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Research Article

Providing an Expert System to Manage Energy Consumption in Small- and Medium-Sized Industries Using Soft Computing

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The increasing growth of electricity consumption, the need for its continuous supply, and the impossibility of storing this vital energy are among the primary and essential reasons for preventing any interruption in supply and proper planning regarding energy consumption management, especially in industry. The innovation of this research is the design of a decision-making system to help decision-making in energy management in small- and medium-sized industries using the knowledge of experts in small- and medium-sized industries and the electricity industry in the field of energy consumption management and extracting relevant expertise rules to create a knowledge base. Therefore, the main advantage of the research is to provide an expert system for the correct management of energy consumption in small and medium industries using soft computing. Another advantage of the research is the use of uncertain decision-making variables in this field; instead of using words and linguistic restrictions in this research, modeling them in the system using the principles of fuzzy logic is used. The main objectives of this research include determining the effective variables in determining the amount of energy production for small and medium industries, explaining the existing tacit knowledge and turning it into explicit knowledge, and providing an expert system for managing energy consumption in this field. Based on the results of field studies and the research literature, effective variables in determining the amount of electricity generation were identified. By extracting the knowledge of industry experts, the tacit knowledge available as explicit knowledge in the storage knowledge base and the system was designed to manage electrical charge consumption. One of the achievements of this system is its creation and measurement using various data and results obtained from small and medium industries. Finally, the results obtained from the expert system in comparing the output of expert opinions and the system's performance in managing the amount of energy production showed that the usefulness of the expert system was designed. The system uses the knowledge base to make decisions such as an expert human. According to the main results of the research based on comparing the performance of the system with the Bayesian inference networks, it showed that there is an acceptable correlation between the data and the prediction system. Also, to evaluate the acquisition of data using a statistical test, it has been determined that the total number of blackout hours in different areas of Tehran in the base year was more than the current year.

1. Introduction

The importance of electricity in today's life and the vital and irreplaceable role of this critical energy in daily life, industry, agriculture, and other economic activities are not hidden from anyone. During these years, electricity consumption in the country has been increasing more rapidly than in the past, and this increase in consumption includes a significant share of electricity consumption in the country. Given the growing consumption and the need for continuous power supply and to prevent any interruption in the supply of this vital energy, the importance of proper planning in terms of load management is one of the best ways to protect the common interests of society, electricity companies, and electricity consumers and one of the most important goals of smart grids. In this regard, one of the most fundamental parts of development planning studies is the forecast of electricity consumption in the short, medium, and long terms. Proper load forecasting in distribution networks will have many technical and economic benefits for the electricity industry [1, 2]. Recognizing the patterns of consumer behavior, encouraging and supporting optimal consumption programs, creating organizational, technical, and financial requirements, making appropriate laws, and implementing appropriate advertisements and training are among the goals and programs that should be considered in the energy sector according to the current needs of society and the need to demand it. On the other hand, recognizing the pattern of consumer behavior is the basis for policy-making and setting operational and strategic goals and is also a good process for evaluating the organization's effectiveness [3]. Therefore, any change in consumer behavior is based on recognizing their consumption behavior and on promoting energy management recommendations in the field of energy [4]. It is necessary to subscribe to the consumption pattern of subscribers, including their status, knowledge, attitude, and consumption behavior that should be studied, and with the understanding of the objective conditions of consumers, appropriate strategies and programs should be formulated and presented [5, 6].

There are various methods for forecasting and managing load consumption in the electricity industry, but in a general category, these methods can be categorized as follows:

(i) Expert knowledge-based methods

(ii) Time-series analysis methods

(iii) Methods based on the analysis of causal relationships between the desired quantity and the parameters affecting it

Nowadays, the speed and accuracy of managerial decisions and predictions are very important. Every organization creates a kind of competitive advantage by accessing valuable information and making accurate and fast decisions at the moment. Although in the electricity industry, due to the industry's monopoly, a competitive advantage does not make sense, it can create a point of difference in Tehran Regional Electricity Company among other regional electricity companies in the country. One way to reach this point of difference is to use artificial intelligence in managing organizations and companies. Artificial intelligence (AI) is one of the applications of computers today in management and organization and a way to make the computer smart. In fact, creating the ability of human thinking in the machine is one of the goals of this emerging phenomenon, which has a long way to go to reach its end, that is, to build a machine with the power of human reasoning and perception [7]. Electricity charge generation and consumption are essential in power system planning and optimal operation. Load consumption in power systems depends on several factors such as atmospheric variables such as wind, humidity, and cloud cover and other variables such as holidays, months of the year, and days of the week [8]. Holiday behavior is very different from a normal day, mainly due to the social culture of the area. In companies, operators estimate the load in real time using the previous day's information and their own innovative rules and regulations [9].

In addition to the above, cargo consumption depends on many other unknown factors. Therefore, the use of conventional methods of cargo consumption management for production and the amount of need for consumption are not enough. Using the experiences and opinions of experts and operators can be very effective in managing the amount of production for more accurate consumption. On the other hand, with the development of societies and the advancement of technology in recent decades, electricity consumption has grown significantly. The growth of electricity consumption in recent years, in addition to increasing power losses in power grids and its incompatibility with increasing production, has decreased the reliability of energy distribution systems. Electrical systems have three important features, including the following [10, 11]:

(1) Electricity cannot be widely stored, so the amount of capacity available for generation at all times must be equal to or greater than the total load of the system consumers

(2) Installation of power plant units is costly and time-consuming

(3) The price of electricity varies at different times of the day because, in peak hours, more expensive units must be used to supply power, which will increase the market price

Since electricity cannot be stored, its production and consumption in the electricity industry must be commensurate with demand. Electricity distribution companies announce short-term electrical load forecasts of their covered grids to regional power companies as sellers and purchasers of electricity. Because the load pattern is a nonlinear curve with various parameters, its prediction with conventional statistical methods is not accurate enough. Reducing the error of this prediction impacts the production costs, unwanted blackouts, and economic penalties [12].

