Estimation Of Degree Of Insecurity Of Power System Using Two-Phase Optimization Neural Network

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ABSTRACT: Two-phase optimization neural network has been used to compute the degree of insecurity and the voltages and angles at all the buses of the system corresponding to the closest secure point. Inclusion of security limits on power system variables assures a solution representing a secure system. When compared to conventional non-linear optimization techniques, the proposed neural network is superior, as it does not involve any matrix inversion, can be easily implemented in digital hardware and is highly suitable for real time implementation in energy management system. The proposed model has been tested on IEEE 14-bus test system. The results achieved are compared with results from a conventional method and found to be quite close. Insecurity arising due to increase in load and contingencies has been considered in this work.

I. INTRODUCTION

The increased economic and environmental pressures have forced the power systems to operate closer to their thermal and stability limits. In cases where power-flow solution does not exist or solution exists but the operating point lies in the insecure region, there is a need of determining control actions quickly as otherwise the system may become unstable and move towards voltage collapse [1]. Since insecure cases often represent the most severe threats to secure system operation, it is important that the user be provided with a measure for quantifying the severity of the cases so that corrective actions can be planned to move the system from infeasible to feasible region. A feasible region in a multi-dimensional parameter space can be defined as the set of points where system states are within their limits. The purpose of this paper is to provide a measure of degree of insecurity of power system. The distance (Euclidean norm) in parameter space between an insecure operating point and the closest point on feasible (secure) hyper-surface has been used as a measure of insecurity. The problem has been formulated as a non-linear constrained minimization problem with an objective function defined as one half the square of the power mismatches to find the closest secure point on feasible (secure) hyper-surface. Voltages and angles at the buses are taken as variables of the problem. Conventional optimization methods for solving these problems require more CPU time and therefore are unsuitable for on-line applications. The proposed method is very promising for on-line application in power system as it can be implemented using fast transputers.

II. PROBLEM FORMULATION

The distance (Euclidean norm) in parameter space between an infeasible (insecure) point and the closest point on feasible (secure) hyper-surface has been used as a measure of insecurity. For an N -bus system with bus-1 being slack, 2 to N_s being the PV type buses and N_s+1 to N the PQ buses, the power flow equations can be and expressed as

\[ f_p (V, \delta) = \sum_{i=1}^{N} V'_{i} [G_{ii} \cos(\delta_{i} - \delta_{i}) + B_{ii} \sin(\delta_{i} - \delta_{i})]\]  

for \( i = 2, ..., N \) \hspace{1cm} (1)

\[ f_Q (V, \delta) = \sum_{i=1}^{N} V'_{i} [G_{ii} \sin(\delta_{i} - \delta_{i}) - B_{ii} \cos(\delta_{i} - \delta_{i})] \]  

(2)
for $i = N_q + 1, \ldots, N$

Where $V$ and $\delta$ are voltage magnitude and angle vector respectively. If $S$ is a vector of real power injections at all the buses except the slack bus and the reactive power injections at only load buses, then (1) and (2) can be written in vector form as following

$$S - f(V, \delta) = 0$$

where $S = [P_i, Q_i]^T, i = 2, \ldots, N$ and $j = N_q + 1, \ldots, N$ (3)

If the power flow problem, defined by (3) has no real solution or it has a solution with violating operating limits, the system operation becomes infeasible and corrective control actions are necessary to restore the system variables back to the secure region. The problem has been formulated as a constrained minimization problem with an objective function defined as half the square of the power mismatches to find the closest feasible point in parameter space and is expressed as:

Minimise

$$F(V, \delta) = \frac{1}{2} \{f(V, \delta) - S\}^T \{f(V, \delta) - S\}$$

subject to the operating constraints,

$$V_{i_{\text{min}}} \leq V_i \leq V_{i_{\text{max}}} \quad \text{for } i = 2, \ldots, N$$

$$|\delta_i - \delta| \leq \delta_{\text{max}} \quad \text{for } i = 2, \ldots, N$$

$$QG_{i_{\text{min}}} \leq QG_i \leq QG_{i_{\text{max}}} \quad \text{for } i = 2, \ldots, N_q$$

where $QG_i$ is the reactive power generation of $i$th source.

