Support Vector Machine based Approach for State Estimation of Iraqi super Grid Network

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Abstract

The correct assessment of network topology and system operating state in the presence of corrupted data is one of the most challenging problems during real-time power system monitoring, particularly when both topological and analogical errors are considered. This paper deals with Support Vector Machine method for state estimation problem in power systems including estimation and detection, which can help to improve Iraqi super grid electrical power network state estimation. The results of state estimation using the Support Vector Machine (SVM) and the conventional weighted Least Squares (WLS) State Estimator on basis of time, accuracy and robustness, particularly when both bad data and topological errors are to be considered. It has been established that the SVM based models provide results much faster, and work well even including single and multiple bad measurements, topology branches errors.

1. Introduction

Power system state estimation (PSSE) is one of the important functions executed in energy control centers in order to provide an accurate real-time database to be used by application programs, such as: economic dispatch, security analysis, etc. The system operator has to make, equitable, security related, congestion management decisions to curtail or deny power transfer rights in real time. Fast and accurate state estimation is foundation of locational marginal Pricing methodologies for transmission management costing.

Many power system state estimation (PSSE) methods are available today for the power system industry [1]. Most of the state estimation problems are formulated as over determined system of non-linear equations and solved as a weighted least squares problem. The Weighted Least Squares Estimation is by far the most popular approach in industry [2][3]. The state of the art in state estimation algorithms is presented in [4][5]. Most of the practical implementation of state estimation in electric power systems is based on the Gauss Newton methods. Singh and Alvarado [6] have formulated a topology processing similar to the state estimator algorithm and have solved it using the least absolute value (LAV) method. Singh and Glavitsch [7] used a rule based approach. Although these methods usually perform very well under normal operating conditions (when noisy data corresponds mainly to meters inaccuracies), this is not the case when large measurement errors or topology configuration errors are to be processed. Other methods based on the application of intelligent systems for the analysis of the raw measurements have been proposed [8-10]. However, the dependency of raw measurements on the operating conditions may impose serious difficulties for obtaining representative patterns for the different types of error. Bad data identification is then a very complex and not adequately solved problem during PSSE. Alves da Silva et al. [11] used a neural network based on a multilayer perceptrons model and optimal estimate training to determine network topology.

In this work an original application of Support Vector method (SVM) for state estimation is proposed. The Support Vector method (SVM) is a general method of function estimation which does not depend explicitly on the dimensionality of the problem. The proposed estimator is studied for various cases to show its utility for state estimation in terms of accuracy and time requirements. Test results with a configuration of Iraqi super Grid Network are presented. Aspects such as efficiency, robustness, generalization capability and computational implementation of the proposed method for large-scale systems are also discussed.

2. The Iraq power system description

The transmission level in the Iraqi electrical network consists of the 400Kv network (the super grid network) and part of the 132 kV network connected to it. The aim of this work is limited to the study of only the 400Kv network with all its bus-bars and transmission lines. The network under consideration consists of 19 Bus and 30 transmission lines; the total length is 3711 Km. Fig.1 shows a configuration of this network.

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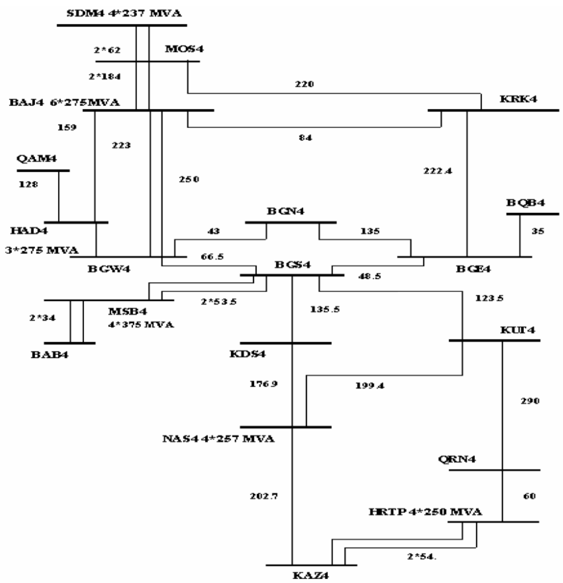

Fig.1.:Iraqi super Gird network"

3. State estimator

The state estimation provides the real time representation of the conditions in a power network. A state estimator is a data processing algorithm, which transforms meter readings and the switch status information into an estimate of the system's state (voltage magnitudes and phase angles at all the nodes). Real and reactive bus power injections, and real and reactive line flows and bus voltage magnitudes are the measurements, which are transmitted to computer control system via telemetry system. These measurements contain random noise due to instrument and phenomenon errors. The state estimation program obtains a best fit for the power system state variables by minimizing these errors. Ideally state estimation should run at the scanning rate of the telemetry system (say at every two seconds). Due to computational limitations, most practical state estimators run every few minutes or when major changes occur.

