<table>
<tr><th rowspan="2">cases</th><th>doc_1</th><th>doc_2</th><th>decision</th><th>id</th></tr>
<tr>
<td>
<table>
<tr><th>authors</th><td>Christian Moya
Guang Lin</td></tr>
<tr><th>title</th><td>DAE-PINN: a physics-informed neural network model for simulating differential algebraic equations with application to power networks</td></tr>
<tr><th>publication_date</th><td>2021-09-09 00:00:00</td></tr>
<tr><th>source</th><td>SupportedSources.SEMANTIC_SCHOLAR</td></tr>
<tr><th>journal</th><td>Neural Computing and Applications</td></tr>
<tr><th>volume</th><td>35</td></tr>
<tr><th>doi</th><td>10.1007/s00521-022-07886-y</td></tr>
<tr><th>urls</th><td>https://www.semanticscholar.org/paper/e6239c8c9ff1c516e2241f66570a3f2e2735990c</td></tr>
<tr><th>id</th><td>id-1606239557483226306</td></tr>
<tr><th>abstract</th><td>None</td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td>
<td>
<table>
<tr><th>authors</th><td>Christian Moya
Guang Lin</td></tr>
<tr><th>title</th><td>DAE-PINN: A Physics-Informed Neural Network Model for Simulating Differential-Algebraic Equations with Application to Power Networks</td></tr>
<tr><th>publication_date</th><td>2021-09-09 14:30:28+00:00</td></tr>
<tr><th>source</th><td>SupportedSources.ARXIV</td></tr>
<tr><th>journal</th><td>None</td></tr>
<tr><th>volume</th><td></td></tr>
<tr><th>doi</th><td></td></tr>
<tr><th>urls</th><td>http://arxiv.org/pdf/2109.04304v1
http://arxiv.org/abs/2109.04304v1
http://arxiv.org/pdf/2109.04304v1</td></tr>
<tr><th>id</th><td>id8794105238381045081</td></tr>
<tr><th>abstract</th><td>Deep learning-based surrogate modeling is becoming a promising approach for learning and simulating dynamical systems. Deep-learning methods, however, find very challenging learning stiff dynamics. In this paper, we develop DAE-PINN, the first effective deep-learning framework for learning and simulating the solution trajectories of nonlinear differential-algebraic equations (DAE), which present a form of infinite stiffness and describe, for example, the dynamics of power networks. Our DAE-PINN bases its effectiveness on the synergy between implicit Runge-Kutta time-stepping schemes (designed specifically for solving DAEs) and physics-informed neural networks (PINN) (deep neural networks that we train to satisfy the dynamics of the underlying problem). Furthermore, our framework (i) enforces the neural network to satisfy the DAEs as (approximate) hard constraints using a penalty-based method and (ii) enables simulating DAEs for long-time horizons. We showcase the effectiveness and accuracy of DAE-PINN by learning and simulating the solution trajectories of a three-bus power network.</td></tr>
<tr><th>versions</th><td></td></tr>
</table>
</td>
<td>NOT DUPLICATES</td>
<td>358</td>
</tr>
</table>