Data-Driven and Machine Learning-Based Load Modeling (S-84G)

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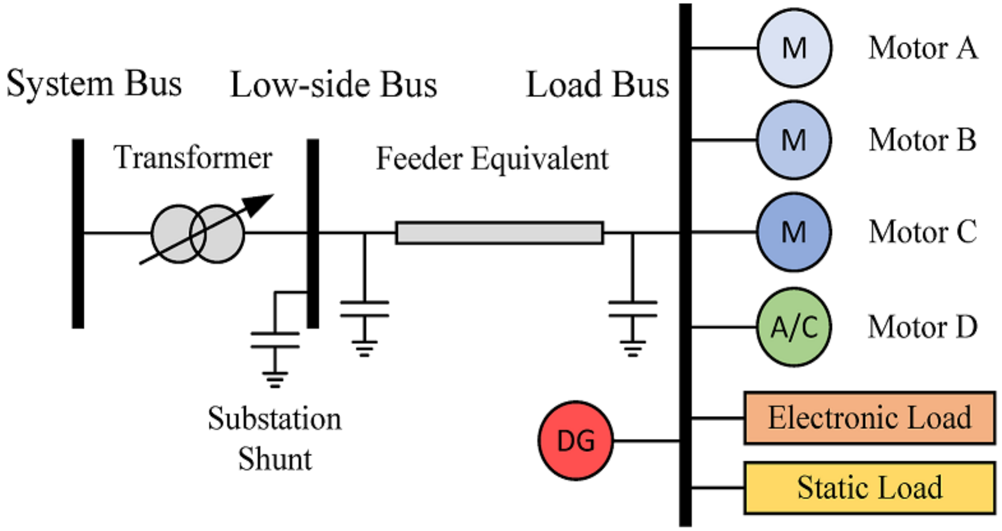
WECC composite load model (CMPLDW)



A highly nonlinear and complex load model

- Transformer and feeder contain 18 parameters
- Three phase motors contain 65 parameters
- Single phase motor contains 34 parameters
- Electronic load contains 5 parameters
- Static load contains 11 parameters
- DG contains 46 parameters (currently unmodeled in the PSSE WECC model)

- Objective: Using event data to identify the parameters of WECC composite load model to fit the active and reactive power measurements.

Research outcomes

- Derived an order reduction technique based on the singular perturbation theory to obtain a reduced load model.

- Developed a general global sensitivity analysis method to reduce the dimension of input space of any nonlinear model with scalar output.

- Developed an autonomous parameter identification approach by calling PSSE dynamic simulation in python-based optimization algorithms.

- Applied the above proposed parameter reduction and identification methods to the identification of WECC composite load model using real PMU data.

Publications

1. J. Xie, Z. Ma, K. Dehghanpour, Z. Wang, Y. Wang, R. Diao, and D. Shi, "Imitation and Transfer Q-learning-Based Parameter Identification for Composite Load Modeling," *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1674-1684, March 2021.
2. Z. Ma, Z. Wang, Y. Wang, R. Diao, and D. Shi, "Mathematical representation of the WECC composite load model," *Journal of Modern Power System and Clean Energy*, vol. 8, no. 5, pp. 1015-1023, September 2020.
3. Z. Ma, B. Cui, Z. Wang, and D. Zhao, "Parameter Reduction of Composite Load Model Using Active Subspace Method", *IEEE Transactions on Power Systems*, Accepted.
4. F. Bu, Z. Ma, Y. Yuan and Z. Wang, "WECC Composite Load Model Parameter Identification Using Evolutionary Deep Reinforcement Learning," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 5407–541, July, 2020.
5. Z. Ma, Z. Wang, D. Zhao, and B. Cui, "High-fidelity large-signal order reduction approach for composite load model," *IET Generation, Transmission and Distribution*, vol. 14, no. 21, pp. 4888–4897, August, 2020.
6. Z. Ma, Z. Wang, Y. Yuan, Y. Wang, R. Diao, and D. Shi. "Stability and Accuracy Assessment based Large-Signal Order Reduction of Microgrids", arXiv preprint.

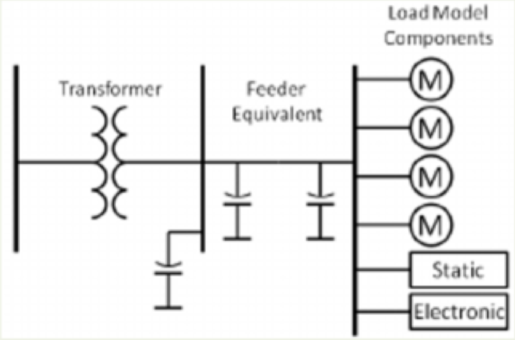
Problem description

Optimization methods:

- Deep reinforcement learning: e.g., asynchronous advantage actor critic (A3C) algorithm
- Bio-inspired methods: e.g., salp swarm algorithm (SSA)

How to talk?