3.1. WLS State estimator

Most state estimation programs in practical use are formulated as over determined systems of nonlinear equations and solved as WLSE problem. Consider the nonlinear measurement model

$$z_j = h_j(x) + e_j \tag{1}$$

Where

zj is the *jth* measurement,

x is the true state vector,

hj(x) is a nonlinear scalar function relating the *jth* measurements to states, and

ej is the measurement error, which is assumed to have zero mean and variance σ_j^2.

The WLS state estimation can be formulated mathematically as an optimization problem with a quadratic objective function and with equality and inequality constraints

$$\min\ j(x) = \frac{1}{2}\sum_{j=1}^{m}(z_j - h_i(x))/\sigma^2)$$

$$\text{Subject to } g_i(x) = 0; \quad i = 1, n_g$$

$$c_i(x) = 0; \quad i = 1, n_g \tag{2}$$

is an objective function, and $g_i(x)$and $c_i(x)$ are the functions representing power flow quantities.

The expressions for each of the above types of measurements can be expressed as follows:.

* Real and reactive power injection at bus i :

$$P_i = V_i \sum_{j\in N_i} V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right)$$

$$Q_i = V_i \sum_{j\in N_i} V_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos{}_{ij}\right)$$

* Real and reactive power flow from bus i to bus j

$$P_{ij} = V_i^2\left(g_{si} + g_{ij}\right) - V_iV_j\left(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}\right)$$

$$Q_{ij} = -V_i^2\left(b_{si} + b_{ij}\right) - V_iV_j\left(g_{ij}\sin\theta_{ij} - b_{ij}\cos\theta_{ij}\right)$$

Where

$V_{i,}\theta_i$ is the voltage magnitude and phase angle at bus i .

$\theta_{ij} = \theta_{i-}\theta_j$

$G_{ij} + jB_{ij}$ is the $ijth$ elements of the complex bus admittance matrix.

3.2. Least squares support vector machine (LS-SVM)

One of the drawbacks of SVMs is tedious computation in the training phase due to the quadratic optimization problem. Suykens & al.[12] have reformulated the standard SVMs to avoid this problem and developed Least Squares Support Vector Machines (LS-SVM). The solution can be found efficiently by iterative methods such as conjugate gradient algorithm. LS-SVMs do not lead sparse solutions such as SVMs but a solution for the optimization problem is found very fast, and pruning techniques can be easily applied to enhance the sparsity.

LS-SVM algorithm is derived in a following way [12]. The estimation problem can be solved from optimization problem with equality constraints:

$$\min_{w,b,e} J(\mathbf{w}, b, e) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \gamma\frac{1}{2}\sum_{i=1}^{M} e_i^2$$

$$\text{subject to } y_i[\mathbf{w}^T\varphi(\mathbf{x}_i) + b] = 1 - e_i,\ i = 1, \ldots, M \tag{3}$$

ei denotes the error in the estimation of the sample xi. One defines the Lagrangian:

$$L(\mathbf{w},b,\mathbf{e};\alpha) = J(\mathbf{w},b,\mathbf{e}) - \sum_{i=1}^{M} \alpha_i \left\{ y_i \left[\mathbf{w}^T \varphi(\mathbf{x}_i) + b \right] - 1 + e_i \right\} \quad (4)$$

where αi are Lagrange multipliers, which can be either positive or negative due to equality constraints. The conditions for optimality can be written as the solution to the following set of linear equations:

$$\begin{bmatrix} \mathbf{I} & 0 & 0 & -\mathbf{Z}^T \\ 0 & 0 & 0 & -\mathbf{Y}^T \\ 0 & 0 & \gamma \mathrm{I} & -\mathbf{I} \\ \mathbf{Z} & \mathbf{Y} & \mathbf{I} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{w} \\ b \\ \mathbf{e} \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vec{1} \end{bmatrix} \quad (5)$$

where $\mathbf{Z} = (\varphi(\mathbf{x}_1)^T y_1, ., \varphi(\mathbf{x}M)^T y_M)^T$, $\mathbf{Y} = (y_1, ., y_M)^T$, $\vec{1}=(1, ..., 1)^T$, $\mathbf{e} = (e_1, ., e_M)$ and $\boldsymbol{\alpha} = (\alpha_1, ., \alpha_M)^T$. The solution is also given by:

$$\begin{bmatrix} 0 & -\mathbf{Y}^T \\ \mathbf{Y} & \mathbf{Z}\mathbf{Z}^T + \gamma^{-1}\mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{1} \end{bmatrix} \quad (6)$$

Hence the estimator (3) is found by solving the linear set of equations (4-6) instead of quadratic programming. The support values αi are proportional to the errors at the data points.

