IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received August 21, 2020, accepted September 15, 2020, date of publication October 6, 2020, date of current version October 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3029090

Fuzzy Cognitive Maps-Based Switched-Mode Power Supply Design Assistant System

YI KUANG[1], ZHIYONG JOHNNY ZHANG[2], (Member, IEEE), BIN DUAN[3], (Member, IEEE), AND PEI ZHANG[4]

[1]School of Materials Science and Engineering, Xiangtan University, Xiangtan 411105, China
[2]Department of Psychology, University of Notre Dame, Notre Dame, IN 46556, USA
[3]School of Automation and Electronic Information, Xiangtan University, Xiangtan 411105, China
[4]Department of Engineering and Technology Management, Portland State University, Portland, OR 97201, USA

Corresponding author: Bin Duan (db61850@163.com)

This work was supported in part by the Development of Innovative Practice Platform Based on Texas Instruments Power Management Lab Kit (TI PMLK), Texas Instruments Semiconductor Technologies (Shanghai) Company, Ltd., through the Reform of the Teaching Content and the Course System, under Grant 201702007038. The work of Yi Kuang (a research scholar) was supported by the Department of Psychology, University of Notre Dame, through the China Scholarship Council under Grant 201908430176.

ABSTRACT Traditional engineering design approaches primarily solve technical problems and often ignore the importance of human factors. To reduce human errors and workload in power electronics, this paper proposes a switched-mode power supply design (SMPS) assistant system based on Fuzzy Cognitive Maps (FCMs). This system incorporates both technical requirements and human factors that involve designers' knowledge and skills in the SMPS design domain. First, we identify the critical concepts from power management lab kits and power electronics books, and extract latent sub-skills of SMPS design using exploratory factor analysis to build the starting concept list of FCM. Second, we use factor analysis and correlation analysis to determine the causal weights between the captured components to build the initial FCM based on the starting concept list of FCM. Third, through interviews with subject-matter experts, we get their inputs on the initial main map and capture their individual FCMs. Then, we integrate experts' individual FCMs with different weights. After that, we determine the degree of fuzzification of the threshold function through analyzing data collected based on the prediction results of the only decision concept in the proposed FCM — SMPS quality. Two WHAT-IF scenarios are analyzed based on different inputs using the FCM Expert tool. The scenario test results provide guidelines to designers in terms of knowledge or skills improvements and power supply debugging. Finally, we evaluate the proposed system using eight scenarios. The evaluation results of components' actual states are consistent with their preferred states, which suggests that the proposed FCM-based assistant system is reliable and effective. The proposed system provides useful guidelines in terms of knowledge or skills improvements for SMPS designers and can help improve the power supply design process.

INDEX TERMS Switched-mode power supply, fuzzy cognitive maps, design assistant system, factor analysis, Pearson analysis.

I. INTRODUCTION

In daily life, all electronic circuits require a clean and constant voltage DC power supply. However, in some special cases, the energy source may be another DC or AC supply. Switched-mode power supplies (SMPSs) can provide reliable performance in the worst circumstances. They have many advantages, such as small size, lightweight, and high efficiency, and are widely applied to different kinds of electric apparatus and systems [1].

Traditional engineering design approaches primarily solve technical problems but typically ignore the importance of nontechnical factors of the system, such as human factors [2]. Human factors involve gathering information about human abilities, limitations, and other characteristics and determining how they interact with tools, machines, systems, tasks, and environments to produce safe, comfortable, and effective human use [3]. The existing literature has shown that human

The associate editor coordinating the review of this manuscript and approving it for publication was Mohsin Jamil.

errors are major causes, for example, of incidents occurred in electric power systems [4], railways [5], [6]. Thus, in SMPS designs, it is crucial to assess human performance to reduce human error by considering both technical factors and human factors. Technical factors include power supply topologies, operation, efficiency, control, stability, accuracy, transient response, noise, and power magnetics [7]. There are some SMPS design tools, including WEBENCH, PI Expert Suite, SIMetrix/SIMPLIS, and SwitcherPro. However, these tools only consider the technical factors in the SMPS design. Designers need to design SMPS with both technical and human factors in mind.

Human performance can be evaluated using different statistical and machine learning techniques. These techniques can be used to construct a causal knowledge system to assess human performance where the knowledge system determines what kinds of knowledge and skills should be evaluated. Bayesian belief networks (BBN) and Fuzzy Cognitive Maps (FCM) have been used to build causal knowledge systems [8]. For instance, Mislevy and Gitomer [9] constructed BBN for an aircraft hydraulics system to help learners conduct troubleshooting tasks. Levy and Mislevy [10] also used the BBN approach to model students' performance in computer-based interactive assessment in the computer network engineering domain. Özesmi and Özesmi [11] created an FCM based on the perceptions of different stakeholders in real environment management to facilitate the development of participatory environmental management plans. Wee *et al*. [12] compared the different roles of BBN and FCM in the development of causal knowledge system, and showed that FCM was in general far superior to BBN in terms of understandability, usability, modularity, and scalability. In terms of expressiveness and inferential capability, BBN is in general superior to FCM. Because the structure of the domain variables in FCM is more intuitive and user friendly than the tabular interface provided by the conditional probability tables of BBN, it will facilitate the process of domain modeling [8]. In this study, we use FCM to construct the knowledge system to integrate different perspectives of stakeholders.

In psychological and cognitive measurement, classical theory test (CTT) and item response theory (IRT) are commonly used to evaluate students' performance. However, the results of the widely used CTT and unidimensional IRT models are single overall scores, which cannot provide more diagnostic information related to student learning. The assessment results of FCM can reflect the role of multiple facets of performance, which can provide more specific and accurate diagnostic information than the CTT or IRT model. Thus, FCM is an useful tool to help decision-makers to structure complex decisions. The results of the FCM model can be used to analyze, simulate and test the influence of parameters, and predict the behavior of the system.

FCM has been used as a systematic way of analyzing real-world problems with numerous known, partially known, and unknown factors. FCM is a mix of qualitative and quantitative approaches [13]. FCMs have been considered as an ideal mechanism for incorporating different stakeholders and combining knowledge by mathematically aggregating individual FCM models. FCM is a dynamic modelling technique and can reflect the cognition of stakeholders. Because of these advantages, FCM has been applied in many fields, including computer science, engineering [14], environmental sciences [11], behavioral sciences, medicine [15], business, autonomous vehicle technology [16], and information technology [17]. Diverse studies show that FCM can provide an understanding of problematic domains or system for strategic purposes [18]. In this paper, we incorporate the technical requirements and non-technical factors to build an FCM-based design assistant system to provide instruction and feedback to designers by explicitly modeling the impact of human performance on the operation of design tools. We focus our analysis on the following research questions: (1) how to extract the SMPS design-related knowledge and skills; (2) how to identify the adjacency matrix of FCM; and (3) how to interpret the scenario test results and provide guidelines to designers. To our knowledge, this is the first paper that demonstrates how FCM is applied in the SMPS design field to provide decision support to designers.

