A Knowledge Based Data Exchange Design for Distributed Mega-RTO Operations

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***Abstract*--During power deregulation, companies and ISOs are releasing their transmission grids to form RTOs/Mega-RTOs. The question then arises: should we design a totally new state estimator for the whole system? To avoid a huge cost of a new estimator for mega RTOs, we propose a cost effective distributed textured state estimator that maintains old state estimators with instrumentation or estimated data exchanges among neighboring entities. The distributed textured state estimator will be more reliable since one computer failure will not jeopardize the whole system estimation result. At the same time, our estimator will achieve high bad data detection capability and high precision as the one estimator for the whole system. The approach also reduced the problem complexity dramatically. In this paper a knowledge-based system is proposed to search for beneficial data exchange scheme. The knowledge base includes the information of Bus Credibility Index, which considers the probability of good measurements. The reasoning machine consists of several principles, where economic factor is also taken into account. Numerical tests on IEEE-14 bus system verify that selected data exchange improves the estimator quality of individual entities for both bad data analysis and estimation accuracy. Accordingly, data exchange has a major impact on traditional measurement design. It is also shown that the benefit of different data exchange schemes can be quite different; some data exchanges are even harmful if our principles are not carefully followed.**

***Index Terms*--Knowledge Based Systems, Power Market, Measurement Placement, Data Exchange Design, Distributed State Estimation, Bad Data Analysis.**

I. INTRODUCTION

STATE estimation is essential for monitoring and control of a power system. In the regulated environment, the whole power system is owned by some locally monopolistic organizations. These utilities have the responsibility and the ownership of the instrumentation in their local region to meet their needs to monitor and control. There is almost no need to exchange data with other organizations. On the other hand, during power deregulation, multiple entities such as member companies and ISOs are releasing their transmission grids to form RTOs while maintaining their own state estimators over their own areas [1]. Furthermore, a recent trend for these ISOs/RTOs is to further cooperate and run the power market on even a bigger grid as a Mega-RTO for a better market efficiency [2]. The grid size of Mega-RTO becomes extremely large, as concluded recently by Federal Energy Regulatory Commission (FREC), that only four Mega-RTOs should cover the entire nation besides Texas [2]. Accordingly, in order to achieve a reliable state estimation, many new problems arise under such a power deregulation environment:

First of all, the state estimation over the whole grid of a Mega-RTO becomes very challenging just for its size. One possible scheme is to implement a totally new estimator over the whole grid, named as one state estimation scheme (OSE), which has many disadvantages in the aspects of investment and computation performance [3]. Recently, we developed a new concurrent non-recursive textured algorithm as an alternative [3], where the currently existing state estimators are fully utilized without using a new estimator. Such a distributed state estimation (DSE) algorithm evolves from the original well-developed textured algorithm in [4] with further distributed computations. The scheme also overcomes the disadvantages of OSE, and the additional cost in DSE is only some extra communication for some instrumentation or estimated data exchanges.

The new issue here is how to exchange instrumentation or estimated data with neighboring entities in a power market. Note that:

1) Data exchange design is critical to the newly developed textured distributed state estimation algorithm [3].

2) Selected data exchange improves the quality of estimators in individual entities, on both bad data detection ability and estimation accuracy.

3) After the introduction of data exchange, the traditional measurement placement methodology will be modified to fully utilize the benefit of data exchange.

Be aware that not necessarily all data exchanges are beneficial. In fact, some data exchange may harm the local estimators and thus the exchange has to be carefully designed. Experience alone cannot resolve the design issues. In particular, for big Mega-RTOs, no one has any experience yet.

Therefore, it is critical to develop a systematic approach to search for appropriate data exchange schemes. Since the computation complexity increases dramatically for large grid,

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data exchange design problem become very challenging.

Instrumentation/Estimation data exchange issues in power market are discussed by us in [5]. Further studies are given in [6], where a new concept of Bus Redundancy Descriptor (BRD) is developed and utilized.

