AASVMES: An Intelligent Expert System for Realization of Adaptive Autonomy Using Support Vector Machine

N. Hassanpour[1], M.A. Zamani[1], A. Fereidunian[1,2], H. Lesani[1]

***Abstract*—We earlier introduced a novel framework for realization of Adaptive Autonomy (AA) in human-automation interaction (HAI). This study presents an expert system for realization of AA, using Support Vector Machine (SVM), referred to as Adaptive Autonomy Support Vector Machine Expert System (AASVMES). 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. SVM is used as an expert system 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 implemented AASVMES in response to GTEDC's network are evaluated against the GTEDC experts' judgment. Evaluations show that AASVMES has the ability to predict the proper LOA for GTEDC's Utility Management Automation (UMA) system, which changes in relevance to the changes in PSFs; thus providing an adaptive LOA scheme for UMA.**

Keywords-Support Vector Machine (SVM); Adaptive Autonomy (AA); Expert System; Human Automation Interaction (HAI); Experts' Judgment; Power System; Distribution Automation; Smart Grid.

I. NOMENCLATURE

Adaptive Autonomy (AA), Adaptive Autonomy Expert System (AAES), Adaptive Autonomy Fuzzy Expert System (AAFES), Adaptive Autonomy Logistic Regression Expert System (AALRES), Adaptive Autonomy Support Vector Machine Expert System (AASVMES), Correct Classification Rate (CCR), Human-Automation Interaction (HAI), Level of Automation (LOA), Performance Shaping Factor (PSF), Supervisory Control and Data Acquisition (SCADA),Support Vector Machine (SVM), the Greater Tehran Electric Distribution Company (GTEDC), Utility Management Automation (UMA), Utility Management Automation Feeder Reconfiguration (UMA-FRF).

II. INTRODUCTION

Expert systems are employed in different applications to simulate human experts' knowledge. Employing expert systems in complex applications, which confront complicated decision makings, are of high functionality.

A simple form of human automation interaction (HAI) was developed by P.M. Fitts in 1951 where two LOA (manual or automate) were considered [1], [2]. Afterwards, Sheridan and Verplank introduced a ten-degree level of automation, to overcome the deficiency of Fitts' two-degree model [1], [3], [4], [5], [6]. Subsequently, Parasuraman, *et al.*, introduced the AA scheme for LOAs; to maintain performance of HAI systems when environmental condition changes [1], [7]. Fereidunian, *et al.*, presented a framework to implement AA and suggested expert systems as a solution for realization of the AA [8], [9], [10]. Fereidunian, *et al.*, also suggested an expert systems which was implemented by decision fusion [11], fuzzy sets [12], logistic regression [13], generalized linear models [14], artificial neural network and logistic regression hybrid [15], Petri net [16], hierarchical Petri net [17], and gradient descent algorithm [18].

More investigations are required to introduce HAI and AA concepts in industries and civil services [3]. Excluding military and aerospace applications, the references [11] and [12] report the first implementation of this concept in civil services. However, the simple model loses its ability in tracking and simulating human experts' judgment in complicated situations (i.e. more PSFs).

This article –as a continuum of a series– presents an expert system by SVM, which is successful in improving the earlier systems characteristics [10], [11], [12], [13], such as correct classification rate (CCR) and complexity of model (i.e., non-linearity). SVM is employed as a powerful and well-defined method in implementing this expert system. Numerical results show that the proposed system maintains its functionality in complex situations. Moreover, the performance of the AASVMES is evaluated with three scenarios.

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

III. BACKGROUND

This section is intended to briefly introduce the main concepts of HAI, AA, AAES Framework and SVM, 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. This framework is shown in Fig.1, which illustrates AAES is used to adapt the autonomy level (LOA) of the UMA system to the changes in environmental conditions.

1) Systems and Machines Research Laboratory (SMRL), Control and Intelligent Processing Center of Excellence (CIPCE), School of ECE, University of Tehran, Tehran, IRAN

2) Electrical and Computer Engineering Department, K. N. Toosi University of Technology, Tehran, IRAN

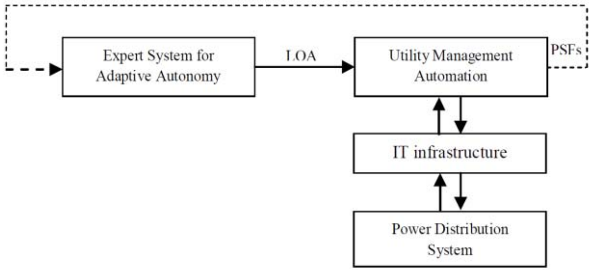

Figure 1. Position of AAES in the UMA total system

The framework considered two major concepts:

1) Performance Shaping Factors (PSFs): Ref. [8] and [9] suggested employing PSFs to extract environmental conditions which affect the performance of HAI system. The derived PSFs are represented in a binary vector, each digit determining existence or non-existence of an environmental condition.