The above equations (4) to (7) form a constrained power flow problem. The closest point on the surface $\sigma$ to $S$ is $S^*$. The degree of insecurity can be measured by Euclidean distance [2] between the closest point on the surface $\sigma$ and $S$, which is given by

$$d(S) = ||S^* - S||$$

$$= \sqrt{(S^* - S)^T (S^* - S)}$$

III. METHODOLOGY

To solve the constrained non-linear optimization problem, the objective function and constraints are mapped into the neural network. For solving the problem,

Minimise $f(x)$, subject to the constraints $g_j(x) \leq 0$.

A lagrange's function is defined as

$$L(s, x) = F(x) + \frac{s}{2} \sum_{j=1}^{r} \left[ g_j(x) \right]^2$$

Where $s$ is a constant penalty parameter and $g_j(x) = \max\{0, g_j(x)\}$; i.e., $g_j(x)$ is the magnitude of violation of the $j$th constraint in the problem. Differentiating with respect to time we get,

$$\frac{dl}{dt} = \sum_{i=1}^{n} \frac{\partial L}{\partial x_i} \frac{dx_i}{dt}$$

$$= \left[ x^T \right] \left[ \nabla f + s \nabla g \right]$$

Where

$$\left[ x^T \right] = \left[ \frac{dV}{dt}, \quad \frac{dV}{dt}, \quad \frac{d\delta}{dt}, \quad \frac{d\delta}{dt}, \quad \cdots, \quad \frac{d\delta}{dt} \right]$$

$(V$ and $\delta$ represent the voltage and angle at the n buses of the power system respectively and represent the optimization variables)

and $\nabla g_j$ is a matrix of the gradients of the constraints whose elements are given by

$$\frac{\partial g_j}{\partial x_i}$$

$$i = 1, 2, \ldots, n \quad \text{and} \quad j = 1, 2, \ldots, r$$

$$[g_j] = [g_1, g_2, \ldots, g_r]$$

To map the objective function and constraints of the problem into a closed neural network, the bracketed part of
the equation (11) is substituted by \(-[x]\) and the following phase-one network dynamics is obtained.

\[
[x] = -[\nabla f] - s[\nabla g_j, g_j^*]
\]  
(16)

The network has two types of neurons, the upper one is the integrator and the lower one is the constraint qualifier. The network satisfies phase-one dynamics of equation, and equation (11) becomes

\[
\frac{dl}{dt} = -[x] \cdot [x] \leq 0
\]  
(17)

The equality holds good only at equilibrium. Thus the Lagrange's energy function \(L(s, Q)\) is a qualified Lyapunov function [4] of equation (16). The energy of the network continuously decreases until it attains a minimum at equilibrium and then the states of the neurons are taken to be the minimizers of the Lagrange's function.

**Phase-2 network dynamics**

The two-phase neural network (TPNN) is a dynamic system, which converges to a minimum of \(L(s, x)\) only at \(s = x^*\) [5]. For a finite value of \(s\), the function \(f(s)\) at the equilibrium of the \(L(s, x)\) is always less than the value calculated at the exact solution and implies constraint violation particularly if the solution of \(f(s)\) lies on the boundary of the solution space. In phase-one whenever constraint violation occurs, its magnitude and direction are fed back to adjust the states of the neurons. This brings the problem variables close to the boundary of the feasible region. In the following second-phase network dynamics the directional vector of the constraints is gradually replaced by the corresponding Lagrange multipliers and this moves the solution trajectory to the feasible region. The overall energy of the network continuously decreases until it attains a minimum. The states of the neurons are taken to be the minimizers of the optimization problem [3,4,5]. The block diagram of two-phase network is shown in figure 1.

