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Global sensitivity analysis of transmission line fault-locating algorithms using sparse grid regression

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ABSTRACT

Computation of distance to fault on an electrical transmission line is affected by many sources of uncertainty, including parameter setting errors, measurement errors, as well as absence of information and incomplete modelling of a system under fault condition. In this paper we propose an application of the variance-based global sensitivity measures for evaluation of fault location algorithms. The main goal of the evaluation is to identify factors and their interactions that contribute to the fault locator output variability. This analysis is based on the results of Sparse Grid Regression. The method compiles the Functional ANOVA model to represent fault locator output as a function of uncertain factors. The ANOVA model provides a tool for interpretation and sensitivity analysis. In practice, such analysis can help in functional performance tests, especially in: selection of the optimal fault location algorithm (device) for a specific application, calibration process and building confidence in a fault location function result. The paper concludes with an application example which demonstrates use of the proposed methodology in testing and comparing some commonly used fault location algorithms. This example is also used to demonstrate numerical efficiency for this type of application of the proposed Sparse Grid Regression method in comparison to the Quasi-Monte Carlo approach.

1. Introduction

Protective, control and event analysis functions (algorithms) required in operation of an overhead transmission line are implemented in a single device, called Intelligent Electronic Device (IED). Fault-locating algorithms belong to the class of event analysis functions. Commonly used algorithms are described in the IEEE Standard C37.114-2004 [1]. The purpose of distance to fault location function is to estimate the point where a transmission line has faulted in order to repair and speed up the return to service of such line. Furthermore, it provides information used to confirm correct protection function operation and to improve system design. The fault location function relies on very complex hardware and software modules implemented in IEDs. These modules include specialised high-resolution signal processing techniques and in many situations high quality front-end hardware that is comprised of special transducers and Analogue to Digital Converters (ADCs) with high sampling frequency and high resolution.

High accuracy and precision in estimation of distance to fault location is needed for efficient dispatch of repair crews and fast service restoration. Hence, it is very critical to select fault-locating algorithms that are able to achieve the best possible performance under specific filed conditions. Several factors affect the performance of fault location algorithms [2]. These factors include the system parameters not known exactly (representing certain transmission line conditions), measurement errors as well as those quantities that contain essential information but are not measured. The factors can be classified as

(a) *System factors*: High-resistance fault with unknown resistance value, not measured fault current infeeds (remote and other tapped infeeds), not measured load current, not measured pre-fault source condition.
(b) *Setting factors*: Inaccurate line modelling parameters, inaccurate local and remote source modelling parameters, insufficient detail of a line model used in a fault location algorithm.
(c) *Measurement factors*: Error in measurement system composed of transducers, ADCs and signal processing, that is affected by measurement conditions such as very short segment of recorded fault signals (40–80 ms) and presence of nuisance components such as DC offset and high frequencies in those signals.

Uncertainty in the above factors imposes a limit on the confidence in fault location function results. If we consider that variation in each factor can be described, it would be possible to

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obtain a quantitative assessment of the fault location uncertainty together with fault location estimate [3]. This additional information will improve dispatch of repair crews. In addition, it will be useful to understand and quantify how uncertainty in fault location can be divided up among different sources of uncertainty (variation) represented by the above listed factors. This analysis can be done as a part of the functional performance tests [4]. These tests are devised to determine the suitability of a fault location function for a specific application. Test conditions are derived from testing models that replicate accurately the behaviour of a power system under various fault conditions. The optimal settings of the fault location function can be determined based on the results of these tests.

In this paper, we present the Sparse Grid Regression (SGR) technique that can be used in a systematic evaluation of fault-locating algorithms as a part of the function performance test. The test is performed by executing power system simulation model and fault locator repeatedly for a large number of factor values sampled from a specified grid of factor points (factor space). For each point in the factor space, the power system model produces voltages and currents at the fault locator device measurement connections. These values are passed to the fault locator function and distance-to-fault results are collected. It is assumed that a smooth and continuous function is sufficient in modelling dependence of distance-to-fault on input factors. A dimension d of this function is equal to the number of input factors. For the purpose of formulating the SGR method, it is useful to represent this function using the finite dimension-wise expansion with 2^d terms, called the Functional Analysis of Variance (ANOVA) [5,6]. The expansion consists of a constant term plus a sum of d one-dimensional component functions, each referred to as the main effect of the corresponding factor, and a sum of multi-dimensional component functions that represent interactions between different dimensions. The Functional ANOVA is unique representation if the line integrals of every component function over any of its own variables (i.e. factors) are equal to zero [6]. In such an expansion all component functions are orthogonal. This condition is achieved by representing the function using a linear combination of tensor products of the orthogonal Legendre polynomials. Because of the orthogonal basis, the coefficients in this expansion, when squared, are directly related to the variance-based global sensitivity measures [5,6]. Hence, the goal of the SGR method is to approximate the function linking input factor space and fault locator output using the proposed expansion model. The coefficients of the expansion are used to perform the Global Sensitivity Analysis (GSA) [6]. This analysis can determine factors that mostly contribute to the fault locator output variability. Significant interactions between factors can be also determined. In this way the GSA can provide critical evaluation and comparison of the fault location techniques as well as calibration and optimal setting for specific application.

