Exploration of AI-Oriented Power System Transient Stability Simulations

Tannan Xiao, Ying Chen*, Shaowei Huang, Tirui He
Department of Electrical Engineering, Tsinghua University
Beijing, China
eexiaoxh@gmail.com, chen_ying@tsinghua.edu.cn, huangsw@tsinghua.edu.cn, hetirui@qq.com

Jianquan Wang
College of Electrical Engineering, Zhejiang University
Hangzhou, China
wangjq@zju.edu.cn

Weilin Tong
Wuxi Power Supply Company, State Grid Corp. of China
Wuxi, China
tongwl1994@qq.com

Abstract—Artificial Intelligence (AI) has made significant progress in the past 5 years and is playing a more and more important role in power system analysis and control. It is foreseeable that the future power system transient stability simulations will be deeply integrated with AI. However, the existing power system dynamic simulation tools are not AI-friendly enough. In this paper, a general design of an AI-oriented power system transient stability simulator is proposed. It is a parallel simulator with a flexible application programming interface so that the simulator has high simulation speed, neural network supportability, and network topology accessibility. A prototype of this design is implemented and made public based on our previously realized simulator. Tests of this AI-oriented simulator are carried out under multiple scenarios, which proves that the design and implementation of the simulator are reasonable, AI-friendly, and highly efficient.

Index Terms—Application programming interface; artificial intelligence; parallel computing; power system dynamic simulation

I. INTRODUCTION

Power system dynamic simulation is still the most reliable and widely used approach for power system stability analysis [1]. Electric power companies and developers from all over the world have developed many dynamic simulators including ① electromechanical simulators such as PSASP [2] and PSD-BPA [3] by the China Electric Power Research Institute (CEPRI), PSS/E [3] by Siemens, DSATools [4] by Powertech, Eurostag [5] by Tractebel, PYPOWER-Dynamics [6] by Susanto, STEPS [7] by Shandong University, etc., ② electromagnetic simulators such as PSCAD/EMTDC [8] by Manitoba, CloudPSS [9] by Tsinghua University, etc., and ③ real-time simulators such as RTDS [10] by Manitoba, HYPERSIM [11] by OPAL-RT, ADPSS [12] by CEPRI, etc. The commercial simulators are well tested in the practical power system, which means they support a lot of functions and are very reliable. However, the commercial simulators are usually designed and implemented years ago, which means their architecture is usually old and the application programming interface (API) may be stiff or even not be supported. On the other hand, the free and open-source simulators are commonly not as functionally mature as the commercial ones, but much more flexible. The source code can be directly modified, so APIs can be developed as needed.

Research on artificial intelligence (AI) has achieved a growth spurt in the past few years. AI algorithms such as graph neural networks (GNN), reinforcement learning (RL), etc., have been applied to a variety of power system studies such as measurement enhancement [13], dynamic component modeling [14], parameter inference [15], optimization and control [16], stability assessment [17], etc. AI models can learn and approximate any functions with enough samples. AI technology will be more and more important in the research field of power systems, especially with the rapid development of renewable generation and power electronics. The safe and efficient operation of power systems is facing great challenges, e.g., we may need to model new devices to analyze stability although some devices’ operating mechanisms are still under research, dimensionality reduction is needed to scale down the complexity, the significantly increased uncertainty of power systems requires fast and flexible stability analysis and control, etc. AI-assisted power system analysis and control might be a solution to these challenges, or at least a mitigation measure.

Currently, the relationship between power system dynamic simulation and AI is relatively fragmented. The simulator usually works only as a data generator and provides limited prior knowledge, whereas the trained AI model usually works independently as a black-box surrogate model with poor interpretability and cannot be easily integrated into simulators. In one word, the simulator is not AI-friendly enough. In [18], the idea of a learning simulation engine that combines AI and simulation is proposed. Simulation-assisted AI and AI-assisted simulation mutually support each other. This might be the future of power system simulators.

Inspired by the learning simulation engine proposed in [18], in this paper, we provide a general design of an AI-oriented power system dynamic simulator. A prototype of this design is implemented based on a self-developed, fast, flexible, and C++-written electromechanical simulator. Some
tests are shown to illustrate the validity, flexibility, and efficiency of the proposed design and implementation.

