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Measurement-Based Parameter Estimation for the WECC Composite Load Model with Distributed Energy Resources

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***Abstract*—The development of advanced composite load models is imperative for accurate dynamic stability analysis of electric power systems. In North America, the Load Modelling Task Force (LMTF) endorsed the WECC composite load model for dynamic simulations of transmission networks. However, due to its complex dynamics and large number of parameters, little attention has been paid to the estimation of its parameters from online measurements. This load model incorporates the switching action of different built-in protection devices, which negatively affects the performance of conventional nonlinear programming algorithms. This paper introduces a hybrid optimization approach to estimate the parameters of the WECC composite load model. Parameters associated with dynamic and static equations, which are constrained by the physical interpretation of the model, are estimated by nonlinear programming techniques. On the other hand, protection parameters are estimated using a surrogate model of the objective function based on Radial Basis Function (RBF) optimization. The proposed scheme is validated with simulated and actual measurements collected across Australia.**

***Index Terms*—Load Modelling, Distributed Energy Resources, Power System Modelling, Nonliner Optimization.**

I. Introduction

The accurate modelling of system loads has been recognized as one of the most important aspects for the proper analysis of planning, operation and control in power systems. Over the past decades, an extensive pool of static and dynamic load models have been proposed and used in the industry [1]. Recently, due to the high penetration of Distributed Energy Resources (DER), the Western Electricity Coordinating Council (WECC) developed an advanced composite load model with various components, including different types of motor loads, electronic/static loads as well as the representation of grid-connected DER. The North American Electricity Reliability Corporation (NERC) recommends the use of the WECC composite load model, also known as CMPLDWG, for dynamic studies in power systems [2].

Measurement-based load modelling is a widely used technique in which the parameters of the model are estimated from measurement data [3]–[7]. The existence of multiple local optimal solutions to the parameter estimation problem via measurements has been investigated in [3]. To mitigate this limitation, various parameter-reduction techniques based on perturbation analysis have been proposed [5]–[8]. For instance, a pair-wise correlation between parameters and sensitivity analysis were proposed in [5]. Similarly, researchers in [7] reduced the number of parameters by applying identical updates to parameters with similar sensitivity at every iterative step. The work in [6] employed a K-medoids algorithm to cluster and visualize parameters with similar sensitivity values. Previous works on measurement-based load modelling [4]–[7] formulated the parameter estimation procedure as a box-constrained (or unconstrained) nonlinear least-squares optimization routine, without paying close attention to the physical constraints and the interpretation of the different parameters within the model.

The default parameters of the CMPLDWG are provided in [2]. However, after comparing the model outputs with recorded events in Australia, it was determined that the default parameters may not always be suitable for accurate modelling of system loads and a measurement-based technique is required to calibrate them. Unfortunately, due to the high complexity of the CMPLDWG, little attention has been paid to the estimation of its parameters from online measurements. Although the dependency analysis in [6] was applied to the CMPLDWG, the DER component and the physical constraints on the model parameters were not considered in their work. Addressing this gap, we present a hybrid optimization approach to estimate the parameters of this composite load model considering DER dynamics. The proposed hybrid approach makes use of conventional nonlinear programming solvers and a recently developed derivative-free optimization technique [9]. Additionally, unlike previous works, physical constraints on the parameters are imposed in order to limit the number of feasible solutions to the optimization problem.

In the proposed framework, parameters are categorized into: i) model equation parameters and ii) model protection parameters. Model equation parameters are related to the static and dynamic equations of the model, including the state equations of induction motors, electronic/static loads and the state equations of the DER model. Using the trajectory sensitivity method [8], a selection of the model equation parameters is considered in the estimation process. Since these parameters are constrained based on the physical interpretation of the model, a nonlinear optimization solver is used for estimation. On the other hand, the model protection parameters are related to the under- and over-voltage protection of the load components. These parameters are unsuitable for conventional nonlinear programming solvers, therefore, a derivative-free approach based on Radial Basis Function (RBF) optimization [9] is used for estimating the protection parameters.

