A systemic analysis of green computing adoption using genetically evolved fuzzy cognitive map: a Philippine scenario

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Abstract

Purpose – This paper aims to propose a new genetically evolved fuzzy cognitive mapping approach as a decision-making framework for analyzing the relationships between the drivers and strategies for green computing adoption.

Design/methodology/approach – A focus group discussion among stakeholders in the Philippines is used to establish the relationships between the drivers and strategies of green computing adoption.

Findings – The proposed approach significantly reduces the time complexity for developing the fuzzy cognitive maps and provides a basis for comprehensively clustering drivers and strategies that share similar characteristics.

Research limitations/implications – This paper's results provide insights into how the drivers and strategies of green computing adoption facilitate the intention of adopting stakeholders. Moreover, it provides a framework for analyzing structural relationships that exist between factors in a compliant manner.

Originality/value – To the best of the author's knowledge, the paper is the first to analyze the drivers and strategies of green computing under a complex systems' perspective. Moreover, this is the first study to offer lenses in a Philippine scenario.

Keywords Genetic algorithm, Innovation adoption, Fuzzy cognitive mapping, Green computing, Innovation in a developing country

Paper type Research paper

1. Introduction

In recent years, scholars in the literature have become widely interested in integrating green initiatives in different domains. Such movement is influenced by the growing need to address climate change, pollution and other environmental issues. With this, green initiatives have been integrated in several domains such as transportation (Xia *et al.*, 2017), manufacturing (Leong *et al.*, 2019), supply chain management (Jabbour and Sousa Jabbour, 2016), construction (Cianciarullo, 2019) and consumerism (Chekima *et al.*, 2016). In computing, the integration of green initiatives has brought forth the emergence of green information technology (IT) or green computing (Murugesan, 2008). Green computing is defined as *the study and practice of designing, manufacturing, using, and disposing of computers, servers, and associated subsystems efficiently and effectively with minimal or almost no impact on the environment* (Raza *et al.*, 2012). It has become popular in developed

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countries because of its benefits, including capital improvements, maintenance savings, e-waste reduction and social benefits.

Green computing can be considered an innovation in IT that advocates the use of eco-friendly computing initiatives. While the expectations and benefits of green computing are mounting, not all organizations are willing to adopt its practices (Hu *et al.*, 2016). Green practices are perceived to induce additional costs for firms, privacy issues and frequent changes in technology, to name a few (Khandelwal and Dhir, 2018). It is then crucial to understand the adoption of green computing among stakeholders to facilitate its successful implementation. In a technology management point of view, such an understanding is elicited by looking into factors that influence its adoption. In the literature, these factors are termed as adoption drivers. As such, these adoption drivers are widely pronounced in the innovation literature. For instance, Obiso *et al.* (2019) studied adoption drivers of Industry 4.0 to develop relevant managerial guidelines. Talukder *et al.* (2020) studied the adoption drivers of information and communication technology (ICT) among small and medium enterprises to draw out organizational insights. Moreover, Bossle *et al.* (2016) studied adoption drivers to develop a conceptual model for eco-innovation. In the green computing literature, efforts have been made to understand the adoption drivers and strategies of green computing. For instance, Al-Zamil and Saudagar (2018) studied the drivers and challenges of applying green computing for sustainable agriculture. Hu *et al.* (2016) provided a hierarchical view of the key drivers of green computing by examining firms' practices. Finally, Hernandez and Ona (2014) explored the green computing adoption drivers of business process outsourcing (BPO) firms.

While the current literature has provided some attention to the analysis of green computing drivers, such efforts are still limited. Very few works explored on the analysis of green computing drivers. Moreover, existing works focused only on particular organizational settings. For example, Hernandez and Ona (2014) studied the green computing drivers in the context of BPO firms, whereas Al-Zamil and Saudagar (2018) studied green computing drivers in agriculture. Consequently, the scope of the derived framework becomes limited. Current works have also considered only the interrelationships between the green computing drivers. With this, strategies and policies for green computing adoption are excluded in their analysis. As such, current works only provided a limited view of how such drivers influence green computing adoption. To address such gaps, this study analyzes the interrelationships of green computing adoption drivers in a more general setting. That is, the framework derived in this paper is not restricted to a particular organizational setting. As such, a multi-stakeholder perspective through expert decision-making is provided. Hence, this paper treats the drivers and strategies of green computing adoption more holistically. As a result, a more comprehensive framework for modeling green computing adoption is developed in this paper.