The rest of the paper is organized as follows. Section II briefly describes the FCM theory. Section III presents the knowledge and skill capturing process. Section IV presents the methods of the adjacency matrix calculation. We focus on imputing missing data using Markov Chain Monte Carlo (MCMC) method, factor analysis and correlation analysis. Section V demonstrates the process and content of providing guidance to the designer and evaluates the proposed FCM-based assistant system with eight extreme cases. Section VI highlights the contribution of work presented in the paper and discusses the directions of future work.

II. FUZZY COGNITIVE MAPS

A. FCM THEORY

FCMs were proposed by B. Kosko as a knowledge-based methodology for modeling and simulating dynamic systems in order to improve a decision maker's ability to understand the dynamic behavior of causal cognitive maps [19]. FCMs are inference networks using cyclic digraphs, which originated from the combination of fuzzy logic and neural networks for knowledge representation and reasoning [17]. Using FCMs, a specific domain system could be modeled in terms of concepts and causal relations between these concepts.

In FCM, domain knowledge is a connected network in which nodes represent major concepts, and edges between nodes represent causal relationships and the strength of the causality. A fuzzy cognitive map F is a quadruple (C, W, A, f) [20], [21]. Each component is explained below.

(1) $C = \{C_1, C_2, \ldots, C_n\}$ is a set of n concepts forming the nodes of a graph.

(2) $W : (C_i, C_j) \rightarrow w_{ij}$ is a function of each of the $n \times n$ pairs of concepts (C_i, C_j) taking values in the range of -1 to 1, with w_{ij} denoting a weight of directed edge from C_i to C_j. $W(n \times n) = (w_{ij})$ is a connection or edge matrix [19]. There are three possible types of causal relations between concepts:

(a) If $w_{ij} > 0$, there is a positive causality, where increasing C_i leads to an increase in C_j with intensity w_{ij}.
(b) If $w_{ij} < 0$, there is a negative causality, where an increase in C_i leads to a decrease in C_j with intensity $|w_{ij}|$.
(c) If $w_{ij} = 0$, there is no causal relationship.

(3) $A(t) = \{A_1(t), A_2(t), \ldots, A_n(t)\}$ is a sequence of concept activation degrees at time t. $A(0)$ indicates the initial vector and specifies initial values of all concept nodes and $A(t)$ is a state vector at time t.

(4) f is a threshold function, which includes recurring relationship on $t \geq 0$ between $A(t+1)$ and $A(t)$. The Kosko's activation rule with self-memory is

$$A_i(t+1) = f\left(\sum_{j=1, i\neq j}^{n} w_{ji} A_j(t) + A_i(t)\right), \tag{1}$$

where $A_i(t+1)$ is the state of effect concept C_i at iteration $t+1$, $A_j(t)$ is the state of cause concept C_j at iteration t, w_{ji} is the weight of the interconnection between C_j and C_i, and f is a threshold function [22]. The commonly used threshold functions include bivalent, trivalent, sigmoid, and hyperbolic tangent functions [23]. In our FCM, because the values of concepts can be negative and their values belong to the interval $[-1, 1]$, we use the hyperbolic tangent function as the threshold function [21],

$$f(x) = tanh(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}, \tag{2}$$

where λ is a parameter through which one can specify the function slope or the degree of fuzzification. The hyperbolic tangent function makes it possible that the components of the vector acquire negative values. The iteration of this process continues until the state vector reaches a stable status or a stopping criterion [24]. Finally, the last state and the behavior of each element in the state vector can be interpreted according to the objective of the analysis [23].

B. FCM-BASED SMPS DESIGN ASSISTANT FRAMEWORK

The procedure of an FCM-based SMPS design assistant system includes four phases. First, identify the critical concepts from power management lab kits and power electronics books and extract latent sub-skills of the SMPS design using exploratory factor analysis to build the starting concept list of FCM. Second, calculate the causal weights between the captured components of the starting concept list of FCM using exploratory factor analysis and correlation analysis to create an initial FCM. Third, interview subject-matter experts (SMEs) to get their inputs on the initial main map and capture their individual maps. Finally, integrate these individual maps to get the final FCM for the simulation analysis. The flowchart of the methodological steps of building the FCM-based SMPS design assistant system is presented in Fig. 1.

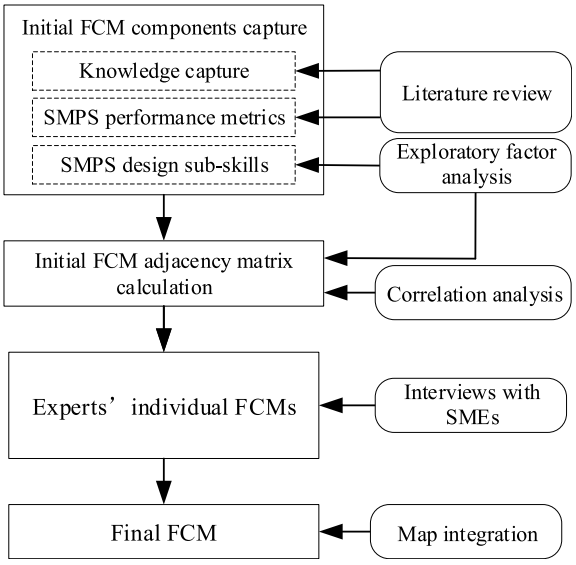

FIGURE 1. The flowchart of methodological steps of building the FCM-based SMPS design assistant system.

In this study, the FCM-based SMPS design assistant system plays a decision support role. The design assistant system and designers collaborate to make decisions on each design case [25]. Fig. 2 shows the approach of the decision service offered by the design assistant system to support the designers.

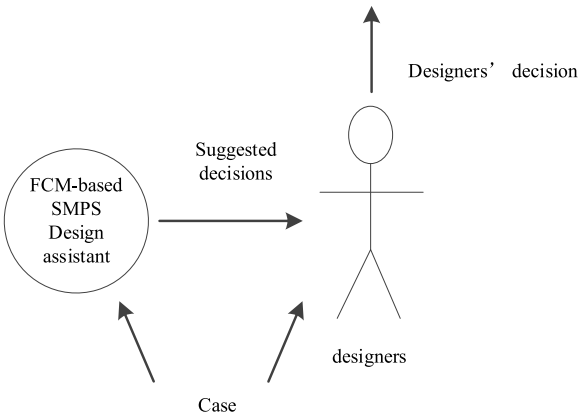

FIGURE 2. Design assistant advises designers.