Therefore, the issue we will address in this dissertation is "providing an expert system for managing load consumption in the electricity industry."

Because expert systems have been effective strategies in improving decision-making, their benefits have been shown in various matters. Given the importance, conditions, and nature of the expertise of experts in this field, on the one hand, and considering the features and functions of expert systems, on the other hand, designing an expert system to apply and implement the existing expertise and knowledge in this field and use it in the form of a decision-making system can be very useful and practical. For this purpose, the main purpose of this research was to provide an expert system for properly managing energy consumption in small and medium industries using soft computing. However, since the main decision variables in this field are inaccurate and uncertain and usually presented using words and linguistic constraints, they will be modeled in the system using fuzzy logic principles in this research. According to the above mentioned, the most important contributions to this research are as follows:

(i) Designing an expert system to apply and implement expertise and knowledge in the field of proper energy management

(ii) Providing an expert system to determine effective solutions to improve decision-making and benefit from its benefits in proper energy management

(iii) Considering the main variables of inaccurate and uncertain decision-making in the expert system using words and linguistic constraints

(iv) Applying the framework provided for proper management of energy consumption in small and medium industries

The rest of the article is organized, as it turns out. In the second part, a literature review is provided. In the third section, the proposed methodology in this research is presented. The fourth section shows the main results obtained in this research. In the fifth section, managerial insight and discussion are presented. Finally, the sixth section presents conclusion and suggestions for future research.

2. Literature Review

2.1. Review. This section introduces studies related to the main research topic that researchers in the past have studied. For example, Valentin [13] proposed a model for developing demand forecasts for electricity consumption in commercial, office, and residential buildings. Factors and variables affecting the demand for cargo consumption are the seasons, holidays, GDP, the number of consumer goods, etc. Another variable studied in this study is population and growth factors, including population growth rate. In their study, Fan et al. [14] developed a data-based method for developing group models for forecasting daily energy consumption and peak demand to improve forecasting accuracy. The approach presented in this study has three main stages. First, output detection, which focuses on integrating extraction characteristics, cluster analysis, and extreme deviation (GESD), is performed to eliminate elements of abnormal energy consumption per day. Second, RFE, an embedded variable selection method, is used to select the desired inputs to the prediction models separately using eight popular prediction algorithms. Third, the cross-validation (LGOCV) parameters of each model are evaluated. Finally, they designed the model to develop a model using a genetic algorithm (GA). Pourghader Chobar et al. [15] showed that electricity consumption depends on the seasons. Different methods of generating electricity using renewable sources such as sunlight, wind, rain, tides, and waves are also seasonal. They showed that many of the traditional methods previously used to forecast electricity demand on a seasonal basis could be replaced by developing tools and methods with advanced, efficient forecasting techniques. In this study, WEKA time series method predicts electricity demand for summer, winter, and autumn seasons. WEKA learning algorithms such as multilayer perceptrons, support vector machine, linear regression, and Gaussian process have been used for execution. This study showed that the WEKA learning algorithm is suitable for forecasting seasonal electricity demand, and this article became an introduction to such activities. Ganguly and Kumar [16] provided a framework for economic production and increasing load forecasting power in this study. This study presents the results of a fuzzy logic model for short-term (hourly) load prediction. The fuzzy logic model can predict short-term load demand for different days and times. The proposed method uses historical load data and daytime to design a fuzzy law basis to predict the daily load curve. The results prove that the fuzzy law basis can effectively predict short-term load demand with minimal error. Jifri et al. [17] showed that modeling electric charge demand is considered one of the most important areas among researchers because electricity is evolving. This study aimed to evaluate the performance of time series and regression in predicting load demand. Time-series models are considered univariate data sets, while regression models are considered multivariate data sets. In this study, they studied several regression models and several time-series models and finally concluded that the multistage regression method is more appropriate. Based on the Bayesian fuzzy theory and expert system forecasting, a new probability forecasting model is proposed for China's power consumption (PEC) and the change interval between 2010 and 2030. The structure of the proposed model can improve the reliability and accuracy of experts' predictions through econometric methods. This model consists of three components: the fuzzy relation matrix, the prediction, and the fuzzy Bayesian formula. Preventive forecasting has been implemented to prevent long-term uncertainty in order to combine the benefits of expert experience with other time-based methods from a probability perspective [18]. Ganguly and Kumar [16] showed that the electricity demand had constantly increased over the years. A prediction model used ARIMA models concerning wide time series to understand future consumption. In this study, an attempt has been made to predict the amount of electricity consumption for the future using the ARIMA model. Using the mean absolute percentage error (MAPE) to measure the prediction accuracy, the model could predict with an error of 6.63%. The results show that the ARIMA model has the potential to compete with existing methods for predicting power consumption. In their study, Bakiri et al. [1] developed an efficient data purge model that extends the multivariate nonlinear regression (MNLR) method and calculates the appropriate random distribution. For this purpose, the k-mean algorithm is used to detect and analyze the size of a throwing point in the data. Tahmasebinia et al. [19]. This study aimed to identify the critical design parameters for building energy performance to assist architects in the early stages of building design and investigate their relationship. For this purpose, a simulation model is designed in which the energy simulation results of the original model are used to construct nonlinear regression models. In addition, linear regression models have been used for other independent variables of building design and analyzing the relationship between them and energy consumption. To

Table 1: Literature categorized.