Because these drivers and strategies may exhibit significant interdependence; their relationships are best described using a structural model. Current literature tackles such problems using structural equation modeling (SEM) frameworks such as the technology acceptance model (TAM), the theory of planned behavior and the green IT adoption model (GITAM) model. Although SEM is a consistent approach, this technique only provides a static snapshot of the interrelationships. Thus, they do not provide machinery for dynamically analyzing the system, such as through scenario analysis. Moreover, as a multivariate statistical model, SEM frameworks are usually expensive (i.e. requiring a large number of samples) to carry out. Hence, it may be impractical to use in some decision-making environments. In such cases, relevant literature resorts to using the fuzzy cognitive mapping (FCM) approach. FCM is a structural modeling technique that uses decision-maker judgment for specifying causal relationships. As such, unlike SEM, it is not constrained with the number of samples. However, the traditional FCM becomes computationally expensive as the number of factors increases because it requires comparing each factor. For n factors, FCM would require n^2 comparisons in the worst case. Moreover, with a large number of comparisons, inconsistencies can become an issue in the decision-making process. This paper proposes a genetically evolved fuzzy cognitive map for analyzing the drivers and strategies of green computing adoption to address such issues. The proposed algorithm requires only specifying the value for each factor in contrast to comparing each factor. Using the Big-O notation $O(\cdot)$ in algorithm analysis, a time complexity reduction from $O(n^2)$ to $O(n)$ is achieved in specifying the FCM. In other words, the time complexity is reduced from quadratic to linear time.

The proposed algorithm provides a decision-making model for establishing causal relationships in a tractable manner. That is, the time spent by decision-makers in specifying the causal relationships is greatly reduced. In many practical decision-making environments, a large number of factors are usually involved. As such, the proposed algorithm would be beneficial for stakeholders and decision-makers. The case in this paper provides a comprehensive framework for analyzing the drivers and strategies of green computing in a complex systems perspective, which has not yet been tackled in the current literature. With existing works in the current literature focused on determining how green computing drivers affect green computing adoption, this paper offers a more systemic view of green computing adoption by considering the interaction of strategies and drivers. Moreover, with most of the actual work conducted in developed countries, this paper contributes significantly to the literature by providing lenses to the perspective of developing/emerging economies, which is not well pronounced in the literature. The paper has four primary contributions to the literature. First, the paper is one of the very few works that analyzes the green computing adoption drivers' causal relationships. Thus, it offers fresh insights about green computing adoption to scholars in both domain and relevant fields. Second, the paper pioneers the analysis of drivers and strategies of green computing while considering their interrelationships. With this, the paper provides a more comprehensive framework for understanding green computing adoption. Furthermore, this would enable policymakers and other stakeholders to test how a proposed policy would impact green computing adoption in organizations. Third, the paper provides a novel methodology for causal analysis, which combines structural modeling and evolutionary learning. As such, the paper opens a new avenue that would be interesting for scholars working in structural modeling, evolutionary algorithms, soft computing and innovation studies. Finally, the paper provides an emerging country perspective, which is not well pronounced in the current literature. With most of the works in the current literature conducted in developed economies, the paper offers insights regarding green computing adoption dynamics in a developing country.

The paper is organized as follows. Section 2 presents a literature review on the current trends of green computing research. Section 3 presents the case background and the methodological approaches used in the study. Section 4 presents the computational results of the study and the implications of the proposed algorithm. Section 5 discusses the implications of the results in the context of green computing. Key managerial, policy and scholarly implications are streamlined in this section. Finally, Section 6 discusses the conclusions and potential future works of the study.

2. Literature review

2.1 Integration of green initiatives in computing

With the increasing awareness of environmental sustainability, green initiatives have gained significant interest from scholars in various fields. The adoption of green initiatives has been extensively discussed in the current literature such as in transportation (Xia *et al.*, 2017), manufacturing (Leong *et al.*, 2019), supply chain management (Jabbour and Sousa Jabbour, 2016), construction (Cianciarullo, 2019) and consumerism (Chekima *et al.*, 2016), among others. Likewise, it has also captured attention in the computing literature and is currently coined as green computing (or green IT) (Murugesan, 2008). Enterprises, governments and societies have relied on the use of IT. However, it has been contributing to adverse environmental impacts (Murugesan, 2008).

