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An Expert System Realization of Adaptive Autonomy in Electric Utility Management Automation

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Abstract: Earlier we introduced a novel framework for implementation of Adaptive Autonomy (AA). This study presents an expert system realization of the AA framework, referred to as Adaptive Autonomy Expert System (AAES). The proposed AAES is based on the extracted rules from the Expert's Judgment on proper Levels of Automation (LOA) for various environmental conditions, modeled as Performance Shaping Factors (PSFs). Decision fusion method is used as expert system inference engine, where eight decision fusion methods are developed as prospective ones. The AAES is realized in the practical case of electric power Utility Management Automation (UMA) for the Greater Tehran Electricity Distribution Company (GTEDC). The practical list of PSFs and the judgments of GTEDC's experts are used as the expert system rule base in this research. The results of implementing the proposed AAES to GTEDC's network are evaluated according to two criteria: average error and error margin. Five out of eight decision fusion methods are proven to be suitable inference engines, due to both criteria. Evaluation of the results shows that the proposed AAES can estimate proper LOAs for GTEDC's UMA system, which change due to the changes in PSFs; thus providing a dynamic (adaptive) LOA scheme for UMA.

Key words: Human-automation interaction, level of autonomy, power distribution automation, expert's judgment, performance shaping factors

INTRODUCTION

Expert systems are information systems that emulate judgments of experienced experts in a particular field. Therefore, they can be used to solve problems associated with Complex Adaptive Systems (CASs) that ordinarily require human expertise (Turban, 1992).

Electric power plays a vital role in modern civil life (Ghaderi *et al*., 2006). Continuity of service is the main goal of electric power utility companies; therefore, they need to be rapidly recovered in contingency situations. This is performed by Utility Management Automation (UMA) system, in which, human experts and automated systems work collaboratively. This collaboration needs to be harmonized, to achieve a best-fit allocation of functions.

Human-Automation Interaction (HAI) has been studied for more than a half century (Parasuraman and Wickens, 2008). A static list was introduced by Fitts in 1956, to allocate functions between human and automation, referred to as MABA-MABA (Men Are Better At …-Machines Are Better At …) (Parasuraman *et al*., 2000). To overcome the shortages of Fitts' two-degree (manual or automate) automation policy, Sheridan and Verplank suggested a ten-degree levels of automation (LOA) in 1978 (Parasuraman *et al*., 2000). Parasuraman *et al*. (2000), Endsley *et al*. (2003), Itoh and Inagaki (2004), Endsley and Kaber (1999) Kaber *et al*. (2005) and Fereidunian *et al*. (2007a, 2008) developed the LOA idea, introduced more sophisticated HAI models or implemented the existing models.

Human-automation systems performance is affected by environmental conditions; therefore, the fixed determination of LOA fails to maintain full advantages of the basic idea of LOA. As a result, the LOA should be adapted to the environmental conditions. This adaptation necessity, paves the way toward more advanced HAI approaches, referred to as adaptive automation (Parasuraman *et al*., 2000; Kaber *et al*., 2005), adjustable automation (Bradshaw *et al*., 2003), or Adaptive

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Autonomy (AA) (Fereidunian *et al*., 2007b, 2008). Figure 1 shows a chronological illustration of the conceptual development of HAI.

Despite the considerable significance of AA in literature, most implementation reports of AA are only within few high-tech industries such as aerospace, aviation and military. While, many safety-critical civil infrastructure systems like electric power utility industry (as good instances of CASs (Samad and Weyrauch, 2000)) are fertile grounds for implementations of the AA notion. Consisting complex entities of humans and automation systems, the AA approach to HAI can be regarded as a CAS issue. Consequently, expert systems are ideal solutions for realization of AA for HAI systems.

This research group presented a general, yet practical, framework for implementation of AA in Fereidunian *et al*. (2008), applying experts' judgment concept to tackle the complex issue of human reliability assessment. In the proposed framework, the LOA of UMA was determined adaptively as a function of environmental conditions, represented as Performance Shaping Factors (PSFs) (Rosqvist, 2003).