In this paper a knowledge-based system is proposed to efficiently search for beneficial data exchange scheme, and the additional new features include:

1) Based on BRD in [6], a new concept of Bus Credibility Index (BCI) is proposed, where the probability of good measurements is taken into account. Both BRD and BCI form the basis of the knowledge.

2) The improvement of estimation accuracy is discussed.

3) The economic factor on the implementation of data exchange is considered. Activities used to improve the quality of state estimation, including data exchange among member companies, are market-based and the economical cost must be taken into account.

4) The impact of data exchange on traditional measurement placement methodology is discussed.

This paper is organized as the following: the concept of Bus Credibility Index (BCI) is discussed in Section II. The knowledge base of the expert system is described in Section III. Furthermore, in Section IV the reasoning machine with the corresponding principles based on BCI is discussed. Numerical tests are studied in Section V. In the last section, a conclusion is drawn.

II. Bus Credibility Index (BCI)

A sample system *S* in Fig.1 as in [6] is used in this section to explain our newly developed concept.

A. Basic analysis of state estimation

SE problem is based on the model [7]:

$$z = h(x) + e$$

Where

z represents measurements,

e is the measurement noise vector,

x is the state vector composed of the phase angles and the magnitudes of the voltages on network buses,

$h(\bullet)$ stands for the nonlinear measurement functions.

WLS algorithm has been used to solve the SE problem in many commercial software packages for electric power system, which is based on a nonlinear iteration method. At each iteration i, the following equations is solved:

$$\Delta x_i = (H^T R^{-1} H)^{-1} H^T R^{-1} \Delta z_i = G^{-1} H^T R^{-1} \Delta z_i$$

Where

R is the measurement covariance matrix

H is the Jacobian matrix $\partial h / \partial x$,

$G = H^T R^{-1} H$ is the gain matrix.

B. Critical p-tuples

Critical p-tuples is first proposed in [8,9], and it is defined as a set of *p* measurements with respect to a specific system, where the removals of all the p measurements in the set will make the originally observable system unobservable. In addition, removals of any *p-1* measurements in the set will still keep the system observable.

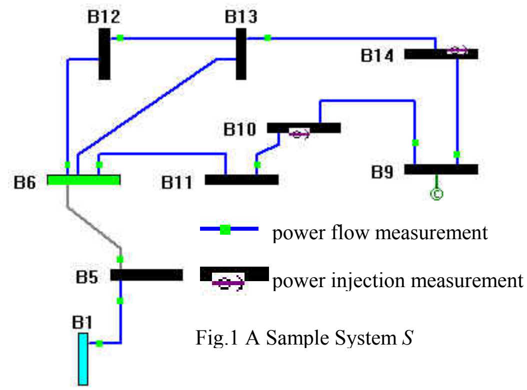

Fig.1 A Sample System *S*

The size of the critical *p*-tuples is defined as *p*. One can find critical p-tuples based on analysis of symbolic Jacobian matrix *H* [10]. For example, the methodology in [11] can be used to determine the critical tuples. For the sample system *S*, *9-10*,*10*,and *12-13* are a critical 3-tuples, which is denoted as (*9-10,10,12-13*|*S*).

Note: "*10*" stands for the pair of active and reactive power injection measurement in Bus 10, while "*9-10*" stands for the pair of the active and inactive power flow injection measurements from Bus 9 to Bus 10.

C. Weak Bus Sets of Critical p-tuples

The weak bus set of a critical *p*-tuples is determined as:

Step1: Remove all the *p* measurements in the critical *p*-tuples, and *S* becomes unobservable now;

Step2: Mark those lines with power flow measurements;

Step3: Select an unmarked line; if all the lines have been marked, stop and exit.

Step4: Add a pair of active and reactive flow measurements to this line for the time being and mark the line;

Step5: If *S* turns to be observable again, then the buses located on the two ends of this line belong to the Weak Bus Set of the critical *p*-tuples;

Step6: Remove the flow measurements just added in Step4, and go back to Step3.