III. KNOWLEDGE AND SKILLS IN FCM

The DC-DC Buck converter is the most basic SMPS topology, as shown in Fig. 3. It is widely used in industry to convert a higher input voltage to a lower output voltage. Thus, in this study, we use the Buck converter as an example to describe the reasoning process of the FCM-based design assistant system.

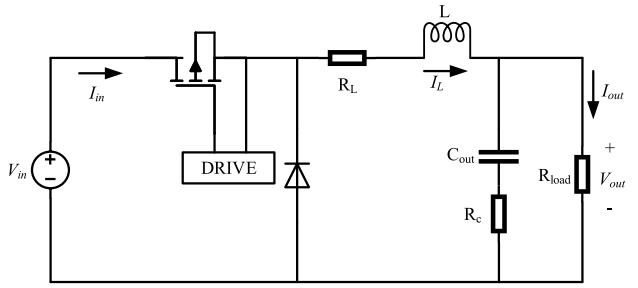

FIGURE 3. DC-DC Buck converter topology.

We use several methods to capture knowledge and skills, including the research on Power Management Lab Kit (PMLK) series and power electronics books, exploratory factor analysis, and interviews with SMEs.

PMLK, released by Texas Instruments (TI), covers the basic topics and issues of the low power DC-DC non-isolated power supplies design. In the TI-PMLK Buck, there are six real-life engineering scenarios, including the impact of operating conditions on efficiency, impact of passive devices and switching frequency on current and voltage ripples, impact of cross-over frequency and passive devices on load transient response, impact of the inductor saturation on current and voltage ripples, impact of inductor characteristics on current limiting operation, and switching frequency, ripple, offset and line immunization capabilities of hysteretic control [7].

To offer suggestions on the necessary sub-skills of the SMPS design to designers, we use the exploratory factor analysis method to identify what specific underlying sub-skills a good designer must possess. The process includes data collection, missing data imputation, parallel analysis, factor extraction, and factor rotation.

A. DATA COLLECTION

To collect data, we asked 75 students to complete an SMPS design task. Students were asked to design an aerospace SMPS using TI WEBENCH. The design requirements were: input voltage $V_{in} = 5V$, output voltage $V_{out} = 3.3V$, output current $I_{out} = 1.5A$, switching frequency $f_s = 465$kHz and efficiency $\eta = 85\%$. In addition, steady state and thermal simulations should be carried out based on the designed power supply.

The data contains 15 observed power supply performance metrics, including efficiency, IC junction temperature, total power dissipation, IC power dissipation, temperature rise of inductor, inductor power dissipation, peak-to-peak output ripple voltage, output capacitor RMS ripple current, peak-to-peak inductor ripple current, dynamic inductance, footprint area of inductor, total foot print area of BOM (Bill-of-Materials) components, switching frequency, output capacitor power dissipation, and the total BOM cost. There are about 29.3% missing data in this study because some power supplies cannot conduct thermal simulation using the WEBENCH tool.

The following constraints have been adopted as criteria of feasible and reasonable power supply performance metrics [26]:

(1) Efficiency η: $\eta \geq 85\%$,
(2) Inductor loss $P_{L,loss}$: $P_{L,loss} - 0.15\, V_{in} V_{out}(1-\eta)/\eta \leq 0$, in $20\% \sim 30\%$ of total loss,
(3) Dynamic inductance L_d: $L_d - 0.2L_{nom} \geq 0$, L_{nom} is nominal inductance,
(4) Footprint area of inductor S_L: less than 30% of total footprint S_T,
(5) Peak-to-peak output ripple voltage V_{outpp}: $V_{outpp} < 10mv$,
(6) Inductive component temperature rise: less than $10°C$,
(7) Total BOM cost less than \$2.5.

B. MISSING DATA IMPUTATION

In our study, some of the data generated from thermal simulation were missing. The missing mechanism can be viewed as missing at random. We use an MCMC method to conduct multiple imputation for missing data. Ten imputed complete datasets were obtained through the R package *mi* [27].

C. EXPLORATORY FACTOR ANALYSIS

Parallel analysis was used to determine the number of factors to be retained. The results are shown in Fig. 4, which indicates that four factors should be extracted.

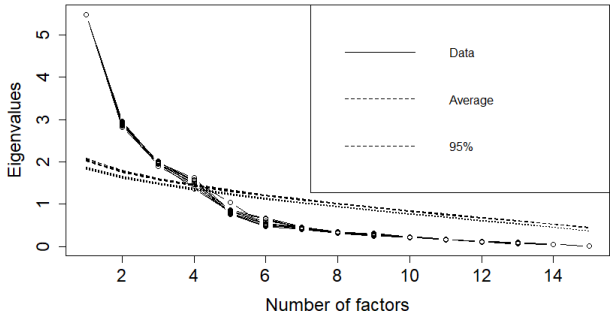

FIGURE 4. Parallel analysis results.

Using principal components analysis and the PROMAX rotation method, the result shows that the value of Kaiser-Meyer-Olkin is 0.752 (>0.6) and the Bartlett's test of sphericity is significant, which suggest that the correlations between pairs of variables can be explained by latent variables. Table 1 shows that 80.8% of the cumulative variance in the 15 performance variables can be explained by the four factors. Based on the patterns of factor loadings, we named the four factors as efficiency design skill, passive device design skill, power magnetics reduction design skill, and power economy design skill, respectively. The FCM mainly consists of five parts – passive components design-related knowledge, IC design-related knowledge, SMPS performance metrics, SMPS components design quality, and SMPS design-related skills.

TABLE 1. Exploratory factor analysis results for SMPS design.

Variables	Efficiency design (ED)	Passive device design (PD)	Power magnetics reduction design (PM)	Power economy design (PE)
Efficiency	-0.887			
IC junction temperature	0.961			
IC power dissipation	0.890			
Temperature rise of inductor	0.810			
Total power dissipation	0.901			
Inductor power dissipation	0.713			
Output capacitor RMS ripple current		0.918		
Peak-to-peak inductor ripple current		0.903		
Peak-to-peak output ripple voltage		0.840		
Switching frequency			-0.811	
Total foot print area of BOM components			0.686	
Dynamic inductance			0.727	
Footprint area of inductor			0.704	
Total BOM cost				0.908
Output capacitor power dissipation				0.754
Eigenvalue	5.684	3.064	1.792	1.585
% of Variance	37.9	20.4	11.9	10.6
Cumulative %	80.8			

IV. ADJACENCY MATRIX OF FCM

After reviewing the TI-PMLK Buck, power electronics books, and other literature, a starting concept list of FCM is constructed, as shown in Fig. 5. Based on this, we further determined the adjacency matrix through a mixed-methods analysis, as shown in Table 2 (see page 6). As mentioned in the previous section, we classify the FCM into five parts. We first identified four sub-skills related to the 15 SMPS performance metrics. Then, we used factor loadings to determine the weights between skills and SMPS performance metrics, and used cumulative variance to determine the weight between SMPS design-related skills. Correlation analysis was conducted to calculate the weights between SMPS performance components. The weights among inductor

FIGURE 5. A starting concept list of FCM. Notes: The blue components are" passive components design-related knowledge", the orange components are "IC design-related knowledge", the red components are "SMPS performance metrics", the yellow components are "SMPS components design quality", and the green components are "SMPS design-related skills".

