Load Identification in Neural Networks for a Non-intrusive Monitoring of Industrial Electrical Loads

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Abstract. This paper proposes the use of neural network classifiers to evaluate back propagation (BP) and learning vector quantization (LVQ) for feature selection of load identification in a non-intrusive load monitoring (NILM) system. To test the performance of the proposed approach, data sets for electrical loads were analyzed and established using a computer supported program - Electromagnetic Transient Program (EMTP) and onsite load measurement. Load identification techniques were applied in neural networks. The efficiency of load identification and computational requirements was analyzed and compared using BP or LVQ classifiers method. This paper revealed some contributions below. The turn-on transient energy signatures can improve the efficiency of load identification and computational time under multiple operations. The turn-on transient energy has repeatability when used as a power signature to recognize industrial loads in a NILM system. Moreover, the BP classifier is better than the LVQ classifier in the efficiency of load identification and computational requirements.

Keywords: Load identification, neural network, non-intrusive load monitoring, Electromagnetic Transient Program.

1 Introduction

Traditional load-monitoring instrumentation systems employ meters for each load to be monitored. These meters may incur significant time and cost to install and maintain. Furthermore, increasing numbers of meters may impact system reliability. Therefore, a method for minimizing the number of instruments using non-intrusive load monitoring (NILM) is needed.

To develop such a monitoring system, a number of load identification techniques have been proposed [1-10]. Hart proposed several load identification methods that examined the steady-state behavior of loads [1]. Hart conceptualized a finite state

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machine to represent a single appliance in which power consumption varied discretely with each step change. Leeb used finite-impulse response filters [3-6] and Robertson employed a wavelet transformation technique [7] matched to transient envelopes in particular load-switching models. Cole [8] examined data extraction methods and steady-state load identification algorithms for NILM. The algorithms developed by Cole could be employed for load switching between individual appliances when one or more appliances are switched on or off.

However, some appliances have transient features and steady-state features with quite different indications and meaning at different times, particularly in an industrial plant. For example, appliances may have variable power during operation, such as water pumps in a steel mill. These appliances have no sufficient features to identify load which is starting or operating, if these features are only steady-state features or transient features. These features, when selected, enhance the capability of a NILM system to distinguish from industrial loads under multiple operations using the turn-on transient energy feature (U_T) and traditional steady-state power features by analyzing the physical industrial load characteristics. They also improve computational time.

In an industrial environment, an Electromagnetic Transient Program (EMTP) computer supported program allows convenient comparison of load prototypes or templates under normal load operation. To maximize recognition accuracy, analysis of turn-on transient energy signatures uses a window of samples, Δt, to differentiate adaptively a transient representative class of loads. The experiments in this study reveal some contributions below. The turn-on transient energy signatures can improve the efficiency of load identification and computational time under multiple operations. The turn-on transient energy has repeatability when used as a power signature to recognize industrial loads in a NILM system. Moreover, the back propagation (BP) classifier is far better than the learning vector quantization (LVQ) classifier, within the efficiency of load identification and computational requirements.

This paper is organized as follows. The power signature problems and turn-on transient energy algorithm are addressed and described in Section 2. The event detection is described in Section 3. The turn-on transient energy repeatability is described in Section 4. Based on the algorithm and load recognition techniques, a series of load recognition experiments for the feature selection of power signals are conducted in Section 5, which also includes comparisons of recognition accuracy and computational performance using selected features by turn-on transient energy algorithm and traditional power signal features under individual operation or multiple operations. Advantages of load recognition using the turn-on transient energy algorithm and BP are concluded in Section 6.

2 Power Signature Problems and Turn-On Transient Energy Algorithm

2.1 Power Signature Problems for Feature Selection

In general, an appliance may have many load representations and a load may involve many physical components. For example, a dryer has two loads, a motor and a heater. A refrigerator has only one load, a compressor, but has different physical components for defrosting and freezing. Most appliances are distinguishable by unique power signatures that can be observed from voltage and current waveforms supplied to the appliance, or from processed reproductions of these signals such as the delivered real power (*P*) and reactive power (*Q*) or harmonics [2].

According to the switch continuity principle, steady-state signatures, for example, real power and reactive power, are additive when two signatures occur simultaneously. In contrast to steady-state properties, transient properties are not addition [1]. Distinguishing different loads may be problematic when they have equivalent real power and reactive power but no harmonic components, and/or when the sums of real power and reactive power of two load types are equal to that of another load during multiple load operations. Since most steady-state data is processed in batch format within a period of one or a few days, they cannot make real-time identification for load operation. Load detection, based on steady-state power, makes an industrial NILM system, which is susceptible to confusion, if two loads start up at nearly the same time.