II. WECC Composite Load Model Representation

A. Introduction

NERC proposed a composite load model to represent the behavior of DER and several types of end-use loads [2]. This load model is composed of different subsystems, as depicted [2, Fig. 35]. The electrical distance between the power substation and the loads is emulated with a step-down transformer and a model of the distribution feeder. Similarly, the complex dynamics of end-use loads is represented by various components, including: i) three-phase induction motors with different torque-slip characteristics, ii) a single-phase phase induction motor to emulate air-conditioning units iii) electronic loads and iv) constant impedance, constant current and constant power loads (ZIP). Electrical devices such as induction motors and electronics loads are equipped with a model of their built-in protection equipment in order to emulate partial load tripping after the occurrence of extreme disturbances. Lastly, a salient feature of the CMPLDWG is the representation of the various grid-connected DER in the low voltage network. This is possible by appending an aggregate power inverter model operating in parallel with the load components [10].

B. Motor A/B/C

This composite load model uses a Type I double-cage induction motor model for dynamic simulations. The combination of electrical and mechanical equations of each motor forms a fifth-order dynamical system, represented by the CIM6BL load characteristics model in PSS/E. A block diagram of the electrical model can be observed in [11, p.2]. The mechanical load torque T_L is modelled as $T_L = T_{L0}\omega^{Etrq}$, where T_{L0} is the initial load torque and ω is the speed. In order to represent different load characteristics, the values of $Etrq$ for motors A, B and C are fixed to 0, 2, and 2 respectively.

In steady-state, induction motors are represented by an equivalent circuit [11, p.1]. The relationships between the parameters of the equivalent circuit and the parameters in the block diagram of the electrical model in [11, p.2] are as follows:

$$L_a = L_l; \tag{1}$$

$$L_m = L_s - L_l; \tag{2}$$

$$L_1 = \frac{(L_p - L_l)(L_s - L_l)}{L_s - Lp} \tag{3}$$

$$L_2 = \frac{L_s - L_l}{(L_s - L'')/(L'' - L_l) - (L_s - L')/(L' - L_l)} \tag{4}$$

$$R_1 = \frac{(L_s - L_l)^2}{(L_s - L')T_0'\omega_0} \tag{5}$$

$$R_2 = \frac{L_2 + L_1 L_m/(L_1 + L_m)}{\omega_0 T_0''} \tag{6}$$

If the initial active power at the load bus is P_L, motor $k \in \{A, B, C\}$ has an initial active power consumption of $F_{mk}P_L$, where parameters $F_{m,k}$ are known as load fractions. The initial reactive power is obtained using the operating power factor of the machine.

C. Motor D

Motor D component is a single-phase induction motor model used to represent single-phase residential air-conditioner compressor motors. The model is governed by static equations that can emulate the motor behaviour in three operating modes: i) running state I ii) running state II and iii) stalled state. A more detailed description of the static equations for each of the running modes explained above can be found in [12]. The initial power consumption of motor D at nominal voltage is given by $P_D = F_{mD}P_L$, and the initial reactive power is determined by the user-defined power factor PF_D.

D. Electronic Loads

These loads are represented as constant active and reactive power when the terminal voltage $|V|$ is greater than a user-defined voltage threshold V_{d1}. The initial active power of electronic loads at $|V| = 1p.u$ is given by $P_{el} = F_{el}P_L$, and the initial reactive power is determined using the user-defined power factor PF_{el}. Both the active and reactive power are linearly decreased to zero if $V_{d2} \leq |V| \leq V_{d1}$. Voltage V_{d2} is a second user-defined voltage threshold that indicates the minimum voltage at which electronic loads remain connected. Therefore, electronic loads consume zero active and reactive power if $|V| \leq V_{d2}$.