2) A subjective approach to expert system: The AA concept suffers from the complexity of implementation. In order to overcome this problem, the AAES is designed in accordance with human experts' judgments.

B. Adaptive Autonomy Expert System

As a powerful tool, the proposed AAES is capable of determining LOAs, according to the changing environmental conditions (PSFs), as shown in Fig. 1 [10]. This article is based on Sheridan's model [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 an LOA for that. Although this model succeeds in determining the level of automation, it slightly suffers from the lack of intelligence when large number of PSFs is activated (i.e. when represented PSF vector contains several "1" digits).

C. Support Vector Machines (SVM)

SVM is a non-probabilistic binary classifier, categorized under supervised learning methods used for data analysis and pattern recognition via classification and regression analysis. In this section, a very brief introduction to SVM is presented. For more details refer to [19], [20].

SVM, like other data-driven methods, needs a training set. The form of training data set presented to SVM is as (1)

$$\text{Training data set } = \{(x_i, c_i) | x_i \in \mathbb{R}^p, c_i \in \{-1, 1\}\}_{i=1}^{n} \quad (1)$$

where x_i is a p-dimensional real vector of inputs and c_i is the output class of the system which is distinguished by whether belonging to class -1 or class 1.

Training data set is applied to SVM to construct a hyperplane which separates the space into two different classes. The hyperplane is constructed by employing the closest training set sample vectors to the boundaries of two classes. The aim is to find the maximum margin hyperplane from (2)

$$w \cdot x - b = 0 \quad (2)$$

where w is the slope and b is the intercept.

Afterwards, for any new data presented to the SVM, it predicts to which class it belongs to by putting the data in the boundary's equation and checking whether its result is negative (class one) or positive (class two).

Although SVM is regarded as a binary classifier, some methods are suggested to do multiclass classification with it. Two of these methods are noted here:

1) One-against-all classification, in which there is one binary SVM for each class to separate members of that class from members of other classes.

2) Pair-wise classification, in which there is one binary SVM for each pair of classes to separate members of one class from members of the other.

In this paper one-against-all method is utilized. The initial formulation of the one-against-all method requires unanimity among all SVMs: a sample would be classified under a certain class if and only if that class's SVM accepted it and all other classes' SVMs rejected it. It should be noted that in case of multiclass SVMs, w in (2) is a vector but b is still an scalar.

IV. METHOD

A. Problem statement

The basic idea of this research is dedicated to improve the Greater Tehran Electricity Distribution Company (GTEDC) performance, from which the practical data (such as the practical list of Performance Shaping Factors (PSFs) – suggested to represent the environmental conditions affecting the performance of HAI system – and experts judgments interviews) was obtained. The GTEDC delivers electric power to the Greater Tehran metropolitan area.

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) [21]. This paper introduces an SVM approach to expert system realization for the general framework of [10], determining the LOA in the UMA-FRF system, for AA implementation, called AASVMES.

B. Realization of AASVMES

According to our studies and the judgments of the GTEDC's experts, 10 Performance Shaping Factors (PSFs) are selected which their list can be found in Table I. Note that PSFs with two values such as Time can be represented by 1 bit and PSFs with three values such as Service Area can be represented by 2 bits. Therefore 10 PSFs are to be considered.

TABLE I. PERFORMANCE SHAPING FACTORS (PSFS) VALUES

PSF	PSF's value	Binary bits
Time	Day	$\{PSF_1\} = 0$
	Night	$\{PSF_1\} = 1$
Service Area	Un-crowded urban	$\{PSF_2, PSF_3\} = 00$
	Crowded urban	$\{PSF_2, PSF_3\} = 10$
	Rural	$\{PSF_2, PSF_3\} = 01$
Customer Type	Residential	$\{PSF_4, PSF_5\} = 00$
	Commercial/Industrial	$\{PSF_4, PSF_5\} = 10$
	VIP	$\{PSF_4, PSF_5\} = 01$
Number of Faults per Hour	Few	$\{PSF_6, PSF_7\} = 00$
	More	$\{PSF_6, PSF_7\} = 10$
	Much more	$\{PSF_6, PSF_7\} = 01$
Network Age	New	$\{PSF_8, PSF_9\} = 00$
	Middle-aged	$\{PSF_8, PSF_9\} = 10$
	Old	$\{PSF_8, PSF_9\} = 01$
Load	Low	$\{PSF_{10}\} = 0$
	High	$\{PSF_{10}\} = 1$

