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DEEP LEARNING APPROACH FOR MODEL PARAMETER CALIBRATION IN POWER SYSTEMS

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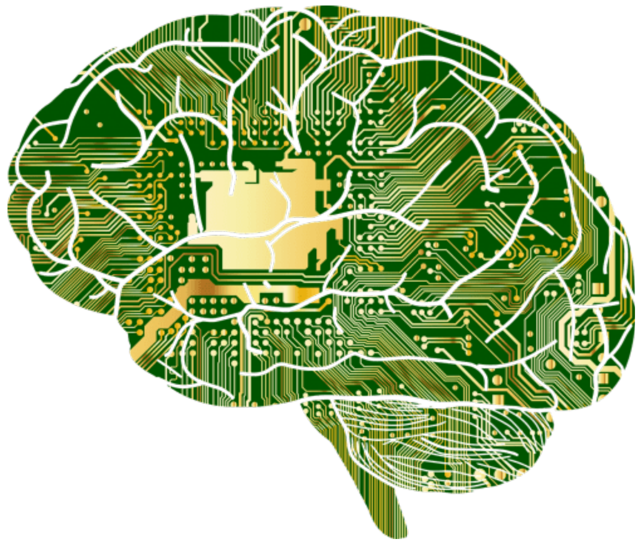
14 April. 2021

VAIL

Vermont Artificial Intelligent Lab



The University of Vermont

Team

Safwan Wshah

Assistant Prof. at Dept. of CS at University of Vermont

- Main research interest is Machine learning and deep learning applied mainly to the energy field and Transportation.
- Director of Vermont Artificial Intelligent Lab (6 PhDs and 2 MS. students) and core member of Complex Systems Center.

Has a broad experience in Machine learning, deep learning, data analytics, computer vision & image processing

From UVM:

- **Mustafa Matar, PhD Graduate Student.**

Collaborating with Senior research scientists with RDSC:

- **Dr. Beilei Xu.**
- **Dr. Wencheng Wu**

Collaborating with Researchers from Power Systems field:

- **Dr. Ramadan Elmoudi - NYPA**
- **Oluwaseyi Olatujoye - NYISO**

Machine Learning in Power Sector

Machine learning has demonstrated its success in many domains such as Healthcare, transportation, etc.

In energy field, its impact is everywhere

- **Smart grid**: managing integration from wind/solar with traditional power generation.
- **Failure management**: prognosis of failures save money, time, and lives.
- **Energy consumption**: supply/demand forecasting.

At Vermont Artificial Intelligent Lab - VaiL

Model Parameters Verification and Calibration

Motivation

- ➢ **Inaccurate model can cause catastrophic consequences**
- ➢ **Current practice in the field is costly and doesn't meet the need**

Current Practice

Staged-test method (Common):

- Testing can cost $15,000-$35,000 per generator per test in the United State.
- Can only be run on a limited set of devices - Heavily rely on expert engineers.

Disturbance based approach:

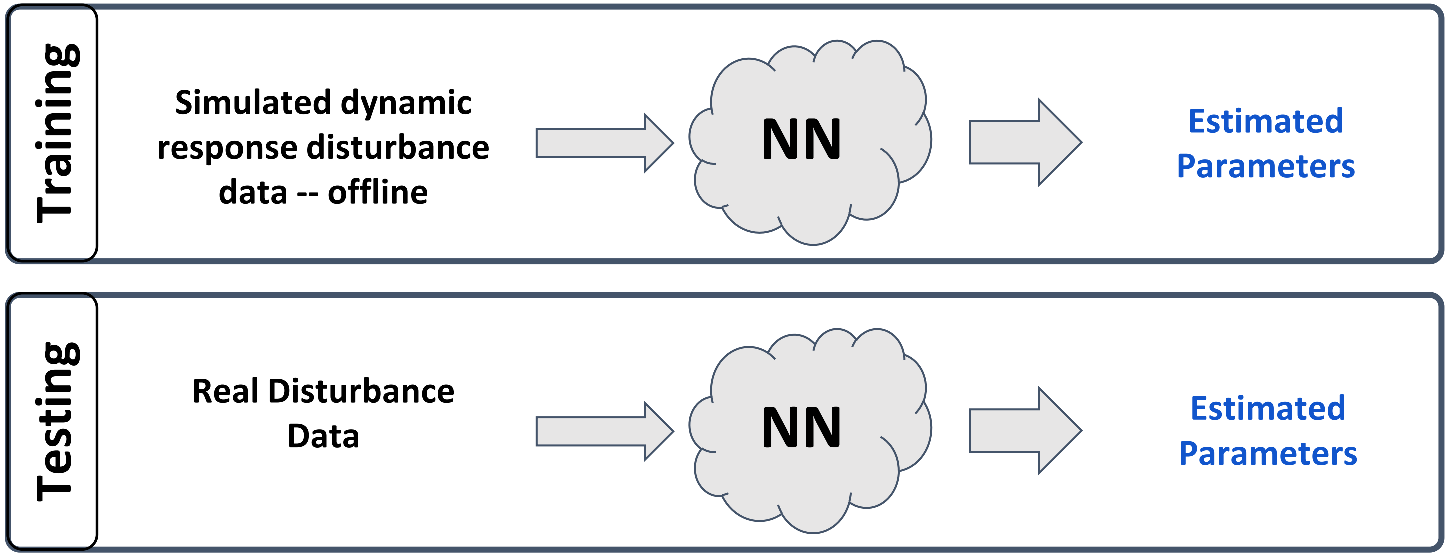
- Low cost, no need to take the generator offline
- Can be widely applied for online model verification

NERC guideline not to rely solely on the current disturbance-based methods without engineer judgment!

Current issue and gaps in existing tools (numerical methods):

- Parameter tuning is an ill-posed inverse, non-uniqueness (multiple solutions), and thus ***these methods need more than one event to be reliable***.
- Slow with the number of parameters increases.

Research Objectives



Introduce machine learning methods for model calibration that:

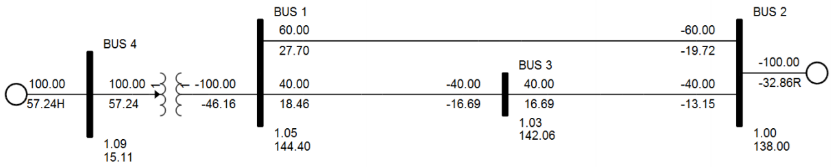
- **More reliable.**
- **Need less engineering intervention.**
- **Scalable.**

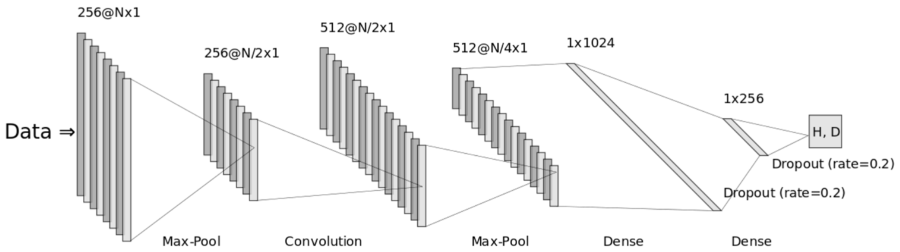
More reliable □ near well-posed solution giving a single or few number of events.

