2009 Ninth International Conference on Intelligent Systems Design and Applications

AAFES: An Intelligent Fuzzy Expert System for Realization of Adaptive Autonomy Concept

Alireza Fereidunian, Mohammad-Ali Zamani, Caro Lucas, Hamid Lesani, Matti Lehtonen

***Abstract*- Intelligent control and automation is associated with expert systems; especially, when it needs to human expertise. Earlier we introduced a framework for implementation of adaptive autonomy (AA) in human-automation interaction systems, followed by a data-fusion-equipped expert system to realize that. This paper uses fuzzy sets concept to realize the AA expert system, in a real automation application. The presented *adaptive autonomy fuzzy expert system* (AAFES) determines the *Level of Automation* (LOA), adapting it to the changing *Performance Shaping Factors* (PSF) of automation system. The paper includes design methodology and implementation results for AAFES, and discussion on results. Results show that AAFES yields proper LOAs, even in the new contingency situations. This is caused by AAFES's higher intelligence than the crisp (binary) one. Moreover, since AAFES deals with fuzzy linguistic PSFs, it more realistically represents the experts' opinion.**

I. INTRODUCTION

INTELLIGENT EXPERT SYSTEMS grasp human expertise in a particular field, to behave like human experts. They are utilized when a system can hardly be modeled with conventional methods [1], [2]. Human-automation interactions (HAI) inherit its complexity from humans and automation systems, which leads to difficulty in modeling. Consequently, intelligence and expertise is needed to deal with this level of complexity.

HAI has extensively been studied in the last half of the century [3], as its underlying theories has been developed in three breakthroughs [4]: In the first step (1956), P.M.Fitts considered automation strategy as full automation and manual action, where he introduced a list of "**M**en **A**re **B**etter **A**t…, **M**achines **A**re **B**etter **A**t…" (MABA-MABA) [3],[4]. In the second step (1978), Sheridan and Verplank introduced the concept of the **L**evel **O**f **A**utomation (LOA), in which, automation level changes from fully-manual to full-automation in ten succeeding levels [5], [6]. In the third step (2000), the idea of **A**daptive **A**utonomy (AA) was introduced to maintain human-automation systems' performance, considering dynamic LOAs [7]-[10].

Despite the importance of the AA concept, few quantitative models and practical implementations of AA are presented in aerospace, aviation and military industries [7]-[10]. Nevertheless, there is a huge gap for research on implementable models for AA.

Our research group has comprehensively studied the application of HAI and AA, having power distribution automation as implementation field [4],[11]-[13]. A model-based framework for implementation of AA in HAI systems was introduced in [12], [13]. Subsequently, [4] realized the presented framework of [12] and [13], using a data-fusion-equipped expert system, referred to as AAES (adaptive autonomy expert system). The AAES acquires environmental conditions (referred to as performance shaping factors (PSFs)), then it recommends an appropriate LOA for the present state of PSFs. The proposed AAES of [4] could rather follow a human expert in recommending proper LOA for the present state of PSFs. However, it slightly suffers from the lack of intelligence in abrupt changes of PSFs. Moreover, real world automation systems include continuous PSFs, already taken as granted as binary values in [4].

In this paper, we furthered the AAES in a real power systems automation implementation using, fuzzy sets concept, thus referring to as AAFES. A conceptual framework of AAFES is illustrated in Fig.1. Main features of the presented AAFES that are enumerated in Fig. 1, are described as follows: AAFES's higher intelligence –as the legacy of the fuzzy concept– helps it to obtain right results, even in the

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978-0-7695-3872-3/09 $26.00 © 2009 IEEE
DOI 10.1109/ISDA.2009.46