AASVM classifies the problem space into the predefined LOAs. After training the AASVMES with the samples, $\mathbf{w}$ and $\mathbf{b}$ parameters in (2) are calculated, where $\mathbf{x}$ represents different PSFs combinations as in (3), which leads to construct SVM hyperplanes separating 10 distinct LOAs.

$$x_i = [PFS_1, PFS_2, \ldots, PFS_{10}] \quad (3)$$

AASVMES can be modeled as Fig. 2. When a new combination of PSFs is presented to AASVMES, the system searches for appropriate subspace among hyperplanes which represents the LOA predicted by the expert system.

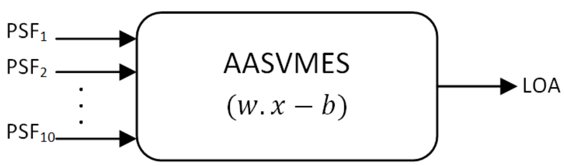

Figure 2. The proposed AASVMES

V. RESULTS

Intelligence of the expert system can be more generational 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 judgment, both training set and test set are asked from a superior expert on the appropriate LOA 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 interview questionnaire [22]. Considering PSFs, all feasible conditions are 324 states. Three scenarios are proposed to choose a training set.

A. Scenario 1: Selection of 100 samples with low level complexity -simple- PSF combinations.

Available data is sorted in an incremental form from simple to complex; this means that samples including less number of ones are in lower levels of complexity -simpler. In this scenario, simplest 100 samples are chosen to be trained to the expert system as AA training set.

Results, as reported in Table II, show a high training CCR, 93%, meaning that system learns very well with simple training data set. Simplicity of the AA training set is the reason of this high training CCR; but, on the other hand, 62% of testing CCR, as reported in Table III, is low which demonstrates that system has not gained a proper generalization power with this simple AA training set.

TABLE II. TRAINING CONFUSION MATRIX

Scenario I		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	12	0	0	0	0
	4	0	14	0	0	0
	5	0	2	31	4	0
	6	0	1	0	20	0
	7	0	0	0	0	16
	Training CCR: 93%					

Other LOAs are out of results scope and are not studied in this paper.

TABLE III. TESTING CONFUSION MATRIX

Scenario I		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	0	3	1	0	0
	4	7	24	15	14	0
	5	0	15	44	4	1
	6	0	0	10	38	0
	7	0	0	1	14	33
	Testing CCR: 62%					

Other LOAs are out of results scope and are not studied in this paper.

TABLE IV. TOTAL CONFUSION MATRIX

Scenario I		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	12	3	1	0	0
	4	7	38	15	14	0
	5	0	17	75	8	1
	6	0	1	10	58	0
	7	0	0	1	14	49
	Total CCR: 72%					

Other LOAs are out of results scope and are not studied in this paper.

B. Scenario 2: Selection of 100 samples, regarding both class and complexity level issues.

All 324data is mapped into Table V where its columns represent the complexity level (number of ones in a sample vector) and its rows represent the class (LOA) of each sample vector. Fig. 3 shows the graphical view of data distribution in different class-complexity levels. Each cell contains number of data belonging to that class and complexity level. 100 samples are selected as the AA training set with a uniform ratio to the whole 324 samples.

TABLE V. DISTRIBUTION PATTERN OF DATA

		Complexity						
		0	***1***	***2***	***3***	***4***	***5***	***6***
Class (LOA)	***3***	0	2	5	8	2	2	0
	4	0	2	7	20	20	8	2
	5	1	4	11	27	32	21	6
	6	0	1	11	19	34	23	6
	7	0	1	7	14	16	10	2

This table shows distribution of the whole samples among different class and complexity levels.

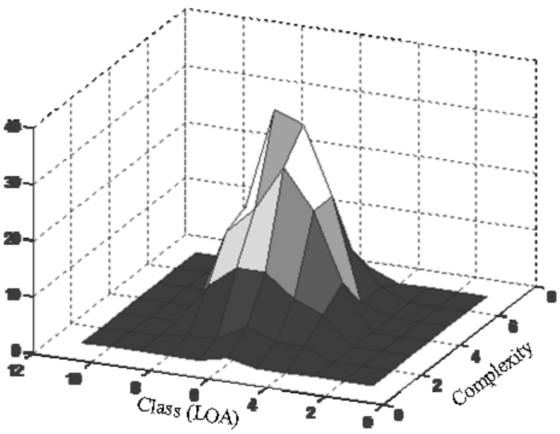

Figure 3. Distribution density in class-complexity levels of the whole 324 data vectors.

