Electric Power Systems Research 142 (2017) 320–328

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Transient stability assessment via decision trees and multivariate adaptive regression splines

Matin Rahmatian [a], Yu Christine Chen [a,*], Atefeh Palizban [a], Ali Moshref [b], William G. Dunford [a]

[a] Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, Canada
[b] Power Systems and Testing, BBA Inc., Vancouver, Canada

ARTICLE INFO

Article history:
Received 29 April 2016
Received in revised form
22 September 2016
Accepted 29 September 2016
Available online 17 October 2016

Keywords:
Classification and regression trees
Decision trees
Multivariate adaptive regression splines
Phasor measurement units
Real-time transient stability assessment
Synchrophasors

ABSTRACT

This paper focuses on the practical implementation of online transient stability assessment (TSA) tools that employ, in conjunction with high-speed synchronized phasor measurements obtained from phasor measurement units (PMUs), classification and regression trees (CART) and multivariate adaptive regression splines (MARS) models. To build CART and MARS models that are amenable to real-time applications, pertinent transient stability-related system characteristics are identified; these include voltage and current phasors, deviations from the centre-of-inertia angle and speed, and potential- and kinetic-energy related quantities. These characteristic quantities are evaluated using PMU measurements and then leveraged to train CART and MARS models for the full Western Electricity Coordinating Council (WECC) system. The resultant models are tested and validated with the full WECC system using credible contingency scenarios in the BC Hydro subsystem. High prediction accuracy rates are observed for both CART and MARS methods, making them attractive options for real-time TSA.

1. Introduction

Real-time dynamic security assessment (DSA) is a challenging issue in modern electric power systems. Uncertainties arising from renewable electric sources, increased electricity demand, and recent blackouts all highlight the need for improved tools to monitor dynamic security in real time [1]. As an enabling technology for accomplishing this goal, phasor measurement units (PMUs) provide synchronized voltage and current phasor measurements with high sampling rate in the milliseconds range [2]. These phasor measurements are collected locally with phasor data concentrators and then transmitted to a central decision maker. Such an architecture, along with fast communication infrastructure, has the potential of realizing accurate and efficient real-time DSA [3]. The broad class of DSA includes assessment of system security with respect to various types of stability, including voltage, transient, and small-signal stability. The focus of this paper is on transient stability assessment (TSA), which is related to the time evolution of a dynamic power system trajectory when subject to a large perturbation, e.g., a fault in a transmission line [4]. (We interchangeably refer to faults as contingencies.) The ability to conduct real-time TSA would enable power systems to operate closer to their limits since the effects of unexpected faults could be accurately assessed in a timely manner.

Given the obvious utility of real-time TSA tools, numerous approaches have been explored in the literature. These approaches can be divided into three main categories: time-domain simulations, direct approaches, and automatic learning methods. The main drawback of time-domain simulation approaches is that they are computational burdensome [5]. In direct approaches, energy functions are difficult to construct for practical large-scale systems [6–8]. On the other hand, recent work has revealed automatic learning methods to be promising for practical real-time TSA [9–15]. For example, in [9], a comprehensive database of the Hydro-Québec power system along with relevant contingency cases are constructed and a decision tree (DT) is used to classify stable vs. unstable scenarios. A random forest classifier is shown to operate efficiently in the presence of small changes in the network topology in [16]. In [10], regression trees are used to indicate the number of overloaded lines and buses with voltage magnitude violations following a fault. In [11], application of multiple DTs leads to improved reliability for determining stable versus unstable scenarios. The support vector machine method is used as the classifier in [14] where energy-based power system features are applied, and accurate prediction rates are demonstrated, albeit for small-scale systems (New England 39-bus power system model) only. In [12] and [17], in order to tailor to online applications, ensemble learning

* Corresponding author.
E-mail address: chen@ece.ubc.ca (Y.C. Chen).

http://dx.doi.org/10.1016/j.epsr.2016.09.030
0378-7796/

machine is used to decrease the required training and decision-making time.

In this paper, we focus on the *practical* implementation of classification and regression models to assess transient stability in real time using PMU measurements obtained from the system. The classification model is developed using classification and regression trees (CART), which is a well-known DT algorithm [18]. We then use the developed model to classify test cases as either stable or unstable with high degree of accuracy. In addition to CART, which returns discrete-valued stable versus unstable classifications, we propose to use multivariate adaptive regression splines (MARS) [19] in conjunction with a continuous-valued transient stability index (TSI) to assess the severity of the contingency and the system's proximity to instability. Application of this method can be useful to determine probable corrective actions. Development of both CART and MARS models proceeds as follows. First, we identify system characteristics that are pertinent to TSA, including voltage and current phasors, deviations from centre-of-inertia angle and speed, and potential- and kinetic-energy related quantities. Next, these characteristic quantities, called "indices" or "features", are evaluated using synthetic measurements obtained from time-domain simulations of the full Western Electricity Coordinating Council (WECC) system. These evaluated quantities are used to build classification and regression models, which are then tested and verified on the WECC system, with emphasis on transient stability issues in the BC Hydro power system that may emerge due to high power exchange rates with the Bonneville Power Administration (BPA) system. We also show the necessity and practicality of updating the obtained models after topology changes or in the presence of high penetration of renewable resources.

