only be calculated and measured with an uncertainty. The Kalman filter works with a prediction step and a correction step. In the prediction step, the desired states of a system are calculated using a state-space model. In the meantime, the uncertainty of the result is calculated from the initial uncertainty (covariance) and an estimation error representing the inaccuracy of the calculation. In the correction step, the estimated value and the measured value are compared, while both contain an inaccuracy. The estimated value and the uncertainty can be set using R. E. Kalman's algorithm as shown in [15].

9.3.1 NILM Through Kalman Filter-Based Power Disaggregation

For the application of the Kalman filter to the energy disaggregation problem of a machine tool, the electrical power consumption of each auxiliary unit is defined as a condition to be determined. There is no state-space model with which the electrical power can be estimated. Furthermore, the individual states cannot be measured directly. Only the total power (P_{total}) consumed by the machine tool is measured by
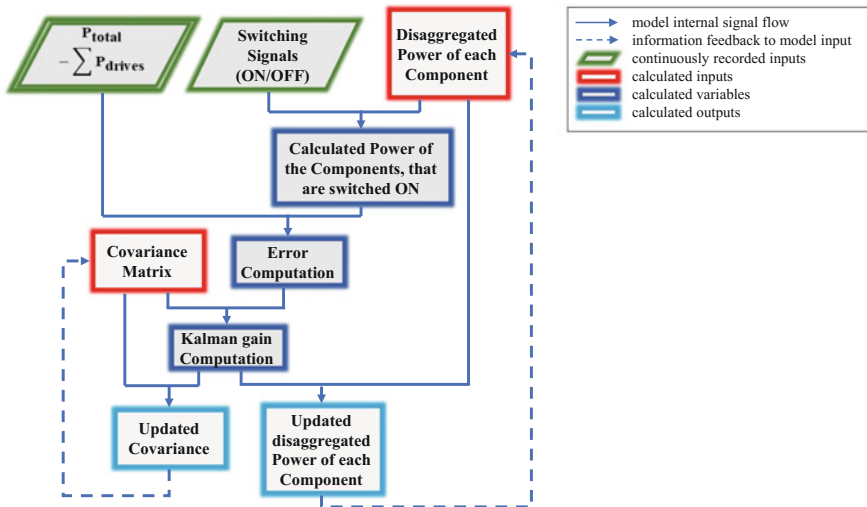
Fig. 9.1 Information flow chart of the applied Kalman filter

an external sensor. In addition, PLC data such as the power of each drive (P_{drive}) and the switching states (on/off) of the individual auxiliary units is used.

The states are updated according to the equations of R. E. Kalman via the so-called Kalman gain by comparing the sum of the power of all switched-on auxiliary units with the total power consumption subtracted by the accumulated power of the drives. The updated states are now used as the basis for a new comparison with the total output of the auxiliary units. Following this procedure, the states are updated successively. An overview of the Kalman filter-based power disaggregation approach is schematically displayed in Fig. 9.1.

9.3.2 Differentiation of Dynamic and Constant Electrical Power Consumers

There are two different consumption patterns for the auxiliary units. On the one hand, there are systems, which are also referred to constant consumers, and on the other hand, there are dynamic consumers. Constant consumers have a uniform performance plateau, which can be determined relatively accurately with the presented approach. In contrast, the power consumption of dynamic consumers, like speed-controlled motors, fluctuates even without a change of state. Other than consumers with constant power consumption, dynamic consumers are assumed to have an uncertainty within the measurements, whereby the inaccuracy (covariance) of the respective state is maintained. For constant loads, the uncertainty of the static loads converges towards zero as time progresses. This means that the performance allocated to the system is

increasingly less affected by fluctuations in the measured total power, while dynamic loads continue to allow performance adjustments.

9.3.3   Extension of the Kalman Filter Using Peak Shaving and Damping Factors

The algorithm for this application case has been extended to counteract undesirable developments. To improve the convergence for constant loads during the teach-in process, a damping factor and a peak shaving factor were introduced.

A single damping factor has been assigned to all auxiliary units with constant consumption behaviour, which artificially reduces the uncertainty of the respective states. Negative consumption, i.e. the generation of energy, is excluded in the model due to the unlikely occurrence. On this account, the Kalman gain must not lead to a negative state. By implementing a nonnegative condition in the filter, the resulting deviation of measured total power and the sum of the switched-on aggregates is distributed to other aggregates. In the case that the approximate power consumption of the auxiliary units or their dynamics is known, this information can be taken into account.

