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DESIGN OF A DECISION FUSION RULE FOR POWER SYSTEM SECURITY ASSESSMENT

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Abstract: An *Integrated Decision Support* system is designed via sensor fusion techniques, for assessing the security of power systems. The Integrated Decision Support system fuses information from various Approximated System Performance (ASP) models in order to minimize the risk of making the wrong decision under changing operating conditions. It uses the classification decisions provided by different ASP models together with information about their statistical performance (e.g. probabilities of misclassifications) to synthesize the globally optimal decision in the Bayesian risk sense. This global decision is often superior (and in no case inferior) to the one obtained using any single ASP model. The design of the integrated decision support system is illustrated for detecting static voltage collapse by fusing the security information from a set of existing security indices.

List Of Symbols

Abbreviations:

ASP Approximate System Performance
DFC Decision Fusion Center
H_0 Hypothesis 0
H_1 Hypothesis 1
IDS Integrated Decision Support
LDM Local Decision Maker
LFF Load Flow Feasibility region
PI Performance Index
TH Threshold
VCPI Voltage Collapse Proximity Index
VID Voltage Infeasibility Detection Curve

General Conventions:

$\underline{\bullet}$ underline implies that the variable is a vector
[•] denotes that the variables is a matrix
E(•) denotes the mean of random variable •
σ(•) denotes the standard derivation of random variable •
P{•} denotes the probability of random variable •
p(•) denotes the probability density function of •

Superscript:

G denotes global
m denote m-th local decision maker

Index Set

$\mathbb{G}$ denotes the index set of generator buses
$\mathbb{L}$ denotes the index set of load buses

Symbols	Description
$\rho_0(\underline{D})$	function indicating the amount of correlation between $\underline{D}$ under H_0
$\rho_1(\underline{D})$	function indicating the amount of correlation between $\underline{D}$ under H_1
C_{ij}	the cost of LDM said hypothesis i while hypothesis j is true
$\underline{D}$	$= [d^{(1)}, ..., d^{(M)}]$ = local decisions vector
$d^{(m)}$	decision of decision maker m
$d^{(G)}$	global DFC decision
ΔV_i	$= V_i^{(1P\text{-}1Q)} - V_i^0$
E_i	$= V_i \angle \theta_i$
E_{oj}	complex generator voltage observed from bus j
F_{ij}	the complex distribution factor from generator bus j to load bus i
f_{P_i}	real power balance at bus i
f_{Q_i}	reactive power balance at bus i
P_D	denotes the probability of detection
Pe	denotes the probability of error
P_{FA}	denotes the probability of false alarm
P_M	denotes the probability of missed detection
P_{ij}	the real power flow from bus i to bus j
S_i^{Dt}	the equivalent complex power at bus i due to all the complex powers at all load buses
$[Y_{bus}]$	= (G + j B), admittance matrix

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I. Introduction

To avoid the high computational burden of security assessment, energy management systems use one or more *Approximate System Performance* (ASP) models (such as performance indicators, dc load flow, sensitivity matrices, Jacobian of the 1P1Q load flow, or distribution factors) for evaluating power system security[1]. These models are also used in constructing corrective strategies. There are many ASP models available, each making different assumptions on the network or the operating conditions, such as decoupling of real and reactive power, high X/R ratio, radial network and impedance loads. Since in actual operation the conditions under which the system was designed may not be met, vendors of energy management systems spend much effort in testing performance indicators and in developing masking techniques to reduce their probabilities of missed detection and false alarm. However, these tests are not exhaustive and the masks are not adaptive, and so there is always room for design improvement. This paper shows that by fusing the security information from a set of ASP models one can achieve an overall security assessment which is better than that achieved by any of the individual ASP models.

This paper describes an *Integrated Decision Support* system which fuses information from a set of ASP models (specifically, performance indicators) in order to minimize the risk of making wrong decisions under changing operating conditions. The determination of the security of the power system using a set of ASP models, can be viewed as a distributed detection problem i.e., the process of combining decisions from distributed local sensors (the ASP models) and using a *decision fusion center* to provide a combined decision about the system status. The decision fusion center uses information about the quality of the ASP models that it integrates, and the correlation between their decisions, in order to weigh the contribution of the various local decisions in making the final global classification.

The distributed-detection hypothesis-testing integrated decision support system considered in this paper is shown in Fig.1. The phenomenon (such as steady state security or static voltage collapse) is observed by a set of performance indicators which compute locally the state of the system. A decision $d^{(m)}$ (by the m^{th} decision maker, based on the m^{th} ASP model) is sent to the data fusion center which combines the set of local decisions $\{d^{(m)}, m=1,.., M\}$ to obtain the global decision, $d^{(G)}$. The resulting integrated decision support system should effectively integrate several distinct performance criteria into a classifier which is optimal with respect to a global Bayesian criterion.

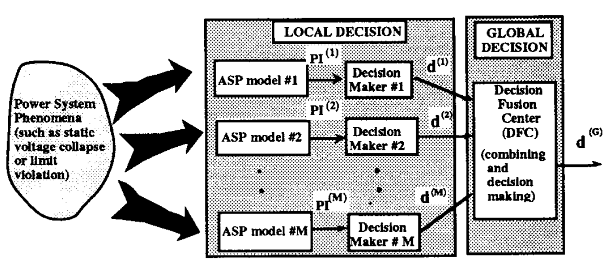

Fig. 1 : The structure of the Integrated Decision Support (IDS) system

Thus, the best use of an existing bank of local decision makers is sought, even if the global performance criterion which the user specifies is different from the original local criteria used for synthesis of the original local decision makers. The IDs system architecture is similar to that used in multiple sensor detection systems [2-5].

II. Decision Fusion System Design Consideration

To design of a decision fusion system of Fig. 1 requires knowledge of the *power system phenomena* which need to be detected, the *local decision maker structure* and the statistical *uncertainty* in the observation about each phenomenon. In power system security assessment, one is interested in detecting contingencies which produce operating violations, static voltage collapse, dynamic limit violations, transient instability, etc. Thus in the framework of the integrated decision support system of Fig. 1, these are the phenomena to be detected. In this paper, we consider the problem of detecting static voltage collapse, i.e., if the operating point will exceed the maximum system loading condition. This section gives a description of this problem in the framework of Fig. 1.

