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Abstract—We have introduced a novel framework for realization of Adaptive Autonomy (AA) in human-automation interaction (HAI) systems, as well as several expert system realizations of that. This study presents an expert system for realization of AA, using logistic regression (LR), referred to as Adaptive Autonomy Logistic Regression Expert System (AALRES). The proposed system prescribes proper Levels of Automation (LOAs) for various environmental conditions, here modeled as Performance Shaping Factors (PSFs), based on the extracted rules from the experts' judgments. LR is used as the expert system's inference engine. The practical list of PSFs and the judgments of GTEDC's (the Greater Tehran Electric Distribution Company) experts are used as expert system database. The results of implementing AALRES to GTEDC’s network are evaluated against the exact predictions of the presented expert system. Evaluations show that AALRES can predict the proper LOA for GTEDC’s Utility Management Automation (UMA) system, which change according to changes in PSFs; thus providing an adaptive LOA scheme for UMA.

I. INTRODUCTION

AUTOMATION SYSTEMS should be organized in order to optimize the performance of the whole human-automation system. Thus, a considerable research has been dedicated to optimize the interactions between the human and the automation systems.

A simple form of human automation interaction (HAI) was developed by P.M. Fitts in 1951, where two levels of automation (manual or automate) were considered [1], [2]. Afterwards, Sheridan and Verplank introduced a ten-degree level of automation (LOA), to overcome the deficiency of Fitts’ two-degree model [1], [3], [4], [5], [6]. Subsequently, Parasuraman et al introduced the adaptive autonomy (AA) scheme for LOAs; to maintain performance of HAI system when environmental condition changes [1], [7]. Fereidunian et al, then, presented a framework to implement the AA concept [8], [9], [10], and presented experts systems which was realized by decision fusion and fuzzy sets [11], [12].

Although considerable amount of research have been dedicated to this concept, still more investigations are required to implement HAI and AA concepts in industry and civil services [3]. Excluding military and aerospace applications, [11] and [12] report the first implementations of AA concept in civil services. However, the ability of the simple model introduced in [11], [12] is partially-acceptable in tracking and simulating human experts’ opinion in complicated situations.

This article –as a continuum of a series– presents an expert system, using logistic regression (LR), which is successful in improving the earlier systems' characteristics [10], [11], [12]. An expert system is devised for realization of AA, using logistic regression (LR), referred to as Adaptive Autonomy Logistic Regression Expert System (AALRES). LR is employed as a powerful method in implementing the expert system. Numerical results show that the proposed system maintains its acceptable functionality in complex situations.

The reminder of this paper is organized as follows: a brief background is presented on HAI, AA and LR; then, the proposed methodology, results and discussions on the results is presented. Finally, the paper is concluded at the end.

II. BACKGROUND

This section is intended to briefly introduce the main concepts of human-automation interaction (HAI), adaptive autonomy (AA), adaptive autonomy expert system (AAES) framework and logistic regression (LR), in order to make this paper self-explanatory.

A. Adaptive Autonomy Framework

Fereidunian et al. [10] introduced a novel framework, for practical implementations of the AA concept in UMA system. Fig.1 shows the main concept of this framework; in which, the adaptive autonomy expert system (AAES) adapts the autonomy level (LOA) of the UMA system to the changes in
environmental conditions. The framework considers two major concepts:

1) **Performance Shaping Factors (PSFs):** PSFs were suggested to represent the environmental conditions, which affect the performance of HAI system. These conditions are represented in a binary vector for further calculations. The practical list of PSFs is listed in Table I, where, each of them represents existence or non-existence of an environmental condition. Occurring each of these PSFs transforms the UMA system to a more complex situation.