E. Static Loads

These loads are used to represent the conventional frequency-dependent ZIP model. The equations for active and reactive power for static loads are provided in (7) and (8) respectively. The initial active power of the static loads is calculated as $P_0 = P_L(1 - F_{mA} - F_{mB} - F_{mC} - F_{mD} - F_{el})$ and the initial reactive power Q_0 is determined using the user-defined power factor PF_{st}. As observed in (7) and (8), both equations are divided into three terms: i) constant current ii) constant impedance and iii) constant power. The amount of power assigned to each component of the static loads is specified using parameters P_{1c}, P_{2c}, P_3, Q_{1c}, Q_{2c} and Q_3. The fractions of constant active and reactive power are calculated as $P_3 = 1 - P_{1c} - P_{2c}$ and $Q_3 = 1 - Q_{1c} - Q_{2c}$ respectively.

$$P_{ST} = P_0(P_{1c}(\frac{V}{V_0})^1 + P_{2c}(\frac{V}{V_0})^2 + P_3)(1 + P_{frq}\Delta f), \tag{7}$$

$$Q_{ST} = Q_0(Q_{1c}(\frac{V}{V_0})^1 + Q_{2c}(\frac{V}{V_0})^2 + Q_3)(1 + Q_{frq}\Delta f), \tag{8}$$

F. DER Model [10]

This model is used to represent the aggregate behaviour of distributed inverter-based generation. A block diagram of the utilized DER model is shown in [10, Fig. 2]. The model, also known as DER_A, was proposed by the WECC and has been integrated into several software platforms for power system analysis. Using asymmetric dead-bands, the model allows for emulation of the different features enabled in various inverter-based DER, such as frequency and voltage support. Primary frequency response can be enabled or deactivated for both under- and over-frequency disturbances using parameters D_{up} and D_{dn}. Similarly, the voltage support mechanism can be deactivated by setting Kqv parameter to 0. It is also possible to operate the model in different modes, such as constant power factor and constant reactive power control modes. In this paper, the default parameters that determine the mode of operation of the DER_A model are selected based on [13]. It is assumed that the output power of the DER model is determined by $P_{der} = F_{der}P_L$, where F_{der} is the fraction of load that the DER model generates.

III. Parameter Estimation Problem

A. Formulation

This approach aims at finding the optimal set of parameters (given in vector $\mathbf{x}$) that minimize the difference between the measurements ($P_{m,t}$ and $Q_{m,t}$) and the model outputs for active power at time t ($P(\mathbf{x}, t)$ and $Q(\mathbf{x}, t)$). If the error for active and reactive power at time t is given by $\epsilon_p(\mathbf{x}, t) = P_{m,t} - P(\mathbf{x}, t)$ and $\epsilon_q(\mathbf{x}, t) = Q_{m,t} - Q(\mathbf{x}, t)$ respectively, the model parameters can be estimated by solving the following non-linear optimization problem:

$$\min_{\mathbf{x}\in\mathbb{R}^N} \quad J(\mathbf{x}) = w_p \sum_{t_0}^{t_f} \epsilon_p(\mathbf{x}, t)^2 + w_q \sum_{t_0}^{t_f} \epsilon_q(\mathbf{x}, t)^2 \tag{9a}$$

$$\text{subject to} \quad \mathbf{x}_{min} \leq \mathbf{x} \leq \mathbf{x}_{max}, \tag{9b}$$

$$f_i(\mathbf{x}) \leq 0, \quad i \in \mathbb{E} \tag{9c}$$

In problem (9), constants w_p and w_q are weights assigned to the active and reactive power error functions respectively. Equations (9b) and (9c) represent box-constraints and inequality constraints respectively, where $\mathbb{E}$ is a set of indices containing constraints (9c).