2-1. *Characterization of the Detected Phenomenon* The static voltage collapse phenomenon is characterized by the steady state model given by the power flow equations for the n bus system:

Real Power: $$f_{P_i} \equiv P_i - P_i(\underline{x}, \underline{u}, N) = 0 \quad i = 1,...,n \tag{1a}$$

Reactive Power: $$f_{Q_i} \equiv Q_i - Q_i(\underline{x}, \underline{u}, N) = 0 \quad i = 1,...,n \tag{1b}$$

where P_i and Q_i denote the net injection at bus i, respectively; and

$$P_i(\underline{x}, \underline{u}, N) + jQ_i(\underline{x}, \underline{u}, N) = E_i \sum (Y_{ij} E_j)$$

with $E_i = V_i \angle\theta_i$ = complex voltage at bus i; $Y_{ij} = G_{ij} + j B_{ij}$ = the ijth element of the bus admittance matrix. In (1), the vector $\underline{x}$ denotes the dependent bus voltage variables, i.e., $x_i=(V_i,\theta_i)$; vector $\underline{u}$ denotes the independent variables (i.e., generator real power injections, $\underline{P}_g$; generator voltage magnitude reference settings, $\underline{V}_g$, the load powers, $\underline{P}_d$ and $\underline{Q}_d$); N denotes the network parameters (i.e., bus admittance matrix, $[Y_{BUS}]$).

Based on (1), the presence of the static voltage collapse phenomenon is characterized in terms of the non-existence of a solution $\underline{x}$ to (1) for the specified operating point $\underline{u}$, (i.e., the Load Flow Feasibility problem [6]). Since this phenomenon is binary in nature ("collapse" or "no collapse"), we can characterize the phenomenon as follows:

$$\mathbf{H_1}: \underline{u} \notin \mathbf{LFF} \text{ (load flow is not feasible)} \tag{2a}$$

$$\mathbf{H_0}: \underline{u} \in \mathbf{LFF} \text{ (load flow is feasible)} \tag{2b}$$

where $\mathbf{LFF} = \{ \underline{u} : f_P(\underline{x}, \underline{u}, N) = 0;\ f_Q(\underline{x}, \underline{u}, N) = 0 \}$.

This characterization of the static voltage collapse phenomenon is deterministic in nature and it ignores exogenous disturbances such as weather, uncontrolled loads, etc. These disturbances, however must be taken into account when making decisions about the system's security. This paper considers the static voltage collapse assessment problem in a probabilistic framework, in which the uncertainty of the uncontrolled loads is taken into account. (Although, we do not consider the uncertainty of the weather, our development allows its inclusion.) To consider the uncertainty of uncontrollable loads, we partition the injection vector $\underline{u}$ into two parts $\underline{u} =[\ \underline{u}_g^T\ \underline{u}_d^T\ ]$, where $\underline{u}_g$ is a fixed generation injection and $\underline{u}_d$ is probabilistic load uncertainty given by:

$$\underline{u}_d = \underline{u}_d^0 + \Delta\underline{u}_d \tag{3}$$

where $\underline{u}_d^0$ is the nominal value or the mean value of the $\underline{u}_d$ and $\Delta\underline{u}_d$ is the variation of the load characterized by some probability distribution [7]. Specifically, we assume that the load uncertainty $\Delta\underline{u}_d$ is normally distributed with a zero mean.

With this probabilistic structure of $\underline{u}$, it is clear from (2) that the voltage collapse phenomenon is probabilistic and it is assessed in terms of $P\{\mathbf{H_1}\}$ and $P\{\mathbf{H_0}\}$, the probability of static voltage collapse and the probability of no collapse, respectively. For example, for the 14 bus system given in Fig. A1 of Appendix A when $\underline{P}_d$ and $\underline{Q}_d$ are normally distributed with measured variances given in Table A1, the probabilities are: $P\{\mathbf{H_1}\}= 0.181$ and $P\{\mathbf{H_0}\}= 0.819$.

2-2. *Local Decision Makers*: In the context of the IDS system of Fig.1, the local decision makers are the various criteria used to detect the static voltage collapse. If scalar Voltage Collapse Proximity Indices (VCPIs) are used in the decision process, then the general form of the mth local decision maker employs the following decision criterion:

$$PI^{(m)}(\underline{u}) \le TH^{(m)} \Rightarrow \text{Hypothesis } H_0 \tag{4a}$$

$$PI^{(m)}(\underline{u}) > TH^{(m)} \Rightarrow \text{Hypothesis } H_1 \tag{4b}$$

where $PI^{(m)}(\underline{u})$ and $TH^{(m)}$ is the mth VCPI and its threshold value (determined either from the theory or by the operator), respectively. The notation $PI(\underline{u})$ emphasizes the fact that the VCPIs represent a security measure of the operating point $\underline{u}$. The four (4) VCPIs selected in this paper are:

(i)Voltage-Drop PI[8,9]: $$PI^{(1)}(\underline{u}) = \sum_{i\in \mathbb{L}} w_i \left(\frac{|\Delta V_i(\underline{u})|}{V_i^U - V_i^L}\right) \tag{5}$$

where $\mathbb{L}$ is the load buses index set; superscript U and L represents upper and lower limit of the bus i voltage magnitude, respectively; $|\Delta V_i|$ is the absolute value of the voltage drop from the base case value at bus i. The new value of V_i is based on 1P-1Q computation; w_i is the weight for load bus i.

(ii) Kessel's PI [10]: $$PI^{(2)}(\underline{u}) = \max_{i\in \mathbb{L}} \{ |\ 1- (\sum_{j\in \mathbb{G}} F_{ij}V_j)/V_i(\underline{u})| \}; \tag{6}$$

where F_{ij} is the complex distribution of the generator voltage j to the load bus i; $\mathbb{G}$ is the index set of generator buses.

(iii) P-norm PI[6]: $$PI^{(3)}(\underline{u}) = \| f_j(\underline{u}) \|_2 = \| \frac{r_j}{2} + (\frac{r_j}{2})^3 \|_2,\ j\in \mathbb{L} \tag{7}$$

where

$$r_j = \frac{2|S_j^{Dt}|}{|Y_{jj}||E_{oj}|^2 + 2|S_j^{Dt}|\cos(\phi_{Y_{jj}} + \phi_{S_j^{Dt}})} \tag{8}$$

where ϕ is the phase angle of the complex number; E_{oj} is the complex generator voltage observed from bus j; $S_j^{Dt} = P_j^{Dt} + Q_j^{Dt}$ is the total complex power consisting of the injection of bus j and the distribution of the injections from other load buses.

