Exploration of AI-Oriented Power System Dynamic Simulations

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Abstract—Artificial Intelligence (AI) is playing a more and more important role in power system analysis and control. It is foreseeable that the accuracy and efficiency of future power system dynamic analysis will be greatly improved by the interaction of the deduction-based simulator and the induction-based AI. While some commercial software already supports AI applications to a certain extent, the way in which power system transient simulators interact with AI remains unclear. In this paper, a general design of an AI-oriented power system dynamic simulator is proposed based on the illustration of the interaction mechanism between dynamic simulations and AI. With the support of a flexible application programming interface, the simulator has rapid simulation speed, intrusive parameter accessibility, non-intrusive function usability, and neural network supportability. 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 four scenarios, which proves that the design and implementation of the simulator are reasonable, AI-friendly, and highly efficient.

Index Terms—Power system dynamic simulation, artificial intelligence, application programming interface, parallel computing.

I. INTRODUCTION

POWER 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 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, DIgSILENT PowerFactory [5] by DIgSILENT GmbH, Eurostag [6] by Tractebel, PYPOWER-Dynamics [7] by Susanto, STEPS [8] by Shandong University, etc., electromagnetic simulators such as PSCAD/EMTDC [9] by Manitoba, CloudPSS [10] by Tsinghua University, etc., and real-time simulators such as RTDS [11] by Manitoba, HYPERSIM [12] by OPAL-RT, ADPSS [13] 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 might be 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 [14], dynamic component modeling [15], parameter inference [16], optimization and control [17], stability assessment [18], 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, although some commercial software such as DIgSILENT PowerFactory and CloudPSS have supported AI applications to a certain extent, the relationship between power system dynamic simulation and AI is still 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 model with poor interpretability and cannot be easily integrated into simulators. In one word, the simulator is not AI-friendly enough. In [19], 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. With the support of AI, the simulator can evolve autonomously and become more accurate and efficient, which is also crucial to the realization of power system digital twins [20].
A comprehensive concept of simulation intelligence is proposed. This can be the future of power system dynamic simulators.

A. Contributions

Inspired by the learning simulation engine proposed in [19] and the simulation intelligence discussed in [21], we explore AI-oriented power system dynamic simulations in this paper. The contributions are as follows.

1) The interaction mechanism between power system dynamic simulations and AI is illustrated and a general design of an AI-oriented power system dynamic simulator is provided.

2) A prototype of the proposed design is implemented and made public on https://github.com/xxh0523/Py_PSOPS with detailed code comments based on a self-developed, fast, flexible, and C++-written power system electromechanical simulator.

3) Four typical cases of utilizing the developed simulator are shown to illustrate the validity, flexibility, and efficiency of the proposed design and implementation. All four cases are supported by at least one paper or open-source code we developed on GitHub.

B. Paper Organization

The remainder of the papers is as follows. Section II introduces the design of the AI-oriented power system dynamic simulator and discusses the interaction of dynamic simulations and AI. The implementation details of a prototype simulator based on the proposed design are illustrated in Section III. In section IV, the typical examples of the implemented simulator are explained and tested. Conclusions are drawn in Section VI.

II. DESIGN OF AI-ORIENTED DYNAMIC SIMULATOR

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

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. With the support of this interaction mechanism, the deduction-based simulator and the induction-based AI models can work together to achieve the task of data enhancement [22], awareness enhancement [14], analysis enhancement [23], decision-making enhancement [24], etc., and may finally lead to the creation of a digital twin considering power system dynamics.

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 [25], a data-driven model, or a physics-data-integrated model [26]. A model conversion function for different models of different simulators is preferred. Secondly, parameters of the selected model need to be measured, inferred, or learned, i.e., model calibration [27] 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 [28]. 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. Application Programming Interface

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.

1) No Impact on Simulation Efficiency

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. Therefore, a suggested way is rewrapping the needed internal functions as external functions.

2) Intrusive Parameter Accessibility and Non-intrusive Function Usability

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.

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.

The parameter API, similarly, is used to load and output the parameters of models. A model labeling design is needed to pair the parameters with the model.