II. DESIGN OF AI-ORIENTED DYNAMIC SIMULATOR

In Fig. 1, the overall architecture design of the AI-oriented simulator is demonstrated. The idea is intuitive. In order to support the interactions between the simulator and AI, a reasonable choice is to develop an AI-friendly API to connect each other. Similar to the human body, a bionic interaction mechanism is designed. The simulator, which works as the musculoskeletal system, and AI models, which work as the neuron cell bodies, are connected via an API, which works as the axon and terminal buttons. Via the API, the simulator provides massive data and prior knowledge for AI models, whereas AI models mine the data, discover the hidden patterns, and return well-trained models and posterior knowledge. Therefore, a closed-loop interaction mechanism is established.

![Figure 1. The overall architecture of the AI-oriented simulator.](image)

In this section, the design of the simulator and API, as well as the interactive mechanism between the simulator and AI models will be explained in detail.

A. Simulator

Power system dynamic simulators can be used to generate massive scenarios and simulation results, i.e., generate model-based data. Firstly, a dynamic model is needed for each component in the power system. It can be a mechanism-based model, a data-driven model, or a physics-data-integrated model. A model conversion function for different models from different simulators is preferred. Second, parameters of the selected model need to be measured, inferred, or learned, i.e., model calibration is needed. Thirdly, all the models with measured or inferred parameters are formulated together in a group of high-dimensional equations. Power flow can be solved with the Newton method to obtain the operation state. Power system dynamics are formulated with ordinary differential equations (ODEs) in the electromagnetic simulation and differential-algebraic equations (DAEs) in the electromechanical simulation. They can both be solved with a numerical integration method and a linear solver. Finally, simulation-based functions can be realized based on the solution of power flow and power system dynamics. Here are two required features of the simulator.

1) **Rapid Simulation Speed:** Simulation speed is essentially the basis of AI-assisted power system analysis and control. The training of AI models requires massive data. Data generation can be very time-consuming. The simulation speed is a bottleneck of successfully utilizing AI algorithms and training a model with sufficient performance. Therefore, the simulator must be well optimized. Algorithm-level and task-level parallelism, which is solution-level and function-level in Fig. 1, is required to fulfill the needs in different situations.

2) **Neural Network Supportability:** Another requirement of the simulator is neural network supportability, i.e., being able to load the structure and parameters of neural networks and perform at least forward propagation of neural networks. The simulator should be capable of integrating AI models into any part of the simulator.

B. API

Differ from the API currently existing in the simulators such as PSS/E and Eurostag, an AI-friendly API is more flexible, comprehensive, and efficient in data exchange.

First of all, the API must not affect the efficiency of the simulator. As can be seen in the former subsection, the simulator focuses on efficiency. The source code is usually written with efficient programming languages such as C++, Java, FORTRAN, etc. The implementation is highly organized and optimized. It should not be disturbed by the API.

Secondly, the API ought to support intrusive data access and non-intrusive function management of the simulator, as well as integrating AI models into the simulator. In order to support the interactions between the simulator and AI, the API should be able to call typical functions and perform data transmission in all four parts. Corresponding to the four parts of the simulator shown in Fig. 1, API can also be divided into four categories, namely, model API, parameter API, solution API, and function API.

1) **Model API:** The model API is used to load and output the structure of internal and external models including neural networks. The model expression should be easy to understand and modify, e.g., JSON files.

2) **Parameter API:** Similarly, the parameter API is used to load and output the parameters of models. A model labeling design is needed to pair the parameters with the model.

3) **Solution API:** The solution API is used to control the solution procedures and output the intermediate results during the solution process. For example, we need to select a node ordering algorithm before performing simulations, we could also use the iteration number of the power flow solution to analyze convergence, we might also need the admittance matrix, i.e., network topology access, to design GNN, etc.

4) **Function API:** The function API focuses on task scheduling and simulation results management. It can be used
to call computing functions, such as power flow solution and dynamic simulation, as well as output the needed results.

Thirdly, the data exchanges better happen in RAM instead of in hard drives. If the RAM is insufficient, the data could be cut into several pieces and transferred sequentially or the data could be exchanged using a database or a binary file. Plain text files should be avoided to the greatest extent.

Last but not least, the API is recommended to be written in Python because Python is an interpreted language, which is easy to learn and use, and AI programs are usually written in Python. There are many open-source AI projects published on GitHub. With a Python API, the simulator can be easily integrated into AI applications.