2.2 Turn-On Transient Energy Algorithm

The transient properties of a typical electrical load are mainly determined by the physical task that the load performs [4-6]. Transient energy may assume different forms in consumer appliances, depending on the generating mechanism [1]. Estimating current waveform envelopes at the utility service entry of a building, for example, allows accurate transient event detection in the NILM [5]. Load classes performing physically different tasks are therefore distinguishable by their transient behavior [4-6]. Since the envelopes of turn-on transient instantaneous power are closely linked to unique physical quantities, they can serve as reliable metrics for load identification. Two different appliances consuming identical levels of real power and reactive power may have very different turn-on transient currents. Analysis of these transient currents can accurately determine which of the two is actually present in the load.

In general, the transient behavior of many important loads is sufficiently distinct reliably to identify load type. The long characteristic switching-on transient, the less substantial switching-on transient, the short but very high-amplitude switching-on transient and the long two-step switching-on transient are the principal values measured in pump-operated appliances, motor-driven appliances, electronically fed appliances and fluorescent lighting, respectively [11].

During training phases, a window of samples of time length Δt is examined to differentiate transients representative of a class of loads. This segmentation process delineates a set of transient energy values representing a particular transient shape in each of the input envelopes. To maximize the recognition accuracy ($\hat{\gamma}$) during the test phase, Δt is adaptively changed based on factor δ. Figure 1 shows the algorithm adapted for Δt by factor δ. As demonstrated in Eq. 4, the search for a precise time pattern for instantaneous power turn-on identifies a complete transient.

$$\because dW_{Transient} = v \cdot dq \,. \tag{1}$$

$$dq = i \cdot dt \,. \tag{2}$$

$$\therefore dW_{Transient} = v \cdot i \cdot dt \,. \tag{3}$$

$$W_{Transient} = \int_{t_s}^{t_s+\Delta t} v \cdot i \cdot dt \,. \tag{4}$$

$$P_{Ins\tan\tan eous}(t) = \frac{dW_{Transient}(t)}{dt} = v(t) \times i(t) \,. \tag{5}$$

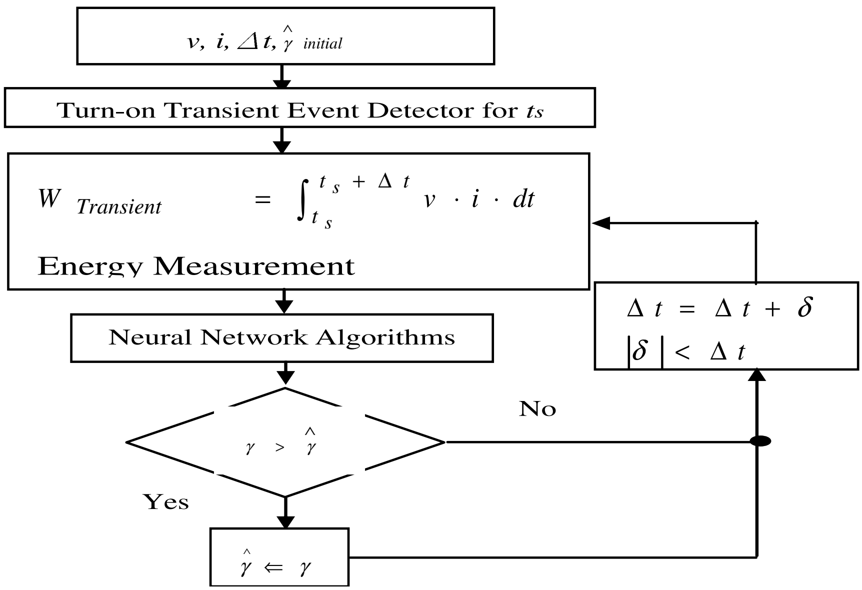

Fig. 1. Adaptive algorithm for Δt by factor δ at the maximum recognition accuracy of the turn-on transient energy

3 Event Detection

Figure 2 shows the measured envelope of instantaneous power in one phase of the turn-on transient of a load bank connected to an A.C. source via a six-pulse power electronic converter. Completion of the turn-on transient in this load bank is followed by the turn-on transient of a three-phase 140-hp induction motor. This study proposes the use of wavelet transformation analysis to detect and localize various turn-on transient events. The underlying concept of this approach is decomposition of a given turn-on transient signal into other signals to enhance the original signal, including shape edges, transitions and jumps [7, 12]. The approach also determines whether the wavelet transformation coefficients (WTC) are unique, since they represent the occurrence of the turn-on event.