For example, after the removal of (*9-10,10,12-13*|*S*), *S* becomes unobservable. If a pair of active and reactive flow measurements is added on line 6-13, the system becomes observable again. Therefore, Buses 6 and 13 belong to the Weak Bus Set of (*9-10,10,12-13*|*S*). In fact, the Weak Bus Set of (*9-10,10,12-13*|*S*) is Bus6, 9, 10, 12 and 13, which is denoted as $\{6,9,10,12,13|(9\text{-}10,10,12\text{-}13)|S\}$.

D. Bus Redundancy Descriptor (BRD)

Every bus has its own Bus Redundancy Descriptor (BRD) with respect to a specific system. BRD of Bus *b* is defined in [6] as a set of critical measurement *p*-tuples whose weak bus set includes Bus *b*.

A bus is said to have a bus redundancy level *g*, if the smallest size of the critical tuples in its BRD is (*g+1*).

For example, it is determined in [6] that:

BRD(5,*S*)={(5-6), (1-5,5-1), …};

BRD(6,*S*)={(5-6), (6-11,6-12), (6-11,12-13), (6-12,12-13), (9-10,10,12-13), …};

BRD(11,S)={(6-11,6-12), (6-11,12-13), …};
BRD(13,S)={(6-11,6-12) (6-11,12-13) (6-12,12-13), (9-10,10,12-13), …}.

Note: BRD(13,S)={(6-11,6-12) (6-11,12-13) (6-12,12-13), (9-10,10,12-13), …}denotes BRD of Bus13 with respect to S consists of three critical pairs (6-11,6-12), (6-11,12-13) and (6-12,12-13), a critical 3-triples (9-10,10,12-13), and other possible critical 4-tuples.

E. A new concept of Bus Credibility Index (BCI)

Bus Credibility Index of Bus b is defined as the state estimation credibility probability on Bus b with respect to a specified system. BCI can be determined as:

$$
\begin{aligned}
BCI(b,S) &= 1 - P(C_1 \cup C_2 \cup \cdots \cup C_k) \\
&= 1 - \sum_{i=1}^{k}\left((-1)^{i-1} \sum_{1\le t1<t2<\cdots<ti\le k} P(C_{t1} \cup C_{t2} \cup \cdots \cup C_{ti}) \right) \\
&= 1 - \Big(\sum_{1\le t1\le k} P(C_{t1}) - \sum_{1\le t1<t2\le k} P(C_{t1} \cup C_{t2}) \\
&\quad + \sum_{1\le t1<t2<t3\le k} P(C_{t1} \cup C_{t2} \cup C_{t3}) - \cdots \\
&\quad + (-1)^{k-1} P(C_1 \cup C_2 \cup \cdots \cup C_k) \Big) \qquad (1)
\end{aligned}
$$

where

BCI(b,S) is the BCI of Bus b with respect to system S;

BCD(b,S) consists of k critical p-tuples C_i, $p=1,2,3,\ldots$;

$P(C_i \cup C_j)$ stands for the failure probability when all measurements in C_i and C_j fail.

If the failure probabilities of measurements are independent from each other, then $P(C_i \cup C_j)$ can be determined by:

$$
\begin{aligned}
P(C_i \cup C_j) &= P(\{M_1, M_2, \cdots, M_l\}) \\
&= P(M_1)\cdot P(M_2)\cdots P(M_l) \qquad (2)
\end{aligned}
$$

where

$\{M_1, M_2, \ldots, M_l\}$ are the measurement set which makes up $(C_i \cup C_j)$,

$P(M_l)$ stands for the failure probability of M_l.

Given the failure probability of every measurement, BCI(b,S) can be determined according to (1) and (2).

For example, suppose the failure probability is fixed to 0.01, BCI(b,S) is determined as Table 1:

TABLE 1. BCI OF BUSES WITH RESPECT TO SAMPLE SYSTEM IN FIG.1

BCI(5,S)	BCI(11,S)	BCI(13,S)
0.9900	0.9998	0.9997

F. Remarks

Remark 1: If BCI($b1$,$S1$)>BCI($b2$,$S2$), then Bus $b1$ with respect to system $S1$ is said to be stronger than Bus $b2$ with respect to system $S2$.