CMPLDW model:



Python environment

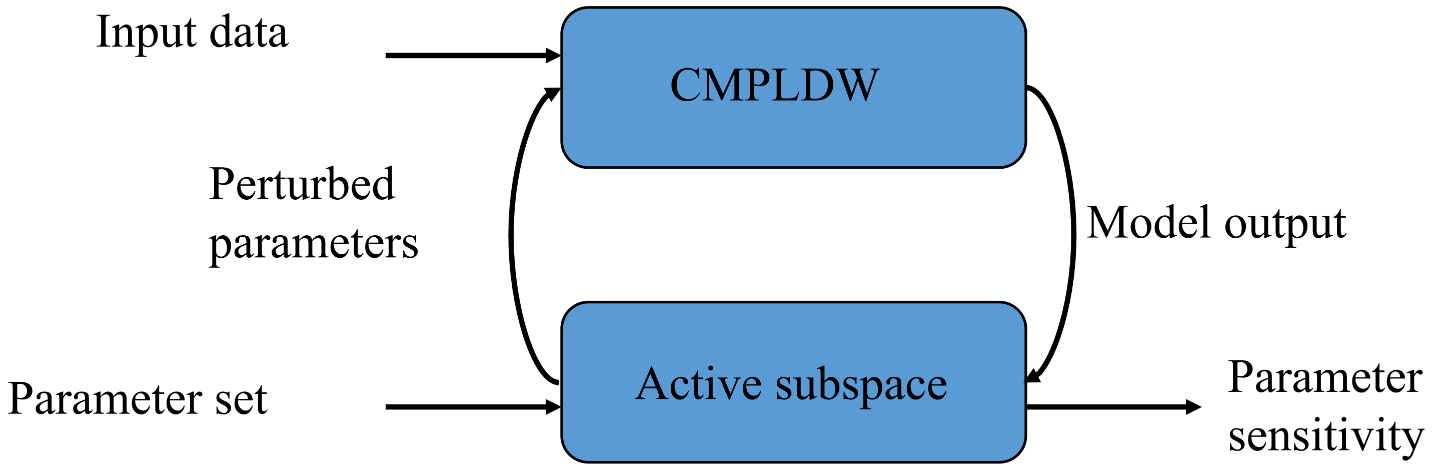
PSSE environment

Challenges:

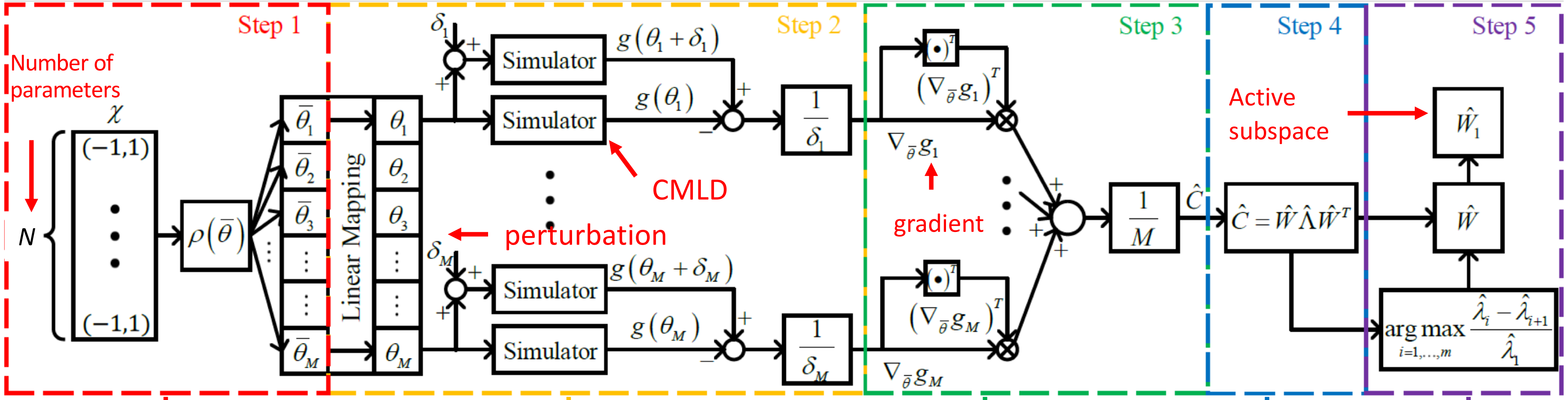
- Large nonlinear searching space (133 parameters need to be identified).
- Establish stable connection between Python and PSSE for information exchange.

Active subspace based parameter reduction

- Motivation: The high dimension of parameter space of WECC model increases the difficulty of searching optimal parameter and computational burden.
- Approach: The active subspace method is used for parameter sensitivity analysis for WECC composite load model. Briefly, active subspace aims to find the most influential direction in the parameter space.
- Advantage: The active subspace discovers not only the parameter sensitivities but also the interdependency among parameters.



Active subspace approach



- Construct a normalized N-dimensional parameter set χ. N is the total number of screened-out parameters.
- Draw M parameter samples $\bar{\theta}$ from χ according to some distribution ρ.

- Mapping normalized parameters to their real range.
- Run CMPLDW model with sampled parameters
- Calculate gradient with finite difference which uses sampled and perturbed evaluation $g(\theta + \delta)$ and $g(\theta)$ for approximation.
- The gradient represents the incremental response of CMPLDW to the perturbation of each parameter.