This scenario was proposed to avoid two issues: 1) high resemblance between chosen training data and 2) excluding higher complexity levels, which lead to low testing CCR in scenario 1. This scenario represents an approach to achieve to a more uniform pattern which not only includes all class-complexity levels, but also their PSF vectors are not in resemblance, instead of all scenarios in [13] in which training set was selected only regarding the complexity level of data.

As shown in Table VI, although 88% of training CCR is not as good as the scenario 1, the generalization power of this scenario is far better as the testing CCR of 72% in Table VII confirms this fact.

In accord with our prediction, an AA training set selected from all kinds of data modifies the generalization power of AASVMES.

TABLE VI. TRAINING CONFUSION MATRIX

Scenario II		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	5	0	0	0	0
	4	2	14	0	0	0
	5	0	5	31	3	1
	6	0	0	1	24	0
	7	0	0	0	0	14
	Training CCR: 88%					

Other LOAs are not studied in this paper and therefore they are zero.

TABLE VII. TESTING CONFUSION MATRIX

Scenario II		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	8	4	0	0	0
	4	4	13	1	0	0
	5	0	22	43	3	0
	6	0	2	25	60	1
	7	0	0	1	4	34
	Testing CCR: 71%					

Other LOAs are out of results scope and are not studied in this paper.

TABLE VIII. TOTAL CONFUSION MATRIX

Scenario II		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	13	3	0	0	0
	4	6	27	1	0	0
	5	0	27	74	6	1
	6	0	2	26	84	1
	7	0	0	1	4	48
	Total CCR: 76%					

Other LOAs are out of results scope and are not studied in this paper.

C. Scenario 3: Selection of 100 most repeated samples regarding the pattern from several randomly generated total CCRs above 80%.

In this scenario, several random selection of AA training set was taught to the system and patterns leading to total CCRs above 80% were studied; 100 most repeated samples were chosen to be the proposed AA training set. These samples are likely to be the most critical data because of their presence in most of training sets leading to high CCRs.

In this scenario, both training CCR of 98%, as reported in Table IX and testing CCR of 75%, as reported in Table X, are considerably higher than two other scenarios which means a better training and more generalization power. In other words, SVM works better when it is taught with appropriate data which lay mostly on boundaries between different classes – data which helps to construct LOA hyperplanes.

TABLE IX. TRAINING CONFUSION MATRIX

Scenario III		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	4	0	0	0	0
	4	1	17	0	0	0
	5	0	0	36	0	0
	6	0	0	1	32	0
	7	0	0	0	0	9
	Training CCR: 98%					

Other LOAs are out of results scope and are not studied in this paper.

TABLE X. TESTING CONFUSION MATRIX

Scenario III		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	5	1	0	0	0
	4	9	20	5	0	0
	5	0	21	51	5	1
	6	0	0	8	57	5
	7	0	0	1	0	35
	Testing CCR: 75%					

Other LOAs are out of results scope and are not studied in this paper.

TABLE XI. TOTAL CONFUSION MATRIX

Scenario III		Actual LOA (Expert's Judgment)				
		3	***4***	***5***	***6***	***7***
Predicted LOA (Expert System's Calculation)	***3***	9	1	0	0	0
	4	10	37	5	0	0
	5	0	21	87	5	1
	6	0	0	9	89	5
	7	0	0	1	0	44
	Total CCR: 82%					

Other LOAs are out of results scope and are not studied in this paper.

Fig. 4 is a scheme of the proposed AA training set distribution among different class-complexity levels. Similarity between Fig. 3 and Fig. 4, plus pure randomness in selection of training sets which lead to high CCRs, reveals that distribution density of the best training set is correlated with distribution density of the whole available data.

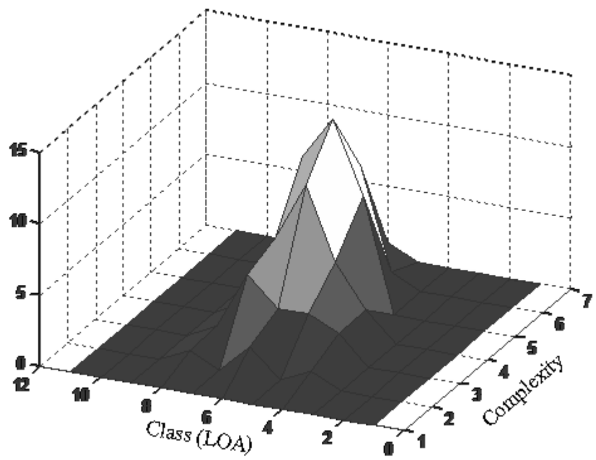

Figure 4. Proposed AA training set distribution density in different class-complexity levels in scenario 3.