Note that data exchanges modify the original system S to S', and the incremental difference of BCI from (b,S) to (b,S') stands for the benefit of such a data exchange on bus b.

Remark 2: As pointed out in [6], a critical k-tuples not necessarily constitutes a connected measurement area, and the weak bus set of a critical tuples is also not limited to the buses linked directly to the measurements of the critical tuples.

Note that the measurements in BRD(b,S) either connects directly with b or locates on a loop that includes b. For example, BRD(b5,S) consists of (5-6) and (1-5,5-1) which connect directly with b5, and BRD(b13,S) consists of critical tuples such as (6-11,6-12), (6-11,12-13), (6-12,12-13) and (9-10,10,12-13), which are all located in the loop b6→b12→b13→b14→b9→b10→b11→b6.

Remark 3: Given the condition that the failure probability of every measurement is very low, the failure probability of the critical k-tuples where k is greater than 3 can be ignored in the computation of BCI. In other words, $BCI(b,S) \approx 1.0000$ if the redundancy level of b with respect to S is greater than 3, And only buses with redundancy level less than 4 are potential weak parts of the system, which we should focus on.

Remark 4: The meaning of BCI depends on the definition of failure probability. If the failure probability of measurements stands for the probability of measurement availability, then BCI(b,S) stands for the credibility of observability on bus b with respect to system S since the removal of all measurements of a critical k-tuples will make S unobservable. If the failure probability of a measurement stands for the probability of bad data in this measurement, then BCI(b,S) reflects the probability to successfully identify bad data since bad data cannot be identified if all the measurements of a critical k-tuples are bad data.

In summary, BCI(b,S) stands for a reliability index of the estimation result on bus b with respect to a specific system S.

Remark 5: With the full consideration of measurement failure probability, BCI(b,S) is a more accurate criterion to evaluate the performance of measurement system compared with local or global bus redundancy level.

III. KNOWLEDGE BASE

The knowledge base of the proposed expert system consists of the following parts:

A. Raw Facts

Raw facts refer to the data input directly by the user, such as:

1) The configuration, parameters and ownership of current power system network and measurement system;
2) The failure probability and accuracy of measurements;
3) The cost of instrumentation and estimated data exchange;

Importance of raw facts is rather clear. However, the knowledge is too primitive to be informative. Therefore, more refined information, such as the BCI information and the estimation accuracy information must be extracted by an expert system based on the raw facts.

B. BCI Information

BCI(b, S) reflects the estimation reliability on bus b with respect to a specific system S, which is very useful in data exchange design.

C. Variance of SE errors

It is well known [12] that the variances of the SE errors stand for the accuracy of SE. Statistically, they represent the "squared distances" of the estimates from their true values.

The smaller the variances are, the better the SE solution is typically.

The state estimation error variances are the diagonal elements of matrix $C = G^{-1}$.

Since the error variances are only slighted influenced by the operation point, the comparison of different data exchange scheme is executed on a uniform given operation point.

Remark: A measurement system can be evaluated through different criteria, among which the most important criterion is the bad data analysis performance that can be reflected by BCI and the estimation accuracy.

IV. A Reasoning Machine

An IEEE-14 Bus system as shown in Fig.2 is used to illustrate how the reasoning machine works, where RTO-A and RTO-B will merge into one Mega-RTO. There are two existing local estimators for system A and B, *where* neither overlapping areas nor data exchange is involved.

Note that the algorithm and principles are not limited to the demonstrating examples, they are applicable to all systems.

We have explored ways in [3] to have a distributed state estimator evolving from the current existing estimators instead of building a totally new estimator for the whole system. In this paper the design of data exchange scheme is the focus. Data exchange is a prerequisite for the algorithm in [3]; when properly designed, it will be beneficial to local estimators.