Driven by the enormously growing consumption of natural resources, increased CO_2 emissions and the rising awareness of environmental issues such as global climate change, the computing society has progressively recognized the importance of sustainable practice in computing (Anthony *et al.*, 2017; Murugesan, 2008; Raza *et al.*, 2012). Academic research and contribution to green computing were first discussed in 2008 (Anthony *et al.*, 2017; Kotze *et al.*, 2014; Loeser, 2013; Murugesan, 2008). Since then, the number of works in the field has exhibited growth in the current literature. Reviews on the field have been comprehensively provided by Anthony *et al.* (2017), Bokolo (2016), Saha (2014), Loeser (2013) and Raza *et al.* (2012).

Green computing can be defined as the study and practice of designing, manufacturing, using and disposing of computers, servers and associated subsystems, efficiently and effectively with minimal or almost no impact to the environment (Raza *et al.*, 2012). Its goal is to reduce the use of hazardous materials, maximize energy efficiency during the product's lifetime and promote the recyclability or biodegradability of defunct products and factory waste (Raza *et al.*, 2012). The adoption of green computing has been associated with a variety of benefits, which are categorized by Raza *et al.* (2012) as tangible benefits, intangible benefits and benefits to an organization. The tangible benefits comprise capital improvements, maintenance savings and e-waste reduction, among others (Raza *et al.*, 2012). Intangible benefits include social benefits, increased user efficiency and emotional risk minimization, to name a few (Raza *et al.*, 2012). Moreover, some benefits to organizations would be the reduction of overall energy consumption, reduced data center footprint and increase in ease of systems and solutions management (Raza *et al.*, 2012). With such benefits, the adoption of green computing has gained increasing support from enterprises, governments and other stakeholders.

2.2 Strategies and drivers of green computing

The benefits of green computing encompass the consumer, business, country and global viewpoints – facilitating the reduction of energy demands, wastes and costs (Raza *et al.*, 2012). With this, current literature explores the factors that influence the adoption of green computing. In relevant literature, the exploration of these factors known as drivers (also called enablers) helps in streamlining the adoption of technology, innovation or policies (Paladino, 2007; Muller and Kolk, 2010; Lima *et al.*, 2018; Jacksohn *et al.*, 2019; Obiso *et al.*, 2019; Talukder *et al.*, 2020). Similar studies have been performed by Harmon and Auseklis (2009), Schmidt *et al.* (2010), Brooks *et al.* (2010), Raza *et al.* (2012), Saha (2014), Campbell *et al.* (2014), Ainin *et al.* (2016), Thomas *et al.* (2016), Radu (2016) and (Al-Zamil and Saudagar, 2018). Such works granularized the adoption drivers of green computing in the current literature.

Despite efforts to explore the drivers and strategies for the adoption of green computing, works in the current literature are relatively fewer compared to other areas (such as green supply chain management, green consumerism and green building, among others). With green computing becoming a strategic consideration in the development of sustainable practices, there is a need to have a clear understanding of its adoption. Such an understanding would enable stakeholders to draw insights on the successful adoption of green computing (Al-Rejal *et al.*, 2019). Molla (2008) proposed the GITAM, which argues that a combination of static green IT contextual variables, dynamic green IT readiness dimensions and strong order green IT drivers can predict green IT adoption intention and explain a significant portion of the variance in the practice of green IT. The proposed model, however, did not include the strategies for the adoption of green computing despite being an explored area in the literature as well as can be seen in Murugesan (2008), Harmon and Auseklis (2009) and Loeser (2013). It is argued that studying these strategies helps in understanding how to increase the adoption rate of green computing. Moreover, Harmon *et al.* (2012) provided a roadmap for the implementation of green and sustainable IT by exploring their strategic dimensions and drivers.

Existing gaps, however, remain visible in the literature despite efforts by scholars. To address the existing gaps in the current literature of green computing, such as the lack of a well-understood framework of its adoption, scholars have made progress in proposing several methodological approaches. For instance, Loeser (2013) studied the definition of constructs as well as provide a comprehensive overview of the practices in green computing. Al-Rejal *et al.* (2019) developed a conceptual framework using the antecedents of green computing adoption. Harmon and Auseklis (2009) conducted an assessment of the impact of green computing practices. Likewise, Bokolo *et al.* (2020) conducted a generic study on green IT/IS practice development in a collaborative enterprise in a developing country. Moreover, Chow and Chen (2009) analyzed the disparity between the intended belief and actual behavior of green computing users.