The peak load factor was introduced to neglect peak loads that occur when the ancillary units are started up from the disaggregated power. For this purpose, the initial condition is held for a few seconds after the component has been switched on, before the actual teach-in process begins. Otherwise, the load peak would falsify the teach-in process. Errors in the teach-in phase due to peak loads can thereby be avoided. Apart from the distinction between dynamic and statistical loads, and if available the average consumption of the components, no further user input is required for the presented approach.

9.4   Implementation and Validation of the Presented NILM Approach

The online monitoring is implemented by integrating the disaggregation algorithm into an existing process and tool monitoring system called Genior Modular of MARPOSS Monitoring Solutions GmbH. This monitoring system can be supplemented with additional sensors by adding additional transmitters. In this case, a transmitter for measuring the total power consumption of the machine is connected to the Genior Modular via CANopen communication. The integration of embedded software, like in this case the disaggregation algorithm, is realised by an additional OPR device of MARPOSS Monitoring Solutions GmbH. Because an existing data acquisition and analysis architecture can be used, the effort for the user and costs are reduced. In this

way, the Kalman filter-based disaggregation approach can be simply retrofitted on existing machine tools.

An exemplary application on the EMAG VLC100Y CNC turning machine is presented in this chapter. This machine is located in the model factory for energy efficiency (ETA-Factory) on the campus of the Technische Universität Darmstadt in Germany. The turning machine is controlled by a programmable logic control (PLC) from Bosch Rexroth, which records the required switching states of the units and the power consumption of the drive units via OPC-UA communication. The modelled power consumption can be visualized locally on a HMI or transferred to a higher-level platform. In addition to power consumption modelling at the component level, an analysis of the available data is also included.

The turning machine contains the following auxiliary units:

- hydraulic pump
- chip conveyor
- cooling lubricant pump
- suction
- electric control cabinet
- combined other consumers.

The hydraulic pump, the suction and the electric control cabinet are classified as a constant consumer, while the cooling lubricant pump is a dynamic consumer. Both consumer types are constantly switched on during machining. The chip conveyor is a constant consumer which is switched on or off sequentially during the manufacturing process. All other dynamic and constant auxiliary units of the machine tool are summarized under combined other consumers. These combined other consumers are attributed with higher measurement uncertainties than normal consumers. In addition, the measurement uncertainty is increased or, respectively, decreased with each switch-on or switch-off process in order to absorb the load peak that occurs.

For the validation of the presented non-intrusive load monitoring approach with a Kalman filter-based disaggregation, a temporary mobile measurement was conducted. The results of the disaggregation are compared to measured mean power signals of the listed auxiliary units in Fig. 9.2. The corresponding evaluation results are discussed in the following sections and are shown in Table 9.1. Besides the measured mean power consumption, the mean disaggregated power consumption, the corresponding root mean square deviation as well as the relative error are listed for all auxiliary units. The root mean square deviation and the relative error are calculated according to Eqs. (9.1) and (9.2), respectively. The relative error is the quotient of root mean square deviation and the measured power at switched-on component state.

$$\text{root mean square error} = \sqrt{\frac{\sum_{i=1}^{N}\left(P_{\text{measured } i} - P_{\text{disaggregated } i}\right)^2}{N}} \tag{9.1}$$