The processes in the reasoning machine is the following:

Step1: Determine the maximum possible benefit on bad data detection ability after data exchange by:

$BCI(b_A, Whole) - BCI(b_A, A)$ and

$BCI(b_B, Whole) - BCI(b_B, B)$

where b_A are the boundary buses in A, such as b1,b5,b10,b14;
b_B are the boundary buses in B, such as b2,b4,b9;
Whole stands for the whole system of Mega-RTO.

Remark: Only boundary buses are concerned here because in most cases BCI of internal buses also improves when BCI of boundary buses improve, while the rate is much smaller.

Step2: If the maximum possible benefit of a boundary bus is less than a pre-defined threshold, then this boundary bus will be ignored during the following searching process.

Step3.1: For a given boundary bus $b \in \{b_A \cup b_B\}$, some principles are used to search for beneficial data exchange:

Principles1 for Instrumentation Data Exchange:

For boundary bus b_A in A, instrumentation data exchange should extend to boundary bus b_B in B given the condition $BCI(b_B, Whole) > BCI(b_A, A)$.

For example, it is reasonable for b2 and b4 in B to extends to include b1 and b5 in A, while it does not follow the principle that b9 in B extends to include b10 or b14 in A.

Principles2 for Instrumentation Data Exchange:

The final configuration after data exchange should avoid forming a radial structure; instead, a loop is preferred. For example, branch b1-b5 and b5-b2 should also be included in B after data exchange to avoid radial branch b2-b1 and b4-b5. On the other hand, b9 in B extend only to b10 in A will form a new radial branch b9-b10, which violates this principle.

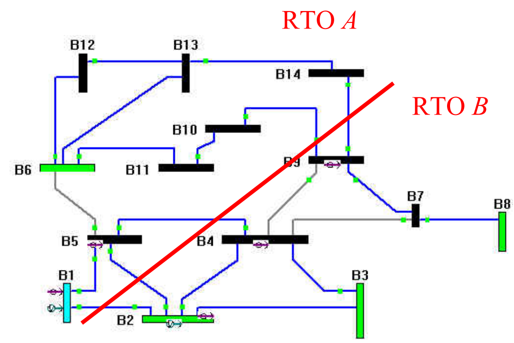

Fig.2 Two RTOs merge into one Mega-RTO

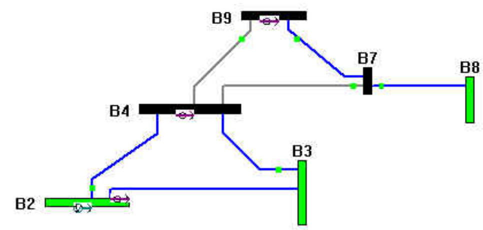

Fig.3 Original System of B before data exchange

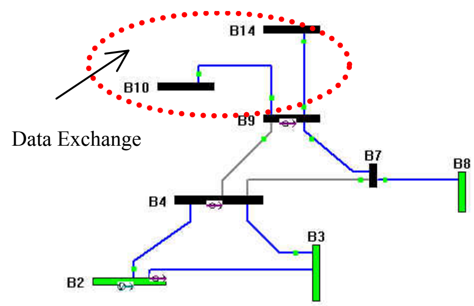

Fig.4 Modified System of B after data exchange

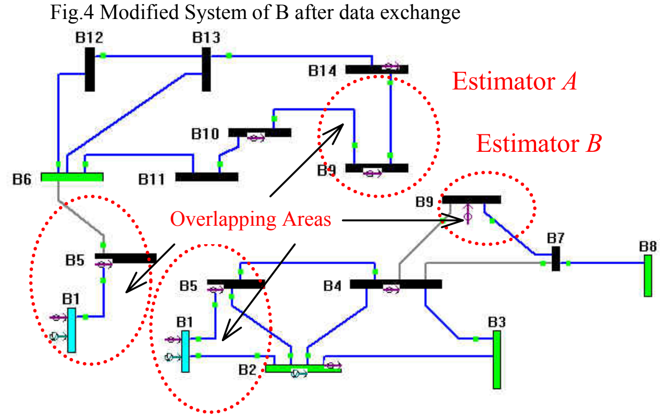

Fig.5 Local estimators after instrumentation data exchange

Principle for Estimation Data Exchange:

If $BCI(b, A) > BCI(b, B)$ where b is in the common part of A and B, then estimation result exchange from A to B on this bus will improve $BCI(b, B)$ to the magnitude of $BCI(b, A)$.

