Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 67 (2018) 69 – 74

www.elsevier.com/locate/procedia

11th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '17

Machine allocation via pattern recognition in harmonic waves of manufacturing plants

Arnim Reger[a,]*, Jonas Dumler[a], Oleg Lobachev[b], Julian Neuberger[b], Rolf Steinhilper[a]

[a] *Fraunhofer Institute for Manufacturing Engineering and Automation, Project Group Process Innovation, Universitaetsstrasse 9, 95447 Bayreuth, Germany*
[b] *Visual Computing of University Bayreuth, 95440 Bayreuth, Germany*

* Corresponding author. Tel.: +49-921-78516-32; fax: +49-921-78516-105. *E-mail address:* a.reger@ipa.fraunhofer.de

Abstract

Non-intrusive load monitoring is currently used to analyze changes in the energy consumption of households. Due to the number of electrical consumers, the associated superpositions and the variety of harmonic waves on the shop floor, current proceedings are not applicable in industrial environment. In this paper, patterns in harmonic waves of four manufacturing plants are analyzed in the time and frequency domain. For machine allocation, features were extracted and classified by k-means and support vector machines with an accuracy of 97.3 and 97.9 %. For comparison, convolutional neural networks were trained with the harmonic profiles in the time domain with an accuracy of 98.7 %.

Peer-review under responsibility of the scientific committee of the 11th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Keywords: Machine allocation; Non-intrusive load monitoring; Production plants; Harmonic waves; Deep learning; Convolutional neural networks

1. Introduction

First introduced by Hart [1], many technologies were developed in over more than 30 years of non-intrusive load monitoring (NILM). There are approaches with sampling rates from 1 Hz up to hundreds of kHz, some of them extracting simple information like difference power signature, others are looking for shapes of transient signatures or complex information like harmonics or electromagnetic interference. [2]

For classification, Khalid et al. [3] generally distinguishes four types of appliances:

- Type I: Two states of operation (on/off)
- Type II: Multi-State appliance with finite operating states
- Type III: Continuously variable devices
- Type IV: Permanent consumer devices

In NILM applications, the appliance signature can be steady state or transient nature. A summary of methods, features and requirements can be found at Zoha et al. [4].

During the long time of NILM research, there are now many real systems in residential applications, but there is a lack of research in industrial environment. Implementing NILM in industrial processes leads to significant difficulties due to a high noise level and a large variety of electrical consumers. In industrial sites, manufacturing plants got many basic electrical appliances, the noise caused by high power motors, fans and invertors can be larger than threshold values in NILM systems. Beyond industrial secrecy, the number of equipment types and temporal patterns would make the research more difficult. [2, 5]

Static power converters are the largest nonlinear loads in the industrial environment. They are used for a variety of purposes e.g. electrochemical power supplies, variable speed drives or arc furnaces. Those nonlinear loads change the sinusoidal nature of the AC power current and cause a harmonic current flow and consequently an AC voltage drop. Each harmonic producing device can have a consistent or load depending variable harmonic current emission characteristic. [6]

For nonlinear device detection, Akbar and Khan [7] and Jonetzko et al. [8] analyzed the harmonic shape of the current signal with high sample rates. The features for classification were extracted by applying the Fast Fourier Transform (FFT). Fuller [9] demonstrated the potential of current spectrum analysis to detect electric machine failures and monitor multiple machines.

Peer-review under responsibility of the scientific committee of the 11th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2017.12.178

In advanced NILM research the time-frequency-domain was examined for feature extraction with wavelet transforms [10]. Khalid et al. [11] trained neural networks with features from s-Transform.

For very fast detections, Uçar et al. used discrete wavelet transform (DWT) for feature extraction in combination with Extreme Learning Machine [12]. Duarte et al. [13] monitored the voltage for power quality detection using wavelets and support vector machines. Bischa et al. [14] fed the signals to autoencoder for feature extraction and compared the classification of support vector machines (SVM) with convolutional neural networks (CNN).

Hereinafter, a NILM application for machine or component allocation in the industrial environment is discussed. Features were extracted with FFT and classified by k-means and support vector machines. In time domain, CNNs were trained with the labeled data sets as well.

2. Methods

2.1. Initial Situation

The research subject was a HAUNI multifilter machine with the main unit A and three auxiliary units B, C and D. Fig. 1 shows the four machines with their related current waveforms connected to the main supply.