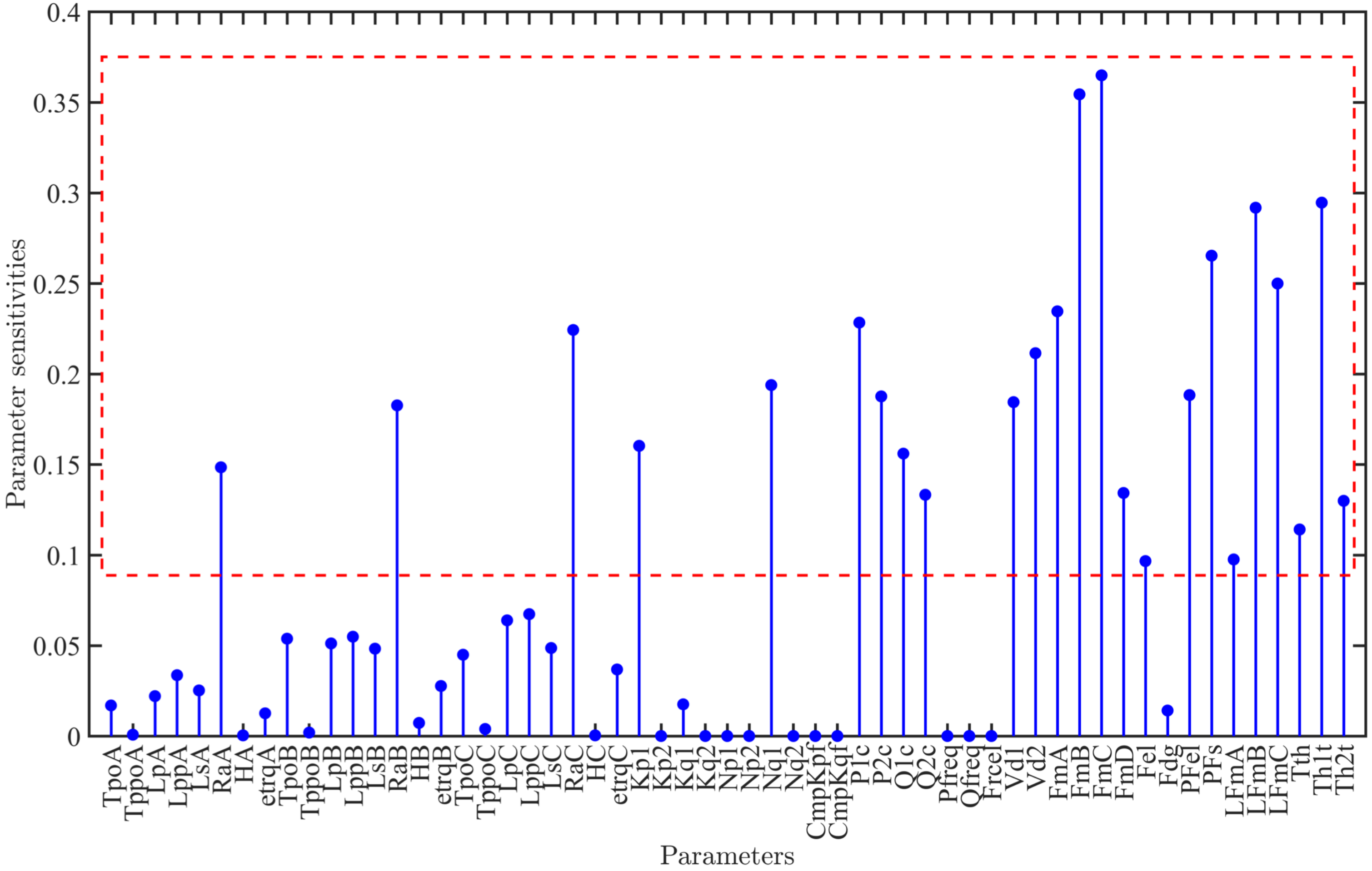
- Estimate average derivative functional matrix C with Monte Carlo simulation.
- From matrix C one can obtain the sensitivity and interdependency of parameters.

Eigen-decomposition: W is the matrix of eigenvectors and Λ is the matrix of eigenvalues.

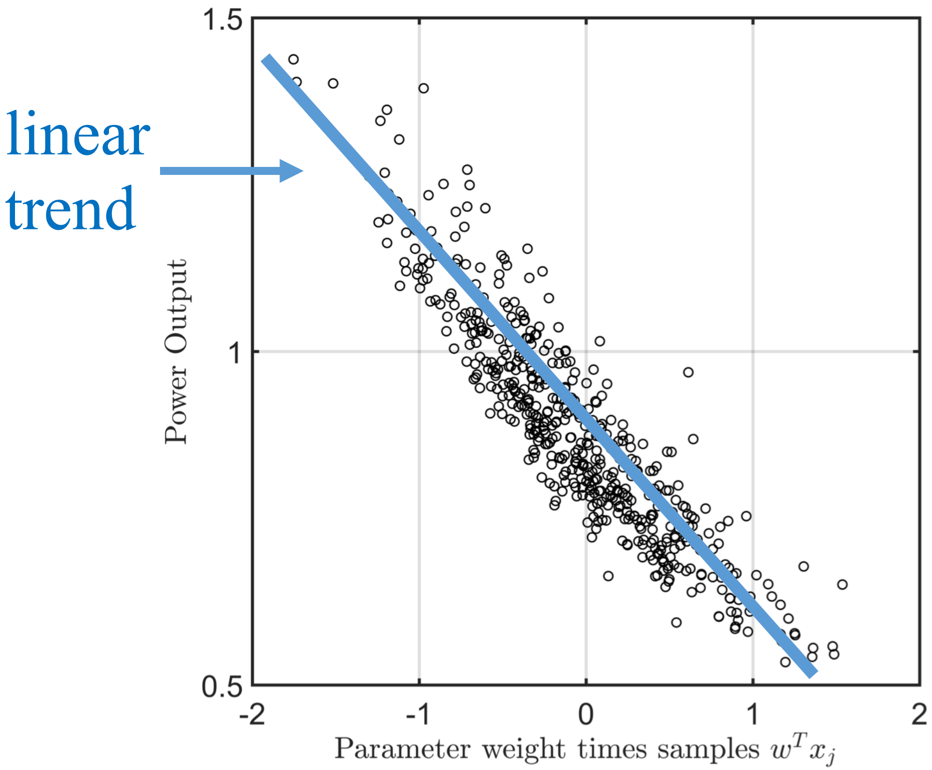
Eigenvalue separation for finding the active subspace which represents the sensitivities of parameters

Parameter sensitivities analysis

Parameter sensitivities of the CMPLDW are calculated by using active subspace method. The parameters in the red rectangle are the sensitive ones.