Remark: Estimation accuracy information is not used here because bad data analysis performance is more important than estimation accuracy in industry application. Furthermore, in most cases estimation accuracy improves with the improvement of bad data analysis performance.

Step3.2: System A and B are modified accordingly based on the data exchange newly found in Step3.1. BCI, estimation accuracy and the economic cost are evaluated on the 'new' system A and B to verify the benefit.

Step3.3: If BCI on the given bus *b* with respect to the post-data-exchange system are already close to that in the whole system, then there is no need to search for new data exchange for bus *b*. Otherwise new data exchange or new measurement devices must be searched further.

Step4: Step 3 is iterated on all boundary buses of *A* and *B*.

Under power market environment, economic factor is especially important and is considered in the reasoning machine as follows:

1) The benefit of different data exchange schemes may differ greatly. The benefit may saturate after some data exchange, which implies no major benefit can be obtained for more data exchange.

2) The hardware/software cost on data exchange implementation should be minimized given the condition that the performance is satisfied. In other words, even if scheme D1 is slightly better than scheme D2 in performance, but it is still possible for industry to select D1 when D1 is much more economical than D2.

3) The price tag of a data reflects not only the installation cost but also its market value. It is possible for system *A* to attach a rather high price tag to a measurement that is especially useful to system *B*. The proposed expert system is critical for the companies to determine the market price based on the benefit of data exchange.

4) Since new measurements can be sold to other companies, the data exchange will have some impact on measurement placement decision. Accordingly, the proposed expert system is useful for both the design of the data exchange scheme and the new measurement placement decision.

V. Numerical Tests

The following cases demonstrate the follows:

1. Not all the data exchange is beneficial. In fact, some data exchange may harm the local estimators in both bad data detection ability and estimation accuracy.

2. With a few data exchanges, the bad data detection ability and estimation accuracy of local estimators can be improved to a level as high as that of the whole system.

3. The data exchange has an impact on traditional new measurement placement approach.

Case1: Harmful Data Exchange Scheme

RTO B with a particular data exchange scheme is given in Fig.4 while the original system before data exchange is given in Fig.3. As mentioned before, such a data exchange does not follow our principles. In fact this data exchange scheme is harmful for Company B, which is verified in the following:

The comparison between the original B and the modified B is given as the followings (given the bad data probability of any measurement is 0.1, and the accuracy of any measurement is 0.01 p.u.):

Table2. Average BCI on the buses of Company B

B in Fig.3	B in Fig.4	B in Fig.5	Whole System
0.9647	0.9643	0.9662	0.9662

Table3. Average Estimation Error on the buses of Company B

B in Fig.3	B in Fig.4	B in Fig.5	Whole System
7.7314e-007	8.1738e-007	2.6471e-007	2.6326e-007

Table 2 implies that the data exchange shown in Fig.4 decreases *B*'s bad data detection ability. Table 3 indicates that *B*'s estimation error also increases after such a data exchange.

Case2: Efficiency of Beneficial Data Exchange

Our expert system suggested an optimal data exchange scheme following our principles:

Instrumentation data exchange: shown in Fig.5.

Estimation data exchange: Estimation result on bus 1 and 5 are exchanged from *B* to *A*. The detailed algorithm to utilize these estimated data is given in detail in [3].

Tables 2 and 3 compare the performance with the whole system estimator. It is clear that:

1) B in Fig.5 improves its bad data detection ability over the original system in Fig.3. Furthermore, the bad data detection ability for B shown in Fig. 5 is as good as the whole system estimation. It shows that little benefit could be further gained through more data exchange.