B. Inequality Constraints

Inequality constraints $f_i(\mathbf{x})$ in (9c) were not considered in previous works [4]–[8]. They are required in order to obtain a solution with meaningful physical interpretation and to reduce the number of feasible local optimal solutions to the optimization problem. These constraints can be summarized as follows:

- The summation of load fractions must be less than or equal to one, that is $F_{mA} + F_{mB} + F_{mC} + F_{mD} + F_{el} + F_{st} - 1 \leq 0$. In addition, based on previous knowledge of the load composition at each load bus, linear inequality constraints of a combination of two or more load fractions may be added.
- The ratio between the feeder's reactance and resistance is usually greater than 1, that is $R_{fdr} - X_{fdr} \leq 0$.
- The fraction for active and reactive power assigned to the constant current and constant impedance loads in (7) and (8) must be less or equal to one, that is $P_{1c}+P_{2c}-1 \leq 0$ and $Q_{1c} + Q_{2c} - 1 \leq 0$.
- The electrical parameters for the equivalent circuit of each induction motor in (1)-(6) must be non-negative. Therefore, the following inequality constraints are needed for the induction motor parameters: i) $L_p - L_s \leq 0$ ii) $L_l - L_p \leq 0$ iii) $L_{pp} - L_s \leq 0$ iv) $L_l - L_{pp} \leq 0$ and vi)$(L_{pp} - L_s)/(L_{pp} - L_l) - (L_p - L_s)/(L_p - L_l) \leq 0$.

IV. Parameter Estimation Solution

A. Radial Basis Function Surrogate Model Optimization

The Radial Basis Function (RBF) method is a black-box optimization algorithm for unconstrained optimization problems. The algorithm builds a surrogate model of the the objective function (9a) using a collection of sample points. Both the construction of the surrogate model and the computation of new evaluation points will be briefly described in this paper, while a thorough description of the algorithm can be found in [9].

1) Surrogate Model [9]: Given k distinct sample vectors $\mathbf{x}^i$ ($i = \{1, 2, ..., k\}$) with objective function values of $J(\mathbf{x}^i)$, the surrogate model $s_k(\mathbf{x})$ of the objective function in (9a) is expressed as

$$s_k(\mathbf{x}) = \sum_{i=1}^{k} \lambda_i \Phi(||\mathbf{x} - \mathbf{x}^i||) + p(\mathbf{x}), \tag{10}$$

where Φ is the selected RBF and $p(\mathbf{x})$ is a polynomial in $\mathbf{x}$ that guarantees the existence and uniqueness of (10). The degree of $p(\mathbf{x})$ depends on the selected RBF. For example, for the cubic $\Phi(y) = y^3$ and the thin plane spline $\Phi(y) = y^2 Ln(y)$ functions—two commonly used RBFs in the literature—the degree of $p(\mathbf{x})$ is one. The values of λ_i and the coefficients of polynomial $p(\mathbf{x})$ can be found by solving a linear system satisfying $s_i(\mathbf{x}) = J(\mathbf{x}^i)$. Given the lower bounds $\mathbf{x}_{min}$ and upper bounds $\mathbf{x}_{max}$, the initial set of sample vectors $\mathbf{x}^i$ is usually generated by a Latin Hyper-cube Sampling technique (`lhd_maximin`).

2) Search Directions [9]: Once the surrogate model is constructed, a method to generate the next search point at which the objective function should be evaluated is required. At each outer iteration, the next point $\mathbf{x}$ should minimize the distance between the previously evaluated points $||\mathbf{x} - \mathbf{x}^i||$ and also decrease the value of the surrogate model $s_k(\mathbf{x})$. Since both requirements are usually conflicting, a level of importance $\alpha \in [0, 1]$ is assigned to each of these objectives and, at each outer iteration, the next point $\mathbf{x}$ is determined by solving a bi-objective optimization problem using a genetic algorithm.

B. Hybrid Approach

We propose a hybrid approach to estimate the parameters of the CMPLDWG. To this end, model parameters are separated into two main groups:

1) Model Equation Parameters: These parameters portray the trajectories of the state variables in the model without considering the action of the protection devices. The estimation problem is formulated as in (9a), (9b) and (9c). Since the optimization problem has inequality constraints, a non-linear programming solver is suggested. The model equation parameters include the feeder resistance and reactance, the load fractions, the static/electronic load equation parameters, the electrical parameters of the induction motors and the parameters of the state equations of the DER_A model. The relevant model equation parameters are selected via trajectory sensitivity analysis.