(iv) P-loss PI [11]: $$PI^{(4)}(\underline{u}) = \sum_{i\ j} (P_{ij} + P_{ij})/2 \tag{9}$$

where P_{ij} is the real power flow from bus i to bus j.

Remark 1: From the computational effort point-of-view, the $PI(\underline{u})$ should be explicit function of $\underline{u}$, however, only $PI^{(3)}$ out of the above four PIs can be evaluated explicitly. The other PIs are implicit functions of $\underline{u}$ and they require the solution of the AC load flow equations of (1). To reduce the computational effort, in general, only the result of one 1P-1Q Newton-Raphson iteration is used to evaluate the PIs. This is the approach we use here.

Since the desired decision using the criteria of (4) is binary (i.e., yes/no), we denote the output from the mth local decision maker by the decision variable $d^{(m)} \in \{0, 1\}$, where

$$PI^{(m)}(\underline{u}) \le TH^{(m)} \Rightarrow \quad d^{(m)} = 0 \tag{10a}$$

$$PI^{(m)}(\underline{u}) > TH^{(m)} \Rightarrow \quad d^{(m)} = 1 \tag{10b}$$

Therefore, in this paper we consider the problem of fusing the four decisions $\{d^{(1)}, d^{(2)}, d^{(3)}, d^{(4)}\}$, to obtain an optimum global decision. This problem is addressed in Section III below. To solve this problem, we need to know the performance of each local decision maker (LDM) in terms of the false alarm and missed detection probabilities ($P_{FA}^{(m)}$, $P_M^{(m)}$, namely

$$P_{FA}^{(m)} = P\{PI^{(m)} > TH^{(m)} \mid H_0\} = \int_{TH^{(m)}}^{\infty} p(\zeta \mid H_0)d\zeta \tag{11}$$

$$P_M^{(m)} = 1 - P_D^{(m)} = P\{PI^{(m)} \le TH^{(m)} \mid H_1\} = \int_{-\infty}^{TH^{(m)}} p(\zeta \mid H_1)d\zeta \tag{12}$$

where $\{p(\zeta^{i}|H_i), i=0,1\}$ are the conditional probability density function (cpdf) of each $PI^{(m)}$, namely, $\{p(PI^{(m)}|H_i), i=0,1\}$ such as those illustrated in Fig. 2 for $PI^{(3)}$ under hypothesis H_0 and H_1. These cpdfs are histograms generated by Monte Carlo simulation (using 10,000 samples) for the case when $PI^{(3)}$ monitors the 14-bus system given in Appendix A when the load uncertainty has Gaussian statistic with variances given in Table A1. These cpdfs of Fig. 2 are used to obtain the $P_{FA}^{(m)}$ and $P_M^{(m)}$ using (11-12) for a specific threshold, TH. A more comprehensive performance measure of each LDM is its ***Voltage Infeasibility Detection*** ($VID^{(m)}$) curve shown in Fig. 3 (This is the ROC curve known for detection theory [12]). The VID curve gives the probability of detection ($P_D^{(m)}$) as a function of the probability of false alarm ($P_{FA}^{(m)}$) for any value of the threshold, $TH^{(m)}$, in the interval $-\infty \le TH \le \infty$. Figure 3 gives the VID curves for the four LDMs using the 14 bus system of Appendix A.

Remark 2: From the power system security point of view, an ideal PI should give a large detection probability (i.e. $P_D \approx 1$) and small false alarm probability (i.e. $P_{FA} \approx 0$). This yields a VID-curve which is close to the left upper most corner of Fig. 3. Based on this, we see from Fig. 3 that the LDM #3 has the best detection performance from all four LDMs.

Remark 3: The shape of the VID curve depends on the operating point $\underline{u}$. This implies that the relative position of the VID curves shown in Fig. 3 change as $\underline{u}$ changes. This is illustrated in Section IV.

In Section III we shall use the set of false alarm and missed detection probabilities $\{P_{FA}^{(m)}, P_M^{(m)}, m=1,...,4\}$ of the four LDMs to develop a global decision rule which integrates the four decisions $\{d^{(1)},d^{(2)}, d^{(3)}, d^{(4)}\}$ generated by the LDMs, so as to minimize the probability of error.

2-3 Decision Fusion Center As shown in Fig. 1, the Decision Fusion Center (DFC) integrates the output of a bank of M local decisions $\underline{D} = [d^{(1)},..., d^{(M)}]$ and generates a global decision. The output of the DFC is the decision

$$d^{(G)} = \begin{cases} 1 \Rightarrow H_1 \\ 0 \Rightarrow H_0 \end{cases}$$

A simple example of a DFC fusion rule is the logical "AND" rule (where the global decision $d^{(G)} = 1$ if and only if all local decisions $d^{(m)} = 1$), or the logical "OR" rule (where the global decision $d^{(G)} = 1$ when at least one local decisions $d^{(m)} = 1$). From the point-of-view of detecting power system voltage problems, the objective of the DFC is

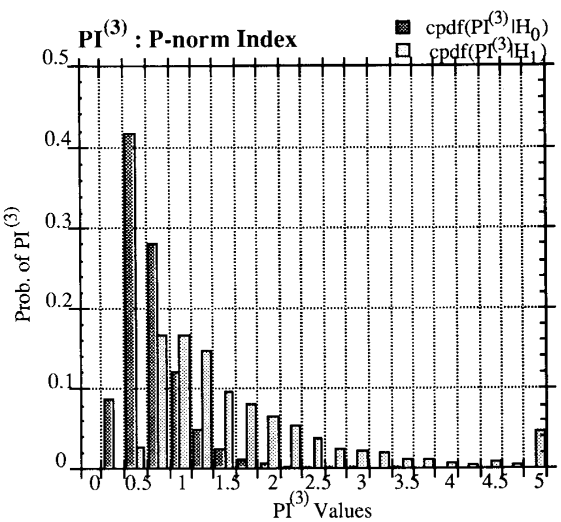

Fig. 2: Conditional probability density function (cpdf) of $PI^{(3)}$ for detecting the static voltage collapse of the 14 buses system under base case operating condition