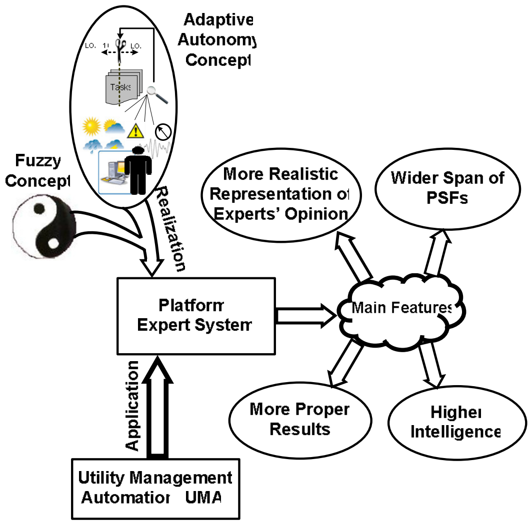


Fig.1. The conceptual framework of this paper for AAFES implementation.

situation that has not foreseen by the experts. Furthermore, AAFES is expected to yield more proper LOAs, as it intelligently acts in multi-PSF conditions, by considering each PSF's contribution into the calculation of the proper LOA. Moreover, fuzzy PSFs in FAEES represent the experts' opinion more realistically than the binary PSFs in AAES; since it deals with linguistic fuzzy PSFs. Indeed, fuzzy concept in AAFES is instrumental in spanning all environmental conditions (PSFs), comparing to that of binary coded PSFs in AAES.

The rest of this paper is structured as follows: after the introduction, AAFES design methodology is presented in Method section, including problem statement, fuzzy representation of the PSFs and realization of AAFES. Subsequently, the implementation results are presented; then, AAFES's performance is evaluated in four prospective scenarios. Finally, the paper is concluded in Conclusion section.

II. METHOD

A. Problem Statements

The basic ideas of this research emerged through implementation of HAI models in Greater Tehran Electricity Distribution Company (GTEDC), where the practical data (such as the practical list of PSFs and experts judgments interviews) were obtained. GTEDC delivers electric power to the Greater Tehran metropolitan area, feeding more than 12000 medium voltage (20 kV/400 V) substations.

Utility management automation (UMA) acts as a SCADA (supervisory control and data acquisition) system for the electric utility, in which, human operators and automation systems works collaboratively. An expert system (referred to as AAFES) is used to adapt the autonomy level (LOA) of the UMA system to the changes in PSFs, in this research, as shown in Fig. 1. Whenever PSFs change, the AAFES expert system recommends a new LOA for the UMA system, using

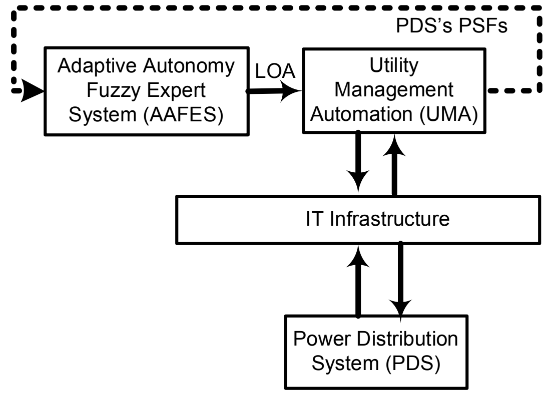


Fig.2. Position of Fuzzy Adaptive Autonomy Expert System in Power distribution system

its fuzzy inference engine, based on its rule-base provided by experts' judgments. Briefly, the AAFES controls the LOA of the UMA system.

AAFES is implemented to one of the power distribution automation functions, referred to as feeder reconfiguration function of utility management automation (UMA-FRF). The UMA-FRF restores the network after occurrence of faults, by reconfiguring the distribution system [14],[15]. Fig.2 shows the proposed expert system role in relation with the other sub-systems of the UMA. The dashed arrow from the UMA conveys the PSFs to the AAFES; where, the other solid line arrows command the LOA that is recommended by AAFES to the UMA.

This study uses an extended version of the original HAI model of [7], introduced by [11], having an additional 1* level. The definitions of the LOAs and HAI model can be found in [7],[8],[11],[12].

B. Fuzzy Representation of the PSFs

According to GTEDC's experts, UMA's LOA depends on six main PSFs: time, service area, customer type, number of faults per two hours, network age, and load [4]. We define fuzzy PSFs as follows:

Time: Time is considered in two sub-PSFs : day-time and night-time [4]. At nights, UMA dispatching operators are faced by problems like lack of sight and operators' in-vigilance. The linguistic variable of the time accepts two values of {day, night} in daily hour's axis with the membership function shown in Fig.3.