Author	Logic		Solution approach							
	Fuzzy	Crisp	GA	WEKA	Bayesian	MNLR	K-mean	DEA	Archicad	ARIMA
Fan et al. [14]		*	*							
Pourghader Chobar et al. [26]		*	*							
Ganguly and Kumar [16]	*				*					
Jifri et al. [17]	*				*					
Jain et al. [26]		*								*
Bakiri et al. [1]		*				*	*			
Liu et al. [20]		*						*		
Mohd Ali [16]		*							*	

measure the efficiency of green building implementation management in China, Liu et al. [20] presented the Chinese Green Building Input-Output Index System based on panel data at the provincial level in China from 2017 to 2021. The basic data envelopment analysis (DEA) model and the DEA-Malmquist index as a method for measuring and analyzing the law of development and the tendency of temporal-regional evolution examined the performance efficiency of Chinese green buildings from a static and dynamic perspective that can help clarify the critical factors limiting green building development. It has been found that the efficiency of managing the comprehensive implementation of China's green buildings is low, but the tendency to develop has shown good performance. Sharma and Sahoo [21] used biodiesel from waste as experimental fuel and biogas from waste as gaseous fuel to power the diesel engine in dual combustion mode. A new approach called augmented tree regression has been used to model the performance and emission of a variable density diesel engine. Model input parameters were selected as load, fuel injection time, and compression ratio. Mohd-Ali et al. [22] modeled performance analysis energy efficiency for high-rise building using Archicad. Consequently, this study revealed that the effective combinations of the window parameters had assisted in improving the infiltration rate and heat transfer coefficient, which allowed a lower cooling load within 3% to 6%, respectively. Kumar and Pal [23] examined the effect of the cetane improver 2-ethylhexyl nitrate (EHN) on the performance and emission characteristics of an engine fueled by an algal biodiesel-diesel blend. The multi-objective response surface technique (MORSM) was used in combination with the Box–Behnken design to decrease the number of trials and conserve precious resources such as human effort, resources, and time. Bora et al. [24] focused on using dual fuels such as Mahua oil biodiesel and biogas in a diesel engine to analyze performance and emission by varying compression ratio (CR) and engine loads. Following the experimental step, the response surface approach was used to model, predict, and optimize. Sharma et al. [25] reviewed recent advances in machine learning research for nanofluid-based heat transfer in renewable energy-consuming systems.

2.2. Research Gap. According to the studies conducted in the above research, the most important research gap identified in the research is as follows:

(i) Lack of an effective expert system for applying and implementing based on expertise and knowledge in the field of proper energy management

(ii) Failure to determine effective solutions to improve decision-making and benefit from its benefits in proper energy management using an expert decision-making system

(iii) Failure to consider the main uncertain decision-making variables in the expert system

Table 1 shows the research literature categorized based on research solution approach.

3. Problem Statement

The research method used in this study is a hybrid or mixed approach. Due to the exploratory nature of this study and the method of data collection and their order, first qualitatively and then quantitatively, this research is among the successive exploratory designs of the classification development model. To accurately determine these variables, library studies, field studies such as interviews with electricity industry experts with open-ended questions for scholarship, and study of documents related to the legislature (Ministry of Energy and Tavanir Organization) on production and consumption were reviewed. Accordingly, after conducting library studies, including reading books, dissertations, and articles similar to the subject of expert systems, electricity load management, and electricity consumption forecasting, the parameters affecting the management of electricity consumption in small and medium industries were identified. Figure 1 shows the picture of problem process.

3.1. Solution Approach. In the first stage, after completing the library studies, scholarly interviews were conducted using in-depth unstructured interviews. This encyclopedia has been done by all 18 experts in the field of forecasting and management (all experts in load consumption management) regarding forecasting and load consumption management based on a question and answer session. Experts commented on the variables, and their results were recorded and analyzed. In the next step, using previous studies and the results of interviews with experts, other variables not stated by experts were presented to them through semi-structured interviews, and their opinions were received. Then, using the

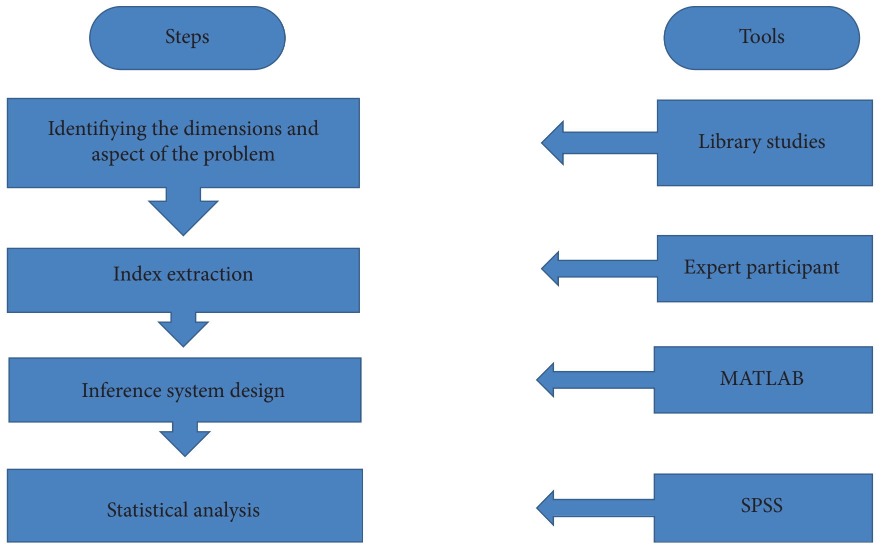

Figure 1: Research methodology framework.

method of content analysis and coding manually, the analysis was performed, the results were presented to the experts at each stage, and their comments and approval were received. At this stage, the variables of this research were obtained. Also, all the identified variables were presented to the experts to determine the rules related to the knowledge base. The rules were determined by them and without any orientation by the researcher. In this way, the relationship between the variables and the importance of each, as well as the importance of each law, was expressed and recorded by experts. In the first session of the interview, which was held in the form of asking unstructured questions and providing open answers about the variables in question and in pairs, first the necessary explanations were given to the experts about the research topic, why and how to do it. In the initial session of the interview, none of the experts was aware of the names of other experts, their answers, and opinions, and only questions were asked about the parameters affecting the research topic. In this meeting, while explaining to the experts in this regard, he also raised other points and asked questions about the ambiguous points. In the second Q&A session, the collected opinions and the extracted variables were provided to the experts in the form of a questionnaire. In this meeting, he was once again asked about the variables and the degree of acceptance or nonacceptance of the variables. In this meeting, experts were informed of other experts' opinions and even read other experts' names. After the second session, conducted with a structured questionnaire, summary opinions and final variables were extracted. After extracting the final variables, it is time to formulate the rules. According to the designed questionnaire, which was prepared regarding the rules, the rules were developed. In the quantitative part, the system's output in different simulated conditions should be examined. Simulation refers to considering and creating different states of the electric charge consumption management situation. In other words, different states of the load consumption situation are considered in simulating the situation. In each case, each of the input variables can receive different values. Thus, each simulated state will be a definite combination of all input variables, each with a definite hypothetical value. Finally, the sum of the simulated conditions is a set of different states that represent different combinations of different values of inputs together. Finally, after extracting the rules and designing the desired expert system, its performance is evaluated in two ways:

(1) Examining the output with data and hypothetical conditions and its acceptance rate by experts
(2) Checking the output with the data and the real situation and its similarity with the opinion of experts

After measuring the performance of the expert system, the desired system was implemented in real conditions, and similar results of the previous year and forecasting by the expert and after launching the management and forecasting system by the expert system were compared. Regarding the assessment of paragraphs 1 and 2, the evaluation can be examined through qualitative analysis and review of opinions and statistics of experts and quantitative analysis of collected data and software. After launching the expert system, areas were selected as pilots and samples, and the results were tested on them. This section was performed using a descriptive survey method and in two stages: a questionnaire and a census of experts. First, data were provided to the expert system, and the results were received. The results were presented to the experts through a questionnaire, and their opinions on the results were recorded. If the opinion of the experts did not comply with the law, that law was again presented to all experts and their opinions were obtained regarding the removal or amendment of the law. In the next step, the same real data were presented to the experts and the expert system, and the results were compared. Using the equality test of the means of the two societies, the hypothesis of equality of the mean of the two societies (experts' opinions and the output of the expert

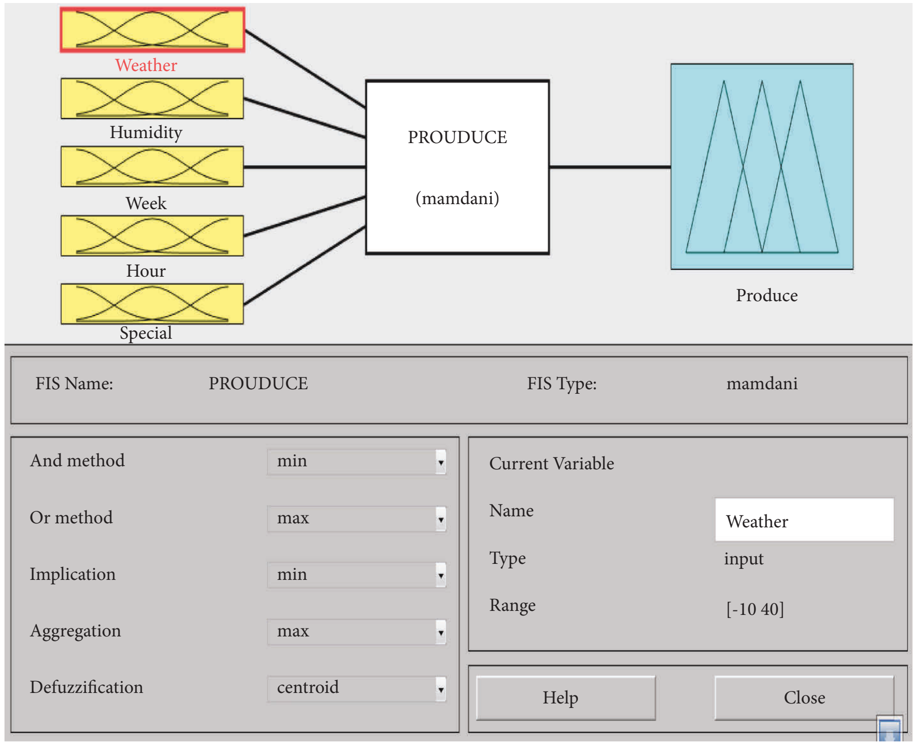

Figure 2: View of input and output variables in the MATLAB fuzzy variable window.

system) was tested. If the assumption of average equality of the two communities is accepted, it indicates the appropriateness of the designed expert system.

4. Research Findings

After collecting basic information, identifying variables, and formulating rules, an expert system with 81 rules was designed. The rules designed in MATLAB software's fuzzy system were loaded, as shown in Figures 2 and 3 of data entry and processing. Also, Figure 4 shows a three-dimensional representation of the shape formed by the rules laid down in the proper energy management system.

4.1. The Rate of Acceptance of System Results by Experts. To do this important, the results were evaluated according to statistical tests. Hypotheses H_0 and H_1 were evaluated to examine the opinions of experts regarding the agreement with the outputs. For this purpose, according to the inputs entered into the designed system, outputs were extracted from this system, and regarding the agreement of the experts with these outputs based on the Likert spectrum according to Table 2, an answer was received.

To validate the system outputs, the opinions of the experts (agreeing with the outputs produced by the system) must be equivalent to the answer in the affirmative or strongly agree. For this purpose, the system output was provided to experts in different simulated modes. 45 outputs of random input data were generated and recorded. The generated outputs according to the inputs were provided to the experts, and the amount of agreement with the system responses was obtained from them. Table 3 shows the results of a survey of experts on system output in each of the simulated selected conditions. Also, Figure 5 shows that the data follow the normal distribution with a mean of 4.35 and a variance of 308.