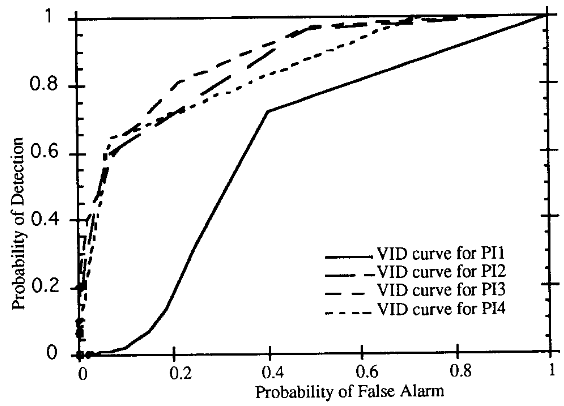

Fig. 3: Voltage Infeasibility Detection (VID) curve for the LDMs for the 14 buses system under Base case operating condition

to minimize the risk of making wrong decision. To achieve this, we need to define a measure of goodness of the decision. In this paper, we shall design a fusion rule which minimizes the *average Bayesian risk*. Thus, the DFC design problem can be stated as follows:

DFC Design Problem: Given a set of local decisions $\underline{D}=[d^{(1)},..., d^{(M)}]$ and the local decision rules, design a global decision rule, $d^{(G)} = f(\underline{D})$, which will minimize the average Bayesian risk cost:

$$C = C_{00}\, P\{d^{(G)}=0|H_0\}P\{H_0\} + C_{10}\, P_M^{(G)}P\{H_0\} + C_{01}\, P_{FA}^{(G)}P\{H_1\} + C_{11}\, P\{d^{(G)}=1|H_1\}P\{H_1\} \quad (13)$$

where C_{ij} is the cost of deciding $d^{(G)} = i$ when hypothesis H_j is true. $P_{FA}^{(G)}$ is the global probability of false alarm defined by:

$$P_{FA}^{(G)} := P\{\, d^{(G)} = 1 \mid H_0 \text{ is true} \,\} \quad (14)$$

and $P_M^{(G)}$ is global probability of missed detection defined by:

$$P_M^{(G)} := P\{\, d^{(G)} = 0 \mid H_1 \text{ is true} \,\} \quad (15)$$

In this paper we solve the above problem for the case when the cost coefficients of (13) are $C_{01} = C_{10} = 1$, and $C_{11} = C_{00} = 0$, that is when the global cost is the probability of error, $P_e^{(G)}$:

$$P_e^{(G)} = P_{FA}^{(G)}\, P\{H_0\} + P_M^{(G)}\, P\{H_1\} \quad (16)$$

III. Global Decision Fusion Center

The decision rule which fuses the M binary decisions (from the M LDMs) represented by $\underline{D} = [d^{(1)},..., d^{(M)}]^T$, where $d^{(m)}=\{0,1\}$, so that the global probabilities of error, $P_e^{(G)}$, of (16) is minimum is (see Appendix B for the detailed derivation) [13]:

$$PI^{(G)}(\underline{D}) \ge TH^{(G)} \Rightarrow \quad d^{(G)} = 1 \quad (17a)$$

$$PI^{(G)}(\underline{D}) < TH^{(G)} \Rightarrow \quad d^{(G)} = 0 \quad (17b)$$

where the scalar index $PI^{(G)}(\underline{D})$ is a function of the set of decisions $\underline{D}$ and the statistical performance of the LDMs while the threshold depends on the probabilities of the phenomenon $\{H_0, H_1\}$ and the statistical performance of the LDMs as follows:

$$PI^{(G)}(\underline{D}) = a_0(\underline{D}) + \sum_{m=1}^{M} a_m\, d^{(m)} \quad (18)$$

$$TH^{(G)} = \log \frac{P\{H_0\}}{P\{H_1\}} - \sum_{m=1}^{M} \log \frac{P_M^{(m)}}{1-P_{FA}^{(m)}} \quad (19)$$

where the coefficients $\{a_0, a_m, m=1,.., M\}$ are given by:

$$a_0(\underline{D}) = \log \frac{\rho_1(\underline{D}) + 1}{\rho_0(\underline{D}) + 1} \quad (20)$$

$$a_m = \log \frac{(1-P_M^{(m)})(1-P_{FA}^{(m)})}{P_{FA}^{(m)} P_M^{(m)}} \quad (21)$$

and where $P_{FA}^{(m)}$ and $P_M^{(m)}$ are the false alarm and missed detection probabilities defined in (11-12) and the $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ represent the amount of correlation between the local decisions for the two hypotheses H_0 and H_1, respectively. The functions $\{\rho_j(\underline{D}), j=0,1\}$ are defined by (B.7-B.8) in Appendix B. They are nonnegative (i.e. $\rho_j(\underline{D}) \geq 0$) and $\rho_j(\underline{D})=0$ implies that the decisions $\underline{D}$ are uncorrelated. In the uncorrelated case, the coefficient $a_0(\underline{D})=0$ in (18).

Remark 4: The optimal decision $d^{(G)}$ performed by the DFC gives at least as reliable decision (in terms of the probability of error) as that obtained by any individual local decision maker. (Otherwise the optimal decision rule will use the best local decision maker only.)

Remark 5: The decision fusion index $PI^{(G)}$ takes 2^M discrete values when fusing M binary decisions.

Remark 6: Although the minimum probability of error criterion (a special case of the Bayesian risk) is used in this paper to design the global decision rule $d^{(G)}$ as (17), other criteria can be used. For example, a Neyman-Pearson Criterion [5,14] which selects the threshold $TH^{(G)}$ based on the solution of

$$\text{Minimize } P_{FA}^{(G)}; \text{ subject to: } P_M^{(G)} \leq \text{specified bound}$$

Remark 7: Simultaneous optimal design of the local detectors and the DFC implies an inordinate search over an exponential number of fusion rules [5]. This approach is impractical.

To obtian the optimal fusion rule, we need to evaluate the probability $P\{H_0\}$ as well as the set of probabilities $\{P_{FA}^{(m)}, P_M^{(m)}, m = 1,\ldots,M\}$ and the functions $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ which indicate the amount of correlation that exists between the local decisions when voltage collapse does not exists (H_0) when it exists (H_1), respectively.

Recall from (2) that $P\{H_0\} = P\{\underline{u} \in LFF\}$, so that its value depends on the statistics of $\underline{u}$. Similarly, the set of probabilities $\{P_{FA}^{(m)}, P_M^{(m)}, m=1,\ldots, M\}$ and the functions $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ depend on the statistics of $\underline{u}$. Therefore knowing the statistics of $\underline{u}$, we can evaluate these probabilities. There are a number of ways to obtain these probabilities, these include:

(1) *Direct evaluation using the probability definitions*:- The evaluation of the probabilities and correlation coefficients by integrating the probability density function $p(\underline{u})$ over the regions of interest, i.e.:
   (i) Get $P\{H_0\}$ by integrating $p(\underline{u})$ over the region LFF.
   (ii) Get P_F and P_M by integrating the conditional probability density functions of (11) and (12).
   (iii) Compute the correlation coefficients for ρ_0 and ρ_1 using (B.7) and (B.8) of Appendix B.