Need less engineering intervention □ No need for deep knowledge for calibration.

Salable □ Can work on wide range of synchronous or inverter-based models.

Research Objectives – Phase 1





H, D

The Achieved MSE error on testing set of 0.0610

We investigated different **bus systems** (IEEE-14, IEEE-39 and WECC-179), **deep learning models** (CNN, LSTM, GRU) and **synchronous machine models** (GENCLS and GENROU).

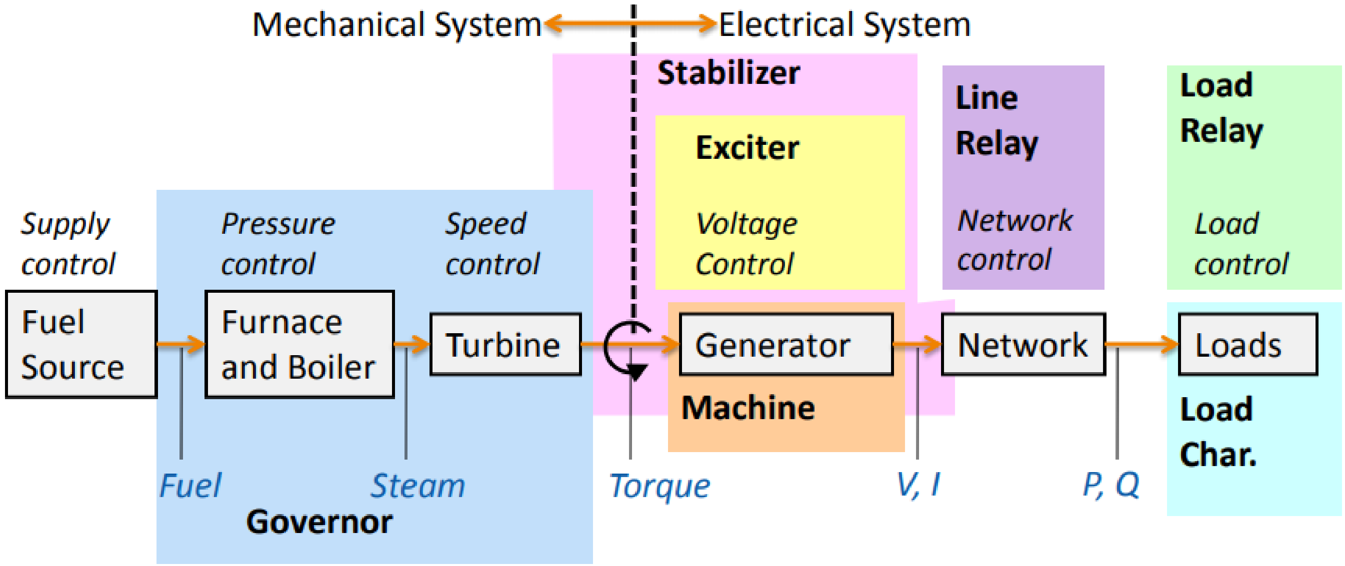
We showed that:
- Deep Learning **has the capacity** to calibrate synchronous machine models even for large bus systems.
- CNN based models are the best.

But we still need to:
- Work on real data (practical solution).
- Scale on large and different bus systems (scalable solution).

Wshah, S., Shadid, R., Wu, Y., Matar, M., Xu, B., Wu, W., Lin, L. and Elmoudi, R., 2020, September. Deep Learning for Model Parameter Calibration in Power Systems. In *2020 IEEE International Conference on Power Systems Technology (POWERCON)* (pp. 1-6). IEEE.

Research Objectives – Phase 2

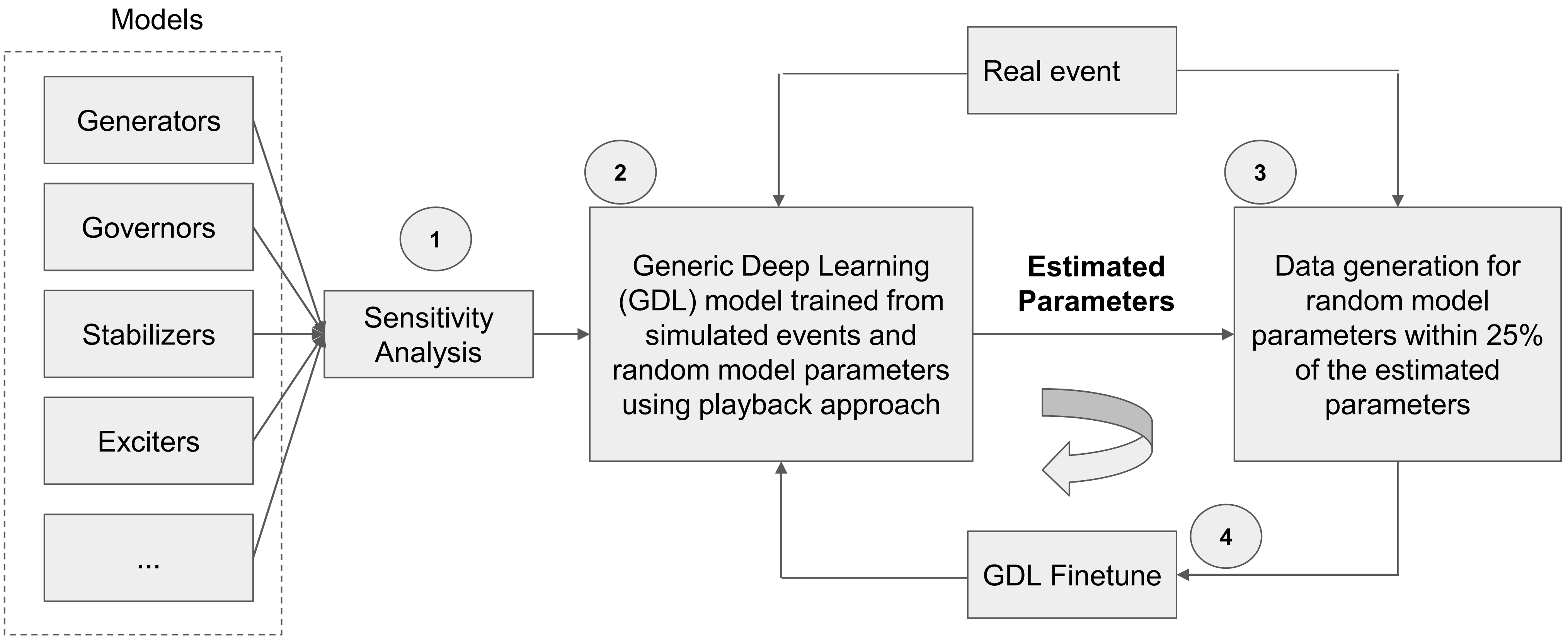
Work on real data (practical and reliable solution) and scale to large and different bus systems (scalable solution).