2) Protection Parameters: If the voltage at the load bus is higher than the voltage set-points of the protection devices during the entire simulation, the under-voltage trip parameters would have zero effect in the output of the load model—they are insensitive to the objective function in (9a). Although these parameters remain constant, their values and derivatives are being used during the entire optimization routine in order to estimate the search directions with finite-difference derivatives. Consequently, the inclusion of these parameters into the optimization problem has a negative impact on computation time required to estimate the entries of the KKT matrices—increasing the complexity of the problem.

Conversely, if the voltage at the load bus is below the under-voltage set-points of the protective devices at any time during the simulation, the action of protection equipment generates step changes in output of the load model. These abrupt changes in the objective function may create inconsistent values of the derivatives via finite-difference method. As a result, protection parameters have a negative impact on the operation of most standard nonlinear programming solvers, making derivative-free methods an attractive solution. A great advantage when optimizing the protection parameters is that inequality constraints in (9c) can be eliminated. The optimization problem is only constrained by the upper and lower bounds in (9b) and this makes the problem suitable for black-box optimization techniques.

3) Proposed approach: The proposed approach requires two types of measurements: 1) Without load tripping behaviour and ii) with load tripping behavior. Each step of the algorithm is described in Algorithm 1.

Algorithm 1 Proposed hybrid parameter estimation approach.

Let the measurements of voltage, frequency, active and reactive power at time t be $V_{m,t}$, $\omega_{m,t}$, $P_{m,t}$ and $Q_{m,t}$ respectively.
Estimate the amount of load being tripped as $\epsilon = (|P_{m,0} - P_{m,last}|)/P_{m,0} \times 100\%$, where $P_{m,0}$ and $P_{m,last}$ are the first and last samples of active power respectively.
Separate the parameter vector into: 1) Model Equation parameters ($\mathbf{x}_1$) and 2) Model Protection Parameters ($\mathbf{x}_2$).
if $\epsilon \geq 10\%$ **then**
    Let $\mathbf{x}_2$ as optimization variables
    Solve (9a)-(9b) by RBF optimization (Sec. IV)
    Let the estimated parameters be $\mathbf{x}_2^*$
else
    Use default protection parameters, $\mathbf{x}_2^* = \mathbf{x}_2$
end if
Let $\mathbf{x}_2^*$ as constants and estimate $\mathbf{x}_1$ by solving (9a)-(9c) with nonlinear optimization techniques.
Let the estimated parameters be $\mathbf{x}_1^*$.
Return $\mathbf{x}^* = [\mathbf{x^*}_1^T, \mathbf{x^*}_2^T]^T$

V. Results

The proposed hybrid approach has been validated using simulated and real measurement data collected at different feeders across Australia.

A. Simulated Measurements

The aim of this experiment is to validate the estimation process using simulated data with the default parameters. It is assumed that the DER component produces 15% of the load power P_L. Using collected measurements of voltage and frequency, the outputs of the model (active and reactive power) are generated by numerical simulation. The outputs are later used as fictitious measurements in order to solve problem (9) using a random initial guess on the parameters. Two sets of measurements are generated: i) without load tripping ii) with load tripping.

1) Model Equation Parameter Estimation: The first estimation is conducted on the model equation parameters using the generated measurement without load tripping behaviour ($\epsilon \approx 0$). Trajectory sensitivities were estimated numerically and 28 parameters, including the load and the DER fractions, were selected to solve problem (9a)-(9c) by Sequential Quadratic Programming (SQP) techniques. The model outputs and the fictitious measurements during the transient period for training and testing sets are compared in Fig. 1(a) and 1(b) . The objective function in (9a) was reduced from 450.68 to 4.30. The average error between the default parameters x_i^* and the estimated parameters x_i was 4.59% with standard deviation of 4.74%. In addition, the estimated parameters produced a physically meaningful and realistic model. If constraints (9c) are not considered, negative values for (4) are found, creating an unrealistic induction motor model.