This study, as a continuum of Fereidunian *et al*. (2008) introduces an expert system methodology for realization of our proposed AA framework, by developing mathematical models based on decision fusion approach. This research advances the premise that the proposed AA expert system can track a human expert judgment on determination of the best-fit LOA. The proposed AAES uses the judgments of GTEDC's experts on proper LOAs

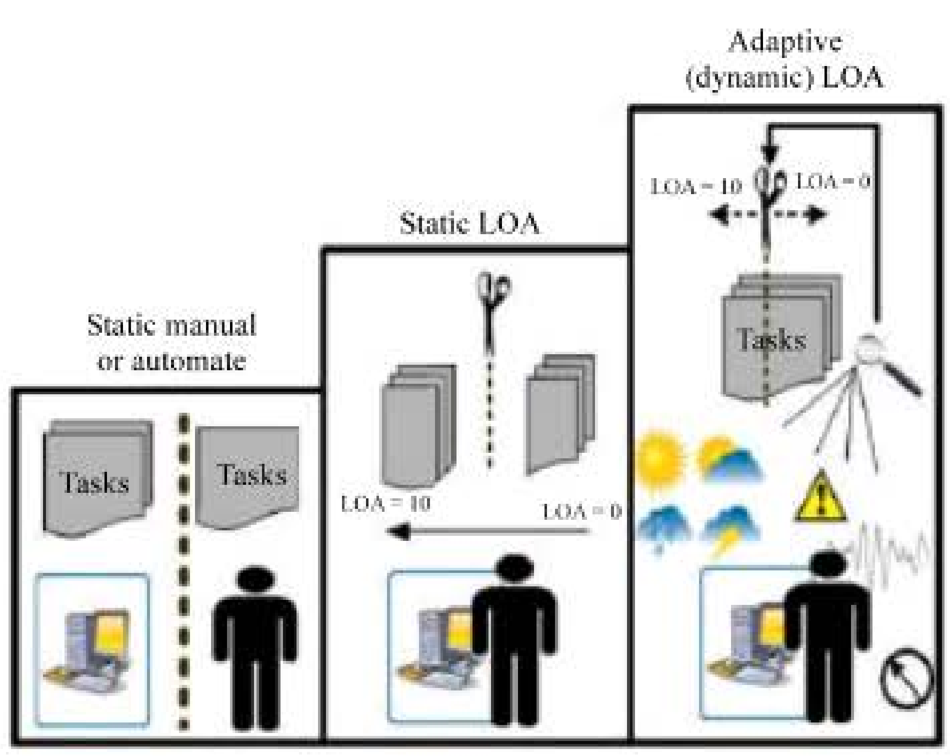

Fig. 1: Development of the Human-Automation Interaction (HAI) in the literature from left to right: Fitts' list (fixed manual or automatic function allocation), Fixed Level of Automation (LOA) (fixed ten-level LOA) and Adaptive LOA (AA or dynamic LOA)

for changing environmental conditions (PSFs) as the expert system rule base. Furthermore, the AAES utilizes decision fusion method as the expert system inference engine. This study presents the first practical implementation of the LOA-TOA model of Parasuraman *et al*. (2000) using the AA implementation framework of Fereidunian *et al*. (2008) in a real power distribution automation case (UMA-FRF in GTEDC) for the first time, to the best of our knowledge, according to the Science Citation Index® and the IEEEXplore®. It can also be regarded as one of the first application reports of LOA-TOA model in the civil services, except to the aviation and cruise control.

MATERIALS AND METHODS

This research is a continuation of Fereidunian *et al*. (2008), which had been initiated at Helsinki University of Technology, Finland in 2005-2006 academic year. The rough ideas developed there were expanded and represented as quantitative models in University of Tehran, Iran from 2006 to 2008. The practical data (such as the practical list of PSFs and Experts' Judgments interviews) were obtained from the GTEDC in 2006 and 2007. This paper presents an expert system realization for the general framework of Fereidunian *et al*. (2008) for AA implementation.