To show the degree of agreement of the experts with the system outputs, since the data are ranked and discrete, the statistical hypothesis test should be performed by converting the data into success (1) and failure (0). To do this, we convert numbers equal to or above 4 on average to 1 (win) and the rest to zero (defeat). The test of the following hypothesis in which P is the probability of acceptance of the answer by the experts has been tested in SPSS software. For this purpose, the statistical test specified below is considered. Table 4 shows the frequency of win and lose modes according to the system output. Also, in Table 5, the intended hypothesis test is examined.

$$\begin{cases} H0\colon\ P = 0.8, \\ H1\colon\ P < 0.8. \end{cases} \tag{1}$$

Therefore, there is no reason to reject the null hypothesis. The result of this test is that if repeated over and over again, a similar response will be obtained with a probability of at least 80%.

4.2. The Degree of Alignment of the System Results and the Opinions of Experts. At this stage, the issue of similarity and proximity of the system output with the opinions of experts in the simulated conditions was also examined. At this stage, 40 modes were randomly considered again to combine the

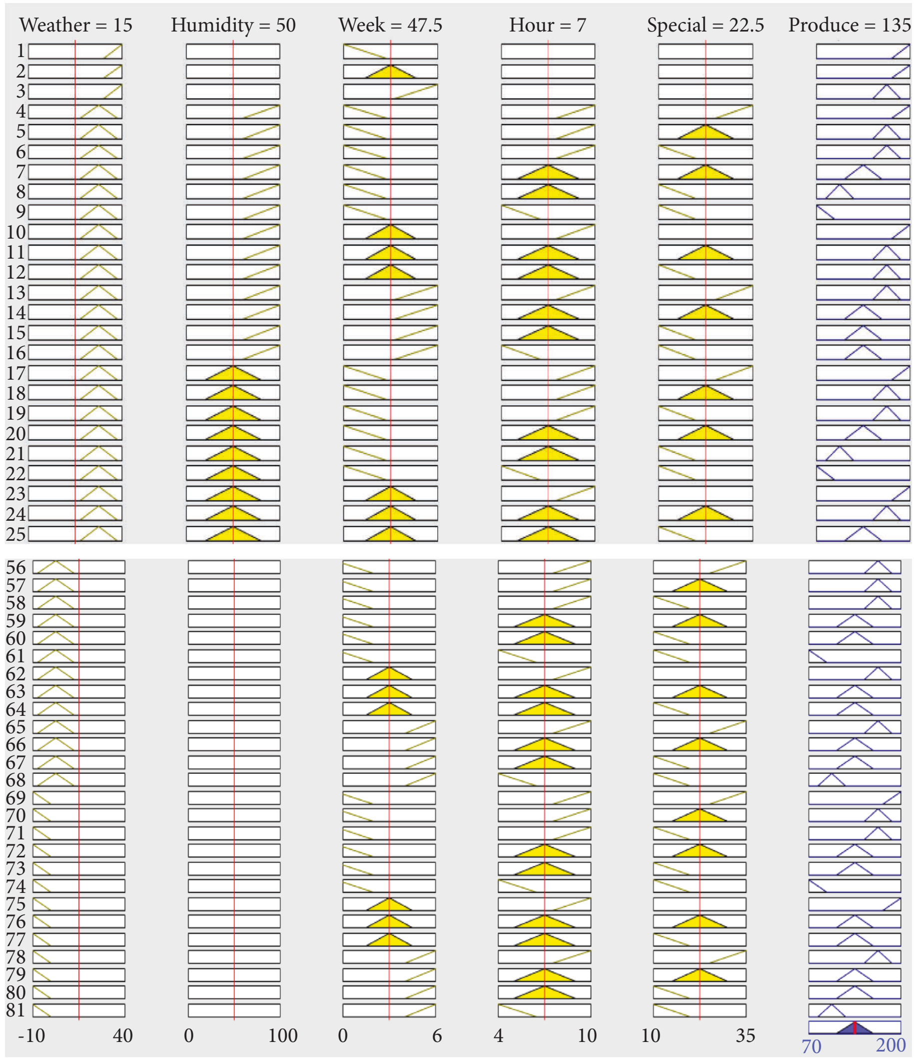

Figure 3: View of the rules designed in the MATLAB fuzzy rule window.

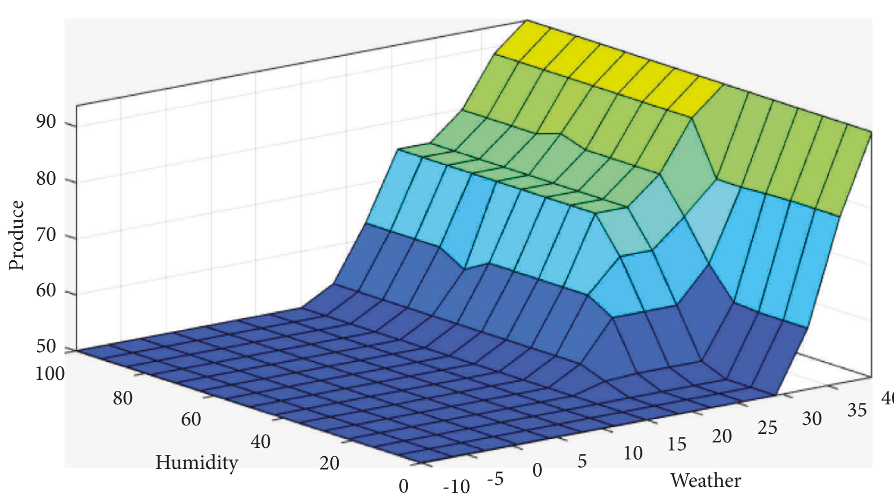

Figure 4: View of the level displayed by MATLAB software designed for rules.

Table 2: Table of how to score each answer.

Options	Completely agree	Agree on	Abstention	Disagree	Completely disagree
Score	5	4	3	2	1

Table 3: Results of expert surveys on system output in each of the simulated conditions.