C. Interaction Mechanism with AI

In contrast to the simulator, AI obtains inductive models based on existing data, i.e., conclude data-driven models. Firstly, a training dataset is needed. The quality and representativeness of the samples will seriously affect the performance of data-driven models. Secondly, a hypothesis set is established, i.e., a learning framework is selected based on the task and the training data. Thirdly, optimization algorithms are utilized to train the model. Finally, the final hypothesis, i.e., an AI model, is obtained.

The interaction mechanism between the simulator and AI is illustrated in Fig. 2. The right part demonstrates simulation-assisted AI and the left part denotes AI-assisted simulation.

1) Simulation-Assisted AI: Firstly, simulations can be used to generate the training data. The actual training dataset also needs sample selection or augmentation, e.g., stability prediction needs simulation results with balanced stability labels. Sampling methods are very important since the data quality determines the performance upper limit of the AI model [19]. Secondly, deductive models, or physical models, can be used as a strong prior knowledge for AI model design. For example, the power network topology can be used to design GNN [17]. Thirdly, physical laws such as conservation laws can be used as constraints in optimization algorithms to limit the feasible region, improve the interpretability of AI models, and speed up the training process [20]. Finally, the simulator can be used as the benchmark for the performance verification of AI models.

2) AI-Assisted Simulation: Firstly, inductive AI models can be used for dynamic component modeling [21], [22]. Although the model may suffer from the problem of interpretability, the AI model can also be accurate, adaptive, and computationally efficient. AI models naturally support auto-differentiation and gradients can support the mechanism research of components. Secondly, AI models can be used for power system model calibration, i.e., parameter inference or parameter estimation [23]. Power system dynamic modeling and parameter estimation are facing increasing challenges because of the rapid development of renewable generation and power electronics. Thirdly, AI models can be used to discover the patterns hidden in the solution procedure. The convergence [24] or the intermediate state changes can be predicted by AI models. Finally, AI models can be used as surrogate models for power system analysis [25] and control [26]. Power system computation can be very time-consuming. Using a surrogate model as an approximation of the actual computation can significantly increase the efficiency of analysis and decision-making.

III. IMPLEMENTATION OF AN AI-ORIENTED SIMULATOR

In Fig. 3, a prototype of the design explained in the former section is implemented based on a high-performance electromechanical simulator called Power System Optimal Parameter Selection (PSOPS). After developing some external functions to support Python API, the simulator is compiled as a dynamic link library PSOPS.so. The Python API of the prototype is developed based on the ctypes library [27]. The dynamic link library PSOPS.so and the open-source Python API can be found in a repository called Py_PSOPS on https://github.com/xxh0523/Py_PSOPS.

![Figure 3. Implementation and tests of Py_PSOPS.](https://github.com/xxh0523/Py_PSOPS)

In this section, the implementation of PSOPS and the API, as well as four typical cases of simulator-AI interactions using Py_PSOPS are illustrated.

A. Implementation of PSOPS

PSOPS can perform AC power flow considering PV-PQ switching and electromechanical transient stability simulations. It is developed by us with C++ based on our previous research [28], [29], and [30]. The Eigen library [31] is used to realize neural network supportability. The structure of neural networks can be loaded by reading a JSON file and the parameters can be loaded by reading binary files saved by PyTorch [32].

In PSOPS, power system dynamics are modeled with a group of high-dimensional nonlinear DAEs including the differential equations shown in (1) and the algebraic equations shown in (2). The alternating approach proposed in
[33] is adopted in PSOPS due to its simplicity, reliability, and robustness [34].

\[ \mathbf{x} = \mathbf{f}(\mathbf{x}, \mathbf{V}) \]
\[ \mathbf{Y}'\mathbf{V} = \mathbf{I}'(\mathbf{x}, \mathbf{V}) \]

where \( \mathbf{x} \) is the state vector of the system, whose time derivatives are equal to \( \mathbf{f}(\mathbf{x}, \mathbf{V}) \), \( \mathbf{V} \) is the bus voltage vector, \( \mathbf{I}' \) is the fictitious injection current vector, and \( \mathbf{Y}' \) is the fictitious admittance matrix. Equations (2) are the nodal voltage equations of an equivalent power network, in which a dynamic device is represented by Norton’s equivalent circuit which consists of a fictitious equivalent current source with a fictitious shunt admittance [33], [34]. In PSOPS, improved sparsity techniques, improved bordered block diagonal form (BBDF) method, and memory allocation techniques are utilized. A brief introduction of these techniques is as follows.