Figure 3 illustrates event detection using the Daub2 wavelet transformation at scale 1 for the envelope of the instantaneous turn-on power signal in Fig. 2. Figure 3 shows a detailed illustration of sharp turn-on transient events occurring in the vicinity of 0.05 and 0.15 s. The WTC at scale 1 show the occurrence of the sharp events of a turn-on transient. Maximum localization of the analytical wavelet is at scale 1.

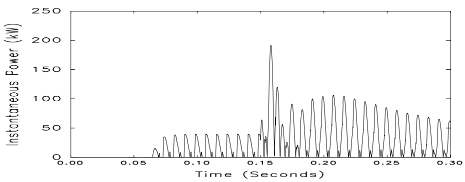

Fig. 2. The envelope of overlapping instantaneous power in one phase of the turn-on transient of a load bank connected to a six-pulse power electronic converter. Completion of the turn-on transient in a load bank is followed by the turn-on transient of a three-phase 140-hp induction motor.

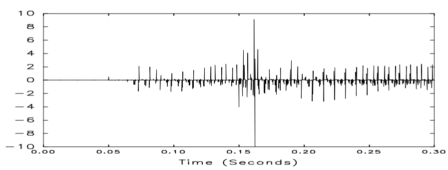

Fig. 3. Event detection uses the Daub2 wavelet transformation of the detailed version at scale1 for the envelope of the instantaneous turn-on power signal in Fig. 2

4 Turn-On Transient Energy Repeatability

Most loads observed in the field have repeatable transient profiles or at least repeatable sections of transient profiles [3]. The load survey reveals that non-linearity in the constitutive relationships of the elements comprising a load model and/or in the state equation describing a load tends to produce interesting and repeatable observable turn-on transient profiles suitable for use in identifying specific load classes [4-6]. Because of the varying transients (which often depend on the exact point in the voltage cycle at which the switch opens or closes), data sets for load identification must provide accurate repeatability of the turn-on transient energy signatures. Pre-training has proven effective for highly repeatable loads that occur frequently, such as commercial and industrial loads.

As Figures 4 and 5 demonstrate, the turn-on transient profiles exhibit repeatable measured current waveforms in one phase at voltage phase 0^0 and 90^0 for the turn-on transient of a three-phase 300-hp induction motor. The turn-on characteristics of a load clearly increase in complexity over time. Closer investigation of the load turn-on is thus required before the characteristics can be used as a distinguishing feature of a load. This information, collected via non-intrusive monitoring, can be used to answer important questions about the statistical validity of power measurements.

Determination of whether or not turn-on transient energy content is repeatable would be useful in developing a turn-on transient energy signature. As Eq. (6) shows, the average value of the sample data (x_i) for the turn-on transient energy of each load is $\overline{x}$. The standard deviation (S) of the turn-on transient energy for each load is computed according to Eq. (7) for all loads monitored in isolation. An experiment is then used to demonstrate that the statistical validity of the turn-on transient energy for each load is repeatable in terms of the coefficient of variation (C.V.) according to Eq. (8).

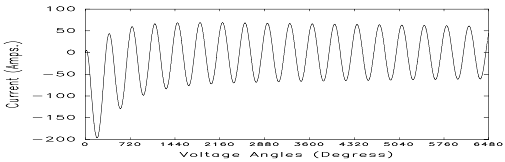

Fig. 4. Current waveform in one phase at voltage phase 0^0 for the turn-on transient of a three-phase 300-hp induction motor

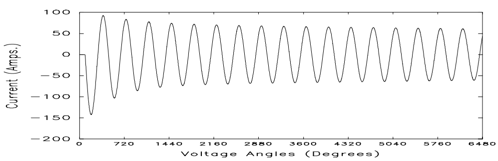

Fig. 5. Current waveform in one phase at voltage phase 90^0 for the turn-on transient of a three-phase 300-hp induction motor

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \,. \tag{6}$$

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})^2} \,. \tag{7}$$

$$C.V. = \frac{s}{\bar{x}} \,. \tag{8}$$

5 Experimental Results and Discussions

5.1 Experimental Environment

The NILM system in this paper monitors the voltage and current waveforms in a three-phase electrical service entry powering representative loads of important load classes in an industrial building. The neural network algorithm in the NILM system identifies five actual loads with transient and steady-state signatures at the 480-V common bus. These loads include a 95-hp induction motor, a 300-hp synchronous motor, a 140-hp induction motor, a 95-hp induction motor driven by line frequency variable-voltage drives and a bank of loads supplied by a six-pulse power electronic converter for A.C. power.