The operating dynamics of the network are changed with a predetermined timing switch. For \(0 \leq t \leq t_1\) the network operates according to the following dynamics

\[
[x] = -[\nabla f] - s[\nabla g_j, g_j^*]
\]  
(18)

This is phase one dynamics already described by (16). When time \(t \geq t_1\), the dynamics of the network becomes

\[
[x] = -[\nabla f] - [\nabla g_j, \nabla g_j^*] + [\lambda]
\]  
(19)

\[
[\dot{\lambda}] = \varepsilon[\nabla g_j^*]
\]  
(20)

where

\[
[\lambda] = \lambda_1, \lambda_2, \ldots, \lambda_r
\]  
(21)

and

\[
[\dot{\lambda}] = \begin{bmatrix}
\frac{d\lambda_1}{dt} & \frac{d\lambda_2}{dt} & \ldots & \frac{d\lambda_r}{dt}
\end{bmatrix}
\]  
(22)

\(\lambda\) is a vector of Lagrange multipliers associated with inequality constraint vector \(g_j\) and \(\varepsilon\) is a small positive
constant. The initial values of vector $\lambda$ are set to zero. At equilibrium $g_j^* = 0$ and $\lambda \leq 0$ and the network satisfies the optimality conditions of the K-T theorem. Thus the equilibrium point of the two-phase neural network (TPNN) is precisely a global minimizer to a convex problem. In phase one ($t < t_1$), for a sufficiently large value of penalty parameter $s$, equation (16) converges to an equilibrium $x^*$ i.e. $(v^*, \delta^*)$ at which $sg_j^*(x)$ are very close to the corresponding lagrange multipliers $\lambda$. In phase two $(t \geq t_1)$ the network shifts the directional vector $sg_j^*(x)$ slowly towards $\lambda$. Hence equations (19,20) attain a minimum of the augmented lagrange's function, given by,

$$L_o(s, x) = f(x) + \sum_{j=1}^{S} \lambda_j g_j^* + \frac{s}{2} \sum_{j=1}^{S} \left[g_j^*(x)\right]^2$$  \hspace{1cm} (23)

The cost term $f(x)$ is minimized during the transient state and the rest of the terms of (19) prevent any constraint violation.

**TABLE I**

IEEE 14-BUS SYSTEM, LOAD VARIATION

<table>
<thead>
<tr>
<th>Method</th>
<th>Degree of Insecurity</th>
<th>CPU Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPNN</td>
<td>0.738 p.u.</td>
<td>0.26 sec.</td>
</tr>
<tr>
<td>SQP</td>
<td>0.749 p.u.</td>
<td>1.30 sec.</td>
</tr>
</tbody>
</table>

**TABLE II**

VOLTAGES AND ANGLES FOR LOAD VARIATION

<table>
<thead>
<tr>
<th>Bus</th>
<th>$V^*$</th>
<th>$\delta^*$</th>
<th>Bus</th>
<th>$V^*$</th>
<th>$\delta^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.060</td>
<td>0.000</td>
<td>8</td>
<td>1.017</td>
<td>-0.15</td>
</tr>
<tr>
<td>2</td>
<td>1.033</td>
<td>-0.098</td>
<td>9</td>
<td>1.043</td>
<td>-0.25</td>
</tr>
<tr>
<td>3</td>
<td>0.965</td>
<td>-0.27</td>
<td>10</td>
<td>1.031</td>
<td>-0.26</td>
</tr>
<tr>
<td>4</td>
<td>1.033</td>
<td>-0.24</td>
<td>11</td>
<td>1.028</td>
<td>-0.25</td>
</tr>
<tr>
<td>5</td>
<td>1.092</td>
<td>-0.23</td>
<td>12</td>
<td>1.013</td>
<td>-0.26</td>
</tr>
<tr>
<td>6</td>
<td>1.011</td>
<td>-0.19</td>
<td>13</td>
<td>1.022</td>
<td>-0.26</td>
</tr>
<tr>
<td>7</td>
<td>1.055</td>
<td>-0.22</td>
<td>14</td>
<td>1.018</td>
<td>-0.28</td>
</tr>
</tbody>
</table>

**IV. SIMULATION RESULTS**

The proposed model has been tested on IEEE 14-bus test system on a 333 MHz Intel Pentium processor based PC. Insecurity arising due to (i) load variation (case A) as well as (ii) contingencies (case B), has been considered in this work. **Case A**