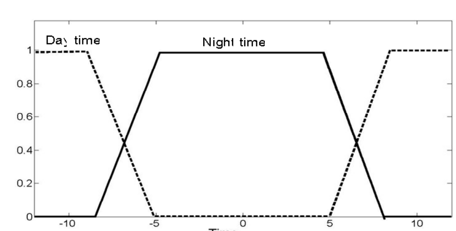


Fig.3. Time fuzzy PSF membership function

Service area: This PSF contains three sub-PSF: uncrowded urban area, crowded urban area, and rural area. [4]. When faults occur in a distribution network, operators' quick access to the local switches is important factor that affect on the UMA's performance. This factor is presented in the form of inconvenient service. The linguistic variable of the service area accepts three values of {uncrowded urban area, crowded urban area, rural area} in service inconveniency percentage axis with the membership functions shown in Fig.4.

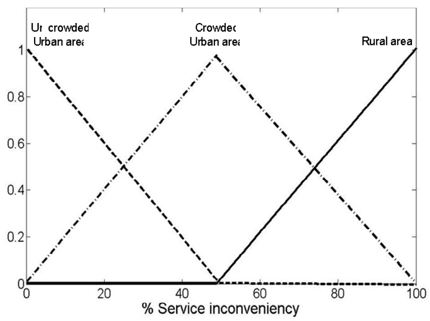


Fig.4. Service area fuzzy PSF membership function

Customer type: Customers are categorized in three sub-PSFs: residential area, commercial/industrial area, VIP customers area [4]. The customer type linguistic variable accepts three values of {residential, commercial/industrial, VIP} in customer importance percentage axis with the membership functions shown in Fig.5.

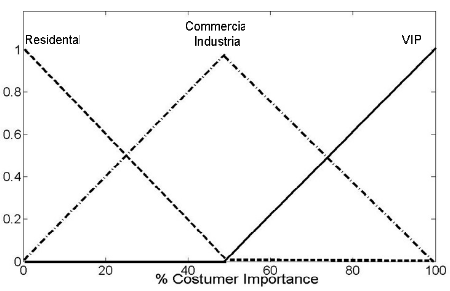


Fig.5. Customer importance fuzzy PSF membership function

Number of faults per two hours: Few, more, and much more faults are the sub-PSFs of this PSF. The linguistic variable of numbers of faults per two hours accepts three values of {few, more, much more} in faults numbers axis with the membership functions shown in Fig.6.

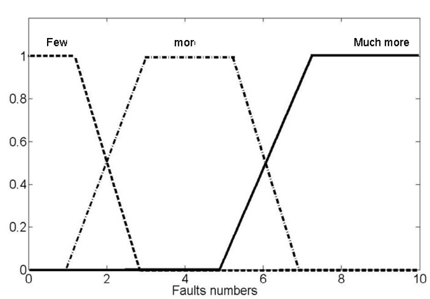


Fig.6. Faults number fuzzy PSF membership function

Network age: Aging of the network increases its failure rate [16, 17]. Newly constructed, middle-aged, and old network are three sub-PSF of the network age [4]. The linguistic variable of network age accepts three values of {new, middle-aged, old} in year axis with the membership function shown in Fig.7.

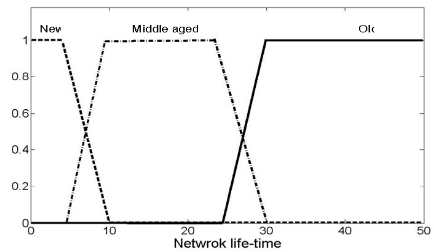


Fig.7. Network age fuzzy PSF membership function

Load: The load PSF includes two sub-PSF of low loading and high loading [4]. The load linguistic variable accepts two values of {low, high} in per unit load axis with the membership functions shown in Fig.8.

