Electrical Power and Energy Systems 105 (2019) 191–200

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Non-intrusive Load Composition Estimation from Aggregate ZIP Load Models using Machine Learning

Mulugeta W. Asres[a,*], Awet A. Girmay[b], Christian Camarda[b], Gebremichael T. Tesfamariam[a]

[a] *School of Electrical and Computer Engineering, Ethiopian Institute of Technology – Mekelle, Mekelle University, Ethiopia*
[b] *Midori Srl R & D (incubated at the Polytechnic University of Turin), Italy*

ARTICLE INFO

Keywords:
Artificial neural network
Load composition estimation
Load disaggregation
Non-intrusive load monitoring
Substation
ZIP modeling

ABSTRACT

Having continuous load structure and composition information of substations has a great relevance in power system analysis such as load modeling, load forecasting and demand-side management. In this paper, a parsimonious approach for load composition estimation using non-intrusive load disaggregation techniques for low voltage substations is presented with a concept of using ZIP load model characteristics of the aggregate active and reactive powers as predictor features. The disaggregation system uses machine learning algorithms such as Function Fitting Multi-Layer Perceptron Artificial Neural Network (MLP-ANN), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). During the study, a simulation dataset was generated using Monte Carlo simulation. Moreover, a comparative analysis with a benchmarked paper has been assessed and the proposed approach significantly outperforms.

1. Introduction

Appropriately capturing the protean load characteristics of substations substantially enhances the ability of system operators and planners in understanding the dynamic performance of the overall system [1]. Unfortunately, acquiring load composition of a substation is extremely challenging as the composition varies temporally and spatially [2]. This is due to the diversity of various factors such as type, size, and technology advancement of appliances and customer behavior [3,4]. Yet, the requirement for an elaborated load composition information has been acknowledged in various power analysis and load modeling literature [3,5,6,7]. Though this need mainly relates to stability issues such as voltage distortion and overvoltage caused by harmonic resonance, which is generated from nonlinear loads such as lighting systems, electronics, and motors, it is also essential for load dynamics characterization [8] and substation classifications [9]. Thus, load composition estimation leverages forecasting of harmonic distortions and growing loads to be refined [10]. Furthermore, disaggregated load information would further enable automated energy management systems to determine appropriate and more effective control/savings strategies for power distribution systems [5,11].

However, the load structure and composition is usually estimated from field surveys or disturbance measurement. Field surveying is very expensive, tedious and time-consuming while disturbance measurement requires system voltage fluctuations to be applied intentionally which is inconvenient for live substations and also needs expensive recording devices [5]. Even recent advanced monitoring technologies of smart grids are complex systems with integration of many telematics and often construed as a very expensive alternative which may require renovation of an entire distribution substation [12].

As a frugal alternative, load disaggregation using non-intrusive techniques are devised to estimate load compositions at substations and bulk supply buses in [13–15]. *Non-Intrusive Load Monitoring (NILM)* is defined as a set of techniques used to obtain estimates of the electrical power consumption of individual loads from single point measurements of electrical parameters [16]. However, most *NILM* studies have focused on domestic domains while *NILM* for substations has been largely unexplored. Of course, substations are complex systems having new challenges such as heterogeneity and highly mixed load compositions [17] in which many of the solutions and techniques developed for residential *NILM* could not be directly applied [11]. Furthermore, the previous proposals from [13–15] have some limitations in their proposed *input* or *predictor features*. Some of them used signal waveforms which have time shifting problem and high sampling rate requirement [13,14] while [15] faced with overlapping due to similar feature values which may have resulted from completely different load compositions. Therefore, there is still a need for improved disaggregation using enhanced predictor features and robust machine learning algorithms

* Corresponding author.
E-mail address: mulugeta.weldezgina@mu.edu.et (M.W. Asres).

https://doi.org/10.1016/j.ijepes.2018.08.016
Received 22 January 2018; Received in revised form 9 June 2018; Accepted 17 August 2018
0142-0615/

Nomenclature

Aggregate Power	Measured Power at Substation Feeder PCC
ANN	Artificial Neural Network
BRBP	Bayesian Regularization Back Propagation
CDF	Cumulative Probability Distribution
CI	Confidence Interval
Ed	Euclidean distance
GD	Gradient Descent
GO	Global Optimization
LV	Low Voltage
MAE	Mean Absolute Error
MC	Monte Carlo
MLP	Multi-Layered Perceptron
NILM	Non-Intrusive Load Monitoring
NW	Nguyen-Widrow layer initialization
P	Active Power
PCC	Point of Common Coupling
PDF	Probability Density Function
Pf_1	Fundamental Power Factor
Q	Fundamental Reactive Power
RMS	Root Mean Square
RMSE	Root Mean Square Error
R-value	Regression Fit
THD_v	Total Harmonic Distortion of Supply Voltage
V	Voltage
w	Weighting Factor (WF)
ZIP	Constant Impedance (Z), Constant Current (I), Constant Power (P)
Zsys	System Impedance
Std	Standard Deviation

along with adequate consideration of the influence of the distribution networks such as voltage distortions and voltage drop on the substation load characteristics.