Real and reactive loads at all the buses were randomly varied between 0.50 to 3.0 pu of the base loading. Voltage and angle at the slack bus were kept constant at their specified values, while voltages and angles at other buses were taken as variables. The degree of insecurity arising due to load variation was computed. The upper limit for voltages at all other buses except the slack bus was taken as 1.1 pu while the lower limit was 0.95 p.u.. The angle limit $|\delta_i - \delta|$ was constrained to be less than 15 degree. The degree of insecurity computed by the proposed model and successive quadratic-programming (SQP) algorithm, along with the values of the voltages and angles at the buses is listed in Table-I and Table-II. respectively. It can be observed that the results obtained by the TPNN are very close to the results of the SQP method and its speed of convergence is much higher. **Case B**

The degree of insecurity has also been computed for single line contingency cases keeping loading fixed at the base value. The results of a few cases are listed in Table-III. Voltages and angles corresponding to the closest secure point are listed in Table-IV.

**TABLE III**

OPTIMIZATION RESULTS FOR CONTINGENCIES

<table>
<thead>
<tr>
<th>Line Outage</th>
<th>Degree of insecurity p.u.</th>
<th>CPU Time seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>From</td>
<td>To</td>
<td>TPNN</td>
</tr>
<tr>
<td>1</td>
<td>8</td>
<td>0.206</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0.255</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>0.201</td>
</tr>
<tr>
<td>4</td>
<td>12</td>
<td>0.192</td>
</tr>
<tr>
<td>7</td>
<td>5</td>
<td>0.191</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>0.199</td>
</tr>
</tbody>
</table>
TABLE IV
POST-OPTIMIZATION VOLTAGES AND
ANGLES FOR THE IEEE 14-BUS SYSTEM

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>Outage of line (1-8)</th>
<th>Outage of line (4-12)</th>
<th>Outage of line (2-8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$V'$ p.u.</td>
<td>$\delta^*$ rad.</td>
<td>$V'$ p.u.</td>
</tr>
<tr>
<td>1</td>
<td>1.06</td>
<td>0.000</td>
<td>1.060</td>
</tr>
<tr>
<td>2</td>
<td>1.00</td>
<td>-0.11</td>
<td>1.043</td>
</tr>
<tr>
<td>3</td>
<td>0.98</td>
<td>-0.27</td>
<td>1.01</td>
</tr>
<tr>
<td>4</td>
<td>1.05</td>
<td>-0.28</td>
<td>1.03</td>
</tr>
<tr>
<td>5</td>
<td>1.04</td>
<td>-0.25</td>
<td>1.09</td>
</tr>
<tr>
<td>6</td>
<td>0.98</td>
<td>-0.23</td>
<td>1.012</td>
</tr>
<tr>
<td>7</td>
<td>1.02</td>
<td>-0.26</td>
<td>1.052</td>
</tr>
<tr>
<td>8</td>
<td>0.98</td>
<td>-0.22</td>
<td>1.013</td>
</tr>
<tr>
<td>9</td>
<td>1.02</td>
<td>-0.28</td>
<td>1.034</td>
</tr>
<tr>
<td>10</td>
<td>1.02</td>
<td>-0.28</td>
<td>1.023</td>
</tr>
<tr>
<td>11</td>
<td>1.03</td>
<td>-0.28</td>
<td>1.016</td>
</tr>
<tr>
<td>12</td>
<td>1.04</td>
<td>-0.28</td>
<td>0.956</td>
</tr>
<tr>
<td>13</td>
<td>1.03</td>
<td>-0.28</td>
<td>0.987</td>
</tr>
<tr>
<td>14</td>
<td>1.01</td>
<td>-0.29</td>
<td>0.991</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

- Under stressed or contingency cases the system variables do not remain within their limits and the operation tends to become unstable if control actions are not implemented fast.
- The present method computes the distance between an insecure operating point and its closest secure point by minimizing the active and reactive power mismatches.