Expert systems have many applications in electric power systems. Utility Management Automation (UMA) system is a sort of Supervisory Control and Data Acquisition (SCADA) system for the electric utility system. In this study, an expert system (referred to as AAES) is used to adapt the autonomy level (LOA) of the UMA system to the changes in environmental conditions (PSFs), as shown in Fig. 2. When one of the PSFs

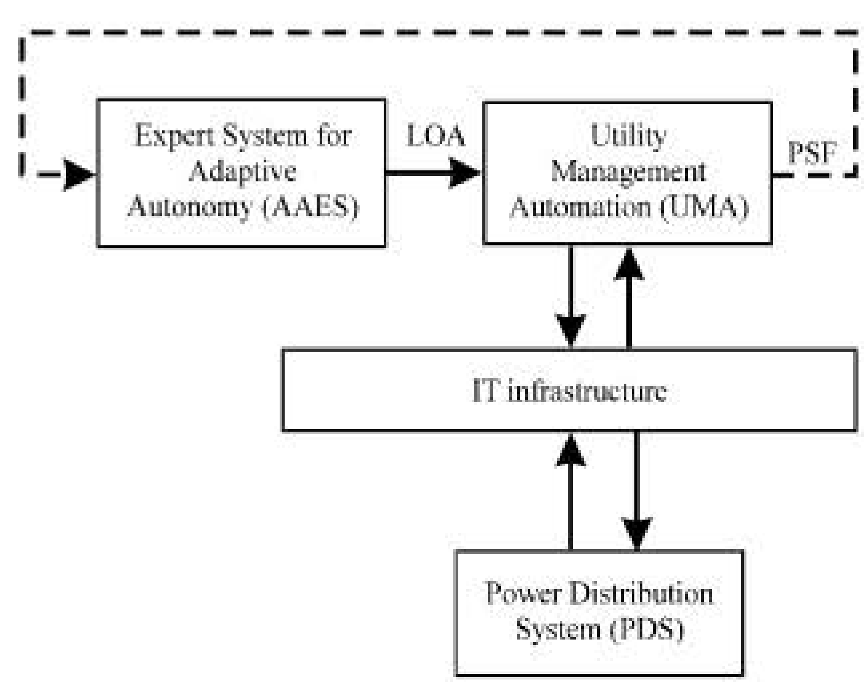

Fig. 2: Position of Adaptive Autonomy Expert System (AAES) in the utility management automation total system

(Table 1) change, the AAES expert system recommend a new LOA for the UMA system, using its fusion-equipped inference engine, based on its rule-base provided by experts' judgments. Briefly, the AAES acts as a controller for UMA system: it controls the LOA of the UMA system.

The AAES is implemented to one of the power distribution automation functions, known as feeder reconfiguration of utility management automation (UMA-FRF: Utility Management Automation, Feeder Reconfiguration Function). The UMA-FRF system (Fereidunian *et al*., 2002) restores the network after occurrence of faults, by reconfiguring the power distribution system. Figure 2 shows the proposed expert system role in relation with other sub-systems of UMA. The dashed arrow from the UMA conveys the environmental conditions (PSFs) to the AAES; where, the other arrow commands the LOA that is recommended by AAES to the UMA.

This study uses an extended version of the original HAI model of Parasuraman *et al*. (2000) introduced by Fereidunian *et al.* (2007a) having a 1* level added to the original model. The definitions of the LOAs, TOAs and HAI model can be found in the Table 2, as well as in (Parasuraman *et al*., 2000; Fereidunian *et al*., 2007a, b; Endsley and Kaber, 1999).

The environmental conditions are represented by the PSFs vector (Fereidunian *et al*., 2007a, 2008). The practical list of PSFs was obtained from the GTEDC. The vector $X = \{x_1, x_2, ..., x_{10}\}$ is a binary vector, depicting the instantaneous PSFs for the UMA. Elements of X are defined in Table 1.

The proper values of LOA are judged by the GTEDC's experts for specific situations (denoted here, as single-one PSFs), by filling in-person interview questionnaires. The single-one PSFs can be written as: [1, 0,..., 0], [0, 1,..., 0], ..., [0, 0,..., 1]; where, their relevant LOAs can be represented as $L_1, L_2, ..., L_{10}$.