To validate the proposed CART and MARS methods in a practical setting, we conduct test cases on the full WECC system model, with emphasis on the BC Hydro power system. It is worth noting that this is the same detailed model that BC Hydro uses for its planning and operations studies. Mindful of practical field implementations of the proposed methods, our studies assume limited number of PMUs installed, in accordance with existing infrastructure in the BC Hydro system. Similarly, we assume only large generating plants of the neighbouring regions are equipped with PMUs. As a consequence of the limitation in the number of installed PMUs, some features, such as the location of the fault highlighted in [20], may not be readily available. Moreover, certain features proposed in the literature may not be available in *real time*, such as the duration of the fault and the time to loss of synchronism considered in [21]. Since this paper focuses on the practical implementation of CART and MARS methods, features used in our studies are carefully selected to ensure they are available in real time while being cognizant of existing infrastructure limitations. In addition to considering practical limitations, we also take advantage of recent advances in PMU technology and assume that synchrophasor measurements are available at the control centre through wide-area monitoring system (WAMS) at every electrical cycle [22].

This paper builds upon our work in [23] and extends it in several directions. First, the modified data set includes 200 power-flow scenarios and 3 different topologies leading to 9474 different simulation cases, which is more comprehensive than the data set used in [23] and highlights the necessity for an adaptive framework. Second, MARS is used to fit a closed-form equation for the transient stability margin of the system. Furthermore, we test the resulting CART and MARS models with data obtained at sampling times other than used to train the models in order to uncover their sensitivity to erroneous data fed from a later or earlier sampling time. Finally, we demonstrate the sensitivity of MARS model prediction accuracy with respect to two relevant parameters.

The remainder of the paper is organized as follows. Section 2 outlines TSA indices used to build CART and MARS models. In Section 3, fundamentals of CART and MARS model building procedures are described. Section 4 presents WECC system specifications, data set generation, PMU measurement sampling, and model training. Simulation results are reported and the necessity for updating models is discussed in Section 5. Finally, Section 6 offers concluding remarks and directions for future work.

2. Transient stability assessment indices

The first step to building classification and regression models for TSA is to identify system characteristics that are relevant to determining transient stability. With regard to this, numerous features have been used in the literature, including direct phasor measurements and computed quantities involving these measurements [10–12,21,9,16]. (We interchangeably refer to features as indices.) In this section, we enumerate and describe TSA indices used in our work.

2.1. Direct measurement indices

Most commonly used indices are time-synchronized measurements of, e.g., generator rotor angles, rotor speeds, bus relative voltage phase angles and magnitudes, and current flows [10–12,21]. Note that generator rotor and voltage phase angles are obtained as relative angles with respect to a system reference. Other basic indices are obtained from simple calculations involving voltage and current phasors, such as active and reactive generation, active and reactive load, and voltage drop across transmission lines [10–12].

Based on the practical availability of WAMS, we select several synchronized measurements from the pre- and post-fault systems and use them as TSA indices. In a practical power system, major power plants with large generation capacity as well as critical transmission corridors are candidates for PMU installations and real-time monitoring [24]. Under pre-fault normal operating conditions, we collect the total and individual active-power generation of major power plants in each balancing authority region (with respect to the WECC system, the balancing authority regions are BC Hydro, BPA, and Alberta power systems). We also use the relative voltage phase angles of buses connected to these major power plants and those of buses that interface between two regions. Furthermore, we make use of the active-power flows across inter-ties connecting the regions and along critical long transmission lines. Under post-fault conditions, we use only measurements of relative voltage phase angles of buses connected to major power plants and of buses that interface between two regions.

2.2. Centre-of-inertia-referred indices

Since deviation from the centre-of-inertia (COI) angle can indicate system stress, below, we introduce COI-referred system characteristics. Consider an interconnected power system in which the monitored region has $K-1$ neighbouring regions. Assume we monitor region k which contains N buses. Also assume region k contains G major synchronous generators that are equipped with PMUs. Denote, by $P_{mi}(t)$ and $P_{ei}(t)$, the mechanical-power input [p.u.] and the electrical-power output [p.u.], respectively, of generator i at time t. Let $\delta_i(t)$ and $\omega_i(t)$ denote the rotor angle [rad] and speed [rad/s], respectively, of generator i at time t; and let M_i denote the inertia constant [s^2/rad] of generator i. Then, the COI angle of the monitored region is defined as [4]

$$\delta_{\mathrm{COI},k}(t) := \frac{1}{M_{\mathrm{total}}}\sum_{i=1}^{G} M_i\delta_i(t), \tag{1}$$