1) Improved Sparsity Techniques [28]: The AMD-MNSP algorithm (approximate minimum degree, minimum number of source predecessors) can enhance the efficiency of the sparse vector method by reducing the number of nodes in the factorization path set of source nodes while maintaining the sparsity of the factorized matrix. The multi-path sparse vector method can avoid the unnecessary computation in the iterative solution process of the network equations, whereby the idea of the method is to form different paths for different types of source nodes.

2) Improved BBDF Method [29], [30]: At the algorithmic level, a fully parallel BBDF method and a fully parallel nested BBDF method are used, which can solve the subnets and the cut-node network in parallel, instead of solving network equations in the order of parallel forward substitutions of subnets, serial forward and backward substitutions of the cut-node network, and parallel backward substitutions of subnets. From the perspectives of task decomposition and algorithm implementation, an efficient mapping between network topology, CPU core structure, and the parallel communication topology is created to reduce parallel overhead based on subnet-core mapping and mixed programming of MPI and OpenMP.

3) Memory Allocation Tricks: Power system transient stability simulation is a compute-intensive and memory-intensive computation. In PSOPS, the sparse matrices are saved using linked lists. Symbolic network topology is constructed for factorization, inverse factorization, and path tree establishment. The admittance matrix, the equation coefficient matrix, and the independent vector are saved in a contiguous memory block to increase the cache hit rate when solving network equations. Meanwhile, besides buses, other components such as transmission lines, transformers, generators, and loads are also reordered after node ordering based on the new node order to increase the hit rate.

After utilizing all the techniques mentioned above, the time consumption of transient stability simulations can be reduced dramatically. Meanwhile, task-level parallelism is realized using the ray library [35] of Python.

In TABLE I, the basic information and average time consumption of 10-second simulations are displayed. The 2383wp system is a widely used test system in MATPOWER. Sys13490 and Sys24886 are two practical power systems. All the dynamic components are modeled in detail. The test HPC platform is Sugen 1950r-G installed with 8 Intel Xeon E7-8837 2.67 GHz processors. Each processor is integrated with 8 CPU cores, i.e., the total number of CPU cores is 64. As can be seen, super real-time simulations of a 24,886-node practical power system are realized and the 10-second simulations averagely cost about 0.64 seconds in parallel.

### TABLE I. Basic Information and Average Time Consumption of 10-Second Simulations of Three Test Systems

| Test Systems | Number of components | Time Consumption (seconds) |
|--------------|----------------------|----------------------------|
| Bus | Branch | Generator | Load | Serial | Parallel |
| 2383wp | 2383 | 2892 | 327 | 1822 | 2.655 | 0.365 |
| Sys13490 | 13490 | 22544 | 1797 | 3550 | 9.911 | 0.587 |
| Sys24886 | 24886 | 39512 | 1919 | 5646 | 13.525 | 0.639 |

B. Implementation of API

As shown in Fig. 3, the API can be divided into two parts, i.e., the external functions in PSOPS and the Python API. The external functions are the basic implementation of model API, parameter API, solution API, and function API. The details are as follows.

1) Model API: The structure of neural networks can be directly established in the simulator by modifying the basic computation data file and reading a JSON file containing the names and structure of layers in the neural network.

2) Parameter API: Components’ parameters such as the name, the total number, the constraints, the default settings, dynamic model parameters, connectivity, etc., can be obtained or set. However, the parameters of neural networks are directly loaded by the simulator via modifying the basic computation data file and reading a binary file.

3) Solution API: The intermediate results during simulation processes can be reached. Power systems can be set to state at any integration step. Basic data of the solutions such as the iteration number, the simulation time, the integration step, faults, disturbances, etc., can be accessed. More importantly, the network topology accessibility is realized. Network topology data such as the admittance matrix, the impedance matrix, the number of fill-ins, and the factorized lower and upper triangular matrix can be obtained. Components’ connectivity to the power network can be changed and network connectivity check is supported, i.e., asynchronous subsystems can be identified. Other settings such as power flow solution methods, integration methods, node ordering algorithms, and sparse vector methods can be modified by changing the basic computation data file.
4) **Function API:** The function API supports calling power flow solutions and transient stability simulations and gets simulation results including rotor angles, rotation speed, inner electric potential, active and reactive power, regulators' outputs, nodal voltages, etc.