Std. dev	μx	X	Std. dev	μx	x	Std. dev	μx	X	Std. dev	μx	x
0/92	4/44	34	0/70	4/44	23	0/75	4/28	12	0/98	3/61	1
0/38	4/83	35	0/51	4/50	24	0/89	4/28	13	0/90	3/89	2
0/51	4/56	36	0/71	4/50	25	0/77	4/33	14	0/76	4/11	3
0/50	4/61	37	0/78	4/56	26	0/69	4/33	15	1/02	3/89	4
0/32	4/89	38	0/61	4/61	27	0/84	4/33	16	0/71	4/17	5
1/13	3/89	39	1/11	3/94	28	0/70	4/39	17	0/96	3/89	6
0/70	4/44	40	0/57	4/72	29	0/61	4/39	18	0/81	4/22	7
0/50	4/61	41	0/51	4/83	30	1/02	3/89	19	0/73	4/22	8
0/61	4/61	42	0/46	4/72	31	0/85	4/39	20	0/65	4/22	9
1/17	3/78	43	0/70	4/44	32	0/78	4/39	21	0/83	4/28	10
0/78	4/39	44	0/57	4/72	33	0/78	4/44	22	1/00	3/94	11

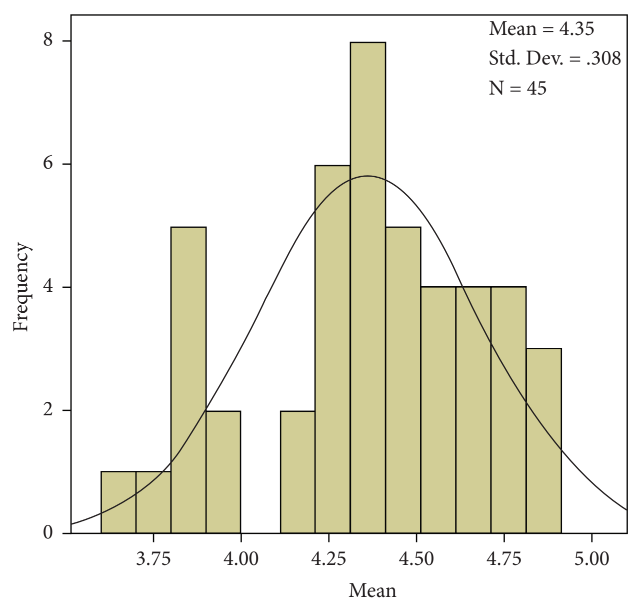

Figure 5: Histogram diagram of average expert opinions about system output.

Table 4: Table of frequency of win and lose mode (for and against) system output.

Binomial results		Frequency	Percent	Valid percent	Cumulative percent
Valid	Lose	9	20.0	20.0	20.0
	Win	36	80.0	80.0	100.0
	Total	45	100.0	100.0	

Table 5: Output table of SPSS software regarding the assumption.

Binomial test		Category	N	Observed prop.	Test prop.	Exact sig. (1-tailed)
Binomial	Group 1	Win	36	0.8	0.8	0.559
	Group 2	Lose	9	0.2	—	—
		Total	45	1.0	—	—

inputs, and the simulated conditions were given to the experts as inputs. Also, these conditions were entered into the system, and the result of the experts' opinions and the system's output were evaluated (Table 6).

In the continuation of this test, the statistical assumption was tested whether the system output is different from the output of experts. To do this, according to the ranking of the data, the Mann–Whitney test was used. This test examines the differences between two independent groups regarding a variable with rank or sequential data. In this case, the data are first ranked, and then, the rankings' differences are examined. The test statistics used according to equation (2) is as follows, in which n_1 and n_2 are the numbers of members of each group and R_1 and R_2 are the sums of the ranks of each group.

$$W = n_1 \times n_2 + \frac{n_1 (n_1 + 1)}{2} - R_1, \tag{2}$$

$$W' = n_1 \times n_2 + \frac{n_1 (n_1 + 1)}{2} - R_2. \tag{3}$$

Because the sample size is more than 20, according to the mean and variance W, we use the following index, which has a standard normal distribution, and it compares its value at the level of 0.05 with the value of 1.96 of the standard normal table.

$$U = Z = \frac{\left|W_1 - n_1 n_2/2\right|}{\sqrt{n_1 n_2 (n_1 + n_2 + 1)/12}}. \tag{4}$$

The hypothesis test is as follows:

$H0$: there is no difference between the two groups

$H1$: there is a difference between the two groups

Table 7 shows the output value of expert opinions and system output. The data obtained based on the results of experts were rounded to one decimal place and then used. Table 8 shows the similarity of the experts' opinions according to the software output.

Based on the extracted information in Table 9, the value of the t-test statistics is −1.314, and the P value is 0.189. Given that the error level of the first type of test was 5% and the level of error is less than P value, there is no reason to reject the assumption of zero, which is the average equality of the two communities. Therefore, based on the data and their testing, the assumption of the equality of the mean of the two societies is correct.

Table 6: Table of how to score each answer in the similarity of the system answer with the opinions of experts.

Options	Very much	Much	Medium	Low	Very little
Score	5	4	3	2	1

Table 7: System output results in expert output of actual data.

$\mu2$	$\mu1$	X	$\mu2$	$\mu1$	x	$\mu2$	$\mu1$	X	$\mu2$	$\mu1$	x
4.17	5	31	2.78	2	21	2.11	2	11	3.56	3	1
2.50	2	32	2.44	2	22	2.50	2	12	4.28	4	2
4.89	5	33	4.33	4	23	1.89	2	13	2.06	2	3
4.83	4	34	4.44	4	24	3.89	3	14	2.72	3	4
3.28	3	35	1.44	1	25	4.17	4	15	4.78	5	5
3.67	3	36	1.56	1	26	3.44	3	16	2.22	2	6
2.72	3	37	3.28	3	27	4.78	5	17	4.72	4	7
2.22	2	38	3.61	3	28	4.56	4	18	4.72	4	8
3.06	3	39	2.44	2	29	3.94	3	19	1.72	2	9
4.17	4	40	4.78	5	30	3.78	3	20	1.61	1	10

Table 8: SPSS software outputs regarding the similarity of software output and expert opinions.