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 use the iteration number of the power flow solution to analyze convergence, we might also need the admittance matrix, i.e., network topology accessibility, to design GNN, etc.

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.

3) Efficient Memory Exchange

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.

4) Interpreted Language-Written

Last but not least, the API is recommended to be written in an interpreted language such as Python because it is easy to learn and use, not to mention that 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 modified for AI applications.

C. Interaction Mechanism with AI

In contrast to the simulator, AI produces inductive models, i.e., conclude data-driven models, based on existing data. 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.

Fig. 2. Interactions between simulation and AI.

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 [29]. 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 [18]. 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 [30]. 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 [31], [32]. 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. 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 [33]. 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 [34] or the intermediate state changes can be predicted by AI models. Finally, AI models can be used as surrogate models for power system analysis [35] and control [36]. 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 [37]. The dynamic link library file PSOPS.so and the open-source Python API can be found in a repository called Py_PSOPS on 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 with C++ based on previous studies [38], [39], [40], and [41]. The Eigen library [42] and the LibTorch library [43] are used to realize neural network supportability. As for the Eigen library, 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 [44], whereas the neural modules saved by PyTorch, i.e., both the structures and the parameters, can be directly loaded for the LibTorch library.

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 [45] is adopted in PSOPS due to its simplicity, reliability, and robustness [28].

\[
\begin{align*}
\mathbf{x} &= \mathbf{f}(\mathbf{x}, \mathbf{V}) \\
\mathbf{Y}'\mathbf{V} &= \mathbf{I}'(\mathbf{x}, \mathbf{V})
\end{align*}
\]

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 [45], [28]. 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

The Approximate Minimum Degree, Minimum Number of Source Predecessors (AMD-MNPS) algorithm [38] 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 [38] 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

At the algorithmic level, a fully parallel BBDF method [39] and a fully parallel nested BBDF method [40] 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 [41] 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 computation-intensive and memory-intensive task. 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 [46] 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 Sugon I950r-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.

| 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
As mentioned before, when using the Eigen library, the structure of neural networks can be 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. When using the LibTorch library, the whole neural model can be established by directly loading the modules saved by PyTorch.

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, currently, 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. The simulated power system 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 re-organizing the external functions loaded from the dynamic link library into a NumPy [47] style. The source code is organized in a component-based manner, which means the functions of the same kind of component are put together. The Python API can be extended easily to fulfill the needs in different situations. A more well-rounded API will be a future working direction.

IV. CASE STUDIES
In this section, four typical cases of utilizing the prototype, namely, sample generation, spatiotemporal graph convolutional networks (STGCN)-based stability prediction, neural ODE-based dynamic modeling [48], and RL-based stability-constrained optimal power flow (SOPF), are demonstrated to show the simulator-AI interactions based on Py_PSOPS, as shown in Fig. 3. All four cases are supported by at least one paper or open-source code we developed on GitHub. 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
1) Step-wise Power Flow Sampling Scheme
Sample generation is one of the most basic applications of Py_PSOPS and can be used for any AI application. It is supported by the rapid simulation speed of PSOPS. As for power flow sampling, simple random sampling, grid sampling, and a step-wise sampling scheme are implemented. We implemented the scheme and the source code of sample generation can also be found on GitHub https://github.com/xhh0523/Py_PSOPS.

The step-wise scheme is shown as follows.

| Step-wise Power Flow Sampling Scheme |
|-------------------------------------|
| Input \( N \) (the total number of required samples). |
| set \( n = 1 \) |
| while \( n < N \) : |
| \( P_a \) and \( Q_a \) within their upper and lower limits. |
| Calculate \( \sum(\cdot) \). |
| Simple random sampling of \( P_a \) within their upper and lower limits |
| until \( \sum(\cdot) \). |
| Simple random sampling of \( V_c \) |
| if power flow calculation converges: |
| save \( (P_a, V_c) \). |
| \( n \leftarrow n + 1 \) |

where \( P_a \) and \( Q_a \) are the active power vector and reactive power vector of loads, respectively, \( \sum(\cdot) \) denotes the sum of elements in the vector, \( P_a \) is the active power vector of generators, \( P_{\text{low}} \) and \( P_{\text{up}} \) are the upper limit vector and the lower limit vector of slack generators, \( V_c \) 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) Test Results
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
This is a typical example of simulation-assisted AI. The simulator provides training data as well as prior knowledge to support AI model design.