4. Test result and discussions

The performance of the proposed estimator is compared with conventional WLS state estimator both the programs were coded in MATLAB for fair comparison and executed on a P4 AMD64 personal computer with 512-MB RAM.

For same data set and file operations input measurements for the Iraqi super Grid network were 98, respectively. These measurements consist of bus power measurements (real and reactive) and line measurements (real and reactive). The training patterns were generated for the 20% to 120% range of loading conditions corresponding to the base configuration. The performance comparison is made for following test cases.

4.1. All the measurements are correct (no gross errors) (case 1)

Table 1 shows the Average Absolute Error (AAE) in voltage magnitudes (p.u.) and phase angles (deg.) for the two methods, where no gross errors were present. It is observed that the accuracy of the WLS method was slightly superior when compared to the proposed method for test case 1. However, estimated states by the proposed method were quite more accurate for practical purposes. It can be seen that the CPU time required by proposed method model is much lower than the testing time of WLS.

Table1: State estimator results for Iraqi super Grid network (Case 1)

	Voltage (AAE)	Phase angle (AAE)	Time (Sec.)
LS-SVM	0.0345	0.771073	0.016
WLS	0.0788	1.131608	0.61

4.2. Gross errors in the measurement data (case 2)

Table 2 shows the estimates for voltage and bus angle for test case 2. The gross errors were introduced randomly in four measurements. The gross errors were introduces in real power on MOS4, reactive power on KRK4, real power flow in line (KRK4-BEG4) and reactive power flow in line (KRK4-BQB4). It is observed from tables 2 that the proposed estimator outperformed the WLS estimator both on account of average error for voltage magnitude and bus angles (as 0.047488< 0.07482 for V, and 0.643178<1.21107 for angles). The proposed estimator was robust when compared with WLSE state estimator. Also shows that the gross errors present in the measurement data can deteriorate the performance of the conventional state estimator and have to be removed or reweighed and are to be re-estimated by going through state re-estimation. However, the proposed state estimator is robust in such cases. The bad data can easily be detected in case of proposed method, as there is no data smearing possible unlike conventional state estimation.

4.3. Topological errors in the measurement data (case 3)

For case 3 a topological error was simulated as inclusion error of line (KRK4-BEG4). The line was actually out but the status (measurement) showed it to be in the system. WLS program was run with the line flow measurement as zero (both real and reactive), as acceptable. It is observed that the proposed estimator out performed the WLS estimator both an account of average error for voltage magnitude and bus angles (as 0.035905<0.060783 for V, and 0.771073<1.208551 for angles). The average time for the proposed neural network was 0.0550 seconds, whereas for WLS.

Table2: State estimator results for Iraqi super Grid network (Case 2)

Bus N.	True value		WLS		LSSVM		WLS		LSSVM	
	Phase angle	Voltage absolute error	Phase angle Absolute error	Voltage absolute error	Phase angle Absolute error	Phase angle	Voltage absolute error	Phase angle Absolute error	Voltage absolute error	Phase angle Absolute error
SDM4	1.0091	2.056	0.97739	2.1545	1.0154	2.1359	0.031713	0.09847	0.006315	0.079932
BAJ4	1.0199	5.9126	1.2216	6.2635	1.0131	6.0173	0.20173	0.3509	0.006813	0.10473
MOS4	1.0395	19.963	1.0672	19.728	1.133	20.971	0.027711	0.23475	0.093518	1.0078
BQB4	1.0225	7.7632	0.95437	7.6615	1.0478	7.9263	0.068134	0.10171	0.025319	0.16311
KRK4	0.9042	35.761	0.82107	38.751	0.94934	36.737	0.083129	2.9896	0.045136	0.97611
QAM4	1.05	21.28	1.2392	23.671	1.1261	21.986	0.18917	2.3911	0.076135	0.70639
BGN4	1.0116	23.762	1.0121	24.995	1.046	24.09	0.000531	1.2327	0.034428	0.32782
HAD4	0.9807	31.063	1.0393	32.848	1.0287	32.206	0.058596	1.7854	0.048002	1.1432
BAB4	1.0102	30.043	1.1724	29.667	0.98748	30.042	0.16223	0.37607	0.022725	0.00143
MSB4	1.0182	8.0142	0.98659	8.5458	1.072	8.2971	0.03161	0.53156	0.053846	0.28288
BGS4	1.0229	38.441	1.0011	42.058	1.0913	39.068	0.021829	3.617	0.068393	0.62674
BGW4	0.9021	27.083	0.82066	28.577	0.86656	26.588	0.081437	1.4939	0.035542	0.4954
KAZ4	1.0491	21.181	0.94825	22.163	1.1073	22.546	0.10085	0.98207	0.058205	1.3649
NAS4	1.0244	18.938	0.97091	20.143	1.0315	19.581	0.053495	1.2045	0.00711	0.64308
KDS4	1.0119	16.237	1.083	15.978	1.1111	17.384	0.071123	0.25939	0.099151	1.147
HRTP	0.97	19.963	0.92883	20.751	0.93795	19.878	0.041168	0.78823	0.032047	0.085484
QRN4	1.0147	49.868	1.0477	52.024	1.08	51.594	0.032953	2.1556	0.065347	1.726
KUT4	1.029	37.784	1.17	39.378	1.1139	38.728	0.14104	1.5938	0.084917	0.94414
BGE4	1.0394	28.038	1.0625	28.862	1.0001	27.644	0.023131	0.82371	0.039316	0.39424
Maximum Average error							0.07482	1.21107	0.047488	0.643178
CPU time in seconds			0.83		0.02					