	Example
Machine Models (51)	GENROU
Exciter Model (122)	ESST1A
Stabilizer Model (36)	PSS2A
Governor Model (82)	GGOV1

- Can data-driven approaches from a single or few events reliably calibrate model parameters ?
- Can data-driven approaches model large number of different types of models ?

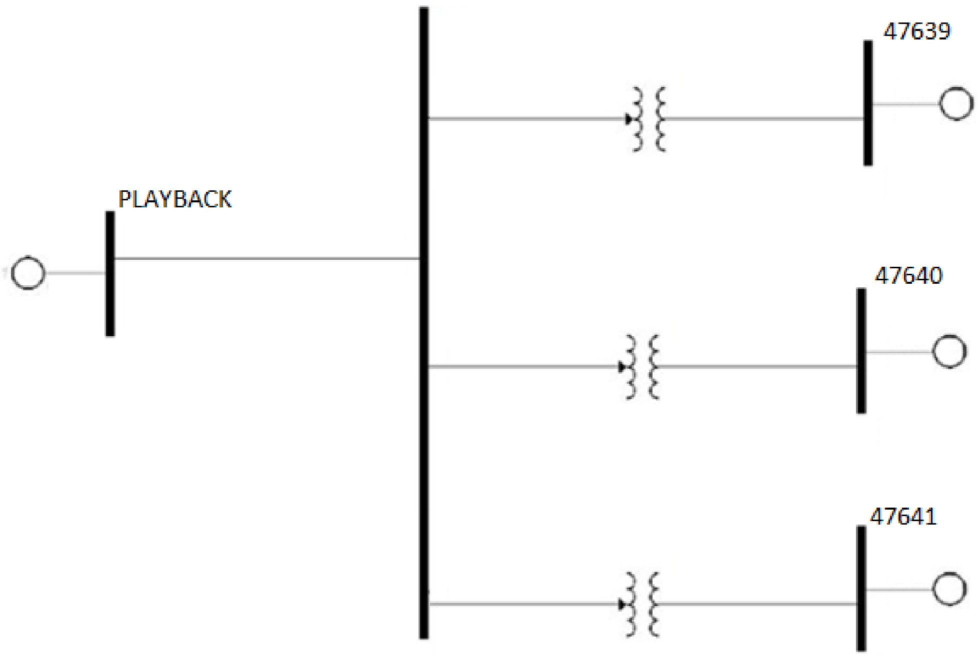
Proposed approach



- Data will be generated offline for any model combinations using PSSE.
- A generic deep learning model will be trained.
- The generic model can be finetuned from real events.

Use Case

Generator 1	GENROU, PSS2A, ESST1A, GGOV1
Generator 2	GENROU, PSS2A, ESST1A, GGOV1
Generator 3	GENROU, PSS2A, ESST1A



- We used real case events and structure.
- Our objective is to calibrate “Generator 1”.
- Total number of parameters for “Generator 1” is 82 parameters. This includes governor, generator, stabilizer and exciter.

Sensitivity Analysis

- ➢ Sensitivity analysis can be performed to identify key parameters that should be considered for calibration [8].
- ➢ The sensitivity analysis results quantify the change in the generator response for change in each parameter [9].
- ➢ The standard models used are **GENROU**, **ESST1A**, **GGOV1**, and **PSS2A** (82 parameters in total).
- ➢ Based on the sensitivity analysis, 13 sensitive parameters are used for calibration.

$$S(\alpha) = \frac{1}{n}\sum_{i=0}^{n} \left| \frac{x_1 - x_2}{2(\frac{\Delta\alpha_o}{\alpha_o})} \right| \qquad (1)$$

$$\begin{cases} \alpha_1 = \alpha_o + \Delta\alpha_o \\ \alpha_2 = \alpha_o - \Delta\alpha_o \end{cases} \qquad (2)$$

Where:
α0 is the initial value of parameter α;
Δα0 is a small perturbation of α0;
x1 and x2 are the time responses obtained using α1 and α2, respectively;
n is the total number of time steps.
S(α) is the derived parameter sensitivity metric.

[8] Li, Y., Diao, R., Huang, R., Etingov, P., Li, X., Huang, Z., ... & Ning, A. (2017, July). An innovative software tool suite for power plant model validation and parameter calibration using PMU measurements. In 2017 IEEE Power & Energy Society General Meeting (pp. 1-5).
[9] Huang, R., Diao, R., Li, Y., Sanchez-Gasca, J., Huang, Z., Thomas, B., ... & Zhao, J. (2018). Calibrating parameters of power system stability models using advanced ensemble Kalman filter. IEEE Transactions on Power Systems, 33(3), 2895-2905.