The proposed AAES fuses (i.e., combines or aggregates) the recommended LOAs for single-one PSFs (i.e., L_i s), in order to determine the proper LOA for other situations. According to a comprehensive study on various sorts of fusion methods in the relevant literature ((Daniels *et al*., 2001; Sinha *et al*., 2006; Alexandre *et al*., 2001; Bloch, 1996), we made the following methods candidate for our expert system purpose: Linear Fusion, Product Fusion, Compromised Fusion, Minimum and Maximum. A summary of the five prospective fusion methods, which is customized and derived for our specific case, is as follows:

Table 1: Practical list of PSFs for UMA-FRF system

Attribute	Normal state of PSFs	PSF	PSF symbol
Time	Day	Night	x_1
Region type	Un-crowded urban area	Crowded urban area	x_2
		Rural area	x_3
Costumer importance	Residential area	Commercial/ industrial area	x_4
		VIP area	x_5
Detected faults in 2 h	1 fault	5 fault	x_6
		10 fault	x_7
Network lifetime	Newly constructed	Middle-aged network	x_8
		Old network	x_9
Load	Low-loading	High-loading	x_{10}

Table 2: Definitions of the LOAs, according to (Parasuraman *et al*., 2000; Fereidunian *et al*., 2007a)

LOA	Description
10:	Fully autonomous: The automation systems decide everything; act autonomously, yet collaborating with other automation systems, ignoring the human.
9:	The automation systems inform the human supervisor only if they decide to.
8:	The automation systems inform the human, only if asked.
7:	The automation systems execute autonomously and then necessarily inform the human supervisor.
6:	The automation systems allow the human supervisor a restricted time to *veto* before automatic execution.
5:	The automation systems execute that suggestion if the human supervisor approves.
4:	The automation systems suggest one decision action alternative.
3:	The automation systems narrow the decision choice selection down to a few.
2:	The automation systems offer a complete set of decision/action alternatives.
1*:	The automation systems acquire the data from the process and register them without analysis.
0*:	Fully manual: The automation systems offer no assistance: the human decides and acts.

- Linear fusion can be written in our case as:

$$\mathrm{LOA}(X) = \mathrm{round}\left(\sum_{i=1}^{n} w_i L_i x_i\right) \tag{1}$$

where, LOA(X) is the overall LOA value of X, round operator rounds the calculations to the nearest LOA, x_i is the PSF i, L_i is the recommended LOA for x_i, w_i is the x_i corresponding weight and n is the number of PSFs.

- Product Fusion as follows:

$$\mathrm{LOA}(X) = \mathrm{round}\left(\prod_{i=1}^{n} L_i^{w_i x_i}\right) \tag{2}$$

- The Compromised fusion as, r = 2, 3, 4, 5:

$$\mathrm{LOA}(X) = \mathrm{round}\left(\left[\frac{\sum_{i=1}^{n}(L_i w_i x_i)^r}{\sum_{i=1}^{n}(w_i x_i)^r}\right]^{\frac{1}{r}}\right) \tag{3}$$

where, r is scaling factor.

- The Minimum method (voting/ranking method) as:

$$\text{LOA(X)} = \text{Min}\{L_i x_i\}_{i=1}^{n} \tag{4}$$

- The Maximum method (voting/ranking method) as:

$$\text{LOA(X)} = \text{Max}\{L_i x_i\}_{i=1}^{n} \tag{5}$$

The eight candidate fusion methods were subsequently used as the core computational instruments of the AAES, i.e., as the expert system inference engine.

RESULTS AND DISCUSSION

The results of the implementation of the eight candidate fusion methods to the AAES for UMA-FRF case, as well as evaluation and comparison of the methods are presented here. Here, the prospective fusion methods (as AAES inference engines) are evaluated using two criteria: average errors and error margin graphs.

First, the AAES inference engines (fusion methods) are evaluated using average errors. Since the main duty of an expert system is to behave like a human (Ng, 2003); hence, the proposed fusion methods should be evaluated against superior human experts, whose recommended LOAs are indicated by LOA_j^{Ref}. The Superior Experts are experts, whose superiority (in higher and more reliable expertise) has been verified according to the consistency of their expert judgments interview questionnaire.

The method error can be defied as:

$$\text{Error} = \frac{1}{m}\sum_{j=1}^{m}\left|LOA_j^{AAES} - LOA_j^{Ref}\right| \tag{6}$$

where, Error is average error of a method, LOA_j^{AAES} is the calculated LOA for sample j of the PSFs by AAESs, LOA_j^{Ref} is the recommended LOA by superior expert (as reference value) in sample j of PSFs and m is total number of PSF samples. Since X includes ten binary elements, it can take 2^{10} = 1024 sample at most. However, only 324 samples are practically feasible ones for each proposed method.