The Python API published on GitHub is developed by reorganizing the external functions loaded from the dynamic link library into a NumPy [36] style. The source code is organized in a component-based manner, which means the functions of the same kind of component are put together. It should be noted that the Python API is still under development and only part of the aforementioned functions is realized. The Python API can be extended easily to fulfill the needs in different situations.

C. **Cases of Simulator-AI Interactions**

Four typical scenarios, namely, sample generation, spatiotemporal graph convolutional networks (STGCN)-based stability prediction, neural ODE-based dynamic modeling [37], and RL-based stability-constrained optimal power flow (SOPF), are introduced to show the simulator-AI interactions based on Py_PSOPS, as shown in Fig. 3.

1) **Sample Generation:** Sample generation is the most basic application of Py_PSOPS and can be used for any AI application. It is supported by the rapid simulation speed of Py_PSOPS. As for power flow sampling, simple random sampling, grid sampling, and a step-wise sampling scheme are implemented. The step-wise scheme is shown as follows.

**Step-wise Sampling Scheme**

| Input \( N \) (the total number of required samples),| set \( n = 1 \) |
|-------------------|-------------------|
| while \( n < N \) : | Simple random sampling of \( P_p \) and \( Q_p \) within their upper and lower limits. |
| Calculate \( \text{sum}(P_p) \) . | Simple random sampling of \( P_p \) within their upper and lower limits until \( \text{sum}(P_p) + \text{sum}(P_{\text{slack}}) < \text{sum}(P_p) + \text{sum}(P_{\text{slack}}) \) |
| Simple random sampling of \( V_u \) | if power flow converge: |
| if power flow converge: | save \((P_p, P_v, V_u)\). |

end if  

end while

where \( P_p \) and \( Q_p \) are the active power vector and reactive power vector of loads, respectively, \( \text{sum}(\bullet) \) denotes the sum of elements in the vector, \( P_p \) is the active power vector of generators, \( P_{\text{slack}} \) and \( P_{\text{slack}} \) are the upper limit vector and the lower limit vector of slack generators, \( V_u \) is the nodal voltage vector of generators other than slack generators.

After power flow sampling, random contingencies can be sampled by randomly choosing a transmission line or transformer, randomly choosing the fault location, and randomly setting a fault clearing time.

2) **STGCN-based Stability Prediction:** This is an example of simulation-assisted AI. The simulator provides training data as well as prior knowledge to support AI model design. An STGCN-based stability prediction model is designed. The implementation is supported by the network accessibility of Py_PSOPS. The network structure is shown in Fig. 4. The input features include \( Y_t, Y_{t+1}, \) and \( Y_{t+2} \), i.e., temporal data of state variables obtained by a short-time simulation from \( t = 0 \) to \( t = T \), which can be obtained with the function API. The fault is cleared at the instant \( t = t_f \). The output of the model is the stability label of the input case.

![Figure 4. The architecture of the STGCN model.](image)

3) **Neural ODE-based Dynamic Modeling:** This is an example of AI-assisted simulation. The trained AI model is integrated into the simulator and supports the transient simulation. A simple introduction of the neural ODE-based dynamic modeling method is as follows. The idea of neural ODE is to keep the framework of numerical integration and formulate a parameterized derivative function such as neural networks for derivative regression, as shown in (3).

\[
\dot{x} = f_\theta(x, V; \theta) \tag{3}
\]

where \( \theta \) denotes the parameters of the parameterized derivative function. After inputting the initial value \( x = x(0) \), the variation of \( x \) can be calculated with a numerical integration method. The parameters of neural ODE can be trained using a set of sampled curves of \( x \). The loss function is the sum of errors between the predicted curves and the ground-truth curves of \( x \).