$$\text{relative error} = \frac{\text{root mean square error}}{P_{\text{measured (when switched on)}}} \tag{9.2}$$
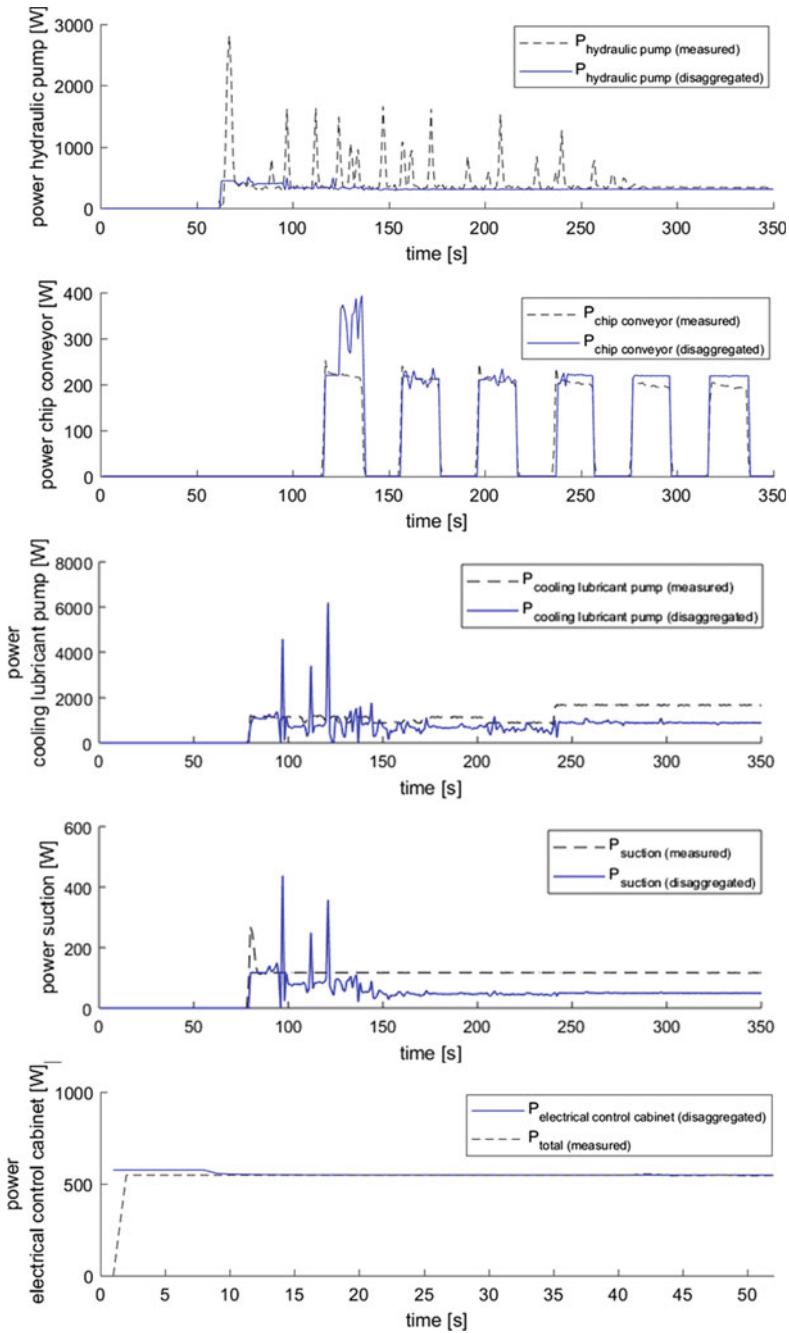
Fig. 9.2 Comparison of disaggregated and measured power for the auxiliary units with the corresponding switching states

Table 9.1 Evaluation results of the Kalman filter-based disaggregation approach on the EMAG VLC100Y turning machine

Auxiliary unit of the machine tool	Consumer type	Mean measured power consumption[a] [W]	Mean disaggregated power consumption[a] [W]	Root mean square deviation [W]	Relative error [%]
Hydraulic pump	Constant	448.5	328.29	114.2	25.5
Cooling lubricant pump	Dynamic	1288.0	847.7	439.4	34.1
Chip conveyor	Constant	201.0	229.47	12.1	6.0
Suction	Constant	535.3	551.8	49.8	42.2
Electrical control cabinet	Constant	546.3	551.8	16.9	3.1
Combined other consumers	Dynamic	Not measureable	1368.1	–	–

[a]The mean includes only power signals at switched-on component state

Since the hydraulic control of the turning machine is an accumulator charging control, the measuring signal (first diagram in Fig. 9.2) has large peak loads that can be attributed to the reloading of the hydraulic accumulator. Since the hydraulic unit is defined as a constant load, these load peaks are not transmitted to the disaggregated signal. Even when defining the hydraulic pump as a dynamic consumer, these sudden peaks cannot be assigned to a single component without additional information about the hydraulic recharging process. Instead, these load peaks are now distributed among the dynamic consumers, but the major part of the peak is attributed to the combined other consumers due to its higher measurement inaccuracy. In order to integrate the hydraulic load peaks into the disaggregated power, an additional model input signal would be necessary which describes the state of the hydraulic accumulator charging process. These inaccuracies explain the high relative error, but when neglecting the load peaks in the measured signal, the base load of the hydraulic pump was met very well with the disaggregation.

The example of the chip conveyor clearly shows how the sensitivity of the algorithm decreases over the time in which the component is switched on (second diagram in Fig. 9.2). While the disaggregation is initially falsified by other disturbances during the first switch-on process, the required power of the chip conveyor is better met during the subsequent switching processes and is ultimately properly trained. The teach-in phase can be better used with sequentially switched consumers, since the individual switching processes are each accompanied by the interference of varying intensity, which is why the actual power requirement is met more accurately.