Sensitivity Analysis

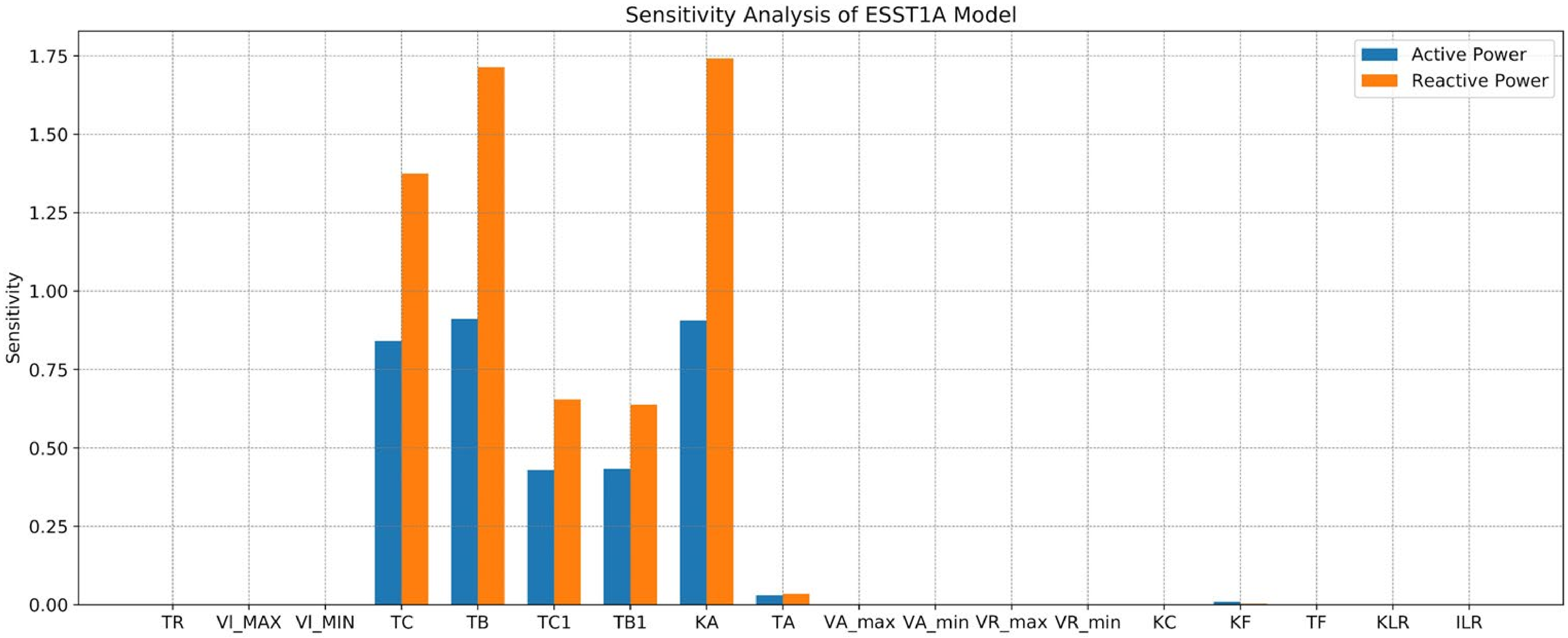


Fig. Sensitivity Analysis of Active power and Reactive power to ESST1A model parameters.

Sensitivity Analysis

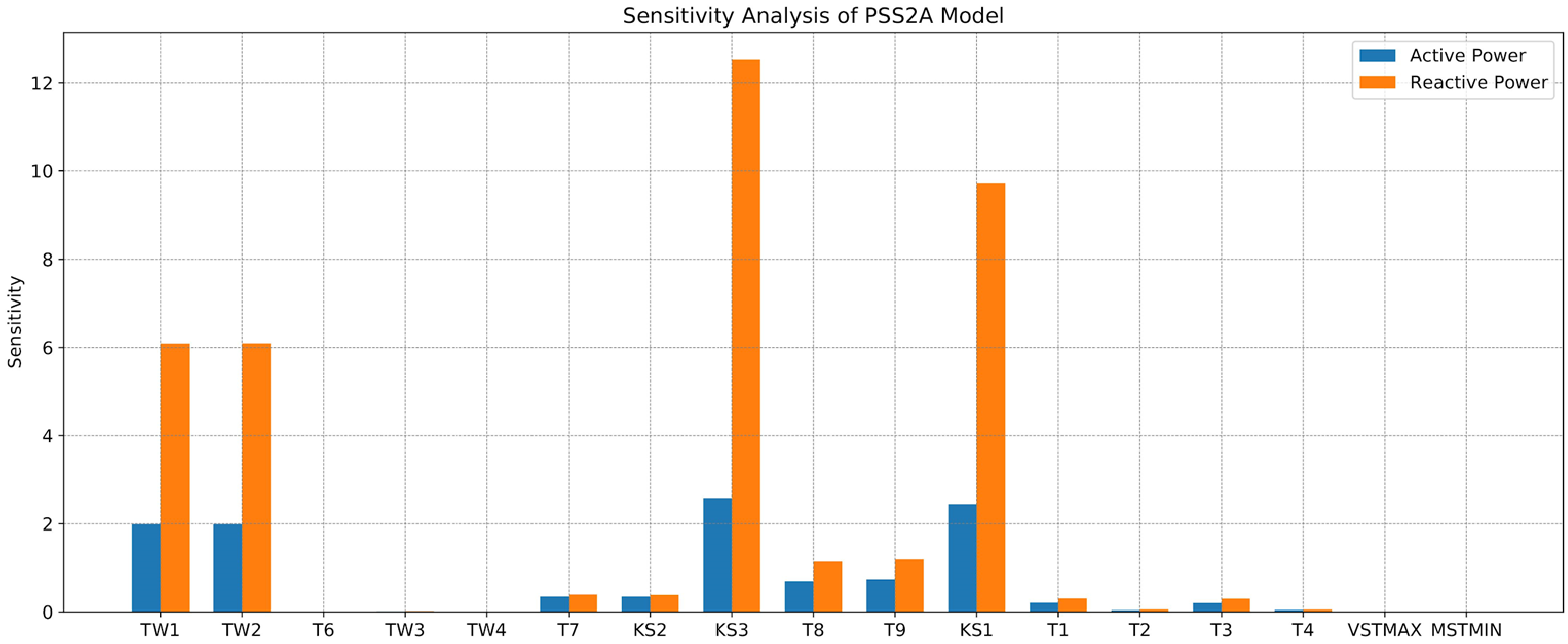


Fig. Sensitivity Analysis of Active power and Reactive power to PSS2A model parameters.

Sensitivity Analysis

The most sensitive parameters are:

Generator model
T_prime_do, Xd, S1_point_2, H, X_double_prime_d

Stabilizer model :
TW1, TW2, KS1, KS3

Exciter model :
KA, TB, TC, TC1

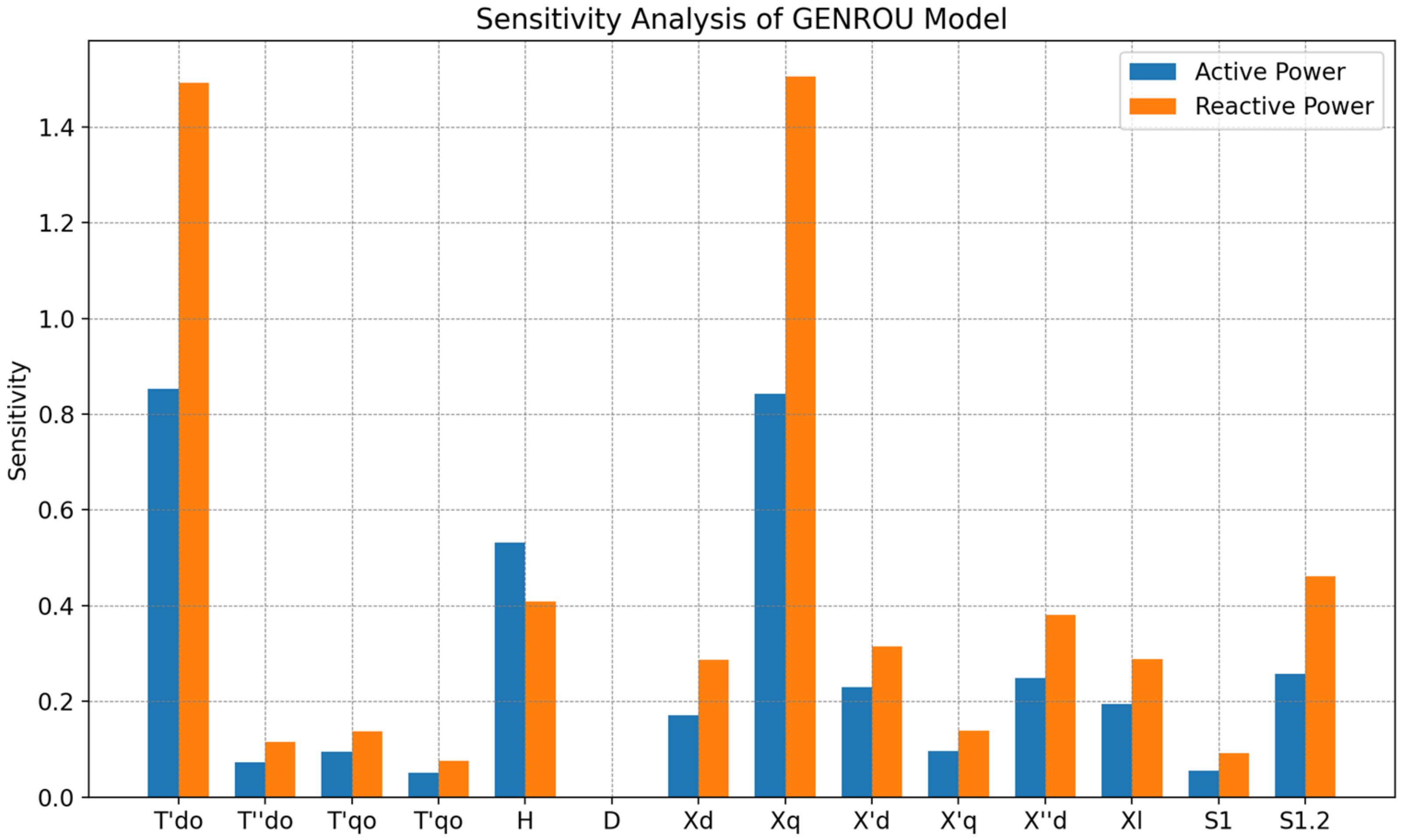
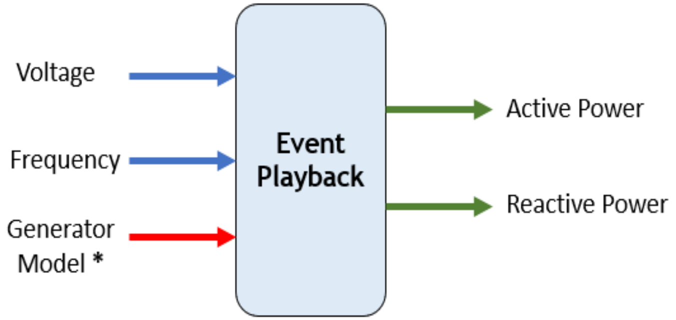


Fig. Sensitivity Analysis of Active power and Reactive power to GENROU model parameters.

Data generation

- Event playback applies Voltage, freq measurements to a sub-system model and simulates the model's response.



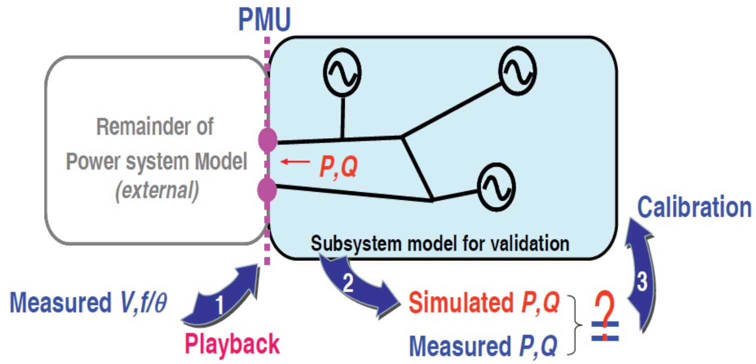
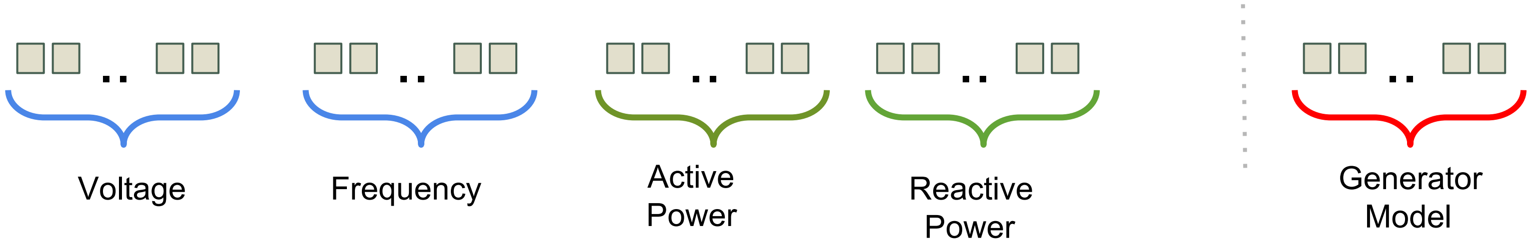


Fig. Concept of event playback [10][11].

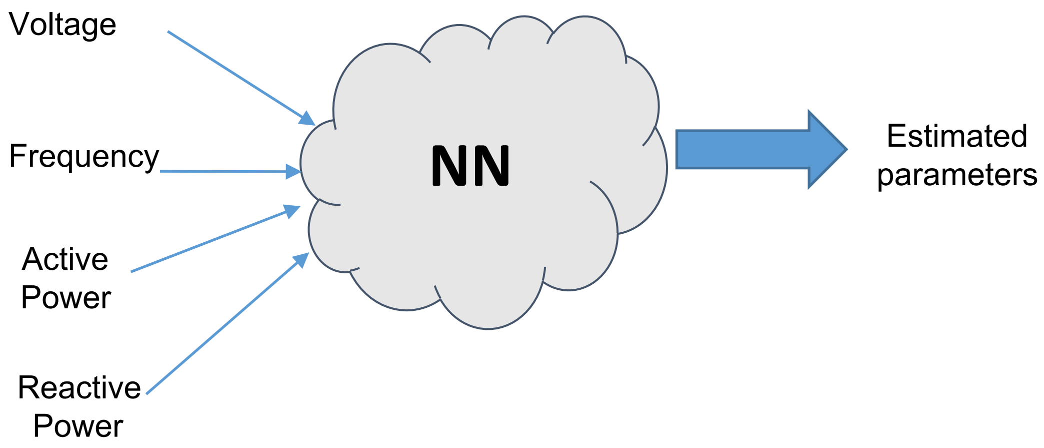
- Organization and normalization of the data.