4) **RL-based SOPF:** This is an example of the simulator and AI mutually supporting each other. SOPF is one of the traditional problems of power systems. In SOPF formulation, a target function needs to be optimized under the equality constraints of power flow and DAEs, as well as the inequality constraints of static security constraints and dynamic security constraints [38], [39]. RL can solve this problem in a simulation-based optimization manner. With the support of Py_PSOPS, an RL environment for solving SOPF based on OpenAI Gym [40] can be established. The target is to minimize the total generation cost. We use the twin-delayed deep deterministic policy gradient (TD3) algorithm [41] to train the agent.
The source code of sample generation can also be found on GitHub [https://github.com/xxh0523/Py_PSOPS](https://github.com/xxh0523/Py_PSOPS), whereas the other three cases are still under research and the source code will be made public on GitHub soon after the submissions of corresponding papers.

IV. NUMERICAL TESTS

In this section, test results of the four aforementioned cases of utilizing the prototype are demonstrated. The success of these tasks proves the validity, flexibility, and efficiency of the design and implementation.

The test system is the IEEE-39 system. The test high-performance server used is consists of an NVIDIA P100 GPU, 250 gigabytes RAM and two Intel Xeon Gold 5118 processors, which contains 24 CPU cores in total, and hyperthreading is enabled, i.e., there are up to 48 threads available.

A. Sample Generation

On the test server, over 1.29 million power flow samples and over 50 million simulation samples of the IEEE-39 system are generated using 40 threads within 9 hours. This sample dataset is used to support the research on STGCN and neural ODE.

B. STGCN-based Stability Prediction

The STGCN-based stability prediction model is trained. Samples in the training dataset are randomly selected in the sample dataset. The training dataset contains 10240 samples, whereas the testing dataset contains 33600 samples. The comparison results of the STGCN model, convolutional neural network (CNN) model, long short-term memory (LSTM) model, and multi-layer perceptron (MLP) model are displayed in Fig. 5.

![Figure 5. Results of STGCN, CNN, LSTM, MLP models.](image)

C. Neural ODE-based Dynamic Modeling

We established a neural ODE-based model for the classic generator model. Samples in the training dataset are also randomly selected in the sample dataset including stable contingencies and unstable contingencies. After training, a neural dynamic model is obtained. The neural model is integrated into the simulator. The comparison between the simulation results obtained with the original classic generator model and the trained neural model is shown in Fig. 6.

![Figure 6. Comparison results of the classic generator model and the neural generator model.](image)

D. RL-based SOPF

The training process is demonstrated in Fig. 7. After the agent is trained, further tests are carried out to check the control effectiveness. 50,000 power flow samples with dynamic constraint violations are sampled. The agent gets the operation state and outputs the control strategy. The agent cost 122.525 seconds, including generate strategy and perform transient simulation once to check the strategy. After control, 49602 samples return to safe operating points, whereas 398 samples violate static stability constraints. The success rate is 99.204 percent and the new operating points are 100 percent sure to have dynamic security.

![Figure 7. The training process of the agent with the TD3 algorithm.](image)

V. CONCLUSIONS

To conclude, an AI-oriented power system transient stability simulator called Py_PSOPS is designed, implemented, tested, and made public. Although it is merely an exploration of AI-oriented power system dynamic simulators, Py_PSOPS shows promising capabilities to support AI development in power system stability analysis and control. A more sophisticated and complete implementation of this design has recently been published by the CloudPSS. The development of Py_PSOPS will continue and it may be packed as an external module of CloudPSS in the future.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China under Project No. 52107104.

REFERENCES

[1] N. Hatzigiorgiou et al., “Definition and Classification of Power System Stability – Revisited amp; Extended,” IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 3271–3281, Jul. 2021.
[2] W. Zhongxi and Z. Xiaoxin, “Power System Analysis Software Package (PSASP)—an integrated power system analysis tool,” in PSC/IEEE ’98. 1998 International Conference on Power System Technology. Proceedings (Cat. No.98EX151), Aug. 1998, vol. 1, pp. 7–11 vol.1.

[3] H. Song, R. Na, S. Ting, and P. Xiaojun, “Study on conversion between the common models of PSD-BPA and PSS/E,” in 2013 IEEE 11th International Conference on Electronic Measurement Instruments, Aug. 2013, vol. 1, pp. 64–69.

[4] K. Morrison, L. Wang, and P. Kundur, “Power system security assessment,” IEEE Power and Energy Magazine, vol. 2, no. 5, pp. 30–39, Sep. 2004.

[5] S. Cole and B. Haut, “Robust Modeling Against Model-Solver Interactions for High-Fidelity Simulation of VSC HVDC Systems in EUROSTAG,” IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 2632–2638, Aug. 2013.