2.3 Methodological approaches in analyzing strategies and adoption drivers

In relevant fields, the analysis of driver and strategies are extensively studied topics. Many studies come from innovation, sustainability and social domains. For instance, Bossle *et al.* (2016) studied the adoption drivers of eco-innovation using a systematic literature review. Micheli *et al.* (2020) conducted a comprehensive study on the drivers, practices and performance of green supply chain management using a moderation analysis. Zhang *et al.* (2019) analyzed the drivers, motivations and barriers to the implementation of corporate social responsibility practices of construction enterprises using content analysis. Obiso *et al.* (2019) explored the intrinsic and extrinsic drivers of Industry 4.0 through a literature review to aid in management decision-making.

Several scholars have found structural modeling techniques such as the Decision-making Trial and Evaluation Laboratory (DEMATEL), interpretative structural modeling (ISM) and FCM. For instance, Li and Mathiyazhagan (2018) adopted the DEMATEL approach in identifying influential indicators toward sustainable supply chain adoption in the auto components manufacturing sector. The DEMATEL approach enables the determination of influential factors by classifying a set of factors or indicators into cause (dispatcher) and effect (receiver) groups. On a different point of view, Kaswan and Rathi (2019) analyzed and modeled the enablers of green lean six sigma implementation using the ISM approach. The ISM approach allows the hierarchical modeling of a set of factors by drawing out underlying structural relationships between the factors. Moreover, Hawer *et al.* (2016) used the FCM approach to analyze the interdepencies between factory change enablers. The FCM approach enables the elicitation of causal relationships between factors while taking into account the ambiguity of the decision-makers.

The FCM is a promising tool, as unlike the other structural modeling approaches which only statically depict the relationships between drivers, it provides a mechanism for performing dynamic (time-based) scenario analysis of the system (Osoba and Kosko, 2017).

Despite its usefulness in modeling complex structural relationships, it is not as extensively used as the DEMATEL and ISM in modeling relationships between factors. Hence, the disparity between the amount of work being put into FCM and the other structural models constitutes a gap in the literature. The lack of significant efforts on the role of FCMs in modeling structural relationships between factors implies a lack of a comprehensive understanding on its modeling capability. However, in modeling structural relationships for domains such as green computing (which is a relatively newer field in environmental sustainability), there is a need to take into account ambiguity of decision-makers (because of the lack of strong expertise) as well as being able to see how the interrelationships evolve over time. As such, the use of FCM in modeling green computing is a gap that must be filled in the current literature.

2.4 Fuzzy cognitive mapping

In many decision-making problems, analyzing structural relationships between known factors is one of the first steps in obtaining valuable insights (Gandía-Aguiló *et al.*, 2017; Jerusalem, 2019). Knowing existing interrelationships provides a useful framework in model development (Jerusalem, 2019; Kadoić *et al.*, 2019; Uzoka *et al.*, 2018). FCM is a structural modeling technique for establishing causal relationships between factors (concepts) using only expert judgment (Kosko, 1986; Tzeng and Huang, 2011). Moreover, it is extensively used to develop scenario analysis and complex systems simulation (Nápoles *et al.*, 2018; Mourhir *et al.*, 2020; Osoba and Kosko, 2017; Mohammadian and Yamin, 2017; Mehryar *et al.*, 2019). With the growing relevance of FCMs in many domains, several drawbacks become visible regarding its usability. FCMs are:

- highly dependent on expert opinion, which may be biased; and
- may uncontrollably converge to undesired states (Papageorgiou *et al.*, 2003).

Because of limitations of the original FCM, extensions and scholars in the current literature have made improvements (Felix *et al.*, 2019). Papageorgiou (2011) and Felix *et al.* (2019) provide a comprehensive review of such modifications. The review emphasized that the major improvement made on FCM is the addition of the so-called *learning algorithms*. These algorithms enable the fine-tuning of the FCM matrix to derive a more desirable matrix. Hence, the purpose of learning FCMs is the estimation of FCM weight matrices that meet predefined criteria (Felix *et al.*, 2019; Papageorgiou, 2011). Works on learning FCMs can be classified into three different paradigms:

(1) Hebbian-based approaches;
(2) error-driven approaches; and
(3) hybrid learning approaches (Felix *et al.*, 2019; Papageorgiou, 2011).

The preference of a particular paradigm depends on the nature of the decision-making problem. The differences between the three paradigms will be discussed in the following subsections.