Figure 3 shows average errors for all of the proposed decision fusion methods. The results show that all of the proposed fusion methods are within the acceptable range, expect to the Minimum method (Fig. 3). As depicted in Fig. 3, Linear, Product, Compromised (for r taking 2, 3, 4, 5) and Maximum fusion methods calculate the LOA with less than 0.5 average error, however, Minimum fusion method exceeds the 0.5 error value. Since the outputs of the AAES are LOAs (which take integer values from 0 to 10) the average errors less than 0.5 show reasonably tolerable error for the AAES.

Second evaluation criterion is error margin graphs in Fig. 4. This study also evaluates the proposed fusion methods (AAES inference engines) by comparing the calculated LOA with the superior expert's recommended LOA, as shown in Fig. 4. The calculated LOAs are the best-fit LOA, in accordance with the superior expert's judgment, if they appear on the dashed line. The two margin lines show maximum deviations from the best-fit LOA. In the worst case, Linear, Product, Compromised (for r = 2, 3, 4) calculate only one level away from the superior expert's judgment; while, the Minimum, Maximum and Compromised (for r = 5) determine two levels away from the superior expert's judgment.

Shortly, eight decision fusion methods proposed to realize the AAES and the AAES expert system was benchmarked by a superior expert. The benchmarking process was performed by two evaluation criteria: average error and margins error.

Since LOAs include integer values, less than 0.5 average error indicates that in average the calculated LOA (LOA^{AAES}) are near to recommended LOA (LOA^{Ref}), thus they are far from the neighbors of recommended LOA (LOA^{Ref} ±1); hence, average tolerable error range is less than 0.5, as indicated in Fig. 5. The tolerable error margin is at most 1. The benchmarking results express the five methods of the eight proposed methods satisfy both criteria. The five suitable methods for this case study are Linear, Product, Compromised (for r = 2, 3, 4).