Table3: State estimator results for Iraqi super Grid network (Case 3)

Bus N.	True value		WLS		LSSVM		WLS		LSSVM	
	Voltage magnitude	Phase angle	Voltage magnitude	Phase angle	Voltage magnitude	Phase angle	Voltage absolute error	Phase angle Absolute error	Voltage absolute error	Phase angle Absolute error
SDM4	1.0125	2.0560	1.016	2.0612	0.99595	2.1292	0.006944	0.073241	0.013153	0.005229
BAJ4	1.0199	5.9126	1.0553	5.8448	1.0243	5.9185	0.03539	0.005927	0.004433	0.067757
MOS4	1.0395	19.9630	1.1081	20.153	1.0644	20.677	0.068567	0.71415	0.024938	0.18995
BQB4	1.0225	7.7632	1.049	8.4858	1.0075	7.8946	0.026548	0.13137	0.014992	0.72259
KRK4	0.9042	35.7610	1.0026	36.273	0.90641	38.144	0.098415	2.383	0.002208	0.51184
QAM4	1.0520	21.2800	1.0615	21.141	1.1267	20.892	0.01155	0.38814	0.076745	0.13918
BGN4	1.0126	23.7620	1.1613	25.351	1.0523	25.307	0.14973	1.5449	0.04069	1.5894
HAD4	0.9817	31.0630	1.0579	34.118	0.98388	32.123	0.07718	1.0601	0.003182	3.0547
BAB4	1.0132	30.0430	1.1101	32.43	1.0593	31.32	0.099922	1.2766	0.049131	2.3873
MSB4	1.0182	8.0142	1.0106	8.4013	1.0566	7.9383	0.007624	0.0759	0.038397	0.38711
BGS4	1.0229	38.4410	1.096	39.362	1.1017	41.176	0.073076	2.7346	0.07881	0.92089
BGW4	0.9021	27.0830	0.86491	28.355	0.90916	29.194	0.037185	2.111	0.007064	1.2716
KAZ4	1.0491	21.1810	1.1401	21.321	1.0898	23.129	0.090876	1.9475	0.040684	0.14041
NAS4	1.0244	18.9380	0.97641	19.077	1.0567	20.761	0.047991	1.8229	0.032254	0.13947
KDS4	1.0119	16.2370	1.0357	16.008	1.0723	16.47	0.023793	0.23281	0.060399	0.22918
HRTP	0.9765	19.9630	1.0096	21.798	0.99612	21.245	0.039645	1.2821	0.02612	1.8352
QRN4	1.0147	49.8680	1.1059	50.123	1.0508	53.964	0.091163	4.0959	0.036129	0.25495
KUT4	1.0291	37.7840	1.0703	38.476	1.0697	38.716	0.041315	0.9318	0.040682	0.69203
BGE4	1.0394	28.0380	1.1674	28.15	1.1316	27.887	0.12797	0.15054	0.092191	0.11161
Maximum Average error							0.060783	1.208551	0.035905	0.771073
CPU time in seconds			0.61		0.016					

5. Summary

A proposed two-stage Support Vector Machine (SVM) scheme has been applied in this paper to solve the problem of power system state estimation for bad data detection and processing topology during real-time power system monitoring. LS-SVM is designed and tested for Iraq super Grid network. The test results presented on three systems reveal the following:

- The proposed method can be implemented for large-scale power systems.
- Both the LS-SVM estimator provide state estimation results accurately as compared to WLSE for no-gross and topological error present.
- The LSVSM state estimator is found fairly accurate even gross error and topological error present in the measurement data.
- The computation time required for the proposed LS-SVM is much better than WLSE.

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