   **TABLE I. PRACTICAL LIST OF PERFORMANCE SHAPING FACTORS (PSFs)**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Normal State of PSFs</th>
<th>PSF</th>
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<tr>
<td>Time</td>
<td>Day</td>
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<td>Region type</td>
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<td>time</td>
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<td>Old network</td>
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<td>Load</td>
<td>Low loading</td>
<td>High Loading</td>
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</table>

2) A subjective approach to expert system: The AA concept implementation is a complex problem. In order to manage this complexity, [10] suggested expert systems as a subjective approach. The AAES is designed to track superior experts' judgments in different conditions of UMA system.

**B. Adaptive Autonomy Expert System (AAES)**

The proposed AAES is capable of determining proper LOA, based on environmental conditions of UMA system. The position of AAES in UMA system is illustrated in Fig.1 [10]. This article is based on Sheridan's model “Ref. [1]” which is modified by Fereidunian et al. [8]. In this model, the expert system (which is named AAES) gets a PSF vector and recommends the proper LOA. Although this model succeeds well in determining level of automation but it slightly suffers from the lack of intelligence when it faces more complex situations (here it means more than four ones in PSFs).

![Figure 1. Position of AAES in the UMA total system](image)

**C. Logistic Regression**

Due to the space limitation only a very brief introduction to LR is presented here. The less familiar readers are recommended to see: [13], [14].

LR is one of the most practical forms of generalized linear models (GLMs), which have been employed in many fields such as natural, medical and social sciences. Although there exists other similar models in this category, LR possesses special properties, such as the capability of linearizing the relationship between P(x) (probability occurrence vector) and x (predictor vector). Furthermore, LR best suits to the binary variables, as in our application.

The ability of LR as a well behaved machine learning algorithm and its robustness in classification has been already confirmed [15]. In LR probability of occurrence is modeled with (1):

$$\Pi(z) = \frac{1}{1 + e^{-z}}$$  \hspace{1cm} (1)

Where z is predictor vector and \(\Pi(Z)\) is the probability of occurrence. In the most common models, the explanatory vector (X) is linearly related to the predictor variables, which is expressed by (2)

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$$  \hspace{1cm} (2)

Where \(x_s\) represent explanatory vector's elements and \(\beta_s\) are coefficients that are determined by training samples. The approach which is applied to determine these unknown parameters (\(\beta_s\)) is maximum likelihood estimation (MLE).

**III. METHODOLOGY**

This research is the continuation of [8], [9], [10], [11], [12]; where, its practical data (such as practical lists of PSFs and experts' judgment interviews) were obtained from the GTEDC. This paper introduces a LR approach to expert system realization for the general framework of [10] for AA implementation.

LR is employed in implementation of this expert system. The capability of LR in dealing with multidimensional variables makes it suitable for realizing the expert system. LR can learn functions in the form P(Y | X). For this, the LR training algorithm assumes a parametric form for the function P(Y | X), and then estimates its parameters according to the training data. According to [13], [14], this parametric function can be written as (1) and (2).

The expert system works as an input-output system which receives a multi-dimensional PSF vector as input, and recommends a scalar number (LOA) as output. The PSF representation vector of $\mathbf{PSF} = \mathbf{X} = [x_1, x_2, \ldots, x_n]$ indicates the PSFs of HAI system, where \(x_i\) represent the \(i^{th}\) PSF and \(n\) is the number of the PSFs. The eqs.(1) and (2)
describe the relationship between input vector (PSF) and output scalar (LOA) [8].

The regression coefficients are determined by employing maximum likelihood estimation (MLE). MLE is the generalization of least mean square method for nonlinear models [13], [14]. For a fixed set of data and underlying probability model, MLE picks \( \beta \)'s that make the data "more likely" than any other values of these parameters (\( \beta \)'s) would make them. In order to determine these coefficients (\( \beta \)'s), some samples are selected as a training set and are trained to the expert system. This process will continue until the differences between \( \beta \)'s in two succeeding iterations become less than a particular small value.