(2) *Monte Carlo simulation*:- Perform a Monte Carlo simulation to obtain the desired probabilities and correlation coefficients.

(3) *Adaptive estimation*:- That is use on-line stochastic-approximation rules in order to obtain estimates of the probabilities[15]. This method has been successfully used in distributed detection. Even though the approximate estimates are biased, this bias is negligible when the observation signal to noise ratio exceeds 10 dB.

In this paper we use the Monte Carlo simulation method to obtain the necessary probabilities. The direct evaluation method requires the knowledge of the LFF region in the $\underline{u}$-space, which is difficult to obtain. The adaptive estimation method needs further work before one can apply it to the power problem at hand.

IV. Illustrative Examples

Three examples are given to illustrate the design of a four-criterion IDS system of Fig. 1 for detecting static voltage collapse using the 14 bus power system described in Appendix A. The first (representing the base case operation) illustrates the computation of the DFC's decision rule and shows the improvement one gets by using the optimal DFC strategy as compared to the "AND" and "OR" strategies. The other two examples show how the DFC decision rule changes when the system load changes (Example 2) and a line is outaged (Example 3).

Example 1(Base-case): To illustrate the design of a four-criterion IDS system of Fig. 1 for detecting static voltage collapse we use the 14 bus power system described in Appendix A. The four local decision makers (LDMs) use the four PIs defined in (5-9), where $PI^{(1)}$, $PI^{(2)}$ and $PI^{(4)}$ are evaluated using only 1P-1Q Newton Raphson iteration (see Remark 1). It is assumed that for each $PI^{(m)}$ a threshold $TH^{(m)}$ has been selected so that we have the output of the four LDMs, namely the binary decision vector $\underline{D} = [d^{(1)}\ d^{(2)}\ d^{(3)}\ d^{(4)}]^T$, where $d^{(m)}=\{0,1\}$. The objective is to design the DFC which will minimize the global probability of error, $P_e^{(G)}$. Specifically, the evaluation of the five coefficients $\{a_0, a_m, m=1,\ldots,4\}$ of (18) and the threshold $TH^{(G)}$ of (19). To achieve this, we need to evaluate the probability $P\{H_0\}$ as well as the probabilities $P_{FA}^{(m)}$, $P_M^{(m)}$ and the functions $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ which indicate the amount of correlation that exists between the local decisions when the voltage collapse does not exists (H_0) and exists (H_1), respectively. This is done via Monte Carlo simulation using the statistics of $\underline{u}$ given in Table A1. The results of this simulations are illustrated by the histogram of Fig. 2 and the VID curve of Fig.3. These results are used to obtain the set of probabilities $\{P_{FA}^{(m)}, P_M^{(m)}, m=1,\ldots,4\}$ given in the column of Table I labeled "Base case." Note that the first row gives the probability of static voltage collapse $P\{H_1\} = 0.181$.

Knowing the probabilities given in Table I, we can obtain the coefficients $\{a_m, m=1,\ldots,4\}$ and the threshold, $TH^{(G)}$, using (20) and (19), respectively. The resulting values are given in column 2 of Table II. The coefficient $a_0(\underline{D})$ of (20) requires the knowledge of the local decisions $D=[d^{(1)}, d^{(2)}, d^{(3)}, d^{(4)}]^T$ and the functions $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$. Table III gives these values for the base case example. Moreover, the last column of Table III gives the values of $PI^{(G)}(\underline{D})$ using the $a_0(\underline{D})$ and $\{a_m, m=1,\ldots,4\}$ of Table II. Note that based on the criterion of (17) all $PI^{(G)} \geq 9.412$ imply that $d^{(G)}=1$, i.e., hypothesis H_1 that voltage collapse exists.

Let us examine the performance of this decision fusion criterion relative to some other ones (such as the "AND" or "OR" rules). Recall that our decision fusion rule of (17-21) is based on minimum probability of error $P_e^{(G)}$ of (16). The values of $P_e^{(G)}$ together with $P_{FA}^{(G)}$ and $P_M^{(G)}$ are given in the last three row of the "base case" column of Table II. Let us now compare this $P_e^{(G)}$ with the probability of error for the "AND" decision rule (i.e., the case when all $d^{(m)}=1$, m=1, ..., 4) and the "OR" rule (i.e., the case when at least one $d^{(m)}=1$). These two decision rules performances are given in the last two rows of Table IV. Note that they give larger probability of error than the optimum $Pe^{(G)} = 0.089$. Moreover, Table IV gives the probability of error of the LDMs. Note that these probabilities are also greater than the optimum $P_e^{(G)}$ which verifies our claim (Remark 4) that the DFC improves the reliability of the decision process. Moreover, such improvement in performance holds for other values of the threshold, $TH^{(G)}$, as shown by the VID curve of the DFC given in FIg.4. Since for this example the $PI^{(G)}$ takes on $16 = 2^4$ discrete values (shown by the dots in Fig. 4), the dotted stair-case curve represents the case when the $TH^{(G)}$ is located between two successive values of $PI^{(G)}$. Comparing the VID curve of Fig. 5 with those shown in Fig. 3, we note that the DFC VID curve lies above any one of the LDM's VID curves. This means that for this example the DFC will

Table I : Summary of the LDMs' performances for the three examples

		Base Case (Example 1)	Load increase (Example 2)	Line Outage (Example 3)
$P\{H_1\}$		0.181	0.483	0.539
LDM #1	TH	0.900	0.900	0.900
	P_{FA}	0.428	0.782	0.887
	P_M	0.224	0.196	0.182
LDM #2	TH	0.500	0.500	0.500
	P_{FA}	0.221	0.263	0.352
	P_M	0.182	0.031	0.008
LDM #3	TH	0.750	0.750	0.750
	P_{FA}	0.499	0.728	0.493
	P_M	0.029	0.014	0.055
LDM #4	TH	1.400	1.400	1.400
	P_{FA}	0.402	0.501	0.252
	P_M	0.044	0.016	0.113

Table II: Summary of the DFC performance for three cases

		Base Case (Example 1)	Load increase (Example 2)	Line outage (Example 3)
	a_1	1.533	0.134	-0.558
$PI^{(G)}$	a_2	2.782	4.488	5.456
Coefficients	a_3	3.515	3.270	2.891
	a_4	3.476	4.119	3.151
Threshold	$TH^{(G)}$	9.412	9.822	7.910
DFC	$P_{FA}^{(G)}$	0.046	0.219	0.129
Performance	$P_M^{(G)}$	0.283	0.043	0.140
	$P_e^{(G)}$	0.089	0.134	0.127

give a better performance even for other performance criteria such as the Neyman-Pearson (Remark 6).