Scenario 3 follows almost the same class-complexity pattern as scenario 2, with this subtle difference that in scenario 3, critical data has been identified and distinguished from the whole data by randomly generated training data patterns with high (i.e., over 80%) CCRs in order to train the expert system; but in scenario 2, training set is chosen regardless of nature of the data, meaning that less important data (i.e. those which are close to center of each class, not boundaries) may have been selected. Therefore our prediction of higher CCR in scenario 3 than scenario 2 is confirmed.

VI. Discussions

The presented expert system is able to recommend the proper LOA, according to the superior expert judgment. The AAES was partially successful to calculate the proper LOA, however, it failed to fully track human experts judgment in more complicated situations (i.e. working with more number of PSFs). 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).

In comparison, AAES, AAFES, AALRES and AASVMES applied decision fussion, fuzzy logic, logistic regression and support vector machine to realize the expert system respectively; which AAES and AAFES are model-oriented, while AALRES and AASVMES are data-oriented.

The AAES facilitates modeling and implementation; however it slightly suffers from lack of intelligence when confronted with data with more active PSFs (i.e., high level of complexity). The AAFES succeeds more intelligence and more proper results. Moreover, it employs a wider span of PSFs, and also applies more realistic representation of experts' judgments.

Ref. [13] has employed the thumb rule suggested in [23], which claims that the number of observations needed to achieve a satisfactory answer is ten times of predictor values (here 10 PSFs). We also trained 100 samples to the AASVMES in order to compare its results with AALRES [13] results.

Although [24] has noted that both the LR and SVM models were good and had no statistically significant differences in their discriminative power, selected training set in SVM apparently should contain a variety of data (i.e., from all available classes and complexity levels). And this is considered a key concept in constructing SVM's separating hyperplanes.

SVM more relies on the nature of the training samples rather than number of them. In other words, the more the selected data lays on the boundaries separating two distinguished classes, the better CCR it will generate.

SVM's simple method for classification, its linear nature, and its reliance on less -but most critical (i.e., samples on boundaries of classes)-number of training samples makes it more applicable than logistic regression as used in [13].

VII. 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. But it slightly suffered from lack of intelligence when large number of PSFs was activated. In order to overcome that, the judgments' of GTEDC's experts were developed as a subjective expert system implemented by SVM, referred to as AASVMES.

The performance of the AASVMES was illustrated in three scenarios. The Scenarios results show that the AASVMES highly depends on its training set. According to the scenarios 2 and 3, the AASVMES is a more accurate expert system when training set includes samples from all classes and complexity levels. This is despite of the GTEDC's judgment which strongly relies on samples with low levels of complexity. It means that the human experts begin their judgment with simple conditions.

The results have shown that the intellectuality of this expert system improves when faced with more complicated situations. All of the evaluations show that the proposed expert system (AAES) tracks human experts' judgments in LOA determination, while changing the environmental conditions. Besides, this method requires fewer samples to achieve fine CCRs than last episodes of these series of papers; which can be considered important in situations where only few vital samples are available.

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BIOGRAPHIES

Negar Hassanpour is a B.Sc. Student at the Control and Intelligent Processing Center of Excellence (CIPCE), School of Electrical and Computer Engineering, University of Tehran. Her research interests include artificial intelligence, machine learning, decision-making, systems engineering, power distribution system automation and human-automation interaction.

Mohammad Ali Zamani is a Research Assistant at the Control and Intelligent Processing Center of Excellence (CIPCE), School of Electrical and Computer Engineering, University of Tehran, Iran. His research interests include System Engineering, Artificial Intelligence, Smart Grid, and Human-Automation Interaction. He is currently working on implementation of system engineering approaches in smart grid.

Alireza Fereidunian is an Assistant Professor at the K. N. Toosi University of Technology and serves as an independent consultant to GTEDC. He received his PhD and MSc from University of Tehran (SMRL, CIPCE), in 2009 and 1997, where he is a Post-Doctoral Research Associate now. His research interests include Smart Grid, 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 INCOSE.

Hamid Lesani is a Professor at the Control and Intelligent Processing Center of Excellence (CIPCE), School of Electrical and Computer Engineering, University of Tehran. He received the M.Sc. 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, Faulty 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.