Ranks				
	Expert 2	N	Mean rank	Sum of ranks
System	1.00	40	37.19	1487.50
	2.00	40	43.81	1752.50
	Total	80	—	—

Table 9: Statistical test results.

Statistical test	System
Mann–Whitney U	667.500
Wilcoxon W	1487.500
Z	−1.314
Asymp. sig. (2-tailed)	0.189

4.3. Comparison of System Performance with Bayesian Forecast Inference Networks. After ensuring the acceptability of the originally designed system according to the opinions obtained from experts, it was time to compare the results of the designed system with the results of Bayesian forecast inference. According to the information in the exquisite system, the conditional probabilities of the root and intermediate nodes can be calculated, which is avoided because this issue does not fit in the research. To test and compare the two systems with each other, 50 different modes of input data were tested for the two systems. The output of R software (exquisite system Bayesian network) and MATLAB software output (fuzzy inference) for electrical charge management are shown in Table 10.

In the analysis of each data, the correlation between the outputs of the two systems was about 87%, which indicates that the changes in both systems are directional. Table 11 shows the Pearson correlation value.

According to Table 11, the correlation is significant at the 0.01 level (2-tailed). Therefore, given that the data extracted from the designed system are expressed as rank and discrete and the exquisite system data are expressed as a probability, no other statistical test can be performed to compare the output of the two systems.

4.4. Evaluate Knowledge Acquisition through Real Data. According to the confirmation of the system output results from the simulated data by the research experts, as well as the similarity of the results of studies on the similarity of system decision-making with expert

Table 10: Comparison table of the output of the two systems.

Exquisite system Bayesian network	Result of the fuzzy inference system	Row	Exquisite system Bayesian network	Result of fuzzy inference system	Row	Exquisite system Bayesian network	Result of fuzzy inference system	Row	Exquisite system Bayesian network	Result of fuzzy inference system	Row
0/6984	4	40	0/9288	5	27	0/1412	1	14	0/3116	2	1
0/2433	2	41	0/98	5	28	0/3808	2	15	0/876	5	2
0/6888	3	42	0/3804	3	29	0/6118	4	16	0/8798	5	3
0/7266	4	43	0/1674	1	30	0/2353	2	17	0/763	4	4
0/3437	3	44	0/655	4	31	0/3343	3	18	0/2203	2	5
0/0887	1	45	0/9287	5	32	0/1739	1	19	0/7042	4	6
0/7067	3	46	0/1677	1	33	0/5118	3	20	0/8938	5	7
0/2138	2	47	0/2871	2	34	0/2287	2	21	0/3632	3	8
0/1743	1	48	0/7685	4	35	0/6939	4	22	0/8832	5	9
0/9217	5	49	0/2419	2	36	0/6524	4	23	0/3925	2	10
0/2164	1	50	0/2202	2	37	0/5157	3	24	0/1602	1	11
			0/3593	3	38	0/1862	1	25	0/3695	3	12
			0/977	5	39	0/7037	4	26	0/2132	2	13

Table 11: Output correlation table of the two systems.

Logic	Statistical test	Fuzzy	Bayesian
Fuzzy	Pearson correlation	1	0.872**
	Sig. (2-tailed)	—	0.000
	N	50	50
Bayesian	Pearson correlation	0.872**	1
	Sig. (2-tailed)	0.000	—
	N	50	50

decision-making, as well as the similarity of the output of the system designed with the existing system, which makes decisions based on Bayesian networks, the similarity and closeness of the system output with the experts' opinions in real conditions will be examined. In this section, we intend to show whether the fuzzy expert decision support system will improve the performance of load consumption management (production coordination with consumption).

We explained earlier that managing the consumption of electric charge is important, given that it is not possible to store more production. Also, in case of less production, we will face blackouts. As explained in the previous chapter, the results of the total number of blackouts and the amount of overproduction load with the same period of the previous year were examined for this purpose. The duration of using the expert system to prevent bias and also due to the time constraints to conduct research was 62 consecutive days in July and September. The constant conditions of the same period last year were also examined.

At this stage, the following hypothesis test was tested:

$$\begin{cases} H0\colon\ \mu 1 \leq \mu 2, \\ H1\colon\ \mu 1 > \mu 2. \end{cases} \tag{5}$$

Here, $\mu 1$ means the total shutdown hours in different areas where the industrial towns of Tehran Province are located in 2020 and $\mu 2$ is the total number of shutdown hours in the same area in 1998 after using the system. The results of studies conducted in this regard are shown in Table 12.

Given that the number of data is small (although more than 50) and the data are discrete, the Shapiro–Wilk test must test the normality of the data. The test shown in Table 13 confirms the normality of the data based on the Kolmogorov–Smirnov test.

Table 14 A (group statistics) shows that in addition to reducing the average of the data, their dispersion around the average parameter has also decreased, which indicates the positive performance of the system. According to the software output in Table 15, the assumption of the equality of variances is rejected and the results are examined from the software output assuming that the equality of variances is rejected. According to the outputs, the equality of the averages regarding the average equality of the total off-hours of two years in August and September 1997 and 1998 is rejected. Regarding the hypothesis test presented in this section, due to the small P value and smaller than the error rate of the first type, which is considered 5%, statistical test in the output of the software, output, the hypothesis H0 is

Table 12: Table of total blackouts in the area and the amount of overproduction of Tehran electricity network.