Example 2 (Load increase): To illustrate the performance of the DFC under a change of load, we consider the case when the load at each bus is increased by 5% for real power and 2.5% for reactive power (see Appendix A for details). This load increase implies a decrease in voltage static stability as exemplified by the decrease of $P\{H_0\} = 0.517$ from the base case value of 0.819.

The performance of the four LDMs is shown in Fig. 5. As expected, the VID curves changed from those shown in Fig. 3. The performance of $PI^{(2)}$ and $PI^{(4)}$ improved while that of $PI^{(1)}$ and $PI^{(3)}$ decreased in the sense that the best VID curve is the one closest to the left hand upper most corner where $P_D \cong 1$ and $P_{FA} \cong 0$. More important from the decision point-of-view is that the relation between the VID curves changed so that if $PI^{(3)}$ is selected to detect the voltage instability based on base case results, when the load increases, $PI^{(2)}$ is a better choice. This is the reason for needing a DFC.

The "Load increase" column of Table I summarizes the performance of the LDMs for the specific choice of the thresholds. This information is used to obtain the fusion rule of (17-19). The specific values for the $PI^{(G)}$ coefficients and the performance of the DFC are given in column "Load increase" of Table II. Note that the a_0 is not listed for this example but they can be obtained using the same method as given in previous example. A comparison between the various probabilities of error for LDMs and DFC given in Table IV shows that the DFC performs better than any of the LDMs or other DFC rules.

Example 3 (Line outage): To illustrate the performance of the DFC under a line outage, we consider the case when line 11-13 is outaged. This line outage implies a decrease in voltage static stability as exemplified by the decrease of $P\{H_0\} = 0.4603$ from the base case value of 0.819.

For this case, the VID curves of the four LDMs are shown in Fig. 6. Again, the VID curves changed from those shown in Figs. 3 and 5. The "Line outage" column of Table I summarizes the performance of the LDMs for the specific choice of the thresholds. This information is used to obtain the fusion rule of (17-19). The specific values for the $PI^{(G)}$ coefficients and the performance of the DFC are given in column "Line outage" of Table II. Note that the a_0 can be obtained using the same procedure as given in example 1. Similarly, a comparison

Table III: List of the values of $\rho_0(\underline{D})$, $\rho_1(\underline{D})$, $a_0(\underline{D})$ and $PI^{(G)}(\underline{D})$ as a function of local decisions $\underline{D}$ for the base case example

$d^{(1)}$	$d^{(2)}$	$d^{(3)}$	$d^{(4)}$	$\rho_1(\underline{D})$	$\rho_0(\underline{D})$	$a_0(\underline{D})$	$PI^{(G)}(\underline{D})$
0	0	0	0	-0.47	-0.26	-0.34	-0.34
1	0	0	0	-0.75	1.69	-2.37	-0.84
0	1	0	0	-1.11	-1.03	1.33	4.11
1	1	0	0	-1.16	-1.02	2.22	6.54
0	0	1	0	-1.01	-0.27	$-\infty$	$-\infty$
1	0	1	0	-1.09	-0.41	$-\infty$	$-\infty$
0	1	1	0	-0.23	0.64	-0.76	5.54
1	1	1	0	0.42	-0.46	0.97	8.80
0	0	0	1	4.34	0.06	1.62	5.15
1	0	0	1	4.55	-0.45	2.31	7.32
0	1	0	1	-0.85	-0.91	0.55	6.81
1	1	0	1	-0.95	-0.94	-0.22	7.57
0	0	1	1	0.33	0.26	0.05	7.04
1	0	1	1	-0.20	-0.82	1.47	10.09
0	1	1	1	-0.05	3.20	-1.49	8.28
1	1	1	1	0.04	0.87	-0.59	10.74

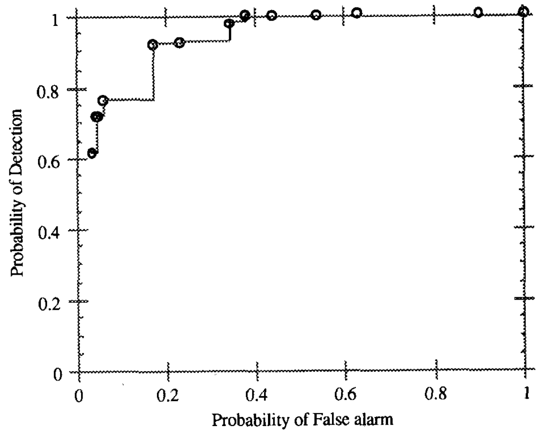

Fig. 4: VID curve of the DFC for the 14 bus under Base case operating condition

between the various probabilities of error for LDMs and DFC given in Table IV shows that the DFC performs better than any of the LDMs or other DFC rules.

Evaluation of Results: Although only three examples have been considered here, all of them showed improvement in the accuracy of predicting voltage instability when using the IDS system of Fig.1. This result is summarized in Table IV, which compares the probability of error in the detection of the DFC using the optimal fusion rule, "AND" fusion rule, "OR" fusion rule and the individual LDMs for all three cases studied.