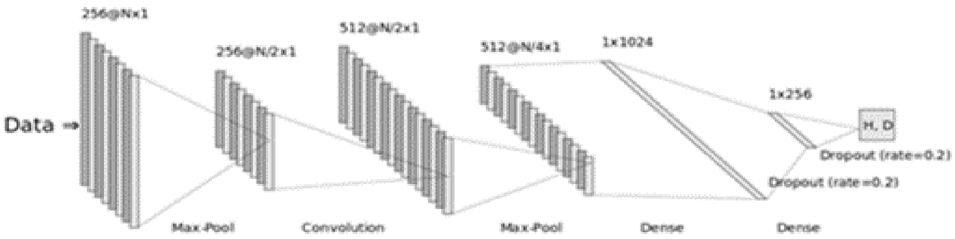


- 100k training data samples have been generated from simulated events at different model parameters.

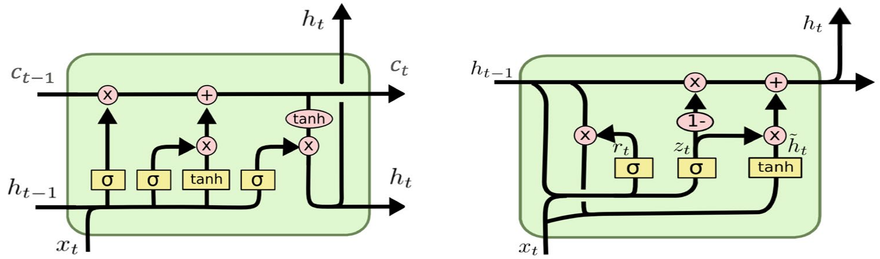
[10] Akhlaghi, S., Raheem, S., & Zhou, N. (2020, August). Model validation lessons learned through implementing NERC MOD-033-1. In 2020 IEEE Power & Energy Society General Meeting (PESGM) (pp. 1-5).
[11] Li, Y., Diao, R., Huang, R., Etingov, P., Li, X., Huang, Z., ... & Ning, A. (2017, July). An innovative software tool suite for power plant model validation and parameter calibration using PMU measurements. In 2017 IEEE Power & Energy Society General Meeting (pp. 1-5).

Training generic deep learning model

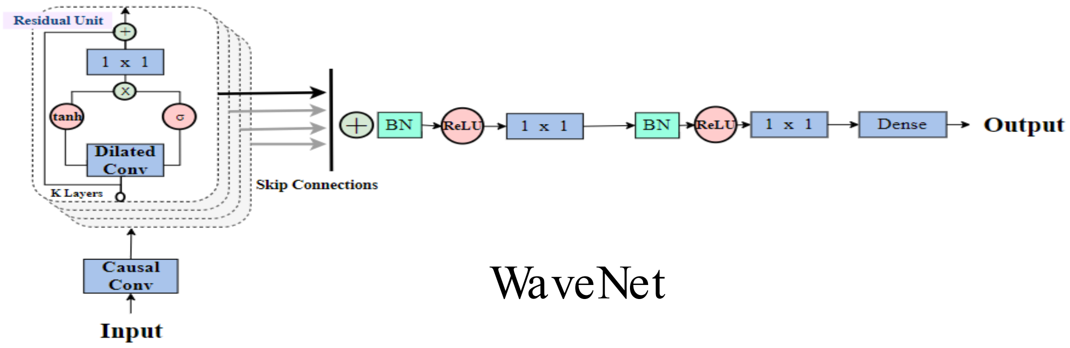




CNN
(Convolutional Neural Network)