Parameter reduction validation using sufficient summary plot



- x axis denotes the product of parameter sensitivity vector and parameter sample
- y axis denotes the combined power output $\sqrt{P^2 + Q^2}$
- The number of samples is 500

- Sufficient summary plot is a method widely used in parameter reduction to verify the results.
- This plot depicts the relationship between the output of interest P or Q, and the linear combination of input parameters.
- If the relationship presents an evidently tight and univariate trend, the discovered active subspace is validated; otherwise, it is not valid.
- The obvious linear trend in the left figure verifies the effectiveness of the active subspace method.

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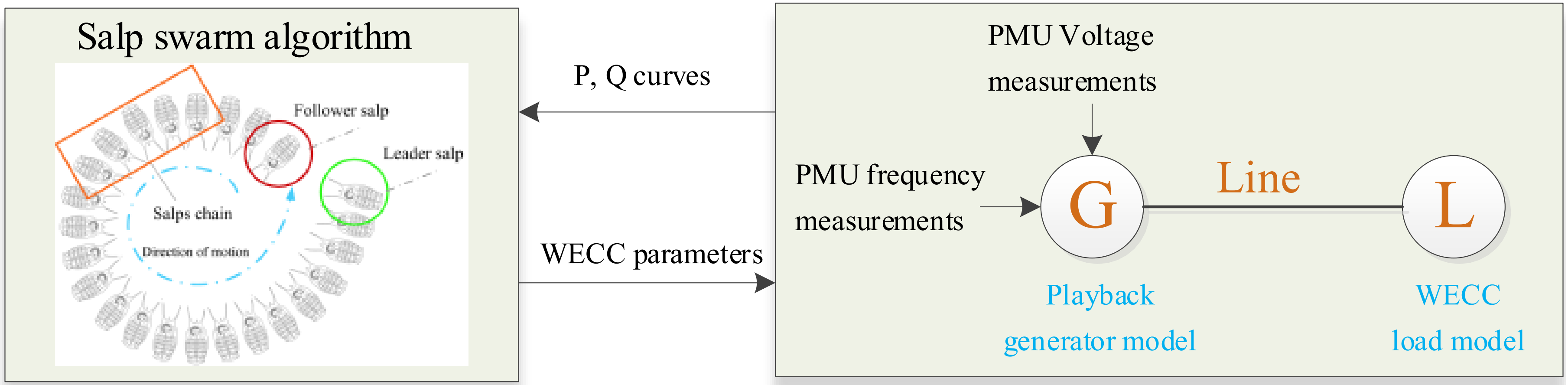
Overview of Python-PSSE autonomous parameter identification approach



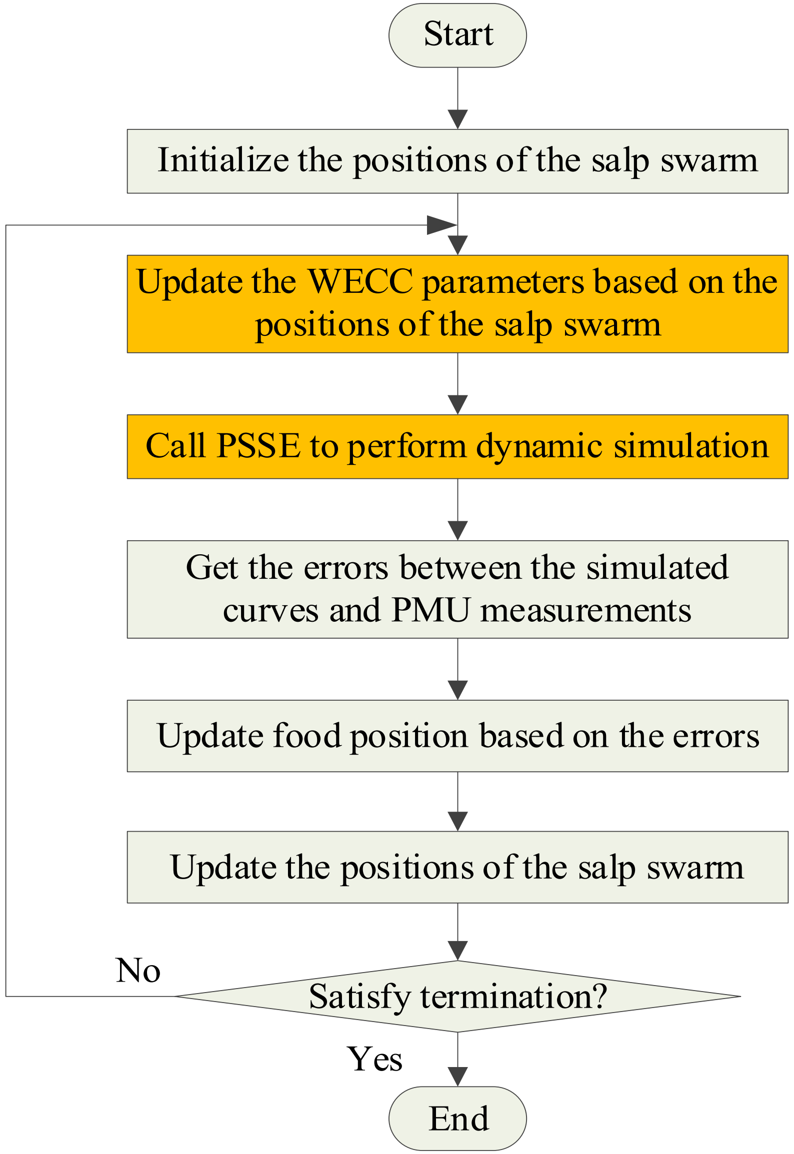
Python environment

PSSE environment

Advantages:

- We can flexibly select various optimization methods to efficiently optimize the CMPLDW parameters. The salp swarm algorithm is used here as an example due to its high efficiency of searching.
- The playback generator model allows us to inject disturbance recorded by real PMU data.

