Application of Machine Learning to Power Grid Analysis

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Agenda

- Introduction
- Open Platform for Applying Machine Learning (ML)
- Power Grid Model Service
- Research on Applying ML to Online DSA
- ML Research Roadmap of CEPRI
Why ML Research Again?

- AlphaGo Showcase – “impossible for at least 10 more years”
- "Artificial Intelligence is the New Electricity“ – Andrew Ng
- Open-source ML tools (Google TensorFlow\(^{[1]}\))

Basic Idea

In power system steady-state analysis, the problem usually can be formulated as to solve a set of non-linear equations, as shown below:

\[ y = f(x) \quad x, y \in \mathbb{R}^n \quad (1) \]

The non-linear equation is commonly solved by some numerical method, such as Newton-Raphson for loadflow analysis.
ML Application Areas

- Image Recognition
- Self Driving Car
- Automation
- Robotics
- **Predictive Analytics**
  - Power grid analysis has been guiding the operation successfully
  - Power grid analysis so far is model-driven
  - Data-driven ML approach will be supplemental
Agenda

• Introduction
• **Open Platform for Applying Machine Learning**
• Power Grid Model Service
• Research on Applying ML to Online DSA
• ML Research Roadmap of CEPRI
NN Model Training Data

• ML Main Steps: 1) Training; 2) Prediction
  – Training data is the foundation for ML

• Training data set collection
  – Large user data set collected by Google, Facebook

• Training data set generation
  – Power grid operation depends on the simulation
    • Guide the grid operation with proven record
    • Contingency analysis could be done only through simulation
  – Need grid analysis training data generation tools/platforms

• Open Platform for Application of ML to Power Grid Analysis has been created
Sample Study Case

- IEEE-14 Bus case as the basecase. Power is flowing from the Gen Area to the Load Area. When the operation condition changes, predict:
  - Bus voltage, P, Q
  - Interface flow
  - N-1 CA max branch power flow

Training Case

- Load bus P,Q adjusted by a random factor [0~200%], load Q is further adjusted by random factor [+/-20%]
- The load changes are randomly distributed to the generator buses
Bus Voltage Prediction
(AC Loadflow)

• AC Power Flow
  – Given bus PQ, compute bus voltage (mag, ang), such that max bus power mismatch (dPmax, dQmax) < 0.0001 pu
  – 1000 training data sets are generated and used to train the NN-model
    • Input: bus P, Q, P²
    • Output: bus voltage, ...

• Prediction Using NN-Model
  – 100 testing cases are generated using the same process as the training data set.
  – The trained NN-Model is used to predict the bus voltage

<table>
<thead>
<tr>
<th></th>
<th>dV(mag)</th>
<th>dV(ang)</th>
<th>dPmax</th>
<th>dQmax</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>0.00118 pu</td>
<td>0.00229 rad</td>
<td>0.00937 pu</td>
<td>0.00619 pu</td>
</tr>
<tr>
<td>Average</td>
<td>0.00028 pu</td>
<td>0.00055 rad</td>
<td>0.00225 pu</td>
<td>0.00171 pu</td>
</tr>
</tbody>
</table>

dV(msg,ang): Bus voltage predicted is compared with the accurate AC Power Flow results
dP/Qmax: Bus voltage predicted is used to compute the network max bus power mismatch
Bus/Interface PQ Prediction
(AC Loadflow)

• Bus P, Q
  – Swing Bus P, Q prediction (100 testing cases)
    • Average difference : 0.00349 pu 0.35 MW/Var
    • Max difference: 0.01476 pu 1.48 MW/Var
  – PV Bus Q prediction (100 testing cases)
    • Average difference : 0.00353 pu 0.35 MVar
    • Max difference: 0.02067 pu 2.07 Mvar

• Interface Flow
  – Interface branch set [5->6, 4->7, 4->9]
  – Interface Flow P,Q prediction (100 testing cases)
    • Average difference : 0.00084 pu 0.08 MW/Var
    • Max difference: 0.00318 pu 0.32 MW/Var
Max Branch Power Flow Prediction

(N-1 CA)

• N-1 Contingency Analysis (CA)
  – In N-1 CA, the branch power flow is calculated when there is a branch outage. Furthermore, the max branch flow of each branch considering all contingencies to check limit violation or for screening.
  – 1000 training data sets are generated and used to train the NN-model
    • Input: bus P, Q, P^2
    • Output: max branch power flow

• Prediction Using NN-Model
  – 100 testing cases are generated using the same process as the training data set.
  – Max branch power flow prediction is compared with the accurate simulation results
    • Average difference : 0.0134 pu 1.34 MW
    • Max difference: 0.0509 pu 5.09 MW
Open Platform for Application of ML to Power Grid Analysis

(Summary)

• Integration of Google TensorFlow and InterPSS\(^2\)
  – TensorFlow as ML engine
  – InterPSS
    • Provides power grid simulation model service
    • Pluggable training data generator

• The Platform has been open-sourced
  – Apache-2.0 License

\(^2\) “The InterPSS Community Site”, www.interpss.org
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Power Grid Model Service

• The Need For Creating the Training Data
  – Power grid measurement data is not enough
  – Training data for security analysis need to be created
    • N-1 CA, transient/voltage stability limit

• Valid NN Model Prediction Accuracy
  – Common ML Approach
    • Collected Data set => Training set + Testing set
  – Model service creates data on-demand randomly or according certain rules

• Based on InterPSS Simulation Engine
  – Accurate power grid simulation model behind
About InterPSS

“Solving power grid simulation problem using the modern software approach”[3]