2.4.1 Hebbian-based approaches. Hebbian-based approaches are unsupervised procedures that use available data and a learning formula (based on several modifications of the Hebbian law) to adjust the weight matrix iteratively (Felix *et al.*, 2019; Papageorgiou, 2011). The goal of this approach is to yield weight matrices based on expert knowledge and improve the accuracy of the expert-defined weights (Felix *et al.*, 2019; Papageorgiou, 2011; Sivabalaselvamani *et al.*, 2018). Because of the ability of this approach to improve expert-defined weight matrices, several works in the current literature have used it for problemsolving in a variety of domains. For instance, Sivabalaselvamani *et al.* (2018) used an adaptive nonlinear Hebbian learning algorithm in training FCM for accident identification. Anninou and Groumpos (2014) modeled Parkinson's disease using FCMs with nonlinear Hebbian learning. Moreover, Zhai *et al.* (2009) applied an FCM trained with active Hebbian learning for performing credit risk evaluation of listed companies. Despite the usefulness of Hebbian-based FCMs, scholars emphasize that such approaches still suffer from their dependence on expert knowledge in defining the initial weight matrix (Chen *et al.*, 2012; Felix *et al.*, 2019; Papageorgiou, 2011). Thus, when modeling systems for which expert knowledge is difficult to obtain but data are available, Hebbian-based approaches would not be useful. As such, data-driven approaches (i.e. use historical data) would be useful in such circumstances.

2.4.2 Error-driven approaches. Error-driven approaches aim at generating weight matrices that minimize an error function based on the difference between the expected responses and the map-inferred outputs (Felix *et al.*, 2019). Consequently, the approach entails expensive optimization problems in which globally optimal solutions are not obtainable in polynomial time as the weight matrix scales up (Felix *et al.*, 2019; Papageorgiou, 2011). As such, population-based algorithms have been adopted to implement error-driven approaches (Felix *et al.*, 2019; Papageorgiou, 2011). For example, Salmeron *et al.* (2019) used a modified asexual reproduction optimization algorithm, Chen *et al.* (2012) used the ant colony optimization algorithm, Papageorgiou and Froelich (2011) used an evolutionary approach and Kannappan and Papageorgiou (2013) used artificial immune systems. While error-driven approaches do not require expert intervention in making the weight matrix, these approaches require a sequence of state vectors that serve as historical data, which the algorithm learns to derive a weight matrix (Felix *et al.*, 2019; Papageorgiou, 2011).

2.4.3 Hybrid learning approaches. Selecting which of the two approaches is better is one of the existing gaps in the current literature. On the one hand, despite the requirement by Hebbian-based approaches for expert knowledge, they preserve the causality between factors because the adjustments made by the algorithm do not deviate mainly from the established relationships. On the other hand, although error-driven approaches do not require expert knowledge in specifying the weight matrix, they would still require a sequence of state vectors to derive the weight matrix. To address such drawbacks, scholars in the current literature explored the hybridization of the two learning approaches. For instance, Natarajan *et al.* (2016) used an FCM trained with a hybrid nonlinear Hebbian learning algorithm and a genetic algorithm (GA) for sugarcane yield classification. Kokkinos *et al.* (2018) used a hybrid nonlinear Hebbian learning and differential evolution algorithm in developing FCMs for modeling social acceptance in establishing waste biorefinery facilities. Moreover, Zou and Liu (2017) proposed mutual information-based two-phase memetic algorithm for learning large-scale FCMs. Although hybrid approaches are successful in learning FCMs, their learning process is more complicated because it involves a two-stage process (i.e. performing the Hebbian approach and error-driven approach) (Felix *et al.*, 2019; Papageorgiou, 2011). Hence, hybrid approaches are more computationally expensive than other approaches.