Program flowchart

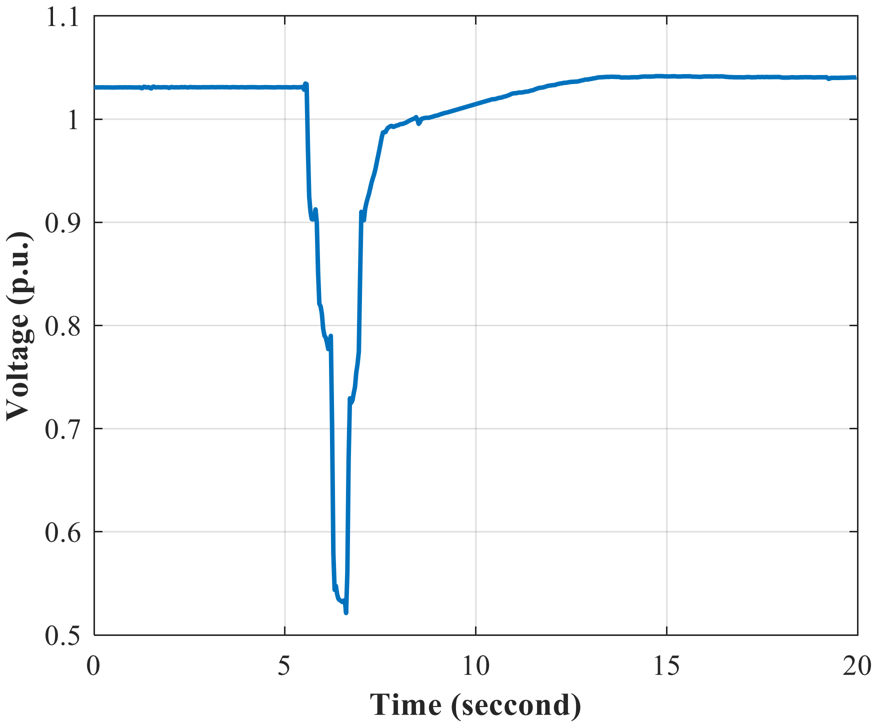


$$\min \sqrt{\frac{1}{2N}\sum_{i=1}^{N}\left[\left(P_i^{sim}-P_i^{PMU}\right)^2+\left(Q_i^{sim}-Q_i^{PMU}\right)^2\right]}$$

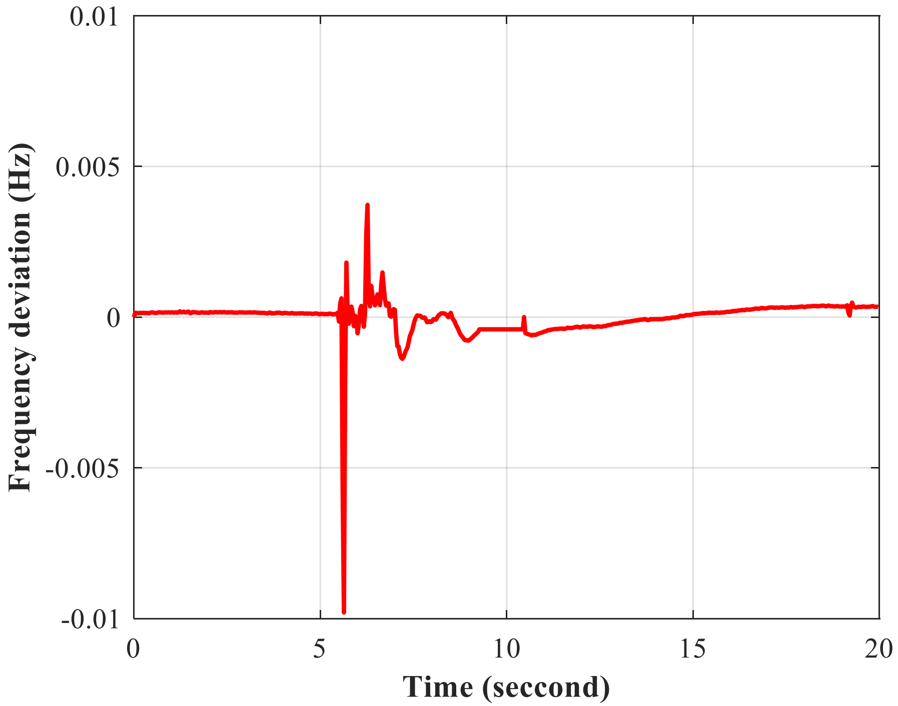
where:

- P_i^{sim}: The simulated active power curve.
- P_i^{PMU}: The active power curve by PMU.
- Q_i^{sim}: The simulated reactive power curve.
- Q_i^{PMU}: The reactive power curve by PMU.
- N: The number of measurements.

Parameter identification using AEP data



Recorded voltage curve



Recorded frequency deviation curve

- A fault happened on a 138 kV line.
- The fault event was recorded by PMU at a nearby 12.47 kV substation.