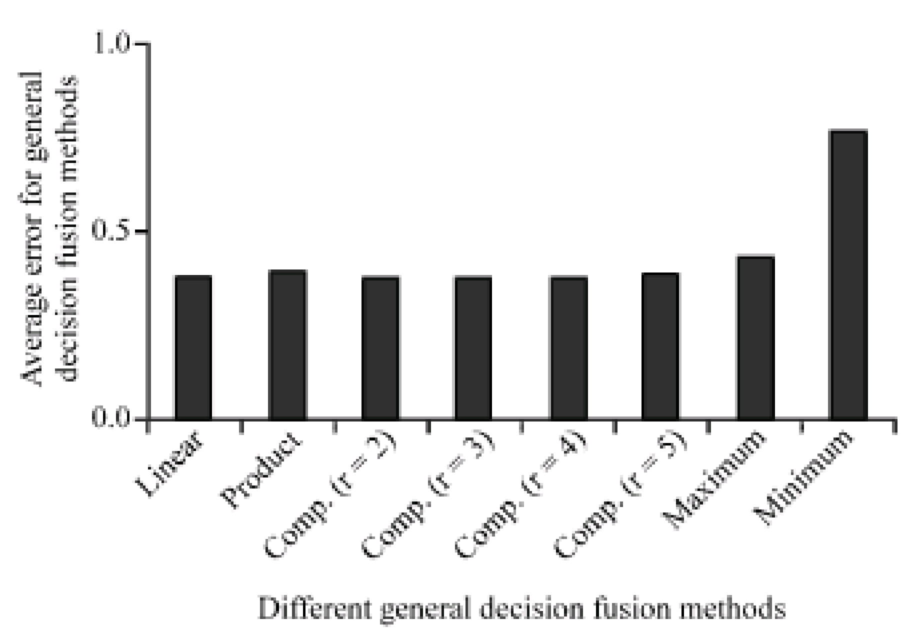

Fig. 3: Average error graph for the candidate decision fusion methods

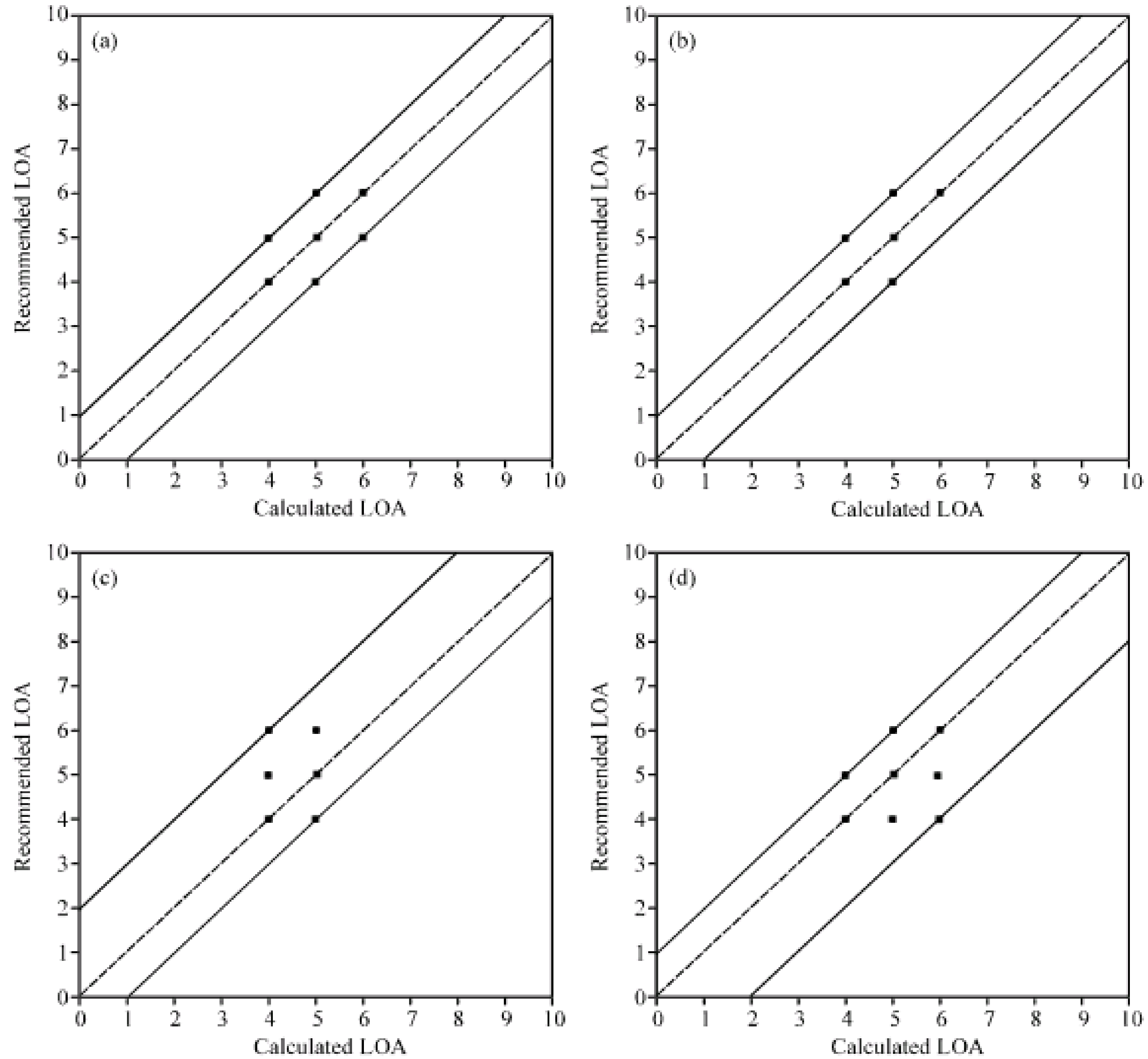

Fig. 4: The recommended LOA verses calculated LOA. (a) Linear, Compromised r = 2, 3, 4, (b) Product, (c) Minimum and (d) Maximum and Compromised r = 5, - - ■ - - Calculated LOA = Recommended LOA, —■— Calculated LOA ≠ Recommended LOA, the most distant