2) Model Protection Parameter Estimation: The second measurements experience load tripping behavior ($\epsilon > 10\%$) and require estimation of protection parameters. A total of 250 evaluations of the RBF optimization technique were executed in order to estimate the protection parameters according to Algorithm 1. A comparison between the simulated measurements (for both training and testing) and the model after executing Algorithm 1 is depicted Fig. 1(c) and 1(d). As observed in Fig. 1(c) and 1(d), the RBF optimization algorithm exhibits a superior performance at estimating the load tripping parameters compared to the nonlinear optimization solver.

B. Real Measurements

Two examples with real measurements in Australia are presented. The first event exhibits no load tripping behaviour

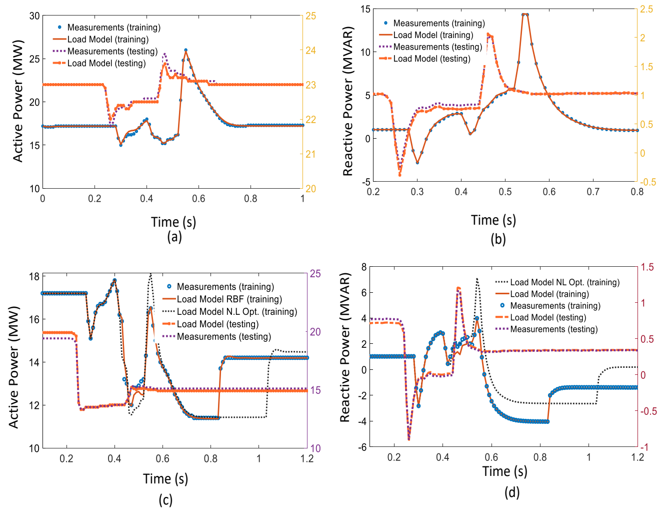

Fig. 1: Active and reactive power: Fictitious measurements vs composite load model (results for the training and testing sets are shown in the left and right axes respectively.)

and the model equation parameters are estimated via SQP. A comparison between the outputs of the model and the measurements is depicted in Figs. 2(a) and 2(b). The second event experiences significant load tripping $\epsilon \geq 10\%$ and the protection parameters were estimated using the RBF optimization strategy (according to Algorithm 1). A comparison between the model outputs with optimized and default parameters and the measurements are provided in Fig. 2(c) and 2(c). As observed, the optimized parameters provide a more accurate representation of system loads compared to the default parameters provided in [2].

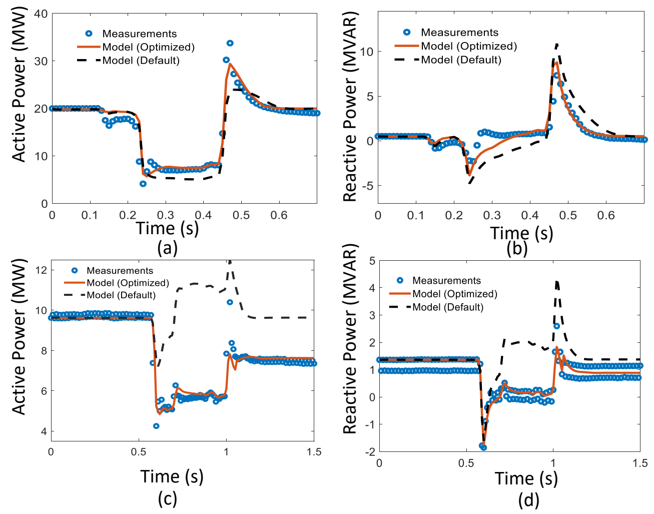

Fig. 2: Active and reactive power: Real measurements vs composite load model

VI. Conclusion

A hybrid optimization approach to estimate the parameters of the CMPLDWG was presented. Parameters related to dynamic and static equations are estimated via non-linear optimization, considering the physical constraints involved in the model. Conversely, protection parameters are estimated using a derivative-free technique based on Radial Basis Function optimization. The addition of constraints into the model parameters not only provides a physically meaningful solution but also reduces the number of feasible local optimum points. Our results corroborate that the use of a measurement-based approach in the CMPLDWG provides a more realistic representation of system loads compared to the default parameters.

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