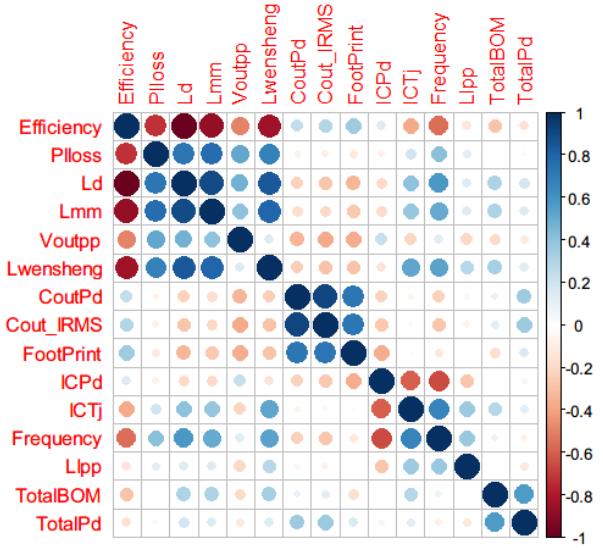

FIGURE 6. Pearson correlation coefficients. Notes: Plloss = Inductor power dissipation; Ld = Dynamic inductance calculation; Lmm = Voutpp = Peak-to-peak output ripple voltage; Lwensheng = Temperature rise of inductor; CoutPd = Output capacitor power dissipation; Cout_IRMS = Output capacitor RMS ripple current; FootPrint = Total foot print area of BOM components; ICPd = IC power dissipation; ICTj = IC junction temperature; Frequency = switching frequency; Llpp = Peak-to-peak inductor ripple current; TotalBOM = Total BOM cost; TotalPd = Total power dissipation.

design-related knowledge, capacitor design-related knowledge, IC design-related knowledge, and SMPS analysis-related components are determined based on the interviews with SMEs. The initial FCM is created with the combination of the starting concept list of FCM and the adjacency matrix which is calculated by factor analysis and correlation analysis.

A. PEARSON CORRELATION ANALYSIS

Pearson correlation analysis is used to measure the relationship among continuous variables. On the basis of the 75 experimental results, we calculated the skewness and kurtosis value of the SMPS design-related variables. The skewness and the kurtosis of the variables are within the acceptable ranges (skewness $< |2.0|$, and kurtosis $< |7.0|$) [28]. The Pearson correlation coefficients are shown in Fig. 6.

B. ADJACENCY MATRIX

We then collected data through individual interviews with SMEs. These experts include three professors, one SMPS engineer, two Ph.D. researchers, and three graduate students. Based on the feature of FCM, we elicited the SMEs' knowledge by showing the initial FCM to SMEs and asking them the following questions [16]: 1) How many designs have you done or how many papers have you published regarding this topic? 2) Do these components make sense to put in the FCMs? 3) Are there any other components you want to add

TABLE 2. The mixed-methods of adjacency matrix calculation.

Category of Components / Category of Components	SMPS performance metrics	SMPS design related skills	Passive components design-related knowledge	SMPS components design quality	IC design related knowledge
SMPS performance metrics	Pearson correlation coefficient from correlation analysis	Factor loadings from factor analysis	SMEs	SMEs	SMEs
SMPS design related skills	Factor loadings from factor analysis	Cumulative of Variance from Factor analysis	SMEs	SMEs	SMEs
Passive components design-related knowledge	SMEs	SMEs	SMEs	SMEs	SMEs
SMPS components design quality	SMEs	SMEs	SMEs	SMEs	SMEs
IC design-related knowledge	SMEs	SMEs	SMEs	SMEs	SMEs

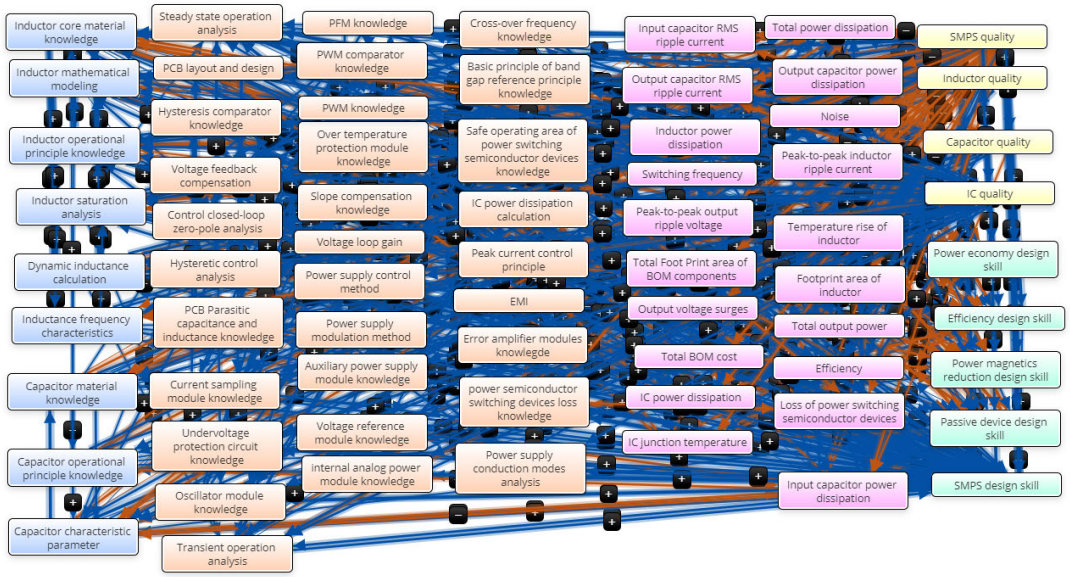

FIGURE 7. An FCM-based SMPS design assistant system.

to the FCMs? 4) What causal weights do you give between the components in the FCMs?

We obtained nine individual maps from SMEs by interpreting their responses to causal weights between all the components. The causal weights between knowledge components are in the interval [0, 1]. We classified the causal weight of one concept or factor to have (a) a huge effect (0.75-1.0), (b) a big effect (0.5-0.75), (c) a moderate effect (0.25-0.5), and (d) a small effect (0-0.25) on the effect concept or factor. We summarized all the components from SMEs' individual FCMs. Then, regarding their expertise on DC-DC power supply design, we determined the weights of these experts in the process of integrating their individual maps, to obtain the weighted adjacency matrix of FCMs. We gave a weight of 0.2 to the data from professors and engineers, and a weight of 0.04 to the data from Ph.D. and graduate students.