Selection of parameters for identification

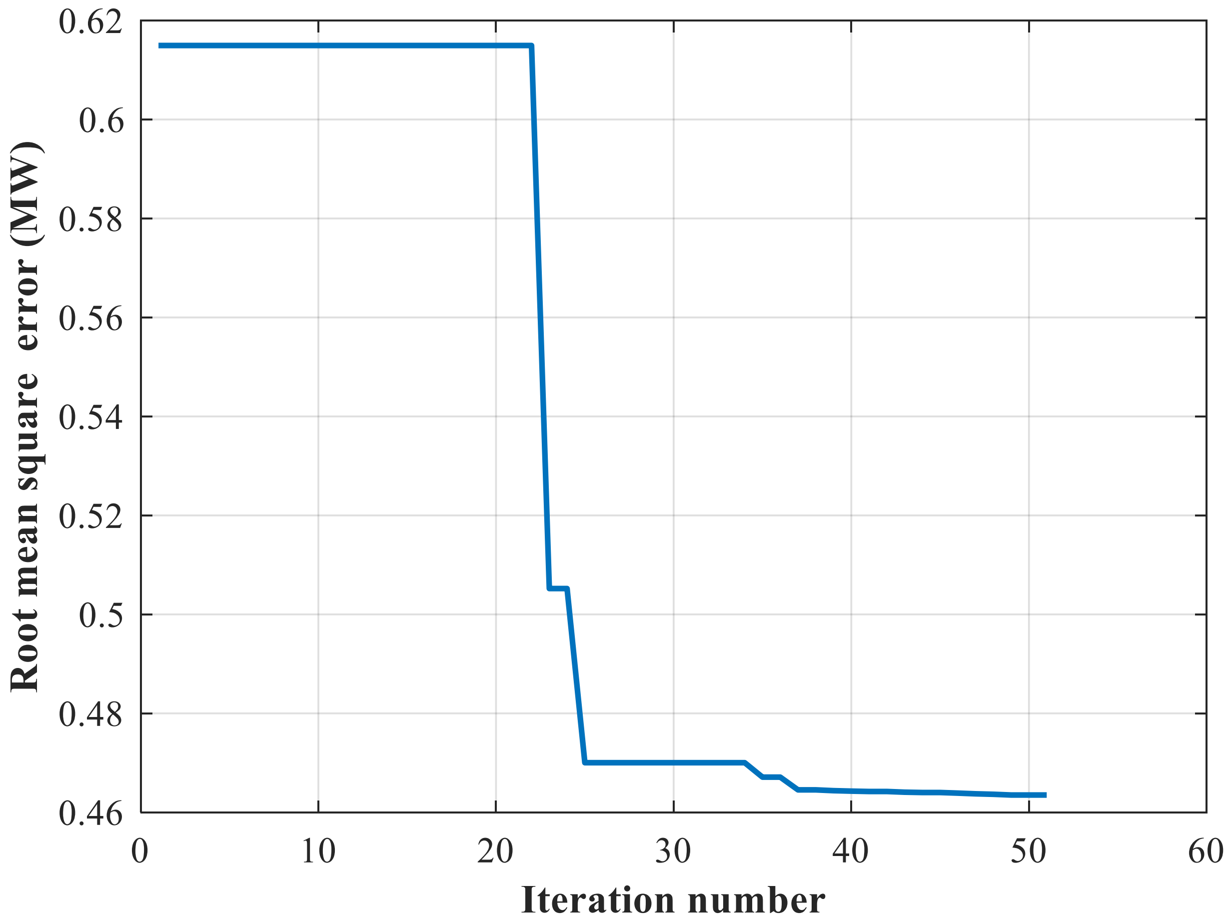
J+ Index	Name	Initial value	Range	J+ Index	Name	Initial value	Range
18	FmA	0.237	[0.0474, 0.711]	35	**Q2c**	1.5	[-3, 3]
19	**FmB**	0.119	[0.0238, 0.357]	38	**LFmA**	0.75	[0.375, 1.125]
20	**FmC**	0.1	[0.02, 0.3]	39	**RaA**	0.04	[0.02, 0.06]
21	**FmD**	0.24	[0.048, 0.72]	58	**LFmB**	0.75	[0.375, 1.125]
22	**Fel**	0.162	[0.0324, 0.486]	59	**RaB**	0.03	[0.015, 0.045]
23	**PFel**	1	[0.95, 1]	78	**LFmC**	0.75	[0.375, 1.125]
24	**Vd1**	0.7	[0.42, 0.77]	79	**RaC**	0.03	[0.015, 0.045]
25	**Vd2**	0.5	[0.3, 0.55]	109	**Kq1**	6	[4.8, 9]
26	**PFs**	1	[0.85, 1]	110	**Nq1**	2	[1.6, 3]
28	**P1c**	0.3	[0.15, 1.5]	124	**Tth**	5	[4, 10]
30	**P2c**	0.7	[0.35, 3.5]	125	**Th1t**	0.4	[0.32, 0.8]
33	**Q1c**	-0.5	[-1, 1]	126	**Th2t**	3	[2.4, 6]

- Ideally, our approach is able to optimize all the parameters within any range.
- However, the random selection of some parameters (such as LsA, LpA, LppA, TpoA, TppoA, HA, EtrqA, Vtr1A, Ttr1A, Ftr1A, Vrc1A) may cause the collapse of PSSE.