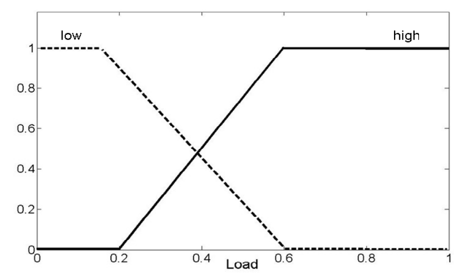


Fig.8. Load fuzzy PSF membership function

C. Realization of Fuzzy Adaptive Autonomy Expert System

The proposed fuzzy expert system (AAFES) first fuzzifies the six UMA's PSFs as described in the previous sub-section. The PSFs are represented as a fuzzy-valued vector of PSF as:

$$\mathbf{PSF} = [PSF_1, PSF_2, PSF_3, PSF_4, PSF_5, PSF_6] \quad (1)$$

Where, each PSF vector element represents one of the PSFs of UMA as:

PSF_1 : Time

PSF_2 : Service area (service inconveniency)

PSF_3 : Customer type

PSF_4 : Number of faults per two hours

PSF_5 : Network age

PSF_6 : Loading

Subsequently, AAFES recalls the embedded rules from its inference engine, then, it calculates and defuzzifies the LOAs values (Fig.9.). The rules are obtained from expert judgment in two steps: first, the recommended LOA is asked for each sub-PSF lonely; second, the experts identify the importance of each PSF.

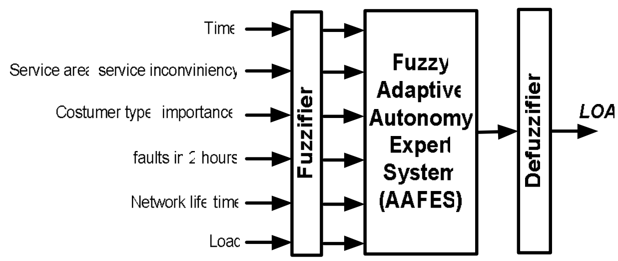


Fig.9. AAFES (Fuzzy Adaptive Autonomy Expert System) receives the 6 PSFs and calculate the proper LOA

III. Implementation Results

In this section, we develop four practical scenarios from the UMA operation, to reveal the performance of our proposed AAFES.

***Scenario 1*: Normal condition**, which means one fault has occurred in an uncrowded urban area with no customer importance in two years old network with 50% of maximum load at 10am, represented by PSF vector as:

PSF = [10 am, 0% service inconveniency, 0% important, 1 [faults/2hours], 2 [years old], 0.5 [p.u.[†]]]
The AAFES proposes LOA 5 for Scenario 1. The AAES of [4] represents this scenario by [0,0,0,0,0,0,0,0,0,1], and it also recommend LOA 5. This Scenario is considered as normal condition, and the other scenarios are compared to this scenario.

***Scenario 2*: High-loading condition,** which means one fault has occurred in an uncrowded urban area with no customer importance in a two years old network with *80% of maximum load* at 10am, represented by PSF vector as:

PSF = [10 am, 0% service inconveniency, 0% important,1 [faults/2hours], 2 [years old], 0.8 [p.u.]]
The AAFES proposes LOA 6 for Scenario 2, one level of automation higher than that of normal condition (Scenario 1). Because, the load is increased and control has become more difficult, thus the increase in LOA is justifiable; however, the AAES representation make no difference in the two scenarios and the vector is [0,0,0,0,0,0,0,0,0,1], therefore, it proposed the same LOA as in Scenario 1 (i.e. LOA=5).

***Scenario 3*: old network condition**, which means one fault has occurred in an uncrowded urban area with no customer importance in a *30 years old network* with 50% of maximum load at 10am, represented by PSF vector as:

PSF = [10 am, 0% service inconveniency, 0% important, 1 [faults/2hours], 30 [years old], 0.5 [p.u.]]
The AAFES proposes LOA 3, two levels of automation lower than that of normal condition (Scenario 1). According to experts' opinion, this can be justified due to network aging, thus the LOA should decrease.