Based on the knowledge elicitation and weight calculation process, the FCM-based SMPS design assistant system was constructed using Mental Modeler [29], an online FCM modeling tool, as shown in Fig. 7.[1] This map contains 69 components, and 714 causal connections.

V. CASE STUDY

A. FCM SCENARIO TESTS ANALYSIS

In Fig. 7, the SMPS quality component was the only decision outcome in the proposed FCM. The input vector was set by activating the components from the FCM, including efficiency, inductor power dissipation, temperature rise of inductor, peak-to-peak output ripple voltage, footprint area of inductor, and total BOM cost, within the range of $[-1, 1]$. The components were activated with 1 when the

[1] Mental Modeler is available from: www.mentalmodeler.org

SMPS performance metrics were high and were set to −1 when the SMPS performance metrics were low. We used the hyperbolic tangent function as the threshold function, where the value of λ refers to the degree of fuzzification. Throughout experimental analysis using the FCM Expert tool, with the Kosko's activation rule with self-memory, we used 75 cases and the SMPS constraints mentioned in Section IV for the determination of values [30]. Based on the experimental analysis of these 75 scenarios, it was observed that when the value of λ was 0.12, the prediction of the SMPS quality components was most satisfactory, because in each case the FCM model reached a stable state and settled down. Furthermore, the relationship between the qualified SMPS performance metrics number and the simulation results of the SMPS quality components were all acceptable, as presented in Table 3.

TABLE 3. The output interval of SMPS quality components with the input of the qualified numbers for SMPS performance metrics.

Numbers of qualified SMPS performance metrics	Output interval of SMPS quality
3	[-1,0.7)
4	[0.7, 0.8)
5	[0.8,0.9)
6	[0.9,1]

Fig. 8 shows the test results of those 75 cases, indicating that 8 cases were qualified for all SMPS performance metrics, 45 cases were qualified for five SMPS performance metrics, 20 cases were qualified for four SMPS performance metrics, and 2 cases were qualified for three SMPS performance metrics.

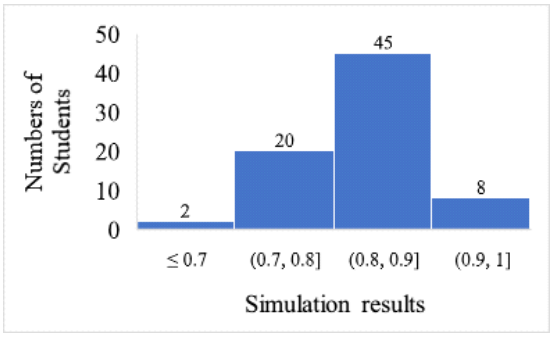

FIGURE 8. Bar plot of the test results of the 75 students.

The input vectors of components in the FCM for designer A and B are shown in Table 4. Figs. 9 and 10 present the scenario test results of the SMPS performance metrics and knowledge type components. The test results show the change of each components in the FCM. For the SMPS performance metrics components, the positive changes revealed that the performance metrics increased, while the negative changes indicated that the performance metrics decreased. We need to look into SMPS performance metrics that were changed to an unacceptable direction, such as the increased dissipation,

TABLE 4. Input vector of components in the FCM for designer A and B.

Concepts	Designer A	Designer B
Efficiency	1	1
Inductor power dissipation	-1	1
Temperature rise of inductor	-1	1
Peak-to-peak output ripple voltage	-1	-1
Footprint area of inductor	-1	-1
Total BOM cost	-1	1
Others	Inactivate	Inactivate

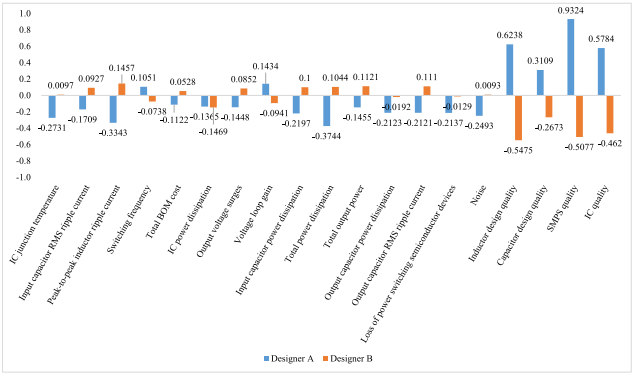

FIGURE 9. Scenario test results of SMPS performance metrics of designer A and B.

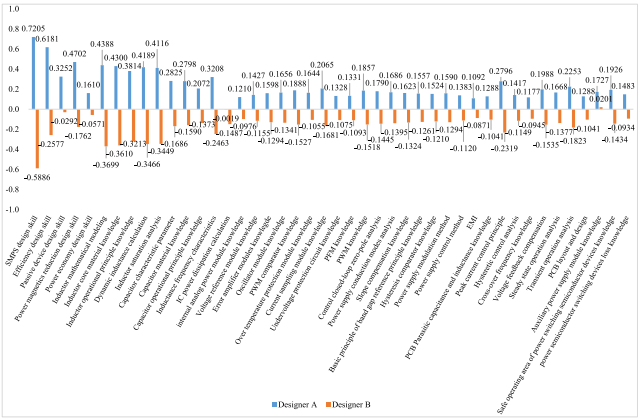

FIGURE 10. Scenario test results of knowledge type components of designer A and B.

decreased efficiency, increased ripple, increased temperature rise, etc. For the knowledge type components, the positive change indicated that the designer possessed this knowledge, while the negative changes revealed that the designer did not possess this knowledge or skill. The difference in test results indicated how much the designer's knowledge had changed.

Fig. 9 shows that designer A designed an acceptable SMPS with the positive change of the SMPS quality component (0.9324), in which all the SMPS performance metrics were qualified. In contrast, designer B designed an unacceptable SMPS with negative change of the SMPS quality (−0.5077). The performance metrics of efficiency, peak-to-peak output ripple voltage, and footprint area of inductor were qualified, but inductor power dissipation, temperature rise of

TABLE 5. Input vector of components of FCM model in eight scenarios.