Figure 6 schematically illustrates the test stand used in experiment. Three-phase 480-V electricity powers the loads, which are representative of important load classes in an industrial building. A dedicated computer connected to the circuit breaker panel controls the operation of each load. The computer can also be programmed to stimulate various end-use scenarios. To compile data for training purposes, either every site of interest or a representative sample of the sites should be monitored. The sample rate is approximately 15 kHz. The appropriate coefficients corresponding to the current and voltage in each harmonic are extracted from the results. For this study, a neural network simulation program was designed using MATLAB. This program was executed on an IBM PC with an Intel 1.5-GHz Pentium M CPU for load identification.

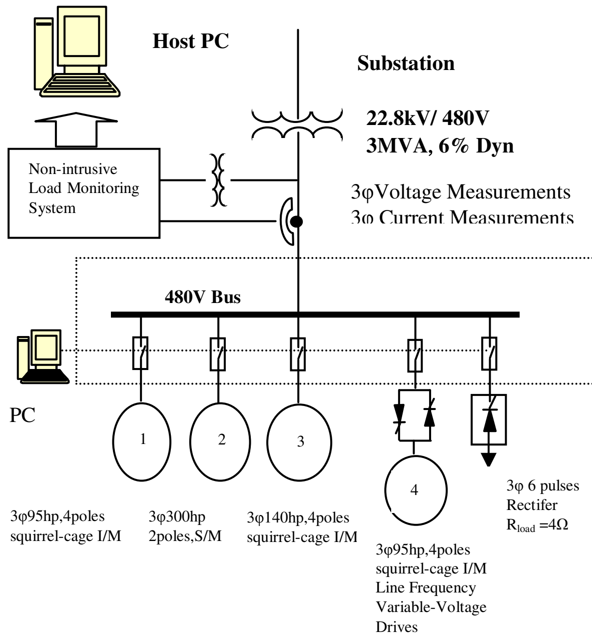

Fig. 6. Electrical schematic of NILM in an industrial plant

5.2 Turn-On Transient Energy Repeatability

To determine whether turn-on transient energy exhibits repeatability, a NILM system with five important loads was examined in an industrial plant, as shown in Figure 6. The turn-on transient energy for each load can be computed from the measured voltage and current waveform at the service entry according to Eq. (4). Because of the varying transients (which often depend on the exact point in the voltage cycle at which the switch opens or closes), it is essential that data sets for load identification have highly repeatable transient energy signatures. Therefore, the instantaneous power profile for each turn-on transient load is sampled when the system utility voltage is switched from 0^0 to 350^0 at 10^0 intervals, i.e., the number of load samples (n) is 36.

Table 1 shows C.V. values during periods of nearly steady energy for each load, all of which are less than 1% [4]. The simulation results indicate that the turn-on transient energy should have good repeatability. Therefore, the turn-on transient energy can be used as a power signature to recognize industrial loads in a NILM system.

Table 1. Variation coefficient during periods of nearly steady energy for each load in a NILM system

Loads	Load 1	Load 2	Load 3	Load 4	Load 5
C.V. (%)	0.36648	0.02245	0.16077	0.47399	0.10885

5.3 Load Identification in Individual Operation

Changing circuit breaker number 1 to number 5 in individual operation yields data for individual load. Five combinations are possible. Each data set includes a voltage variation from –5% to +5% at 1% intervals. The total number of data sets is 55 (5×11). To confirm the inferential power of the neural network, the data are categorized as 28 training and 27 test data sets. Notably, training data and test data are selected randomly from all data.

Table 2 shows that values for the training accuracy of load identification in individual operation are 100% for features with real power and reactive power, and/or with total harmonic distortion and/or with turn-on transient energy for one of the features. Furthermore, the test accuracy of load identification in individual operation is at least 96%.