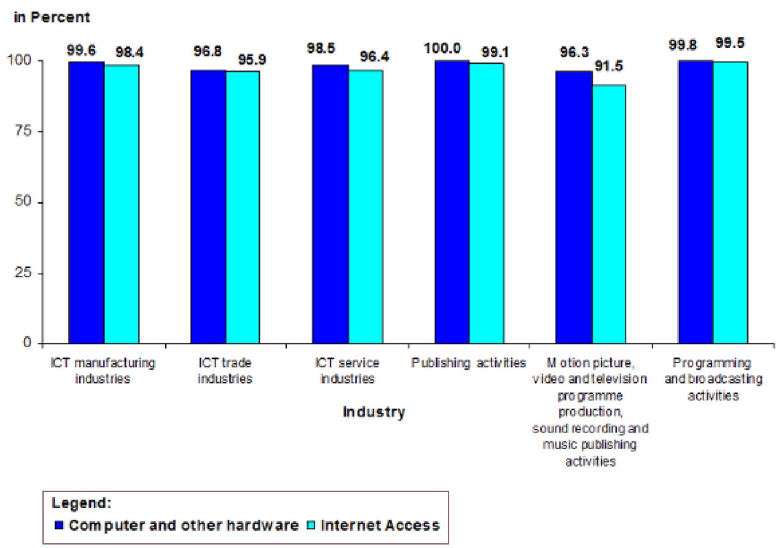
3. Methodology

3.1 Case background

Green computing is one of the most recent initiatives supporting sustainable development. Its implementation lies in the successful adoption of the sectors dependent on ICT. In the Philippines, this sector is termed as information economy (IE). With the large portion of this sector in the Philippine economy, computing resources are expected to be used during an operation. Figure 1 presents the percentage of establishments in IE with computer and other hardware, and with internet access during the year 2015. PSA (2019) found that there are a total of 3,786 establishments using ICT in the Philippines. Moreover, they have also found that:

- about 98.5% of the establishments own and use computers;
- about half of the employees use computers routinely at work;
- almost 30% of establishments maintain websites;
- about 61.6% have wired local area network;
- nearly 14% use the internet for business;
- around 17% do business through mobile phone; and
- about 83.8% use internet in obtaining information from government organizations.

Findings by PSA (2019) suggest that computing resources play a significant role in the Philippine industry. Although such results indicate progress in the economy, adverse environmental concerns may also be implied. In this case, green computing would be a relevant topic for discussion among stakeholders in the Philippines. This paper explores the adoption of green computing in the Philippine setting. As such, the study primarily develops a framework for mapping the relationship between green computing strategies and their adoption drivers. First, a literature review is performed to extract strategies and adoption drivers for green computing studied in the current literature. The search keywords used to find relevant sources are *green computing strategies*, *green computing initiatives*, *green IT*



Source: This figure is taken from a public database by the Philippines Statistics Office. https://psa.gov.ph/content/2015-survey-information-and-communication-technology-information-economy-core-ict-industries

Figure 1.
Percentage of establishments in IE with computer and other hardware and with internet access by Industry: Philippines, 2015

strategies, *green IT initiatives*, *green computing drivers*, *green computing enablers*, *green computing antecedents*, *green computing adoption drivers*, *green IT enablers*, *green IT antecedents* and *green IT adoption drivers*. A total of 135 concepts (99 drivers and 36 strategies) were extracted from the literature search. To screen out redundant and irrelevant drivers and strategies and add potential drivers not tackled in the literature search, content analysis and a Delphi approach were performed composed of seven expert decision-makers with qualifications presented in Table 2. After three rounds of the Delphi process, the group finds the list sufficiently comprehensive. As a result, a total of 15 strategies and 11 drivers were established in the final list, as presented in Table 1.

3.2 Fuzzy cognitive mapping

FCMs are fuzzy-graph structures for representing causal reasoning (Kosko, 1986). It is an extension of the causal cognitive maps and developed by Kosko (1986) to improve decision-makers' ability to understand the dynamic behavior of causal cognitive maps. Scholars in the current literature (Kosko, 1986; Özesmi and Özesmi, 2004; Schneider *et al.*, 1998) collectively maintain that the main advantages of cognitive maps include:

- the ability to allow feedback processes;
- the ability to deal with many variables;
- ability to model relationships between variables that are known with certainty, but can be described in degrees such as *a little* or *a lot*; and

Code	Name	Type	Source
S1	Data center infrastructure	Strategy	Harmon and Auseklis (2009)
S2	Power and workload management	Strategy	Harmon and Auseklis (2009)
S3	Thermal load management	Strategy	Harmon and Auseklis (2009)
S4	Product design	Strategy	Harmon and Auseklis (2009)
S5	Virtualization	Strategy	Harmon and Auseklis (2009)
S6	Cloud computing and cloud services	Strategy	Harmon and Auseklis (2009)
S7	IT governance	Strategy	Loeser (2013)
S8	Process optimization	Strategy	Loeser (2013)
S9	Information and transparency	Strategy	Loeser (2013)
S10	Innovative end products and infrastructure solutions	Strategy	Loeser (2013)
S11	Reducing energy consumption by PCs	Strategy	Saha (2014)
S12	Enabling power management features	Strategy	Saha (2014)
S13	Energy awareness program	Strategy	Hanief, Kartika, Srinadi, and Negara (2018)
S14	Energy conservation	Strategy	Saha (2014)
S15	Eco-friendly design	Strategy	Saha (2014)
D1	The rapid growth of the internet and ICT usages	Driver	Raza *et al.* (2012)
D2	Increasing cooling requirements for equipment	Driver	Raza *et al.* (2012)
D3	Increasing equipment power density	Driver	Raza *et al.* (2012)
D4	Increasing energy costs	Driver	Raza *et al.* (2012)
D5	Restrictions on energy supply access	Driver	Raza *et al.* (2012)
D6	Low utilization rates	Driver	Raza *et al.* (2012)
D7	Growing awareness of IT's impact on the environment	Driver	Raza *et al.* (2012)
D8	Organizational learning capabilities	Driver	Al-Rejal *et al.* (2019)
D9	Innovation capabilities	Driver	Al-Rejal *et al.* (2019)
D10	Institutional pressure	Driver	Hernandez and Ona (2014)
D11	Policy, legal and government conditions	Driver	Hernandez and Ona (2014)