Scenario	A	B	C	D	E	F	G	H
SMPS design skills	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate
Inductor design-related knowledge	1	-1	0	0	0	0	1	-1
Capacitor design-related knowledge	0	0	1	-1	0	0	1	-1
IC design-related knowledge	0	0	0	0	1	-1	1	-1
Inductor quality	inactivate	inactivate	0	0	0	0	inactivate	inactivate
Capacitor quality	0	0	inactivate	inactivate	0	0	inactivate	inactivate
IC quality	0	0	0	0	inactivate	inactivate	inactivate	inactivate
SMPS performance metrics	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate	inactivate

inductor, and total BOM cost were failed. From Fig. 10, we can conclude that designer B has to improve the knowledge of inductor mathematical modeling (−0.3699), inductor core material (−0.361), dynamic inductance calculation (−0.3466), inductor saturation analysis (−0.3449), inductor operational principle (−0.3213), efficiency design skill (−0.2577), inductance frequency characteristics (−0.2463), peak current control principle (−0.2319), transient operation analysis (−0.1823), power magnetics reduction design skill (−0.1762), capacitor characteristic parameter (−0.1686), current sampling module (−0.1681), capacitor material (−0.159), voltage feedback compensation (−0.1535), PWM comparator (−0.1527), PWM (−0.1518), IC power dissipation calculation (−0.1487), control closed-loop zero-pole analysis (−0.1445), safe operating area of power switching semiconductor devices (−0.1434), power supply conduction modes analysis (−0.1395), steady state operation analysis (−0.1377), capacitor operational principle (−0.1373), oscillator module (−0.1341), slope compensation (−0.1324), error amplifier modules (−0.1294), power supply modulation method (−0.1294), basic principle of band gap reference principle (−0.1261), hysteresis comparator (−0.121), voltage reference module (−0.1155), hysteretic control analysis (−0.1149), power supply control method (−0.112), PFM (−0.1093), undervoltage protection circuit (−0.1075), over temperature protection module (−0.1055), PCB parasitic capacitance and inductance (−0.1041), PCB layout and design (−0.1041), internal analog power module (−0.0976), cross−over frequency (−0.0945), power semiconductor switching devices loss (−0.0934), EMI (−0.0871), power economy design skill (−0.0571), and passive device design skill (−0.0292). Designer B needs to conduct power supply debugging with the consideration of peak-to-peak inductor ripple current (0.1457), output capacitor RMS ripple current (0.111), total power dissipation (0.1044), input capacitor power dissipation (0.1), input capacitor RMS ripple current (0.0927), output voltage surges (0.0852), IC junction temperature (0.0097), and noise (0.0093).

B. EVALUATION OF THE PROPOSED FCM-BASED SYSTEM

To evaluate the proposed FCM model, we designed eight scenarios to evaluate the proposed FCM model. We separate the whole FCM into three sub-design parts to do the model evaluation, including inductor design, capacitor design, and IC design.

Scenario A hypothesizes the designer only possesses inductor design-related knowledge and can design an acceptable inductor. This scenario was run by activating all inductor design-related knowledge components as 1, capacitor design-related knowledge, and IC design-related knowledge as 0. The other components were inactivate. The preferred state of the SMPS quality and inductor quality tends to increase, and other components tend to change to an acceptable direction. In contrast, scenario B was run by activating all inductor design-related knowledge components as −1. The capacitor design-related knowledge and IC design-related knowledge are set as 0. The other components were inactivate. The preferred state of the SMPS quality and inductor quality tends to decrease, and other components tend to change to an unacceptable direction. For the other six scenarios, the input vectors were set in a similar way. The input vectors of the components in these scenarios are presented in Table 5.

The test results of these scenarios are shown in Figs. 11 ∼ 14. In Fig. 11, scenario A revealed that the inductor related performance metrics changed towards an acceptable direction, including decreased temperature rise of inductor (−0.4432), decreased inductor power dissipation (−0.618), and decreased footprint area of inductor (−0.4134). The results of the inductor quality (0.6938) and SMPS quality (0.8184) increased, which indicated that this designer tended

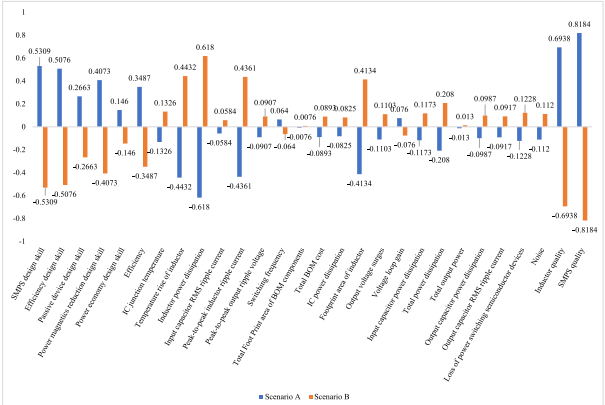

FIGURE 11. Test results of scenario A and B.

to design an acceptable inductor and SMPS with full knowledge of inductor design. In contrast, scenario B revealed that the inductor related performance metrics were changed towards an unacceptable direction, including increased temperature rise of inductor (0.4432), increased inductor power dissipation (0.618), and increased footprint area of inductor (0.4134). The results of the inductor quality (−0.6938) and SMPS quality (−0.8184) are decreased, which indicated that this designer tends to design an unacceptable SMPS without full knowledge of inductor design.

In Fig. 12, scenario C revealed that the capacitor design-related performance metrics changed towards an acceptable direction, including decreased input capacitor RMS ripple current (−0.3119), decreased input capacitor power dissipation (−0.341), decreased output capacitor power dissipation (−0.2101), and decreased output capacitor RMS ripple current (−0.4099). The results of the capacitor quality (0.5419) and SMPS quality (0.7018) increased, which indicated that this designer tended to design an acceptable SMPS with full knowledge of the capacitor design. In contrast, scenario D revealed that the capacitor related performance metrics changed towards an unacceptable direction, including increased input capacitor RMS ripple current (0.3119), increased input capacitor power dissipation (0.341), increased output capacitor power dissipation (0.2101), and increased output capacitor RMS ripple current (0.4099). The results of the capacitor quality (−0.5419) and SMPS quality (−0.7018) decreased, which indicated that this designer tended to design an unacceptable SMPS without full knowledge of capacitor design.

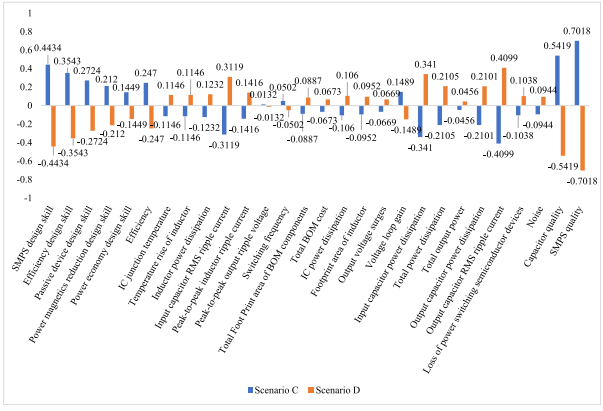

FIGURE 12. Test results of scenario C and D.