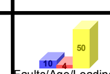
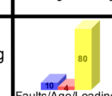
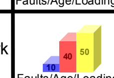
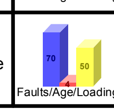
***Scenario 4*: catastrophe**, which means *seven faults* have occurred in an uncrowded urban area with no customer importance in a two years old network with 50% of maximum load at 10am, represented by PSF vector as:

PSF = [10 am, 0% service inconveniency, 0% important, 7 [faults/2hours] , 2 [years old], 0.5 [p.u.]]
The AAFES proposes LOA 7, two level of automation lower than that of normal condition (Scenario 1). This can be justified as number of faults increases, thus the human operators are confused, and consequently a higher LOA is preferred to give more tasks to the automation.

Table.1 summarizes the scenarios and their relevant LOAs recommended by AAFES. It shows that AAFES, as an expert system, successfully follows the experts' opinion in the four prospective scenarios.

The implementation results show that the AAFES spans wider space of UMA's environmental conditions (PSFs), rather than the implementation of its crisp ancestor (AAES of [4]). AAES inputs are limited to 1024 states at most (Fereidunian et al., 2009); while, AAFES spans infinite states, since it accepts continues variables as PSFs. That is, AAFES leads to more discrimination of environmental conditions (PSFs), because of using the fuzzy concept. The results also prove that the AAFES's intelligence is maintained in more combinational PSFs, comparing to that of AAES [4].

Table.1. Summary of the four prospective scenarios and the recommended LOAs by AAFES.

Scenarios	Scenario Name	PSFs Graphs	Changed PSF	$\frac{\Delta LOA}{\%\|\Delta PSF_i\|}$	Experts' Opinion about the LOA
Scenario 1	Happy Condition		—	—	—
Scenario 2	High-loading Condition		Loading	$\frac{+1}{+\%30}>0$	The LOA increases ↑
Scenario 3	Old Network Condition		Age	$\frac{-2}{+\%36}<0$	↓ The LOA decreases
Scenario 4	Catastrophe		Faults	$\frac{+2}{+\%60}>0$	↑ The LOA increases

[†] p.u.: per unit (i.e. a normalized, unit-less value)

IV. CONCLUSIONS

A fuzzy expert system was introduced to realize adaptive autonomy (AA) concept electric utility management automation (UMA). Performance shaping factors (PSFs) of UMA was represented in fuzzy variables. The extracted rules from the GTEDC's experts were utilized in AAFES, as the rule-base, to simulate experts' opinion. Furthermore, four prospective scenarios were developed for AAFES's operation on UMA, and performance of AAFES on the scenarios was presented then.

Results show that the fuzzy expert system hardly limits the PSFs, besides, fuzzy PSFs make the description of the environmental conditions more distinguishable. Moreover, AAFES maintains its intelligence when more PSF change, while the AAES failed its intelligence in the aforementioned conditions.

We are working on implementation and assessment of different adaptive automation strategies, especially the intelligent approaches, in power distribution automation systems.

ACKNOWLEDGMENT

Earlier versions of this work has been supported in part by a British Council Partial Scholarship (UK, funded by shell Development Iran) at the Imperial College London, a CIMO (Finland) Scholarship (Grant Number TM-04-2865) at the Helsinki University of Technology, and an IDB Merit Scholarship (Grant Number 36-1-411) at the University of Tehran for Alireza Fereidunian; each one in a distinct period of time, which is thankfully acknowledged.

The authors thank to the Greater Tehran Electricity Distribution Company (GTEDC), especially to Mr Habib Torabi (GTEDC's Deputy CEO) and Mr Payam Kharazmi (Senior Engineer in GTEDC), as well as GTEDC's SCADA experts for their cooperation, useful suggestions and their patience during AA questionnaire interviews. Authors would also like to thank to Mrs. Bahar Fattah for her help in questionnaire interviews with the GTEDC's experts. The authors would also thank Mr. Besat Elmi for grammatical proofreading of this paper.

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Alireza Fereidunian received his PhD and MSc from University of Tehran (CIPCE, School of ECE), in 2009 and 1997, where he is a Research Associate now. He serves as an independent consultant to GTEDC. His research interests include power systems automation, and application of intelligent systems, human-automation interaction, data mining, decision-support, decision-making, IT and signal processing in power systems. He is a member of IEEE (and IEEE Iran Section) and INCOSE (as INCOSE Iran point of contact).

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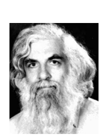

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