Table 1.
List of drivers and strategies extracted from literature

- the ability to model systems where scientific information is limited by expert and/or local knowledge is available; and
- ease and speed of modeling.

There are some disadvantages of cognitive maps discussed comprehensively by Kosko (1992) and (Özesmi and Özesmi, 2004), among others; however, these have been extensively investigated in the current literature. The advantages of cognitive maps (which include FCMs) outweigh their disadvantages; hence, they are widely used in the current literature (Goswami *et al.*, 2017; Jetter and Schweinfort, 2011; Osoba and Kosko, 2017; Pandari and Azar, 2017). The FCM is a 4-tuple (C, W, A, f) where $C = \{C_1, C_2, \ldots, C_M\}$ is the family of M concepts modeled after fuzzy sets, and $W = [w_{ij}]_{M \times M}$ is the matrix containing the weights $w_{ij} \in [-1, 1]$ assigned to each pair of concepts (C_i, C_j). The function $A : C \to A_i^{(t)}$ computes the activation degree $A_i \in \mathbb{R}$ of each concept C_i at the discrete time step $t = \{1, 2, \ldots, T\}$, and the transfer function $f : \mathbb{R} \to I$ aggregates the impact of multiple causal events over the target concept and clamps the result to the predefined activation interval I (Felix *et al.*, 2019). Several works in the literature have presented how the FCM can be constructed such as Jetter and Schweinfort (2011), Singh and Chudasama (2017) and Quiñones *et al.* (2019). As such, the procedure can be summarized by the following steps:

- *Step 1. Obtain FCMs from experts*. There are several ways of obtaining expert knowledge. One way of doing this is to form a focus group discussion (FGD) consisting of expert decision-makers. Krueger *et al.* (2001) provide a comprehensive tutorial on the successful formation of FGDs. The FGD would thoroughly evaluate the status of the problem being solved and establish causal relationships between the identified concepts. In many FGDs for creating FCMs, respondents are asked to draw their desired FCMs similar to concept mapping but with edges of the concept maps having weights representing the strength and proportionality of the relationship. For instance, if the relationship of two concepts is given as 0.4, then the pair is directly related with a strength of 0.4. On the other hand, if the rating is given as −0.8, then the pair is inversely related to a strength of 0.8. The ratings are provided on a linguistic scale to make the relationships close to the human decision-making process. The linguistic scale can then be used to derive the corresponding crisp weights. The transformation relation is presented in Table 3. Expert decision-makers are given questionnaires to rate the relationship of pairs of concepts (C_i, C_j). The FCM is not reflexive. Hence, a concept C_i has no relationship with itself.
- *Step 2. Coding FCMs into weighted adjacency matrices*. The causal relations established on the individual FCMs are encoded into an $m \times m$ weight matrix W

Code	Industry type	Position
Decision-maker (DM) 1	Business process outsourcing	Data Scientist
Decision-maker (DM) 2	System services	Software Engineer
Decision-maker (DM) 3	Manufacturing	IT Manager
Decision-maker (DM) 4	University	System Admin
Decision-maker (DM) 5	University	Faculty/Computer Scientist
Decision-maker (DM) 6	Business process outsourcing	Web Developer
Decision-maker (DM) 7	University	Technology Transfer Officer

Table 2.
Experts and their positions

with elements w_{ij}. The matrix W is equivalent to their corresponding FCM graphs. The matrix form enables easy computational processing for the FCM.