In Fig. 13, scenario E revealed that the IC design-related performance metrics changed towards an acceptable direction, including decreased IC junction temperature (−0.3786), and decreased IC power dissipation (−0.1086). The results of increased IC quality (0.9933) and SMPS quality (0.433) increased, which indicated that this designer tended to design an acceptable SMPS with full knowledge of IC design. In contrast, scenario F revealed that the IC design-related performance metrics changed towards an unacceptable direction, including increased IC junction temperature (0.3786), and increased IC power dissipation (0.1086). The results of the IC quality (−0.9933) and SMPS quality (−0.433) decreased, which indicated that this designer tended to design an unacceptable SMPS without full knowledge of IC design.

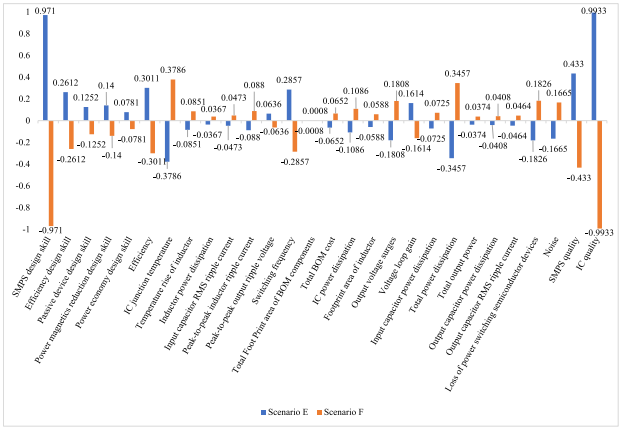

FIGURE 13. Test results of scenario E and F.

In Fig. 14, from scenario G, we can see increased efficiency (0.6635), decreased inductor power dissipation (−0.6269), decreased temperature rise of inductor (−0.4807), decreased peak-to-peak output ripple voltage (−0.4645), and footprint area of inductor (−0.4307). The results of the SMPS quality increased to 0.976, which indicated that this designer had designed an acceptable SMPS. From scenario H, we can see decreased efficiency (−0.6635), increased inductor power dissipation (0.6269), increased temperature rise of inductor (0.4807), increased peak-to-peak output ripple voltage (0.4645), and increased footprint area of inductor (0.4307). The results of the SMPS quality decreased to −0.976, which revealed that this designer had designed an unacceptable SMPS. Clearly, these eight scenario results from our FCM model were consistent with what we hypothesized. Thus, we can conclude that the proposed FCM model is reliable and effective.

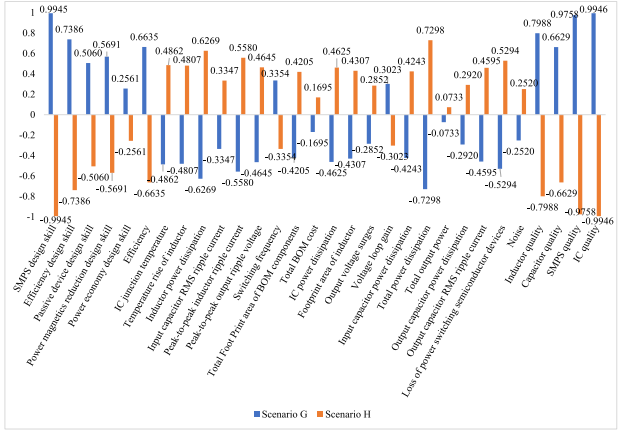

FIGURE 14. Test results of scenario G and H.

VI. CONCLUSION

The paper has presented an SMPS design assistant system based on the FCM model, statistical methods, and interviews with SMEs. This system can reduce human errors and provide optimal technical suggestions. Through two scenario tests, the scenario results show useful guidelines in terms of knowledge or skills improvements for SMPS designers. The results can also provide power supply debugging suggestions on the optimal design process. We showed the reliability and effectiveness of the system by eight scenarios. This system can be applied to the power electronics field to train engineers and help them design acceptable SMPSs. The system can also be implemented in engineering education to help students to become qualified engineers.

One potential limitation of the current study is that same data was used twice for constructing the FCM model and the scenario analysis. This research could be extended by evaluating the proposed FCM model with new SMPS design data. Furthermore, we could refine the concepts and causal relations of the FCM model dynamically with updated experts' knowledge in various design scenarios. To provide more refined and accurate strategies to assist designers, future work can focus on incorporating more fine-grained knowledge concepts to the FCM and disseminating results to students to improve future design performance.

REFERENCES

[1] K. H. Billings and T. Morey, *Switchmode power supply handbook*. McGraw-Hill, New York, NY, USA, 2011.

[2] C. Nan and G. Sansavini, "Developing an agent-based hierarchical modeling approach to assess human performance of infrastructure systems," *Int. J. Ind. Ergonom.*, vol. 53, pp. 340–354, May 2016.

[3] M. Bertolini, "Assessment of human reliability factors: A fuzzy cognitive maps approach," *Int. J. Ind. Ergonom.*, vol. 37, no. 5, pp. 405–413, May 2007.

[4] Y. Bao, C. Guo, J. Zhang, J. Wu, S. Pang, and Z. Zhang, "Impact analysis of human factors on power system operation reliability," *J. Modern Power Syst. Clean Energy*, vol. 6, no. 1, pp. 27–39, Jan. 2018.

[5] D. S. Kim, D. H. Baek, and W. C. Yoon, "Development and evaluation of a computer-aided system for analyzing human error in railway operations," *Rel. Eng. Syst. Saf.*, vol. 95, no. 2, pp. 87–98, Feb. 2010.

[6] M. T. Baysari, A. S. McIntosh, and J. R. Wilson, "Understanding the human factors contribution to railway accidents and incidents in australia," *Accident Anal. Prevention*, vol. 40, no. 5, pp. 1750–1757, Sep. 2008.

[7] N. Femia, *Power Management Lab Kit Buck Experiment Book*. Dallas, TX, USA: Texas Instruments, 2016.

[8] W.-P. Cheah, K.-Y. Kim, H.-J. Yang, S.-H. Kim, and J.-S. Kim, "Fuzzy cognitive map and Bayesian belief network for causal knowledge engineering: A comparative study," *KIPS Trans., B*, vol. 15B, no. 2, pp. 147–158, Apr. 2008.

[9] R. J. Mislevy and D. H. Gitomer, "The role of probability-based inference in an intelligent tutoring system," *User Model. User-Adapted Interact.*, vol. 5, nos. 3–4, pp. 253–282, 1996.