Changing in environmental conditions transits the PSF vector to a new state; as a consequence, the expert system recalculates the appropriate LOA, which may be different from the previous one. The appropriate LOA is determined through the LR algorithm which is previously trained by a set of data. Fig. 2 illustrates the process of training and testing of the LR model.

Considering the fact that the output value of LR model is confined to values between 0 and 1, it should rescale to 0-10 interval. Since the LOA is an integer, the output value should round to the nearest integer (5).

\[
LOA = \text{round} \left( 10 \times \Pi(z) \right)
\]  

IV. RESULTS

This paper follows the implementation of the AA concept in the UMA system. The UMA system is a sort of Supervisory Control and Data Acquisition (SCADA) system for electric utility systems. One of UMA's main functions is restoration by feeder reconfiguration (UMA-FRF) [16]. The expert system which is presented in this article (AALRES) is employed to determine the LOA in the UMA-FRF system. According to our studies and the judgments of the GTEDC's experts, 10 PSFs are selected, where their list can be seen in [11].

Intelligence of the expert system can be well improved by selecting an appropriate training set. To achieve this goal, different training sets are selected and are trained to the expert system. As the expert system is needed to simulate an expert opinion, both training set and test set are asked from a superior expert in various PSFs combinations. The superior experts are experts, whose superiority (in higher and more reliable expertise) has been verified according to the consistency for their expert judgments [11]. All feasible conditions are 324 states. Four scenarios are proposed to choose a training set.

1. Selection of 60 samples and simple-to-complex PSFs combinations.
2. Selection of 60 samples and random PSFs combinations.
3. Selection of 100 samples and simple-to-complex PSFs combinations.
4. Selection of 100 samples and random PSFs combinations.

The results of expert systems' training are presented and compared in the following:

**Scenario 1: Selection of 60 samples and simple-to-complex PSFs combinations.**

Sixty samples are selected to train the expert system. These samples are selected in an incremental order in terms of complexity of the training samples. The training set is selected from low dimensional samples (i.e. PSF vectors -- that are selected as a training set-- does not exceed more than three PSFs). Since this training set include less complexity, thus it facilitates the human experts to judge, and consequently the judgment features more reliable. It should be considered, to perform an evaluation we are obliged to ask all feasible samples in this particular application, in this particular function and in this particular company. On the other hand, this sort of training set may cause the expert system hardly understand the whole problem. Because, the expert system is expected to comprise generalization feature in more complex states, and recommend the proper LOA for the high-dimensional (here it means more than 4 PSFs) PSF vector. The results are presented in the confusion matrix (see Table II), and the Correct Classification Rate (CCR) is also shown in Table III.
Scenario 2: Selection of 60 samples and random PSFs combinations:

The random combinations of the PSFs utilize more chance to expert system that it be trained by more complex samples. In fact, the expert system could be able to learn more how to make a decision in a more complicated situation. However, the scenario of training set selection may lead the human expert hard to judge. The human experts' expertise is more representable in the simple states than the complex states. The results are presented in the confusion matrix (See Table II), and the CCR is also shown in Table V.

Scenario 3: Selection of 100 samples and simple-to-complex PSFs combinations:

In this scenario, more samples are selected to train the AALRES, although the simple-to-complex combination is kept in existence in the training set, the AALRES should include more intelligence and generalization properties since the training set contains more amount of embedded information due to the more number of training samples. The results are presented in the confusion matrix (See Table VI), and the CCR is also shown in Table VII.

Scenario 4: Training set with 100 members and randomly selected:

In this scenario the training set become larger, and also contains more complex combinations. In comparison with other scenarios we expect better results for the system. This training set almost guarantees a uniform distribution of information over least to most complex situations. As a consequence, we expect that the generalization ability of the AALRES improves with this training set. The results are presented in confusion matrix (Table VIII), and the CCR is also shown in Table IX.