[6] J. Susanto, PYPower-Dynamics. 2021. Accessed: Sep. 26, 2021. [Online]. Available: https://github.com/susanto/PYPower-Dynamics

[7] C. Li, Y. Wu, H. Zhang, H. Ye, Y. Liu, and Y. Liu, “STEPS: A Portable Dynamic Simulation Toolkit for Electrical Power System Studies,” IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 3216–3226, Jul. 2021.

[8] J. Jiu, Y. Gu, C. Zhao, Y. Liu, and C. Guo, “Accelerated Model of Modular Multilevel Converters in PSCAD/EMTDC,” IEEE Transactions on Power Delivery, vol. 28, no. 1, pp. 129–136, Jan. 2013.

[9] Y. Liu, Y. Song, Z. Yu, C. Shen, and Y. Chen, “Modeling and Simulation of Hybrid AC-DC System on a Cloud Computing Based Simulation Platform - CloudPSS,” in 2018 2nd IEEE conference on Energy Internet and Energy System Integration (EI2), Oct. 2018, pp. 1–6.

[10] R. Kuffel, J. Giesbrecht, T. Maguire, R. P. Wierckx, and P. McLaren, “RTDS—a fully digital power system simulator operating in real time,” in Proceedings 1995 International Conference on Energy Management and Power Delivery EMJD ’95, Nov. 1995, vol. 2, pp. 498–503 vol.2.

[11] A. Kumar, A. Bjahouei, S. K. Musumuri, and B. Rourt, “Design and Tuning of Multi-Band Based Power System Stabilizer and Implementation in HYPERSIM,” in 2019 20th International Conference on Intelligent System Application to Power Systems (ISAP), Dec. 2019, pp. 1–6.

[12] Y. Wang, S. Xu, Y. Xu, Q. Mu, and X. Zhang, “The Research and Implementation of Power CPS Simulation Platform Based on ADPSS,” in The 16th IET International Conference on AC and DC Power Transmission (ACDC 2020), Jul. 2020, vol. 2020, pp. 706–711.

[13] G. D. Feng, Y. Chen, and X. Liu, “Temporal Graph Super Resolution on Power Distribution Network Measurements,” IEEE Access, vol. 9, pp. 70628–70638, 2021.

[14] P. Zhang and Y. Zhou, “Neuro-Reachability of Networked Microgrids,” IEEE Transactions on Power Systems, pp. 1–1, 2021, in press.

[15] R. Nagi, X. Huan, and C. Chen, “Bayesian Inference of Parameters in Power System Dynamic Models Using Trajectory Sensitivities,” IEEE Transactions on Power Systems, pp. 1–1, 2021, in press.

[16] H. Nie, Y. Chen, Y. Song, and S. Huang, “A General Real-time OPF Algorithm Using DDPG with Multiple Simulation Platforms,” in 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), May 2019, pp. 3713–3718.

[17] J. Huang, L. Guan, Y. Su, H. Yao, M. Guo, and Z. Zhong, “System-Scale-Free Transient Contingency Screening Scheme Based on Steady-State Information: A Pooling-Ensemble Multi-Graph Learning Approach,” IEEE Transactions on Power Systems, pp. 1–1, 2021, in press.

[18] L. von Rueden, S. Mayer, R. Sifa, C. Bauckhage, and J. Garcke, “Combining Machine Learning and Simulation to a Hybrid Modelling Approach: Current and Future Directions,” in Advances in Intelligent Data Analysis XVII, Cham, 2020, pp. 548–560.

[19] Y. Zhang et al., “Encoding Frequency Constraints in Preventive Unit Commitment Using Deep Learning with Region-of-Interest Active Sampling,” IEEE Transactions on Power Systems, pp. 1–1, 2021, in press.

[20] B. Lusch, J. N. Kutz, and S. L. Brunton, “Deep learning for universal linear embeddings of nonlinear dynamics,” Nature Communications, vol. 9, no. 1, Art. no. 1, Nov. 2018.

[21] C. Li, G. Chen, G. Liang, and Z. Y. Dong, “A Novel High-performance Deep Learning Framework for Load Recognition: Deep-shallow Model based on Fast Backpropagation,” IEEE Transactions on Power Systems, pp. 1–1, 2021.