[10] R. Levy and R. Mislevy, "Specifying and refining a measurement model for a computer-based interactive assessment," *Int. J. Test.*, vol. 4, no. 4, pp. 333–369, Dec. 2004.

[11] U. Özesmi and S. L. Özesmi, "Ecological models based on people's knowledge: A multi-step fuzzy cognitive mapping approach," *Ecol. Model.*, vol. 176, nos. 1–2, pp. 43–64, Aug. 2004.

[12] Y. Y. Wee, W. P. Cheah, S. C. Tan, and K. Wee, "An evaluation of the role of fuzzy cognitive maps and Bayesian belief networks in the development of causal knowledge systems," *J. Intell. Fuzzy Syst.*, vol. 37, no. 2, pp. 1905–1920, Sep. 2019.

[13] A. J. Jetter and K. Kok, "Fuzzy cognitive maps for futures studies—A methodological assessment of concepts and methods," *Futures*, vol. 61, pp. 45–57, Sep. 2014.

[14] T. L. Kottas, A. D. Karlis, and Y. S. Boutalis, "A novel control algorithm for DC motors supplied by PVs using fuzzy cognitive networks," *IEEE Access*, vol. 6, pp. 24866–24876, 2018.

[15] A. Amirkhani, H. Nasiriyan-Rad, and E. I. Papageorgiou, "A novel fuzzy inference approach: Neuro-fuzzy cognitive map," *Int. J. Fuzzy Syst.*, vol. 22, no. 3, pp. 859–872, Apr. 2020.

[16] P. Zhang and A. Jetter, "A framework for building integrative scenarios of autonomous vehicle technology application and impacts, using fuzzy cognitive maps (FCM)," in *Proc. Portland Int. Conf. Manage. Eng. Technol. (PICMET)*, Aug. 2018, pp. 1–14.

[17] E. I. Papageorgiou and J. L. Salmeron, "A review of fuzzy cognitive maps research during the last decade," *IEEE Trans. Fuzzy Syst.*, vol. 21, no. 1, pp. 66–79, Feb. 2013.

[18] S. Hossain and L. Brooks, "Fuzzy cognitive map modelling educational software adoption," *Comput. Edu.*, vol. 51, no. 4, pp. 1569–1588, Dec. 2008.

[19] G. Napoles, M. Leon, I. Grau, and K. Vanhoof, "Fuzzy cognitive maps tool for scenario analysis and pattern classification," in *Proc. IEEE 29th Int. Conf. Tools with Artif. Intell. (ICTAI)*, Nov. 2017, pp. 644–651.

[20] A. Garzon Casado, P. Cano Marchal, J. Gomez Ortega, and J. Gamez Garcia, "Visualization and interpretation tool for expert systems based on fuzzy cognitive maps," *IEEE Access*, vol. 7, pp. 6140–6150, 2019.

[21] E. I. Papageorgiou, *Fuzzy Cognitive Maps for Applied Sciences and Engineering: From Fundamentals to Extensions and Learning Algorithms*, vol. 54. Berlin, Germany: Springer, 2013.

[22] Z. Peng and L. Wu, "A new perspective on formation of haze-fog: The fuzzy cognitive map and its approaches to data mining," *Sustainability*, vol. 9, no. 3, p. 352, Feb. 2017.

[23] B. Sung Yoon and A. J. Jetter, "Comparative analysis for fuzzy cognitive mapping," in *Proc. Portland Int. Conf. Manage. Eng. Technol. (PICMET)*, Sep. 2016, pp. 1897–1908.

[24] G. Nápoles, M. L. Espinosa, I. Grau, K. Vanhoof, and R. Bello, "Fuzzy cognitive maps based models for pattern classification: Advances and challenges," in *Soft Computing Based Optimization and Decision Models*. Cham, Switzerland: Springer, 2018, pp. 83–98.

[25] A. N. Fish, *Knowledge Automation: How to Implement Decision Management in Business Processes*, vol. 595. Hoboken, NJ, USA: Wiley, 2012.

[26] G. Di Capua, N. Femia, and K. Stoyka, "Power magnetics volume and weight reduction in aerospace power supply units," in *Proc. IEEE 17th Workshop Control Modeling Power Electron. (COMPEL)*, Jun. 2016, pp. 1–6.

[27] Y.-S. Su, A. Gelman, J. Hill, and M. Yajima, "Multiple imputation with diagnostics (mi) inR: Opening windows into the black box," *J. Stat. Softw.*, vol. 45, no. 2, pp. 1–31, 2011.

[28] H. Xu and Y. Deng, "Dependent evidence combination based on shearman coefficient and pearson coefficient," *IEEE Access*, vol. 6, pp. 11634–11640, 2018.

[29] S. A. Gray, S. Gray, L. J. Cox, and S. Henly-Shepard, "Mental modeler: A fuzzy-logic cognitive mapping modeling tool for adaptive environmental management," in *Proc. 46th Hawaii Int. Conf. Syst. Sci.*, Jan. 2013, pp. 965–973.

[30] G. Nápoles, M. L. Espinosa, I. Grau, and K. Vanhoof, "FCM expert: Software tool for scenario analysis and pattern classification based on fuzzy cognitive maps," *Int. J. Artif. Intell. Tools*, vol. 27, no. 7, Nov. 2018, Art. no. 1860010.

YI KUANG received the B.S. degree in electrical engineering and automation from the Hunan Institute of Engineering, Xiangtan, China, in 2015. She is currently pursuing the Ph.D. degree with the School of Materials Science and Engineering, Xiangtan University. Her research interests include power electronics, engineering education, educational data mining, and the applications of fuzzy cognitive maps (FCM) to engineering educational assessment.

ZHIYONG JOHNNY ZHANG (Member, IEEE) received the Ph.D. degree in quantitative psychology from the University of Virginia, Charlottesville, VA, USA, in 2008. He is a Professor with the Department of Psychology, University of Notre Dame. His current research interests include structural equation modeling, big data analysis, Bayesian methods, network analysis, and statistical computing and programming.

BIN DUAN (Member, IEEE) received the Ph.D. degree in computational mathematics from Xiangtan University, Xiangtan, China, in 2004. He is a Professor with the School of Automation and Electronic Information, Xiangtan University. His current research interests include engineering education, educational data mining, learning outcomes assessment, and learning analytics.

PEI ZHANG received the B.Eng. degree in telecommunication engineering from Information Engineering University, Zhengzhou, China, in 2009, and the master's degree in technology management and business administration in finance from the University of Bridgeport, USA, in 2011 and 2013, respectively. He is currently pursuing the Ph.D. degree with the Department of Engineering and Technology Management, Portland State University. His research interests include fuzzy cognitive maps (FCM) on integrating and completing various stakeholders' cognitions and reducing the impacts of ''tunnel visions'' of the decision-making process regarding cutting-edge technologies.