The measurement data of the cooling lubricant pump (third diagram in Fig. 9.2) shows an example of a component that requires several energy levels within one manufacturing cycle. This is because the cooling lubricant is fed through nozzles of different sizes, depending on the tool used and the current machining process. In this case, a higher power level is reached after about 240 s. From this time on, the cooling lubricant is sprayed in large quantities and at high pressure to rinse away chips from the workpiece during the milling process. Different power levels could be differentiated by taking into account the nozzles switching signals. In this case, the classification of the cooling lubricant pump as a constant consumer would be recommended.

The disaggregated power curve of the suction (fourth diagram in Fig. 9.2) shows how the load peak factor prevents a falsified training due to the initial load peak, which is almost twice as high as the later power consumption. Nevertheless, the further disaggregated power curve is subject to strong fluctuations, and the trained-in disaggregated power is far too low, which primarily results from the load peaks of the hydraulic accumulator charging circuit. For this reason, the disaggregated power consumption of the suction has a high relative error.

The constant energy requirement of the electrical control cabinet can only be trained at the beginning of the measurement. Here, the machine is in an energy-reduced standby mode, which is why all auxiliary units are switched off and only the control cabinet is supplied with power. After about 55 s, the machine is switched to the machining mode and the auxiliary units are turned on successively. At this point in time, the algorithm has already trained the power of the electrical control cabinet due to the damping factor. The disaggregated power and the measured power correlate well (fifth diagram in Fig. 9.2), which is also visible in the low relative error of the component.

In general, the accuracy of disaggregation increases if the individual components are switched on one after the other and have enough time for the teach-in process. However, this is not always possible due to the technical restrictions and the request for short cycle times. The delay of the switching processes of the auxiliary units during the examined turning process is shown in Fig. 9.3. To obtain more precise results, the individual components could be switched on and off one after the other, starting from the standby state of the machine, in which they are initially all switched off. As this is rarely possible in industrial environments and because the goal was to find an automated procedure, which does not require a manual teach-in process, this method has been dispensed within this series of tests.

9.5 Conclusion and Outlook

The presented cost-effective disaggregation approach to monitor the energy consumption at component level is possible through the use of a Kalman filter with the information of the component's switching states and the overall power consumption. The approach was tested on a laboratory machine tool and validated with a
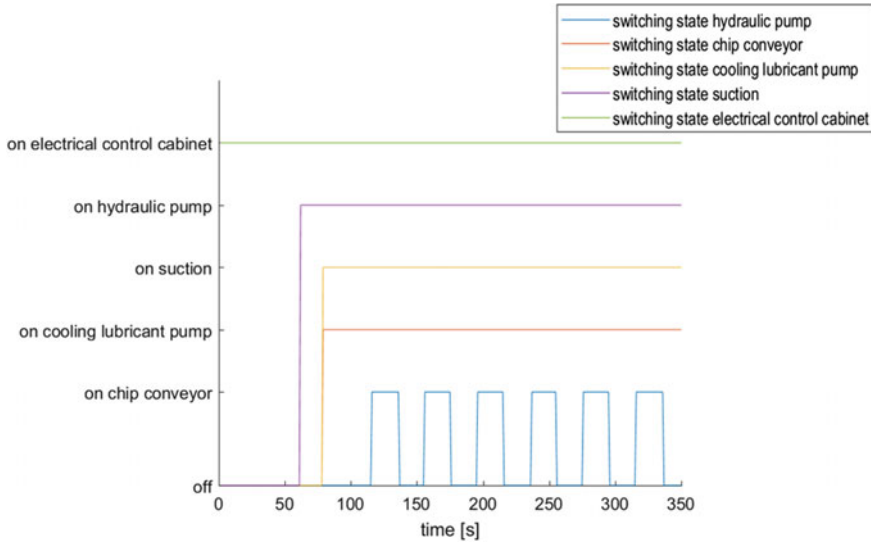
Fig. 9.3 Illustration of the switching states of the auxiliary units over one production cycle

temporal measurement of the component's power consumption. Based on the evaluation results, the limitations of the concept are shown. For example, load peaks, which often arise in hydraulic accumulator charging circuits due to recharging of the accumulator, need further input signals related to the hydraulic recharging process in order to obtain more precise disaggregation results. The distribution of these load peaks to other components can distort the disaggregation results. The advantages of the disaggregation of cyclical loads are discussed, as well as the relevance of the switching state correlation of the individual auxiliary units.

Even if an exact power disaggregation of industrial components is difficult, the presented approach offers a cost-effective and simple possibility to estimate the energy demand on component level. Further investigations are necessary to decrease the influence of the limitations in order to increase the accuracy of the power disaggregation.

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