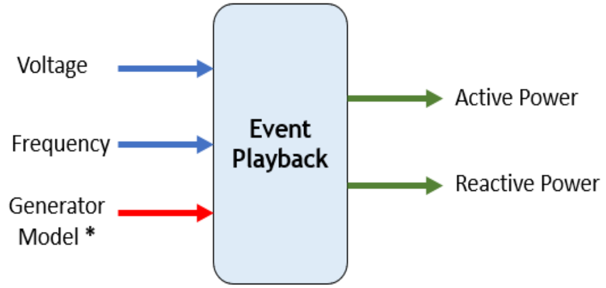
Recurrent neural networks



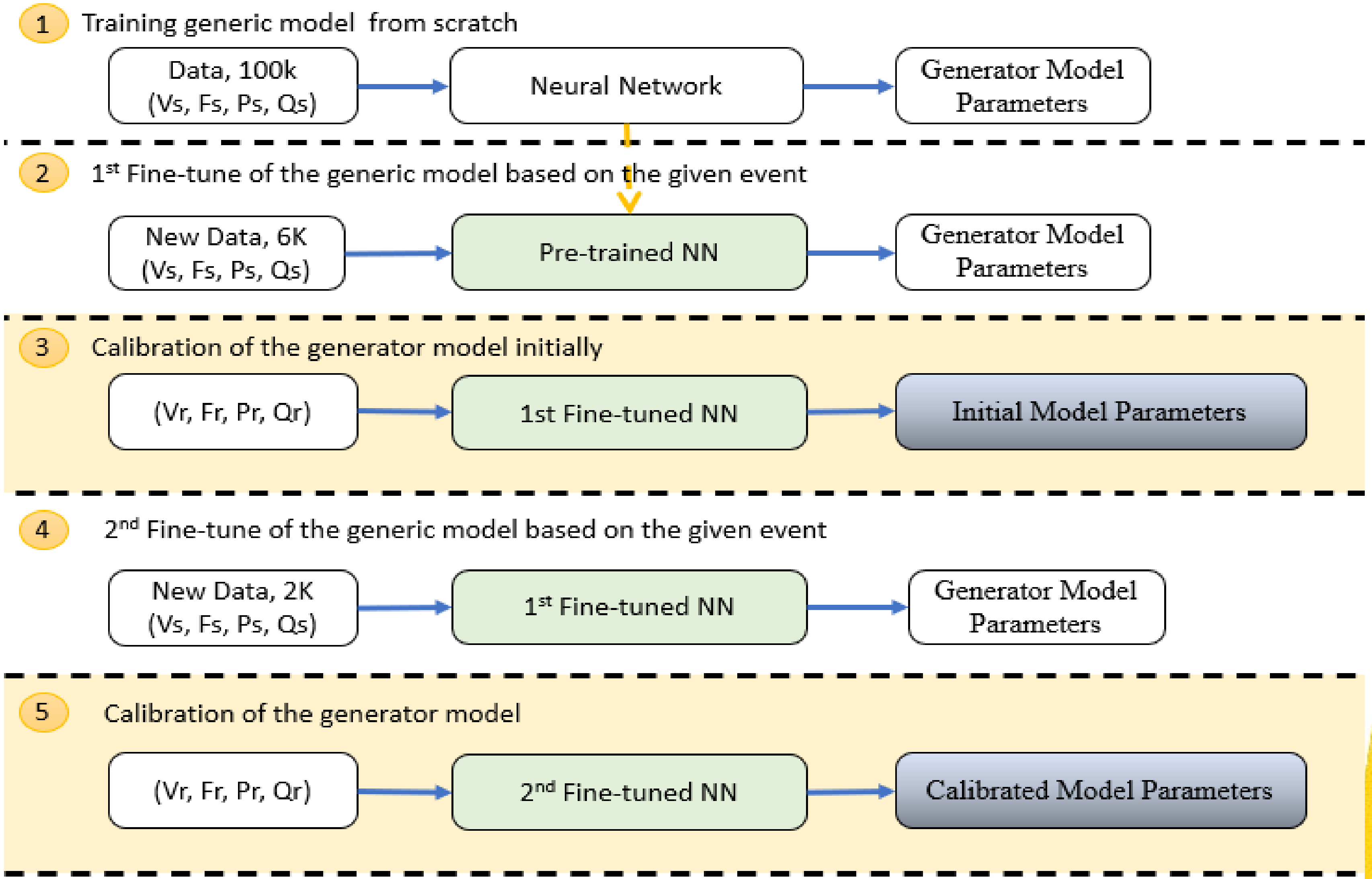
WaveNet

- We investigated the most common Recurrent Neural Network (RNN) architectures, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) in addition to Convolutional Neural Network (CNN) and WaveNet
- We benchmarked the deep learning architectures by training and testing on same data.
- We found out that WaveNets is the best architecture for the calibration problem.

Fine tuning



- From the real event, we used same V,F to generate different P,Q for different model parameters.
- we fine-tuned our generic NN using these events.
- we used the real V,F, P,Q to estimate the final parameters.



Results – Simulated Events

Parameters	Original	Event 1	APE	Event 2	APE	Event 3	APE	Event 4	APE	Event 5	APE
T'do	10	10.04	0.40	9.80	2.00	9.73	2.70	9.68	3.20	9.90	1.00
H	5.712	5.70	0.21	5.73	0.32	5.63	1.44	5.65	1.09	5.71	0.04
Xd	1.9	1.79	5.79	1.89	0.53	1.93	1.58	1.99	4.74	1.90	0.00
X"d	0.2	0.19	5.00	0.21	5.00	0.20	0.00	0.18	10.00	0.20	0.00
S1.2	0.398	0.38	4.52	0.40	0.50	0.40	0.50	0.39	2.01	0.39	2.01
TW1	10	9.99	0.10	10.12	1.20	10.19	1.90	10.31	3.10	10.08	0.80
TW2	10	10.12	1.20	9.86	1.40	9.93	0.70	9.86	1.40	10.00	0.00
KS3	1	1.01	1.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
KS1	30	30.45	1.50	29.71	0.97	29.76	0.80	29.67	1.10	29.56	1.47
TC	5	4.84	3.20	4.96	0.80	4.80	4.00	4.86	2.80	4.90	2.00
TB	40	38.62	3.45	40.14	0.35	39.22	1.95	39.00	2.50	39.28	1.80
TC1	1	1.01	1.00	0.99	1.00	0.98	2.00	1.00	0.00	0.99	1.00
KA	300	293.19	2.27	292.97	2.34	299.93	0.02	295.48	1.51	300.28	0.09
MAPE [%]			**2.28**		**1.26**		**1.35**		**2.57**		**0.79**

- **Five** different simulated testing events are used to test our approach.
- All of them reached almost **same** results within (1.65 ±0.55) %.
- Our approach doesn't need initial parameters and all of them almost landed to the same answer!

Results – Real Events

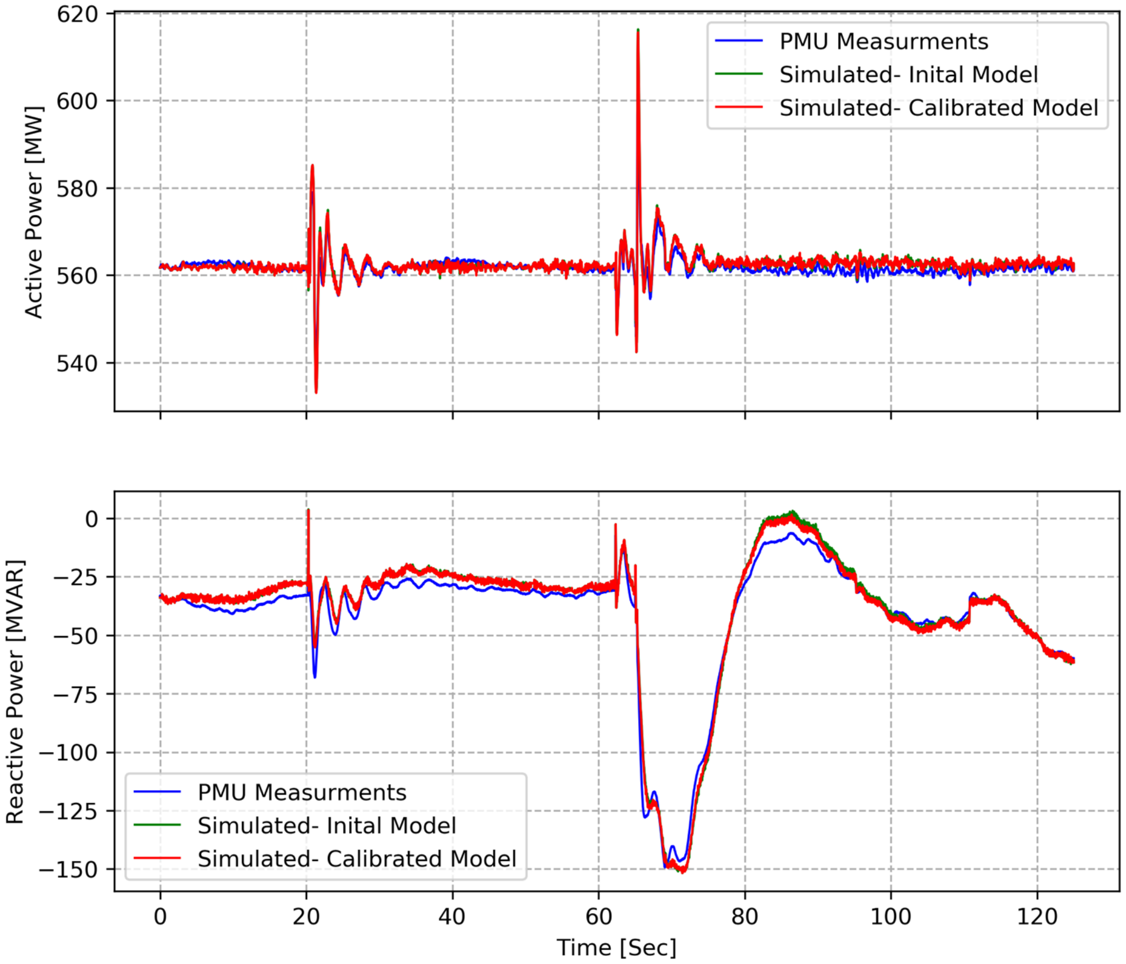
Parameters	Calibrated Parameters using Real Event 1	Calibrated Parameters using Real Event 2	APE
T'do	9.1816	8.7749	4.4300
H	5.6998	5.6690	0.5396
Xd	2.0569	2.0835	1.2920
X''d	0.2195	0.2213	0.8030
S1.2	0.4036	0.4093	1.4256
TW1	11.2015	11.7405	4.8119
TW2	8.3566	8.2632	1.1174
KS3	0.9419	0.9011	4.3366
KS1	28.0161	26.7830	4.4011
TC	4.6415	4.7174	1.6363
TB	38.7362	36.8661	4.8278
TC1	1.1521	1.1727	1.7836
KA	300.6068	300.0199	0.1952
MAPE			**2.4308**

