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Lean data with edge analytics: Decentralized current profile analysis on embedded systems using neural networks

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Summary:

This short paper introduces a system for the detection of operating states based on current profiles of a production plant with an artificial neural network at the machine's edge in almost real-time. The system called "CogniSense" consists of a sensor for signal acquisition, a microcontroller for data preprocessing and a single-board computer for data main processing. With the system, current profiles of a test engine are acquired and analyzed, so that 26 defined operating states can be reliably detected with a classification accuracy of over 95%.

Keywords: artificial neural networks, condition monitoring, edge analytics, embedded systems, IoT

Introduction

Industry 4.0 is characterized by the digitization and networking of machines and systems in production [1]. With this, the amount of data in production is increasing, providing information about processes and thus enables the autonomous monitoring, control and optimization of value creation processes [2, 3]. Condition monitoring uses this data in production plants to obtain relevant information about the condition of plant components in almost real-time [4]. Consequently, production plants can be monitored autonomously, plant faults can be detected early, maintenance requirements can be recognized in advance and measures can be planned according to needs [5]. For this, the analysis of current profiles with the aid of machine learning methods is a promising approach - not least because current profiles are available in every electrical system, have high information content and can usually be recorded with cost-effective sensors [6, 7]. Artificial neural networks (ANN) are already used in production planning and control as well as in process and quality analysis [8, 9]. In [10] further applications of ANN in production are listed.

Experimental design and methodology

This paper shows that classification of different operating states (OS) by using ANN on embedded systems during operation in almost real-time is possible. For this, the "CogniSense", consisting of current sensor, microcontroller (MCU) and single-board computer (SBC) is presented. Current profiles of 26 different OS of a test engine are acquired with 12 kHz and preprocessed at the MCU. A frequency analysis is carried out at the SBC and the training of the ANN is done. After this, the 26 OS can be classified during operation in near real-time.

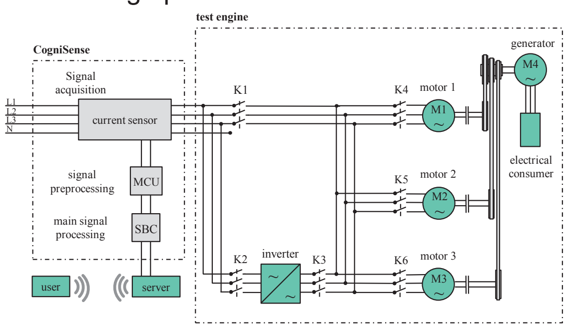

Fig. 1. Schematic of test engine and "CogniSense"

The test engine, as shown in fig. 1 comprises three different electrical motors, operating with or without an inverter. A generator driven by these can be equipped with different electrical loads. This results in the 26 reproducible OS. Fig. 2 shows selected rms-current-profiles of five OS. The individual measurements are not synchronized. The resulting time offset is up to one second and can impair the learning success of the ANN. This is solved by a discrete Fourier transformation. In [10], a system is presented that uses a multilayer perceptron (MLP), a feedforward ANN, to detect six different OS in current profiles of the main supply of the test engine with a classification accuracy (CA) of 99.82%. This ANN is optimized in this paper

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with respect to memory requirements and CA (>95%), to make it suitable for execution on embedded systems in near real-time.

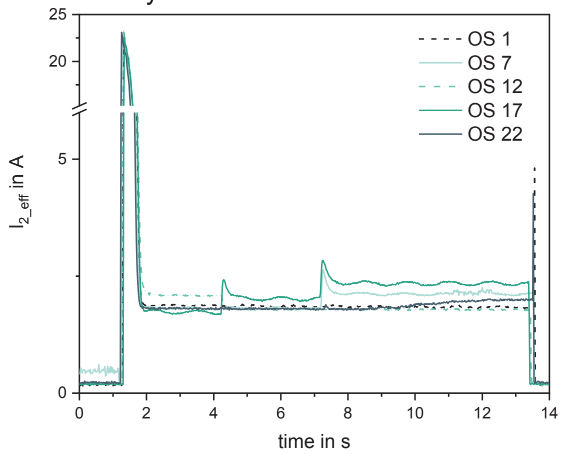

Fig. 2. Comparison between five different OS.

In addition, the limits of the MLP regarding the minimum amount of training data are examined. The basic concept is first mentioned in [11].

Results

Table 1 shows the results. MLP 1 and MLP 2 are close to the optimum, confirming the reliable recognition of the developed system.

Tab. 1: Training parameters and test results

MLP / number of OS	training samples		parameters			test samples		CA [%]
	total	per OS	epochs	batch-size	iter-ations	total	per OS	
1 / 6 OS	420	70	100	60	700	750	25	**99,33**
2 / 11 OS	770	70	100	55	1400	275	25	**98,04**
3 / 6 OS	78	13	225	39	450	150	25	**95,33**
4 / 11 OS	198	18	225	33	1350	275	25	**95,85**
5 / 16 OS	880	55	225	80	2475	400	25	**95,45**
6 / 21 OS	1344	64	225	84	3600	525	25	**95,31**
7 / 26 OS	1950	75	225	78	5625	650	25	**95,23**
8 / 26 OS	1924	74	225	78	5625	650	25	**94,83**

The results of MLP 2 show that detection becomes increasingly complex with rising OS. For MLP 3 to MLP 7 there is a requirement for the lowest possible amount of training data while maintaining the CA. Like MLP 1, MLP 3 classifies six OS, whereby the training data is reduced from 70 to 13 samples per OS. Despite this, the CA is 95.33%, but the number of epochs must be increased. The same applies to MLP 4 with eleven OS where the training data per OS is minimized to 18. This shows that the ANN requires only a small number of training samples per OS for a low number of OS. MLP 5, 6 and 7 show that a further increase of the OS to a rise of the total number of training samples required for reliable classification leads. In addition, the learning process in MLP 7 is significantly slower than in MLP 3, since the number of iterations and the batch size rises. MLP 8 cannot maintain the lower limit of the CA with 94.38% by only removing one training sample. For the classification of the 26 OS of the test engine, at least 75 training samples per OS are necessary. In practice, “CogniSense” can be used for condition monitoring of plants and the automated detection of defects and signs of wear during operation. Further research questions include whether new conditions during operation can be recorded, adapted and continuously monitored.

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