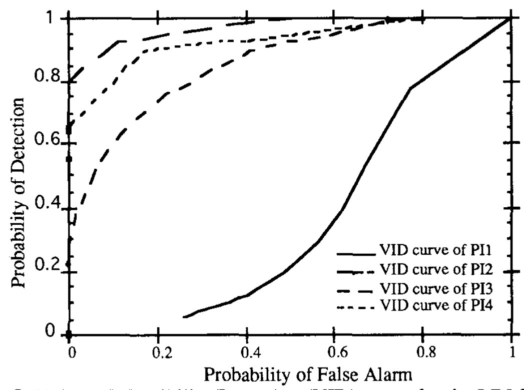

Fig. 5: Voltage Infeasibility Detection (VID) curve for the LDMs for the 14 bus under load increase condition

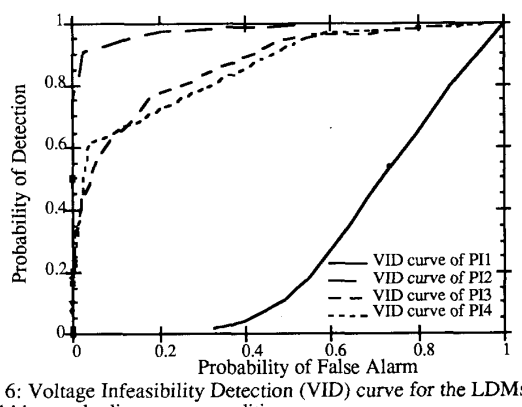

Fig. 6: Voltage Infeasibility Detection (VID) curve for the LDMs for the 14 bus under line outage condition

Table IV: Probability of error, P_e, of the LDMs, the optimum, the "AND" and the "OR" decision fusion rules

	P_e	Base Case	Load increase	Line outage
LDM #1	$P_e^{(1)}$	0.391	0.504	0.509
LDM #2	$P_e^{(2)}$	0.213	0.149	0.166
LDM #3	$P_e^{(3)}$	0.414	0.383	0.255
LDM #4	$P_e^{(4)}$	0.338	0.267	0.177
DFC-optimum rule	$P_e^{(G)}$	0.089	0.134	0.127
DFC-AND rule	$P_e^{(AND)}$	0.099	0.138	0.182
DFC-OR rule	$P_e^{(OR)}$	0.77	0.517	0.46

V. Conclusions

This paper gives an *Integrated Decision Support* (IDS) system which takes a set of possible conflicting decisions from various security indices (referred to as decision makers) and integrates (i.e., fuses) them to produce one global decision as to the security of the system. The key to the IDS system is the fusion rule which does the integration of the binary (yes/no) decisions. The optimal fusion rule developed in the paper fuses the information from four voltage collapse proximity indicators (VCPIs) to obtain a decision which minimizes the probability of error in making the wrong decision in detecting static voltage collapse. This optimal fusion rule guarantees that the global decision will be always more reliable than any of the individual VCPIs. Moreover, if it finds that one VCPI gives a more reliable decision than any of the other VCPIs, then the fusion rule will automatically consider that VCPI's opinion with a much higher weight than the weights for all other VCPI. Since all the VCPIs observe the same power system phenomenon, there is a certain amount of correlation between their decisions, a fact which is taken into account when developing the optimal decision fusion rule.

As the operating conditions change, the fusion rule also change, exemplifying the need for an adaptive decision fusion center (DFC) in the operating environment of power systems. In addition to the set of decisions from the local decision makers (i.e., VCPIs), the decision fusion center needs the probability of insecurity, $P\{H_1\}$, false alarm and missed detection probabilities of each local decision maker (i.e. $P_F^{(m)}$ and $P_M^{(m)}$), and the correlation coefficients between them. In this paper, these quantities were obtained from Monte Carlo simulations. Present work is concentrated on using methods for on-line estimation of the various probabilities needed to implement the fusion rule on-line, in order to minimize the volume of a priori information needed by the decision makers and the decision fusion center.

Finally, although the fusion rule developed in this paper was based on the minimum of probability of error, the DFC design methodology is applicable to other designs which use other design criteria such as the minimax and the Neyman-Pearson criterion. Moreover, although the examples used in this paper refer to the detection of static voltage collapse, the same methodology can be used to detect other power system security problems, such as thermal overloads, var deficiency, etc. These are some of the areas we are currently investigating.

ACKNOWLEDGMENTS

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Appendix A: Data of the 14 buses Example System

A 14 buses power system as shown in Fig. A1 is used to illustrate the design of the IDS system for detecting the static voltage collapse. In Fig. A1, there are 20 lines and 5 generators. Bus 1 is the slack bus. The line data is listed in [16].

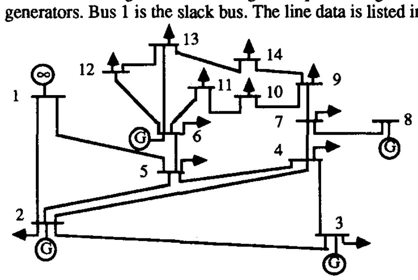

Fig. A1 : The one line diagram of the 14 buses power system

For the system of Fig. A1, the uncontrolled loads, $\underline{u}_d$, is defined as follows:

$$\underline{u}_d = [\,\underline{P}_d, \underline{Q}_d] = [P_{d2}, P_{d3}, \ldots, P_{d14}, Q_{d4}, Q_{d5}, Q_{d7}, Q_{d9}, Q_{d10}, \ldots, Q_{d14}]$$

where P_{di} and Q_{di} are the real and reactive power demand at bus i. The uncertainty of the uncontrolled loads is denoted as follows:

$$\underline{u}_d = \underline{u}_d^0 + \Delta\underline{u}_d = [\underline{P}_d^0, \underline{Q}_d^0] + [\Delta\underline{P}_d, \Delta\underline{Q}_d]$$

where $\underline{u}_d^0$ is the nominal value as given in Table A1; and $\Delta\underline{u}_d$ is the variation of the uncontrolled loads characterized by the normal distribution as given in Table A1. Note that $E(\Delta\underline{u}_d) = 0$.

Table A1: The nodal probabilistic data for the base case example

Bus #	Type	Volt.(pu)	$\underline{P}_g^0$	$\underline{P}_d^0$	$\sigma(\Delta\underline{P}_d)$	$\underline{Q}_d^0$	$\sigma(\Delta\underline{Q}_d)$
1	slack	1.06					
2	PV	1.045	0.4	0.517	0.5		
3	PV	1.01		1.242	0.5		
4	PQ			0.778	0.5	0.221	0.5
5	PQ			0.376	0.5	0.266	0.5
6	PV	1.07		0.412	0.5		
7	PQ			0.300		0.250	
8	PV	1.09		0.300			
9	PQ			0.595	0.5	0.416	0.5
10	PQ			0.390	0.5	0.308	0.5
11	PQ			0.335	0.5	0.268	0.5
12	PQ			0.361	0.5	0.266	0.5
13	PQ			0.435	0.5	0.308	0.5
14	PQ			0.449	0.5	0.300	0.5

In this paper, there are three operating conditions considered in order to demonstrate the need of the DFC due to the variation of the performances of the LDMs while the operating conditions are different. The following is the list of the three operating conditions:

Base case: Nominal bus data and probabilistic data is given in Table A1.