Initial CMPLDW parameters

J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value
0	MVA	-1	27	P1e	2	54	Ftr2A	0.3	81	LpC	0.19	108	Np1	1
1	SubstB	0	28	P1c	0.3	55	Vrc2A	0.1	82	LppC	0.14	109	Kq1	6
2	Rfdr	0.04	29	P2e	1	56	Trc2A	999	83	TpoC	0.2	110	Nq1	2
3	Xfdr	0.04	30	P2c	0.7	57	MtypB	3	84	TppoC	0.0026	111	Kp2	12
4	Fb	0.75	31	Pfrq	0	58	LFmB	0.75	85	HC	0.1	112	Np2	3.2
5	XXf	0.08	32	Q1e	2	59	RaB	0.03	86	EtrqC	2	113	Kq2	11
6	Tfixhs	1	33	Q1c	-0.5	60	LsB	1.8	87	Vtr1C	0	114	Nq2	2.5
7	Tfixls	1	34	Q2e	1	61	LpB	0.19	88	Ttr1C	999	115	Vbrk	0.86
8	LTC	0	35	Q2c	1.5	62	LppB	0.14	89	Ftr1C	0	116	Frst	0.3
9	Tmin	0.9	36	Qfrq	-1	63	TpoB	0.2	90	Vrc1C	999	117	Vrst	0.95
10	Tmax	1.1	37	MtypA	3	64	TppoB	0.0026	91	Trc1C	999	118	CmpKpf	1
11	Step	0.00625	38	LFmA	0.75	65	HB	0.5	92	Vtr2C	0	119	CmpKpf	-3.3
12	Vmin	1.025	39	RsA	0.04	66	EtrqB	2	93	Ttr2C	999	120	Vc1off	0.5
13	Vmax	1.04	40	LsA	1.8	67	Vtr1B	0	94	Ftr2C	0	121	Vc2off	0.4
14	Tdelay	30	41	LpA	0.12	68	Ttr1B	999	95	Vrc2C	999	122	Vc1on	0.65
15	Tstep	5	42	LppA	0.104	69	Ftr1A	0	96	Trc2C	999	123	Vc2on	0.55
16	Rcmp	0	43	TpoA	0.095	70	Vrc1B	999	97	Tstall	0.0333	124	Tth	7
17	Xcmp	0	44	TppoA	0.0021	71	Trc1B	999	98	Trestart	0.3	125	Th1t	0.4
18	FmA	0.237	45	HA	0.1	72	Vtr2B	0	99	Tv	0.025	126	Th2t	3
19	FmB	0.119	46	EtrqA	0	73	Ttr2B	999	100	Tf	0.1	127	Fuvr	0
20	FmC	0.1	47	Vtr1A	0.65	74	Ftr2B	0	101	CompLF	1	128	UVtr1	0
21	FmD	0.24	48	Ttr1A	0.2	75	Vrc2B	999	102	CompPF	0.98	129	Ttr1	999
22	Fel	0.162	49	Ftr1A	0.3	76	Trc2B	999	103	Vstall	0.45	130	UVtr2	0
23	Pfel	1	50	Vrc1A	0.1	77	MtypC	3	104	Rstall	0.124	131	Ttr2	999
24	Vd1	0.7	51	Trc1A	999	78	LFmC	0.75	105	Xstall	0.114	132	FrstPel	1
25	Vd2	0.5	52	Vtr2A	0.65	79	RaC	0.03	106	Lfadj	0			
26	PFs	1	53	Ttr2A	0.33	80	LsC	1.8	107	Kp1	0			