V. DISCUSSIONS

The presented expert system recommends proper LOAs, according to the superior expert opinion. The AAES was partially successful to calculate the proper LOA; however, it failed to fully track human experts opinion in more complicated situations. Therefore, AAES suffers from the lack of proper generalization in [11], for instance the intelligence of the system reduced in complex situations (where the most intelligence is needed). Nevertheless, the expert system implemented by LR (AALRES) not only maintains its intellectuality in complicated situations, but also its intelligence will improve by increasing the number of PSFs.

AAES, AAFES and AALRES systems applied decision fusion, fuzzy logic and logistic regression to realize the expert system, respectively; which AAES and AAFES are model-driven, while AALRES is data-driven [17, 18]. The AAES facilitates modeling and implementation; however it slightly suffers from lack of intelligence when more PSFs occur.

The results have shown that the intellectuality of this expert system improves when it faces with more complicated situations. All of the evaluations show that the proposed expert system (AALRES) tracks human experts' judgments in LOA determination, while changing the environmental conditions.

Although LR has especial features in implementing expert systems, still more samples are needed to train it. In the following we interpret the results, in order to achieve proper training set for maximum training. The number of observations which is needed to achieve a satisfactory answer is ten times of predictor variables (in this application PSFs), this fact has already confirmed in [19].

In contrast to the AAES, the AALRES successfully tracks human expert's opinion in complex situation. Furthermore, it seems that LR is a powerful method to work on binary variables as input data, this fact leads to facilitation in calculation and interviewing with human expert.

Although the process of interviewing with human experts is somehow time-consuming, however, it is retaliated by facilitation in training the model.

Moreover, LR's robustness [15], play an important role in reducing error, which is initiated from human experts' mistakes.

In general, the results confirm LR's capability not only in simulating complex situations, but also for implementing complicated systems.

VI. CONCLUSIONS

An expert system was introduced for realization of AA framework of Fereidunian et al referred to as AAES [10]. The presented AAES adapts the LOA of UMA-FRF (or generally HAI system) to the environmental conditions. The judgments' of GTEDC’s experts were developed as a subjective expert system implemented by LR.

This study continues on more theoretical works on the HAI models, implementation of the proposed method in other developmental environments.
### Table II. Confusion Matrix for Training Set I

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<th>Actual LOA (the experts opinion)</th>
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### Table III. CCR for Training Set I

- Total CCR: 68%
- Training CCR: 82%
- Testing CCR: 65%

### Table IV. Confusion Matrix for Training Set II

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### Table V. CCR for Training Set II

- Total CCR: 80%
- Training CCR: 75%
- Testing CCR: 81.5%

### Table VI. Confusion Matrix for Training Set III

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### Table VII. CCR for Training Set III

- Total CCR: 81%
- Training CCR: 80%
- Testing CCR: 81%

### Table VIII. Confusion Matrix for Training Set IV

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<thead>
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<th>Actual LOA (the experts opinion)</th>
<th>0</th>
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<th>2</th>
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<td>Calculated LOA by Expert System</td>
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### Table IX. CCR for Training Set IV

- Total CCR: 81%
- Training CCR: 80%
- Testing CCR: 81%

### Table X. CCR for Training Set VI

- Total CCR: 88%
- Training CCR: 88%
- Testing CCR: 89%
REFERENCES


BIOGRAPHIES

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Hamid Lesani is a Professor at the Center of Excellence for Control and Intelligent Processing (CIPCE), School of Electrical and Computer Engineering, University of Tehran. He received the M.S. degree in electrical power engineering from the University of Tehran, Iran, in 1975, and the Ph.D. degree in electrical engineering from the University of Dundee, U.K., in 1987. Early in his career, he served as a Faculty Member with Mazandaran University. After obtaining the Ph.D. degree, he joined the Department of Electrical and Computer Engineering, Faculty of Engineering, University of Tehran. His teaching and research interests are design and modeling of electrical machines and power systems. Professor Lesani is a member of IEEE (PES) and IEEE Iran Section.

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