- **Two** real events used to validate our approach.
- The two events reached almost to the **same** results with a difference of 2.43%

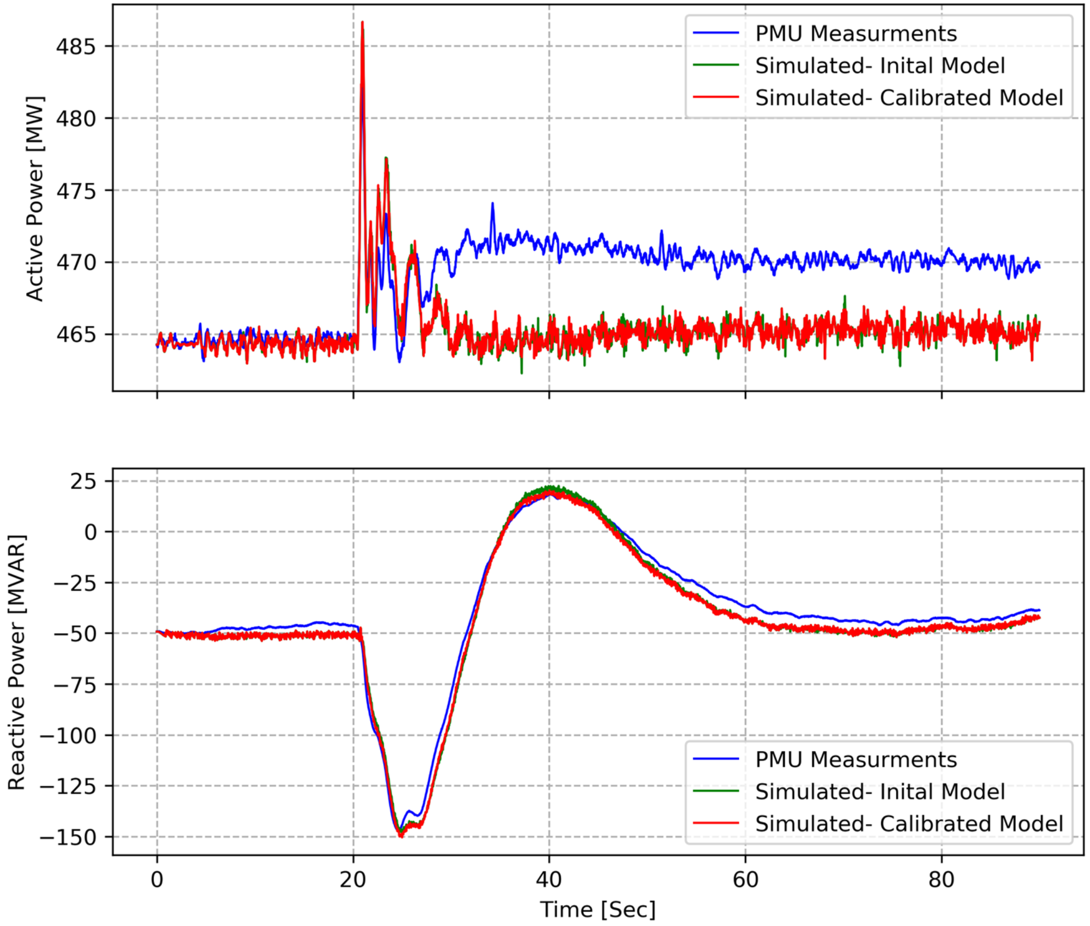
Table III: RMSE values of the real and reactive power.

RMSE	P (MW)		Q (MVar)	
Events	Before	After	Before	After
Event 1	-	0.1702	-	0.4113
Event 2	-	0.1827	-	0.4983
Event 3	-	0.1869	-	0.3830
Event 4	-	0.2275	-	0.3353
Event 5	-	0.2020	-	0.2606
Real-event 1	1.728	1.7159	4.8826	4.4795
Real-event 2	4.5737	4.5538	5.2456	5.0796

Event 2010- 01-01 - 1450



Event- 2010-11-01-0500



Conclusion and future work

- Our research showed that Deep Learning can be used for power systems calibration with high accuracy from a single event.
- Model can be trained offline from simulation then fine-tuned for real-events.
- More work is needed to:
  - Generalize the training for the generic models.
  - Investigate more accurate deep learning approaches.
  - Extend the work to inverter-based models.

References

[1] S. Wshah, R. Shadid, Y. Wu, M. Matar, B. Xu, W. Wu, L. Lin, R. Elmoudi, “Deep Learning for Model Parameter Calibration in Power Systems,” IEEE International Conference on Power System Technology (POWERCON), Sept. 13-16, 2020.

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Thanks