Convergence of SSA

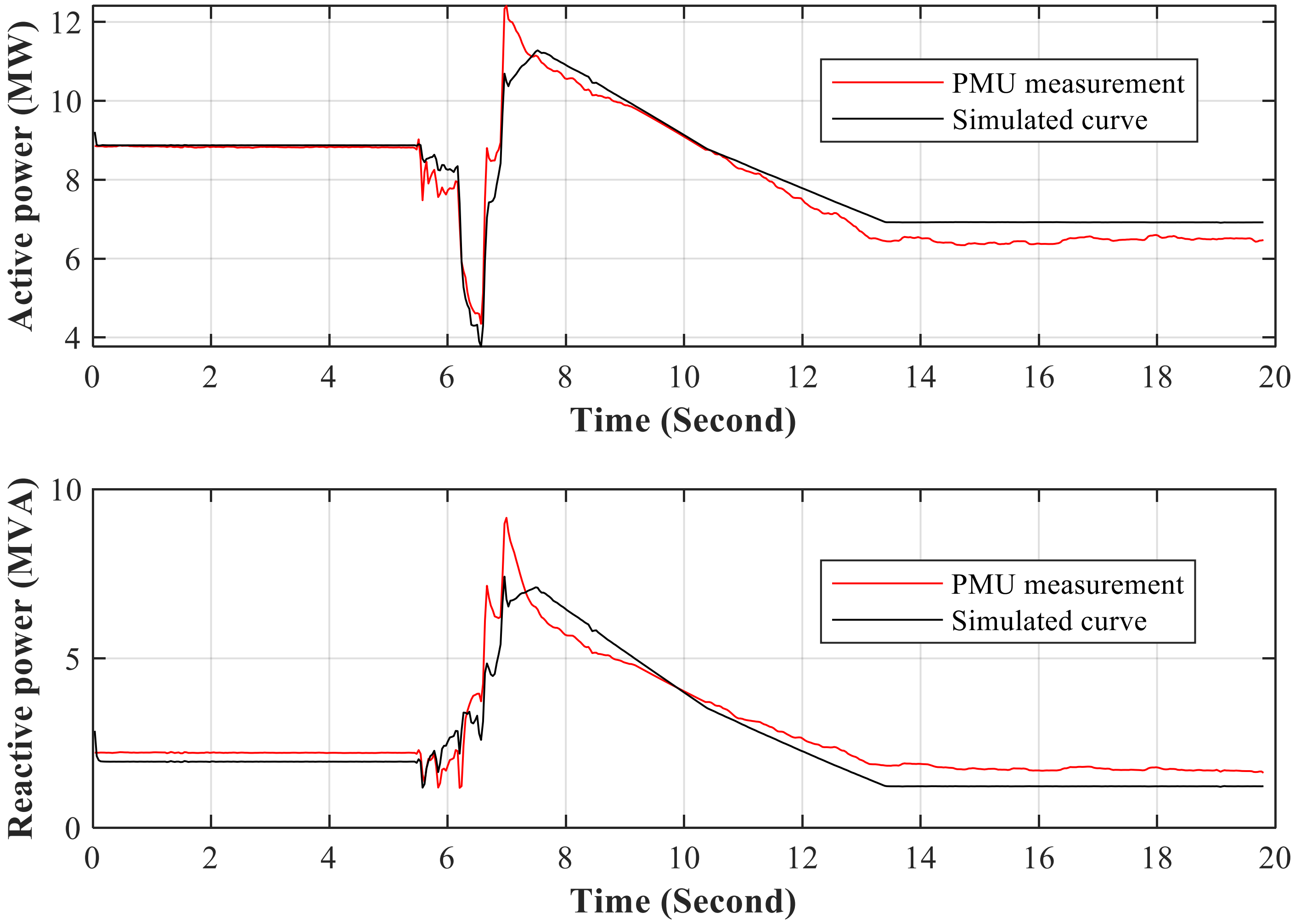


- 30 salps (parallel candidate solutions).
- 50 iterations.
- The simulation takes 39 minutes.
- The main computation time is spent on the PSSE dynamic simulation and output data processing.

Identified CMPLDW parameters

J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value	J+ index	Name	Value
0	MVA	-1	27	P1e	2	54	Ftr2A	0.3	81	LpC	0.19	108	Np1	1
1	SubstB	0	28	P1c	0.679	55	Vrc2A	0.1	82	LppC	0.14	109	Kq1	6.091
2	Rfdr	0.04	29	P2e	1	56	Trc2A	999	83	TpoC	0.2	110	Nq1	2.965
3	Xfdr	0.04	30	P2c	0.352	57	MtypB	3	84	TppoC	0.0026	111	Kp2	12
4	Fb	0.75	31	Pfrq	0	58	LFmB	0.44	85	HC	0.1	112	Np2	3.2
5	XXf	0.08	32	Q1e	2	59	RaB	0.015	86	EtrqC	2	113	Kq2	11
6	Tfixhs	1	33	Q1c	0.234	60	LsB	1.8	87	Vtr1C	0	114	Nq2	2.5
7	Tfixls	1	34	Q2e	1	61	LpB	0.19	88	Ttr1C	999	115	Vbrk	0.86
8	LTC	0	35	Q2c	-1.841	62	LppB	0.14	89	Ftr1C	0	116	Frst	0.3
9	Tmin	0.9	36	Qfrq	-1	63	TpoB	0.2	90	Vrc1C	999	117	Vrst	0.95
10	Tmax	1.1	37	MtypA	3	64	TppoB	0.0026	91	Trc1C	999	118	CmpKpf	1
11	Step	0.00625	38	LFmA	0.837	65	HB	0.5	92	Vtr2C	0	119	CmpKpf	-3.3
12	Vmin	1.025	39	RsA	0.023	66	EtrqB	2	93	Ttr2C	999	120	Vc1off	0.5
13	Vmax	1.04	40	LsA	1.8	67	Vtr1B	0	94	Ftr2C	0	121	Vc2off	0.4
14	Tdelay	30	41	LpA	0.12	68	Ttr1B	999	95	Vrc2C	999	122	Vc1on	0.65
15	Tstep	5	42	LppA	0.104	69	Ftr1A	0	96	Trc2C	999	123	Vc2on	0.55
16	Rcmp	0	43	TpoA	0.095	70	Vrc1B	999	97	Tstall	0.0333	124	Tth	5.663
17	Xcmp	0	44	TppoA	0.0021	71	Trc1B	999	98	Trestart	0.3	125	Th1t	0.422
18	FmA	0.233	45	HA	0.1	72	Vtr2B	0	99	Tv	0.025	126	Th2t	2.80
19	FmB	0.141	46	EtrqA	0	73	Ttr2B	999	100	Tf	0.1	127	Fuvr	0
20	FmC	0.026	47	Vtr1A	0.65	74	Ftr2B	0	101	CompLF	1	128	UVtr1	0
21	FmD	0.197	48	Ttr1A	0.2	75	Vrc2B	999	102	CompPF	0.98	129	Ttr1	999
22	Fel	0.224	49	Ftr1A	0.3	76	Trc2B	999	103	Vstall	0.45	130	UVtr2	0
23	Pfel	1	50	Vrc1A	0.1	77	MtypC	3	104	Rstall	0.124	131	Ttr2	999
24	Vd1	0.743	51	Trc1A	999	78	LFmC	0.686	105	Xstall	0.114	132	FrstPel	1
25	Vd2	0.314	52	Vtr2A	0.65	79	RaC	0.037	106	Lfadj	0			
26	PFs	1	53	Ttr2A	0.33	80	LsC	1.8	107	Kp1	0			

Curve fitting results



The root mean square error (RMSE) is as follows:

- RMSE =0.46 MW (or MVA)

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Thank you!

Q&A