2) B in Fig.5 has improved its estimation accuracy over the original system in Fig.3. Furthermore, the accuracy difference between Fig.5 and the whole system is rather small, which shows that little benefit could be further gained through more data exchange.

Case3: Impact on New Measurement Placement (1)

Suppose the probability of accidents in the SCADA on station of b1 is extremely high for some peculiar reasons. Obviously such an accident will cause the voltage measurement on b1, power injection measurement on Bus1, power flow measurements 1-2 and 1-5 all unusable for the state estimation. Accordingly, the system becomes unobservable, which is unacceptable for RTO A.

From the traditional measurement placement viewpoint, in order to keep state estimation run smoothly, at least one new measurement has to be installed: for example, voltage measurement on Bus5.

However, with data exchange, such a new measurement is not necessarily needed. When we follow the data exchange scheme suggested in Case 2, the state estimation in RTO B can be run normally even after the accident happened because the estimation result on b1 and b5 is exchanged from B to A.

Case4: Impact on New Measurement Placement (2)

Suppose that RTO A wants to improve the estimation accuracy on b5.

From a traditional measurement placement viewpoint, there are basically two alternatives: improve the accuracy from original 0.01 to 0.001 on the measurement 5-1 or 5-6. These two alternatives have basically the same effect to improve the estimation accuracy on b5.

On the other hand, if the accuracy of measurement 5-1 improves, the accuracy of RTO B also improves if measurement 5-1 is exchanged from A to B. Therefore, it makes sense for RTO B to share part of the cost with A to improve the accuracy of 5-1. Accordingly, it is better for A to invest on measurement 5-1 instead of on measurement 5-6.

VI. Conclusions

In this paper a knowledge-based system is proposed to search for beneficial data exchange scheme for distributed state estimations. The knowledge base includes the information on Bus Credibility Index, which considers the failure probability of measurements. The reasoning machine consists of several principles, where economic factor is also taken into account. Numerical tests on IEEE-14 bus system demonstrate that selected data exchange improves the estimator quality of individual entities on both bad data analysis and estimation accuracy. In addition, data exchange has an impact on traditional measurement design. It is also shown that the benefit of different data exchange schemes can be quite different. Properly selected data exchanges will enable the local distributed estimator perform as well as the one estimator for the whole system in both bad data detection capability and precision. On the other hand, poorly designed data exchanges, which did not follow our design principles, may be harmful to local estimators.

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VIII. Biographies

Dr. Garng M. Huang received his B.S. and M.S. in E.E. from National Chiao Tung University, Hsinchu, Taiwan, R.O.C. in 1975, 1977 respectively. He received his doctorate degree in Systems Science and Mathematics from Washington University, St. Louis in 1980. He had been teaching there since then until 1984. He joined Texas A&M University, Department of Electrical Engineering in 1984. He is currently a professor and the director of graduate studies there. He has been working on many funded research projects, such as Emergency Control of Large Interconnected Power System, HVDC Systems, Restoration of Large Scale Power Systems, On-line Detection of System Instabilities and On-line Stabilization of Large Power Systems, Fast Parallel/Distributed Textured Algorithms, Fast Parallel Textured Algorithms for Large Power Systems, Hierarchical Aggregation and Decomposition Algorithm for Data Network Routing Problem, etc. His current interest is the large-scale systems theory, large scale parallel/distributed computing and control and their applications.

Dr. Huang is a senior Member of IEEE, and a Registered Professional Engineer of Texas. He has served as the Technical Committee Chairman of Energy System Control Committee and an associated editor in the IEEE Automatic Control Society; he has also been serving in a number of committees and subcommittees of IEEE PAS Society. Dr. Huang has published more than a hundred papers and reports in the areas of nonlinear distributed control systems, parallel/distributed computing and their applications to power systems, data networks and flexible structures.

Jiansheng Lei received his B.S. and M.S. both in Electrical Engineering from Tsinghua University, Beijing, China, respectively in 1998 and 2000. Presently he is a Ph. D. student under the guidance of Dr. Huang in Texas A&M University. His current research interests include power system analysis and its application in power market.