The amount of additional production in 1998 (MWh)	The amount of additional production in 1997 (MWh)	Total blackout hours in 1998	Total blackout hours in 1997	Day	The amount of additional production in 1998 (MWh)	The amount of additional production in 1997 (MWh)	Total blackout hours in 1998	Total blackout hours in 1997	Day
3	36	3	13	32	10	2	3	15	1
3	18	6	8	33	11	16	8	9	2
13	6	7	8	34	15	12	7	4	3
6	41	2	8	35	11	3	7	16	4
5	11	7	5	36	8	34	8	12	5
2	13	7	15	37	7	41	2	10	6
6	5	9	2	38	8	22	3	9	7
16	17	3	0	39	2	38	2	6	8
10	39	3	1	40	11	8	9	17	9
5	21	7	12	41	6	5	3	3	10
12	18	6	3	42	0	43	3	15	11
6	21	5	15	43	16	9	6	7	12
16	7	0	3	44	12	32	6	15	13
12	27	3	13	45	9	0	9	15	14
11	42	4	8	46	4	37	3	3	15
11	25	2	10	47	6	38	3	1	16
10	17	4	0	48	11	25	1	13	17
10	40	5	1	49	11	7	8	17	18
14	13	8	0	50	9	4	3	9	19
13	40	6	1	51	14	31	1	12	20
13	12	2	5	52	7	35	3	6	21
10	39	3	7	53	4	16	3	3	22
0	9	7	6	54	12	19	9	13	23
16	1	5	15	55	17	0	3	18	24
5	32	8	8	56	15	28	0	5	25
0	38	7	8	57	17	7	6	0	26
1	40	2	4	58	1	42	6	3	27
11	40	1	13	59	13	13	3	17	28
16	23	9	15	60	6	13	2	9	29
8	28	0	18	61	8	16	0	0	30
3	36	3	13	62	9	42	9	17	31

Table 13: Data normality test table.

Year	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistics	df	Sig.	Statistics	df	Sig.
Base—1997	0.122	62	0.022	0.933	62	0.002
Current—1998	0.204	62	0.000	0.929	62	0.002

Table 14: SPSS software outputs for testing the difference in the average number of blackouts.

Year	Observation	Mean	Std. deviation	Std. error mean
97.00	62	8.7258	5.70927	0.72508
98.00	62	4.5806	2.70730	0.34383

rejected. Considering the positiveness of the upper and lower limit of the calculated confidence interval, the average of differences, and the positive average are as follows:

$$\mu 1 - \mu 2 > 0 \Rightarrow \mu 1 > \mu 2. \tag{6}$$

Thus, the initial assumption is rejected. The same problem was performed for the amount of power generation exceeding the required capacity (to waste the resource) with the same assumption, and the same results were obtained (as described in Table 16 based on software output) (Table17).

Table 15: SPSS software outputs for testing the difference in the average number of blackouts.

Treatments	Levene's test for equality of variances		t-test for equality of means					95% confidence interval of the difference	
	F	Sig.	t	df	P value	Mean difference	SD	Lower	Upper
Equal variances assumed	40.955	0.000	5.166	122	0.000	4.14516	0.80247	2.55660	5.73373
Equal variances not assumed	—	—	5.166	87.113	0.000	4.14516	0.80247	2.55020	5.74012

Table 16: SPSS software outputs regarding the different tests of the average amount of overproduction.

Response	Year	Observation	Mean	Std. deviation	Std. error mean
Amount of additional production (MWh)	97.00	62	22.4839	13.86675	1.76108
	98.00	62	9.0806	4.68096	0.59448

Table 17: SPSS software outputs regarding the different tests of the average amount of overproduction.

Treatment	Levene's test for equality of variances		t-Test for equality of means					95% confidence interval of the difference	
	F	Sig.	t	df	P value	Mean difference	SD	Lower	Upper
Equal variances assumed	96.758	0.000	7.211	122	0.000	13.40323	1.85871	9.72372	17.08273
Equal variances not assumed	—	—	7.211	74.724	0.000	13.40323	1.85871	9.70026	17.10619

5. Discussion and Managerial Insights

Based on the results, it has been determined that the total blackout hours in different areas of Tehran have decreased compared with the base year. Accepting this hypothesis in this research provides managerial insights into both upstream and downstream dimensions. In the upstream dimension, the management of energy resource consumption through the establishment of appropriate policies has worked well. In the downstream dimension, households have been able to save by observing the consumption pattern during peak consumption. According to the status of acceptance of this hypothesis, based on the optimal upstream and downstream performance, due to the savings created, the power of the power plants has been saved. Therefore, the proposed framework has been able to analyze the performance of consumption by households and the production of electricity flow by upstream institutions, and the following advantages are obtained:

(i) Providing an expert system for the correct management of energy consumption in small and medium industries using soft computing

(ii) Using uncertain decision-making variables in this field, instead of using words and linguistic restrictions in this research, and modeling them in the system using the principles of fuzzy logic is used

6. Conclusion

This research first tried to collect and extract the existing knowledge about power consumption management and the expert system based on the subject literature, research, and previous studies in all industries. According to the emphasis of most of the previous studies, the need to pay attention to specific consumption conditions, knowledge extraction, and the need to pay attention to macro-policies of governments to create a suitable knowledge base in this field, the opinions of electricity industry experts (a large family of electricity industry) have been explored, and then it has been checked according to those rules. The extracted rules are extracted and examined uniquely for this industry (electricity or electricity industry) and can definitely be used only for this industry. The rules have been reviewed and revised after extraction and used by experts after reapproval. The rules were extracted based on fuzzy logic and using the relevant principles and rules. Due to the type of variables, all of which were linguistic, it was impossible to identify and measure them with definite numbers. Finally, the extracted knowledge in the form of a prototype in the knowledge base, known as expert system knowledge, was prepared and presented in the fuzzy environment of MATLAB software. Therefore, the main results of research are as follows:

(i) Based on comparing the performance of the system with Bayesian inference networks, it showed that there is an acceptable correlation between the data and the prediction system

(ii) Based on evaluating the acquisition of data using a statistical test, it has been determined that the total number of blackout hours in different areas of Tehran in the base year was more than the current year

Performance review, the impact on managing electrical load consumption, was also examined according to the comparison of system results with expert opinions and performance review of last year, before using the system, and this year, after using the system. The results obtained in both cases were largely confirmed by measuring the statistical hypotheses and the obtained data. For further research, it is suggested that a framework for managing electrical charge consumption with an uncertain amount of demand is considered, using mathematical modeling based on robust planning.

Data Availability

The data are included in the article and are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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