The paper is organised as follows. Section 2 describes the Sparse Grid Regression method which is able to fit the Functional ANOVA model. The model represents a fault locator output as a multi-dimensional function of factors. The parameterisation of the ANOVA model is via a linear combination of the multi-dimensional basis functions, which are designed through a tensor product of orthogonal polynomials. To estimate coefficients in this expansion model we solve multi-dimensional integrals using the Sparse Grid Integration (SGI) [7,8], and as a result we obtained a novel Sparse Grid Regression method. The SGI rule is constructed using the approximation of the tensor product of univariate quadratures. In contrast to the classical tensor product approach where number of nodes and corresponding accuracy levels of univariate quadrature rules for all dimensions are the same [9], the SGI is based on a weighted combination of tensor products of univariate quadrature rules with different accuracy levels: a fine sequence of nodes (high accuracy level) in one dimension is always combined with a coarse sequences in the other dimensions (low accuracy levels). The total accuracy level (i.e. a sum of accuracy levels of all univariate rules in a product) is bounded in the SGI formula. The total number of nodes will be significantly smaller than the number of nodes required in the classical tensor product formula. This approximation works for smooth functions which can be represented using Taylor's series expansion with the finite number of terms. In Section 3 we use the GSA [6] as the fundamental technique in automated determination of the model structure. The initial basis size has to be provided, and the GSA is used to reduce the initial basis size by rejecting all insignificant terms. This method will automatically determine which input factors and their interactions are relevant, i.e. it provides the sensitivity measures that explain which factors and interactions among factors have impact on a fault location precision. Section 4 presents the application example results in applying the SGR to fit the ANOVA function. Two fault locators have been selected for this study and their performance has been compared using the GSA. For comparison we applied additionally the Quasi-Monte Carlo approach in the regression procedure [5]. Results of this experiment show that the proposed SGR approach achieves the same approximation accuracy as the regression based on the Quasi-Monte Carlo with the significantly reduced number of the fault location tests. The small number of required tests (samples) makes the SGR suitable for practical applications. Each laboratory test of a fault location device requires few minutes, so it is of high practical value to reduce number of tests.

2. Sparse grid regression

Sensitivities of a fault location algorithm output to various factors (discussed in the Section 1) are obtained after fitting the surrogate function $f(\mathbf{x})$ with specified structure to sampled factor data and corresponding locator output data. We use the SGR technique to fit the surrogate function. This method combines the specific way of the function parameterisation with the SGI [7,8], resulting in the numerically efficient multi-dimensional function regression technique, very well suited for our application. The proposed technique relies on the assumption that factors are independent. Variation of a factor value is represented with uncertainty interval that is obtained from measured data or decided by experts. In this way, the factor space is defined. Each sample in the factor space is represented as a vector $\mathbf{x}\in\boldsymbol{R}^d$ ($\boldsymbol{R}$ is the set of real numbers and d is a dimension of the factor space). For the purpose of computation, all of the factor intervals have been mapped into unit hypercube defined as $\boldsymbol{I}^d=\{\mathbf{x}\in\mathbf{R}^d: 0\le x_i\le 1, 1\le i\le d\}$.

The function $f(\mathbf{x})$ parameterisation is based on the following expansion:

$$f(\mathbf{x})=\sum_{\mathbf{r}}\beta_{\mathbf{r}}\psi_{\mathbf{r}}(\mathbf{x}) \tag{1}$$

where $\mathbf{r}=(r_1,r_2,\ldots,r_d)\in\{0,1,2,\ldots\}^d$ is the multi-index vector. To each vector $\mathbf{r}$ in (1) corresponds a unique tensor product function $\psi_{\mathbf{r}}(\mathbf{x})=\prod_{i=1}^{d}\phi_{r_i}(x_i)$ and a coefficient $\beta_{\mathbf{r}}$. If we select an orthogonal basis $\psi_{\mathbf{r}}(\mathbf{x})$ on $\mathbf{I}^d$ (i.e. $\phi_{r_i}(x_i), i=1,2,\ldots,d$, are orthogonal polynomials), coefficients $\beta_{\mathbf{r}}$ can be calculated by solving the following multi-dimensional integrals:

$$\beta_{\mathbf{r}}=\int_{\mathbf{I}^d}f(\mathbf{x})\psi_{\mathbf{r}}(\mathbf{x})\,d\mathbf{x} \tag{2}$$

The classical technique for numerical solution of the multi-dimensional integral (2) is to extend one-dimensional quadrature rules to multiple dimensions by applying a tensor product of one-dimensional rules [9]. However, computing costs rise exponentially