[22] A. M. Stankovic, A. T. Saric, and M. Milosevic, “Identification of nonparametric dynamic power system equivalents with artificial neural networks,” IEEE Transactions on Power Systems, vol. 18, no. 4, pp. 1478–1486, Nov. 2003.

[23] Z. Bi, F. Wang, and C. Liu, “Getting parameters in power systems based on adaptive linear neural network,” in The 2006 IEEE International Joint Conference on Neural Network Proceedings, Jul. 2006, pp. 1458–1462.

[24] M. Macktoobian, F. Basciani, D. Gillet, and J.-P. Kneib, “Data-Driven Convergence Prediction of Astrobots Swarms,” IEEE Transactions on Automation Science and Engineering, pp. 1–12, 2021.

[25] L. Zhu, D. J. Hill, and C. Lu, “Hierarchical Deep Learning Machine for Power System Online Transient Stability Prediction,” IEEE Transactions on Power Systems, vol. 35, no. 3, pp. 2399–2411, May 2020.

[26] I.-I. Avramidis, F. Capitanescu, S. Karagiannopoulos, and E. Vrettos, “A Novel Approximation of Security-Constrained Optimal Power Flow With Incorporation of Generator Frequency and Voltage Control Response,” IEEE Transactions on Power Systems, vol. 36, no. 3, pp. 2438–2447, May 2021.

[27] “ctypes — A foreign function library for Python — Python 3.9.7 documentation.” [Online]. https://docs.python.org/3/library/ctypes.html (accessed Sep. 29, 2021).

[28] T. Xiao, J. Wang, Y. Gao, and D. Gan, “Improved Sparsity Techniques for Solving Network Equations in Transient Stability Simulations,” IEEE Trans. Power Syst., vol. 33, no. 5, pp. 4878–4888, Sep. 2018.

[29] T. Xiao, W. Tong, and J. Wang, “Study on Reducing the Parallel Overhead of the BBDF Method for Power System Transient Stability Simulations,” IEEE Trans. Power Syst., vol. 35, no. 1, pp. 539–550, Jan. 2020.

[30] T. Xiao, W. Tong, and J. Wang, “A New Fully Parallel BBDF Method in Transient Stability Simulations,” IEEE Trans. Power Syst., vol. 35, no. 1, pp. 304–314, Jan. 2020.

[31] “Eigen: Main Page.” [Online]. https://eigen.tuxfamily.org/dox/ (accessed Sep. 28, 2021).

[32] “PyTorch.” [Online]. https://pytorch.org/

[33] H. W. Dommel and N. Sato, “Fast Transient Stability Solutions,” IEEE Transactions on Power Apparatus and Systems, vol. PAS-91, no. 4, pp. 1643–1650, Jul. 1972.

[34] P. Kundur, N. J. Balu, and M. G. Lauby, Power system stability and control, vol. 7. McGraw-hill New York, 1994.

[35] “Ray - Scaling Python made simple, for any workload,” Ray. [Online]. https://ray.io/ (accessed Sep. 29, 2021).

[36] “NumPy,” [Online]. https://numpy.org/ (accessed Sep. 29, 2021).

[37] R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. K. Duvenaud, “Neural Ordinary Differential Equations,” Advances in Neural Information Processing Systems, vol. 31, pp. 6571–6583, 2018.

[38] S. Abhyankar, G. Geng, M. Amtescu, X. Wang, and V. Dinavahi, “Solution techniques for transient stability-constrained optimal power flow – Part II,” Transmission Distribution IET Generation, vol. 11, no. 12, pp. 3177–3185, 2017.

[39] G. Geng, S. Abhyankar, X. Wang, and V. Dinavahi, “Solution techniques for transient stability-constrained optimal power flow – Part II,” Transmission Distribution IET Generation, vol. 11, no. 12, pp. 3186–3193, 2017.

[40] G. Brockman et al., “OpenAI Gym,” arXiv:1606.01540 [cs], Jun. 2016. [Online]. Accessed: 2020. [Online]. Available: http://arxiv.org/abs/1606.01540

[41] S. Fujimoto, H. Hoof, and D. Meier, “Addressing Function Approximation Error in Actor-Critic Methods,” in International
Conference on Machine Learning, Jul. 2018, pp. 1587–1596. Accessed: Apr. 06, 2021. [Online]. Available: http://proceedings.mlr.press/v80/fujimoto18a.html