Load increase: Base case + Every PV buses real load demands increased by 0.05 pu and Every PQ buses load increased by 0.05 + j 0.025 pu.

Line outage: Base case + line 11-13 out of service.

Appendix B: Derivation of the Global Decision Rule

Recently, Kam et.al. [13] have solved the problem of Bayesian Data Fusion with correlated local decisions, and their solution is summarized by (17)-(21) in the main body of paper.

For Eq. (17), we need the following definitions:

$d^{(m)}$ is the decision of the m^{th} local decision maker $d^{(m)} \in \{0,1\}$; $z_m = \frac{d^{(m)} - p_m}{\sqrt{p_m q_m}}$ (normalization of $d^{(m)}$) where z_m has zero mean and unit variance; $p_m = P\{d^{(m)} = 1\}$; and $q_m = 1 - p_m$.

The *Bahadur-Lazarsfeld polynomials* [17, pp.111-113] are defined as:

$$\varphi_i(\underline{D}) = \begin{cases} 1 & 0 \\ z_1 & i=1 \\ z_2 & i=2 \\ \bullet & \bullet \\ z_M & i=M \\ z_1 z_2 & i=M+1 \\ \bullet & \bullet \\ z_1 z_2 z_3 & i=(M+1)+\frac{M(M-1)}{2} \\ \bullet & \bullet \\ z_1 z_2 \ldots z_M & i=2^M-1 \end{cases}$$

$$\text{let } b_i = E[\varphi_i(\underline{D})] \tag{B.1}$$

The k^{th}*-order correlation coefficients* of $d^{(1)}, d^{(2)}, \ldots, d^{(k)}$, where k is an integer between 1 and M, are defined as the set of all b_i whose index $i \in I_k$ where

$$I_k = \{i \mid \binom{M}{1} + \binom{M}{2} + \ldots + \binom{M}{k-1} + 1 \le i < \binom{M}{1} + \binom{M}{2} + \ldots + \binom{M}{k-1} + \binom{M}{k} + 1\}; \; k \ge 2$$

b_{i0} and b_{i1} are calculated when $d^{(1)}, d^{(2)}, \ldots, d^{(k)}$ are made under hypothesis H_0 and hypothesis H_1, respectively.

The final decision rule is

$$\begin{array}{lll} \text{Decide} & d^{(G)} = 1 & \text{if} \quad PI^{(G)} \ge TH^{(G)} \\ \text{Decide} & d^{(G)} = 0 & \text{if} \quad PI^{(G)} < TH^{(G)} \end{array} \tag{B.2}$$

where the scalar index $PI^{(G)}(\underline{D})$ is a function of the set of decisions $\underline{D}$ and the statistical performance of the LDMs while the threshold depends on the probabilities of the phenomenon $\{H_0, H_1\}$ and the statistical performance of the LDMs as follows:

$$PI^{(G)}(\underline{D}) = a_0(\underline{D}) + \sum_{m=1}^{M} a_m d^{(m)} \tag{B.3}$$

$$TH^{(G)} = \log \frac{P\{H_0\}}{P\{H_1\}} - \sum_{m=1}^{M} \log \frac{P_M{}^{(m)}}{1 - P_{FA}{}^{(m)}} \tag{B.4}$$

where the coefficients $\{a_0, a_m, m=1, \ldots, M\}$ are given by:

$$a_0(\underline{D}) = \log \frac{\rho_1(\underline{D}) + 1}{\rho_0(\underline{D}) + 1} \tag{B.5}$$

$$a_m = \log \frac{(1 - P_M{}^{(m)})(1 - P_{FA}{}^{(m)})}{P_{FA}{}^{(m)} P_M{}^{(m)}} \tag{B.6}$$

where the $P_{FA}{}^{(m)}$, $P_M{}^{(m)}$ are false alarm and missed detection probabilities defined in (11-12) and the $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ are defined as follows:

$$\rho_1(\underline{D}) = \sum_{i \in I_2, j<k} b_{i1} z_j^1 z_k^1 + \sum_{i \in I_3, j<k<m} b_{i1} z_j^1 z_k^1 z_m^1 + \ldots + b_{2^M-1\,1}\, z_1^1 z_2^1 z_3^1 \ldots z_M^1 \tag{B.7}$$

$$\rho_0(\underline{D}) = \sum_{i \in I_2, j<k} b_{i0} z_j^0 z_k^0 + \sum_{i \in I_3, j<k<m} b_{i0} z_j^0 z_k^0 z_m^0 + \ldots + b_{2^M-1\,0}\, z_1^0 z_2^0 z_3^0 \ldots z_M^0 \tag{B.8}$$

$$\text{where } z_m^h = \frac{d^{(m)} - P(d^{(m)} = 1 \mid H_h)}{\sqrt{P(d^{(m)} = 1 \mid H_h)(1 - P(d^{(m)} = 1 \mid H_h))}}; \; h = 0,1 \tag{B.9}$$

As seen from (B.7) and (B.8), $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$ represent the amount of correlation between the local decisions when the power system is secure (H_0) and insecure (H_1), respectively. To calculate the $\rho_0(\underline{D})$ and $\rho_1(\underline{D})$, the b_{i0}, b_{i1} and the performances of LDMs are needed. The techniques of calculating the performances of the LDMs are given in section III. For b_{i0} and b_{i1}, they can be computed by using the direct integration if the probability density function of $\{p(\underline{D} \mid H_i), i=0,1\}$ is known. However, the closed form of $\{p(\underline{D} \mid H_i), i=0,1\}$ is very hard to obtain in real operation. Thus, in this paper, the Monte-Carlo simulation is used for estimating the b_{i0} and b_{i1}. Moreover, if the correlation coefficients above a certain order can be neglected, as is the case in many practical applications, the computational burden can be reduced. If all the conditional correlation coefficients are zero under both hypotheses, then the $PI^{(G)}$ becomes

$$PI^{(G)}(\underline{D}) = \sum_{m=1}^{M} a_m d^{(m)} \tag{B.10}$$

Then, the optimal fusion rule is agree with the optimal fusion rule that Chair and Varshney [4] have developed for fixed local detectors with independent local decisions (and indeed when all the conditional correlation coefficients under both hypotheses are zero, the local decisions are statistically independent). ♦♦

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