2.2. Data Acquisition

For data acquisition, a NI cDAQ-9171 USB-Chassis with a simultaneous analog input module NI 9215 (4 channels, 100 kS/s, 16 bit, ±10 V) and a bandwidth of 420 kHz (-3 dB) was connected to a laptop with a LabView program. For fast measurement, Fluke i200s Rogowski Coils with BNC connector were used. They provide a measurement range up to 200 A at 10 mV/A.

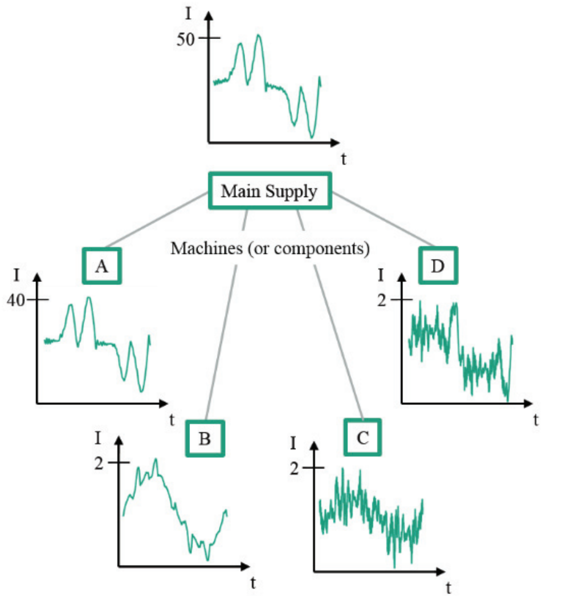

Fig. 1. Schematic of the electric power supply with the related waveforms.

2.3. Generating Labeled Data Sets

A moving average filter followed by a zero-crossing detection algorithm was used in order to cut the signal into single periods of a predefined length of 20 ms (2000 data points) and 1 s (100000 data points) respectively, dependent on the applied feature extraction and learning methods. As shown in Fig. 2, the measured signals from the four single machines were manually overlaid in all 15 possible combinations. The permutation of k out of n machines without repeating can be calculated by the binomial coefficient [15]. For k being a number between 1 and n the number of all possible combinations n_c is given as the sum of these coefficients, see equation 1. In this case 15 different data sets were generated.

$$n_c = \sum_{k=1}^{n} \binom{n}{k} = \sum_{k=1}^{n} \frac{n!}{k! \cdot (n-k)!} \tag{1}$$

2.4. Data Analysis in Time and Frequency Domain

To gain an overview over the statistical distribution, the data sets were analyzed by median, 0.1-quantile and 0.9-quantile in the time domain. In the frequency, first a FFT was used. For advanced analysis, a DWT and a CWT were applied. More

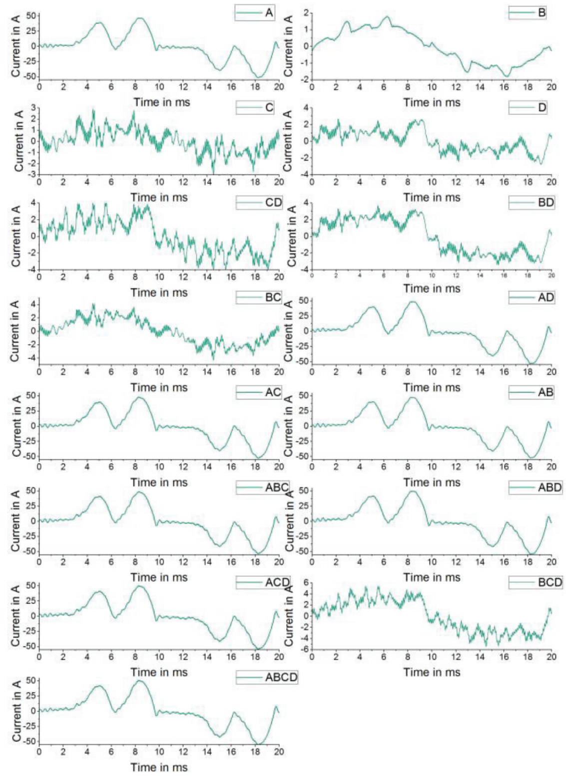

Fig. 2. Distribution of the Signals A, B, C, and D.