• InterPSS: Internet Technology-based Power System Simulator

• InterPSS project started in 2005
  – Object-oriented, Java programming language
  – PSS/E, BPA, PSASP (China EPRI) similar functions
  – Free software

InterPSS Software Architecture

Traditional Approach
Little could be extended and customized

InterPSS Approach
Application created by extension, integration and customization

**Power Network Object Model**

- **Data Processing Patterns**
  - **Algorithm-focused pattern**
    - Procedure programming approach
    - PSS/E, BPA, PSASP (China EPRI) based on this pattern
  - **Model-focused pattern**
    - Object-oriented approach

- **InterPSS uses the Model-Focused Pattern**

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Training Case Generation

- Object and Algorithm Decoupled Relationship
- Common Algorithm Implemented
  - Topology Analysis, Loadflow, N-1 CA, State Estimation
  - Short Circuit Analysis, Transient Stability Simulation
- Training Data Generator
  - Training data generation implemented as a special algorithm
  - Use Py4J\[6\] as the runtime to host the object model and interface with TensorFlow (Python)

Power Grid Model Service

(Summary)

• Based on InterPSS Simulation Engine
• Provide Flexible Power Grid Model Service
  – InterPSS power network model hosted in a Java runtime environment
  – Pluggable training data generator
    • Create custom training data generator using InterPSS power network object model API
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DSA Challenges[7]

• Current Dynamic Security Assessment (DSA)
  – Repackage of off-line simulation programs (TS, Small-signal)
  – Running in the batch mode periodically (15 min)
  – In China State Grid dispatching center, a round trip takes 6-10 min to complete
  – The online analysis model size is large-scale (40K buses)

• Challenges
  – The time-domain simulation has limited speed-up room
  – The simulation results are not intuitive for the operators
  – Remedy actions cannot be directly derived from the results

CCT Prediction

• Critical Clearing Time (CCT)
  – Maximum time during which a disturbance can be applied without the system losing its stability.
  – Determine the characteristics of protections
  – Measure quantitatively system dynamic security margin

• CCT Computation
  – ~100 sec using the simulation approach (40K Bus)
  – ML-based approach: using Neural Network (NN) model to predict CCT
• NN-Model (per contingency) is constructed (trained) for the CCT prediction;
• NN-Model input (First Layer Features): power grid measurement info, such as Gen(P, V); Substation (P,Q), and z(i,j) between substations;
• A set of Last Layer Features are derived and used for CCT Prediction.
Preliminary Results

<table>
<thead>
<tr>
<th>Network Size</th>
<th>40K+ Buses, 3370 Substations</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN-Model Output</td>
<td>CCT for a Fault</td>
</tr>
<tr>
<td>First Layer Features</td>
<td>Gen (P, V); Substation(P, Q); Z_{i,j} between substations; (Dimension : 8772)</td>
</tr>
<tr>
<td>Last Layer Features</td>
<td>About 20</td>
</tr>
<tr>
<td>Feature Reduction</td>
<td>Basic NN unit: AutoEncoder</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CCT Calculation</th>
<th>Average error</th>
<th>Max error</th>
<th>Training case</th>
<th>Testing case</th>
<th>Time NN-Model</th>
<th>Time Simulation</th>
<th>Acc Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>A Fault</td>
<td>2.65%</td>
<td>28.69%</td>
<td>24594</td>
<td>4660</td>
<td>2ms</td>
<td>~100s</td>
<td>1:50000</td>
</tr>
</tbody>
</table>
Basic NN unit: AutoEncoder

“The aim of an AutoEncoder is to learn a representation (encoding) for a set of data, typically for the purpose of dimensionality reduction.”

• About 30 min training time (one GPU, 40K-bus network)
• NN Model Input (First Layer Features)
  – Gen P, V; Substation P, Q; Z_{i,j} between substations (total 8K+ variables)
  – The goal is let AI to select through training a set of last layer features (artificial) for predicting CCT
• The Current Practice
  – A set of key features (physical, such as interface flow) are selected by human expert to monitor the stability
  – Use physical features or artificial last layer features to determine the security margin?
Potential Benefit

• Speed-up DSA System Response Speed
  – For CCT prediction: 50K times faster (40K-Bus, 2ms vs 100s)

• Produce More Intuitive Results
  – NN model to digest large-scale simulation outcome to create more intuitive results
  – The “lookup” approach is very close to human operator experience

• Enhanced Decision Support
  – NN model turns/reduces First Layer Features (P, Q, V) to Last Layer Features
  – Use the Last Layer Features to compare the current case with history simulation cases to identify “similar cases”
  – If remedy actions are needed for the current case, they could be found in the similar history simulation cases.
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ML Research Roadmap(1)

- **New super simulation center** (China State Grid)
  - Massive processing power (750 Blades, 20K cores)
  - Massive storage room (2.4 PB, ~2M cases)
  - Production support for State Grid dispatching centers in China

- **Training data set**
  - Collect real-world simulation cases and results
  - Based on the human experience to generate more scenarios based on the recorded history operation cases
  - Use to train NN-models for the predictive analysis
ML Research Roadmap(2)

• Simulation result processing
  – The new simulation center will generate massive simulation result
  – The human experts are not capable to process the result
  – Digest massive simulation results using NN-model
  – Discover knowledge to guide China’s UHV power grid operation
Summary

• AI, especially ML, landscape has been fundamentally changed over the last 5~10 years
  – The development speed is unprecedented
  – Many breaking-through successful stories
• The enabling technologies are accessible to everyone
  – Powerful computing hardware (CPU+GPU)
  – New open source software tools
• The right time to renew/restart research on application of ML to power grid
  – Open collaboration approach is recommended
Thank You

Q&A