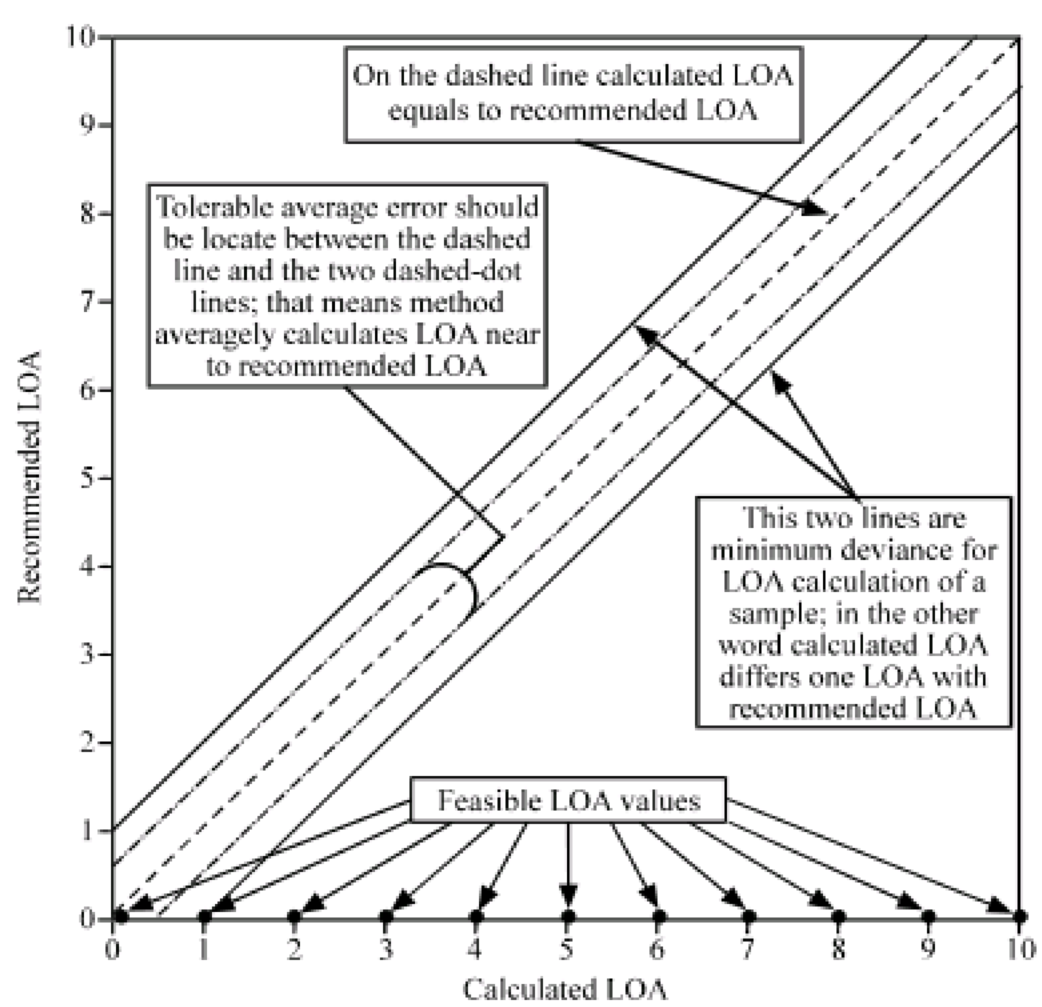

Fig. 5: Average error and error margin tolerable value

CONCLUSION

An expert system was introduced for realization of AA framework of Fereidunian *et al.* (2008), referred to as AAES. The presented AAES adapts the LOA of UMA-FRF (or generally, HAI system) to the environmental conditions. The judgments of the GTEDC's experts were deployed as the expert system rule base and decision fusion method was utilized as inference engine, to generalize the experts' judgment rule-base to new instances.

Eight decision fusion methods were considered as prospective inference engines; subsequently, they were evaluated by two criteria: average errors and error margin graphs. Consequently, five out of eight decision fusion methods were qualified as proper inference engines, according to the evaluation process.

Both evaluations show that the proposed expert system (AAES) tracks a human expert's judgment in LOA determination, while changing the environmental conditions.

This study continues on more theoretical work on the HAI models, implementation of the implementation of proposed method in other developmental environments.

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