In this paper, a study on *load composition estimation* for low voltage (LV) distribution substation using non-intrusive disaggregation techniques is presented. To handle the wide load diversities, the study focuses on *load categories* based on their electrical traits instead of dealing with individual appliances. After studying survey literature [3–6] on load compositions of LV substations, loads with significant contributions have been categorized into thirteen load categories (see Table 2). Then, the load categories were represented by the *ZIP load models* of their active and reactive powers, and the distinctiveness of the *ZIP model features* of the loads was evaluated using *Euclidean distance* analysis to assess their feasibility for non-intrusive load disaggregation. Finally, a two-layered feedforward *Multi-Layered Perceptron Artificial Neural Network (MLP-ANN), Particle Swarm Optimization (PSO)* and *Genetic Algorithm (GA)* were employed to estimate load share percentage (*load compositions*) of the target load categories from the *steady-state ZIP load model coefficients* of the *aggregated active (P)* and *reactive powers (Q)*. In this study, using *ZIP load models* of the target loads, a dataset was prepared from the possible load compositions (per-unit *Weighting Factors, WFs*) [0%, 100%] under normal operation per-unit *voltage (V)* [0.85, 1.15] using a *Monte Carlo (MC)* simulation. Moreover, the factors related to the distribution network i.e. voltage distortions and voltage drops were considered in the proposed disaggregation system design.

The residues or errors between the *estimated WFs* and the *actual WFs* for training and validation sets are analyzed using *Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Regression fit (R-value), Absolute Error Confidence Interval (CI), Probability Density Function (PDF)* and *Cumulative Probability Distribution (CDF)*.

Furthermore, one of the main challenges of *NILM* for substation loads is that there are a few input features to infer from unlike in domestic loads. Thus, in this study, *ZIP model* components of the *aggregate* P and Q are proposed because *ZIP model* expands P and Q separately into three dimensions (*constant impedance, constant current* and *constant power*) which would significantly leverage accuracy of the disaggregation. This was confirmed as the proposed approach outperforms a benchmarked approach [15], which instead proposed disaggregation from *aggregate* P and Q values, with a relative improvement of 30% and 19.6% in *RMSE* and *R-value* respectively.

The remaining part of this paper is organized as follows: background of the study is discussed in Section 2 followed by the proposed methodology, result and discussion, and conclusion in Sections 3, 4 and 5 respectively.

2. Background

Up to now, only a few research on load composition estimation via *NILM* techniques have been published. *Independent Component Analysis (ICA)* in [18], *Reduced Multivariate Polynomial (RMP)* in [13], *Multilevel analysis (MLA)* in [14] and *ANN* in [15] were applied to disaggregate bulk supply bus loads for load composition estimation. In [15], static *P (V) and Q(V)* load models were used to model target load categories. In the LV substation scenario, owing to the large number of appliance switching events with a very high probability of overlapping, disaggregation based on static load models of the target load categories is found as a promising approach. Consequently, in this paper, *steady-state power load models* have been used for modeling the target load categories and the proposed approach of [15] was used as a benchmark.

In the subsequent subsections, the underlining background concepts used in this study are discussed.

2.1. Static load modeling

Static load models (e.g. *Exponential* and *Polynomial* models) express steady-state active and reactive powers as algebraic functions of system voltage and frequency (1)(2) [5,7]. These models are vastly applied in power system analysis for power flow computation, reactive power compensators planning, voltage stability, frequency stability, and analysis of long-term dynamic process [6,19].

$$P = F_p(V, f) \tag{1}$$

$$Q = F_q(V, f) \tag{2}$$

The frequency factor f is, however, often neglected since voltage changes are much more frequent and more pronounced than the changes in system frequency [5].

In *ZIP load model* (a variant of *Polynomial* model), loads are described as a combinational behavior of *constant impedance (Z), constant current (I)* and *constant power (P)* characteristics represented by the coefficients of $Z_{p,q}$, $I_{p,q}$ and $P_{p,q}$ respectively in (3)(4). *ZIP models* have some physical significance since a large portion of the loads may be described as a constant impedance (heating, incandescent), constant current (motors), and constant power (switched mode power supplies (SMPS), drive controlled motors) [7]. *ZIP models* also provide better accuracy than *Exponential models* [6].

$$P(V) = P_0\left(Z_p\left(\frac{V}{V_n}\right)^2 + I_p\left(\frac{V}{V_n}\right) + P_p\right) \tag{3}$$

$$Q(V) = Q_0\left(Z_q\left(\frac{V}{V_n}\right)^2 + I_q\left(\frac{V}{V_n}\right) + P_q\right) \tag{4}$$