Except when the features are real power and reactive power, table 3 shows that values for the training and test recognition accuracy of load identification in individual operation are 100% for features with real power and reactive power, and with total harmonic distortion and/or with turn-on transient energy for one of the features.

Table 2. Recognition accuracy and computational requirements of back propagation classifier

Features	PQ		PQV_{THD}[1]I_{THD}[2]		$PQV_{THD}I_{THD}U_T$	
	Training	Testing	Training	Testing	Training	Testing
Recognition Accuracy (%)	100	96.43	100	100	100	100
Computational Time (s)	5.348	1.752	4.006	1.773	2.219	1.297
The Number of Hidden Neurons	7		9		10	

5.4 Load Identification in Multiple Operations

Changing circuit breaker number 1 to number 5 in multiple operations yields data for multiple loads. Thirty-one combinations are possible. Each data set includes a voltage variation from –5% to +5% at 1% intervals. The total number of data sets is 341 (31×11). To confirm the inferential power of the neural network, the data are categorized as 171 training and 170 test data sets. Notably, training data and test data are selected randomly from all data.

[1] V_{THD} is the total voltage harmonic distortion.
[2] I_{THD} is the total current harmonic distortion.

Table 3. Recognition accuracy and computational requirements of learning vector quantization classifier

Features	PQ		$PQV_{THD}I_{THD}$		$PQV_{THD}I_{THD}U_T$	
	Training	Testing	Training	Testing	Training	Testing
Recognition Accuracy (%)	81.48	78.57	100	100	100	100
Computational Time (s)	15595	0.266	59.526	0.250	12.939	0.24
The Number of Hidden Neurons	1000		250		25	

Table 4 shows that values for the training accuracy of load identification in multiple operations are 100% for features with real power and reactive power, and/or with total harmonic distortion and/or with turn-on transient energy for one of the features. Furthermore, the test accuracy of load identification in multiple operations is at least 94%.

Table 5 shows that values for the training accuracy of load identification in multiple operations are 42.1% for features with real power and reactive power, and with total voltage/current harmonic distortion and with turn-on transient energy for one of the features. Furthermore, the test accuracy of load identification in multiple operations with the same features is 42.94%, which is higher than other features.

Table 4. Recognition accuracy and computational requirements of back propagation classifier

Features	PQ		$PQV_{THD}I_{THD}$		$PQV_{THD}I_{THD}U_T$	
	Training	Testing	Training	Testing	Training	Testing
Recognition Accuracy (%)	100	94.73	100	94.73	100	95.3
Computational Time (s)	313.471	1.843	293.640	1.893	246.719	1.516
The Number of Hidden Neurons	7		9		23	

5.5 Discussions

There are different representations of load patterns for individual operation and multiple operations. In individual operation, a class shows that the representation is only one load. In multiple operations, a class shows that the representation can be one or many loads. In other words, a class may be a combination of more than one load. Therefore, classifications are more complicated for multiple operations.

These features cannot be adequately measured only from steady-state parameters in multiple operations, that is, real power and reactive power. In other words, it is difficult in steady-state power to identify each load, when the sums of real power and reactive power of two loads types are equal to that of another load. In contrast to steady-state properties, transient properties such as the turn-on transient energy can play an

Table 5. Recognition accuracy and computational requirements of learning vector quantization classifier

Features	PQ		$PQV_{THD}I_{THD}$		$PQV_{THD}I_{THD}U_T$	
	Training	Testing	Training	Testing	Training	Testing
Recognition Accuracy (%)	2.34	2.94	20.5	22.4	42.10	42.94
Computational Time (s)	55017	0.765	56772	0.938	59477	0.969
The Number of Hidden Neurons	15000		15000		15000	

important role. Combining transient and steady-state signatures is necessary to improve recognition accuracy for NILM.

In the individual operation, back propagation classifier requires less computational requirements than learning vector quantization classifier. In multiple operations, the computational requirements can not compare with the back propagation classifier and the learning vector quantization classifier, for the algorithm of LVQ classifier can not converge until the number of maximum iterations.

6 Conclusions

The EMTP simulation is invaluable for testing pattern recognition samples and allows the rapid development and implementation of successful prototypes. The NILM system employs an adaptive algorithm of the turn-on transient energy for start-up analysis to improve the efficiency of load identification and computational time. The testing recognition accuracy can be relatively high at 95.3% for back propagation classifier, in multiple operations. Furthermore, the BP classifier is far better than the LVQ classifier, in the efficiency of load identification and computational requirements.

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