1) STGCN
An STGCN-based stability prediction model is designed and implemented in our previous work [49]. The implementation is supported by the network topology accessibility of Py_PSOPS. The STGCN network structure is shown in Fig. 4. The input features include \( Y_0 \), \( Y_1 \), and \( Y_2 \), i.e., the admittance matrices before the fault, during the fault, and after clearing the fault,
respectively, which can be obtained via the solution API, and 
\( f_0, f_1, \ldots, f_T \), 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 
\( t = t_1 \). The output of the model is the stability label of the input 
cases. As can be seen, only a very short-time simulation is 
performed and the efficiency of stability analysis can be 
improved. Meanwhile, STGCN can extract features from the 
temporal topology changes during the fault and learn the 
correlation of these changes with power system stability, leading 
to an accuracy improvement as well.

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

Fig. 4. The architecture of the STGCN model.

2) Test Results

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. Each time of STGCN-based stability prediction 
averagely cost 5 milliseconds, whereas the complete simulation 
averagely cost 25 milliseconds.

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

Fig. 5. Results of STGCN、CNN、LSTM、MLP models.

C. 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.

1) Neural ODE Module for Power System Dynamic Modeling

A simple introduction of the neural ODE-based dynamic 
modeling method, which is one of our previous studies [50], 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).

\[
f(x, V) = x = f_\theta(x, V; \theta)
\]

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 \( x \).

2) Test Results

We developed the source code of common neural ODE 
modules for power system dynamic modeling and published it 
on GitHub [54]. These neural modules provide basic tools for power system 
differentiable physics-based modeling, pure data-driven 
modeling, and physics-data-integrated modeling. We use the 
modules to establish 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 
normal dynamic model is obtained. The neural model is 
integrated into the simulator via the LibTorch Library. The 
comparison between the simulation results obtained with 
the original classic generator model and the trained neural model is 
shown in Fig. 6.

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

Fig. 6. Comparison results of the classic generator model and the neural 
generator model.

D. RL-based SOPF

This is an example of the simulator and AI mutually 
supporting each other.

1) Framework Design

SOPF is one of the traditional control 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 [51]. [52]. RL can 
solve this problem in a simulation-based optimization manner. 
The simulator-based environment and the AI-based agent form 
an interactive mechanism by exchanging rewards and actions. 
With the support of Py_PSOPS, an RL environment for solving 
SOPF based on OpenAI Gym [53] can be established. The target 
is to minimize the total generation cost. We use the twin-delayed 
deep deterministic policy gradient (TD3) algorithm [54] to train
the agent. The framework of RL-based SOPF can be found in Fig. 7. A similar framework of RL-based optimal power flow (OPF) has been proposed in [55] using PSOPS. We further implemented the RL-based SOPF with Py_PSOPS based on this OPF solution method by considering the dynamic security constraints when calculating reward.

**Fig. 7.** The framework of RL-based SOPF.

2) **Test Results**

The training process is demonstrated in Fig. 8. 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 generating strategy and performing 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.

**Fig. 8.** The training process of the agent with the TD3 algorithm.

V. CONCLUSION

To conclude, based on the illustration of the interaction mechanism between power system dynamic simulations and AI, an AI-oriented power system transient stability simulator called Py_PSOPS is designed, implemented, tested, and made public. Although it is currently an exploration of AI-oriented power system dynamic simulations, the four test cases demonstrate promising capabilities of Py_PSOPS to support the development of AI-assisted simulations and simulation-assisted AI applications in power system stability analysis and control. It should be noted that the Python API is still under development. As can be seen, some API functions are realized by modifying the basic computation data file. The development of Py_PSOPS will continue in the future.

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