- *Step 3. Aggregation of multiple FCMs*. With n decision-makers, there would be n matrices modeling a problem. To keep track of a single matrix describing the problem, the n matrices are aggregated. The mathematical aggregation of the individual FCMs enable a superior representation of the system dynamics with more reliable results (Özesmi and Özesmi, 2004; Singh and Chudasama, 2017). The individual adjacency matrices, $W^{[i]}$ for $i=\{1,..,n\}$, were aggregated using equation (1):

$$W^{*} = \frac{1}{n}\sum_{i=1}^{n} W^{[i]} \tag{1}$$

Conflicting connections with opposite polarity decrease the causal relationships, whereas agreement reinforces them (Özesmi and Özesmi, 2004; Singh and Chudasama, 2017). Several calculi have been proposed in the literature to treat such cases. These works are discussed with comprehensive detail in Özesmi and Özesmi (2004) and Singh and Chudasama (2017). The details are not discussed in this paper for brevity:

- *Step 4. Developing the combined FCM graph*. With the aggregated weighted matrix W^*, it is now possible to construct the aggregated FCM graph. The concepts are represented by the vertices of the graph. The causal relationships are represented by the edges of the graph.

3.3 Genetic algorithm

GA refers to a family of computational models inspired by evolution (Whitley, 1994). In a strict interpretation, GA refers to a model introduced and investigated by Holland (1975). Although there are several variants of GA in the current literature, it is still the case that most of the existing theory for GA applies either solely or primarily to the model introduced by Holland. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures so as to preserve critical information (Whitley, 1994). It is one of the first population-based metaheuristic algorithms where every solution corresponds to a chromosome and each parameter represents a gene (Mirjalili, 2019). There are two notions worth to distinguish in

Linguistic variables	Rating	Corresponding crisp values
Positively very high	5	1
Positively high	4	0.8
Positively medium	3	0.6
Positively low	2	0.4
Positively very low	1	0.2
No relationship	0	0
Negatively very low	−1	−0.2
Negatively low	−2	−0.4
Negatively medium	−3	−0.6
Negatively high	−4	−0.8
Negatively very high	−5	−1

Table 3. Membership functions for the fuzzy weights

GA, the *fitness function* and the *evaluation function* (Whitley, 1994). GA evaluates the fitness of each individual in the population using a fitness function defined by f_i/f where f_i is the evaluation associated with chromosome i and f is the average evaluation of all chromosomes (Mirjalili, 2019; Whitley, 1994). In this sense, the evaluation function is the objective function of the optimization problem being solved (Whitley, 1994). There are also other approaches for assigning fitness to a population:

- based on a chromosome's rank (Baker, 1985); and
- sampling methods (Goldberg, 1990), among others.

As maintained by Whitley (1994), GA constitutes the following procedure:

(1) *Step 0*. Choose the parameters for the GA. The parameters needed to be specified before performing the GA are:

- number of generations (M);
- population size (N);
- cross-over probability (p_c);
- mutation probability (p_m);
- selection operator;
- cross-over operator;
- mutation operator;
- loss/objective function; and
- fitness function.

In the current literature, no standard procedure is available for determining such parameters. Bhandari *et al.* (1996) and Hassanat *et al.* (2019) collectively argue that these parameters must be decided properly based on the problem being solved. Some strategies are to try different parameter configurations until a better solution is obtained, use benchmark configurations from related works and use a panel of expert decision-makers. For a detailed discussion on how these parameters are treated in the literature, refer Hassanat *et al.* (2019), Kora and Yadlapalli (2017), Larranaga *et al.* (1999) and Whitley (1994).

(1) *Step 1*. Initialize *population*.
(2) *Step 2*. Evaluate each member of the *population* using a loss/objective function.
(3) *Step 3*. Select a chromosome from the *population* based on a fitness function.
(4) *Step 4*. Perform crossover with probability p_c.
(5) Select mate from *population* with uniform probability.
(6) Select crossover point between 1 and $L - 1$ with uniform probability.
(7) Recombine chromosomes.
(8) *Step 5*. Perform mutation with probability p_m.
(9) *Step 6*. Add the chromosomes to the *New_Population*
(10) *Step 7*. If *New_Population* is not full, go to Step 3. Otherwise,
(11) Set *population* equal to *New_Population*.
(12) Go to Step 2.

3.4 Proposed algorithm

This paper proposes an evolutionary algorithm approach for the automatic building of FCMs. The GA will be used as an evolutionary strategy because of its convenient representation of evolutionary processes. The proposed algorithm works to evolve FCMs while minimizing expert intervention. FCMs are excellent in modeling the interactions within a complex system using expert knowledge. However, they are heavily reliant on specialist knowledge. While expert knowledge is useful in small-scale problems, it becomes highly susceptible to inconsistencies as the problem scales (Brunelli and Fedrizzi, 2015).

The judgments may be inconsistent and/or incomplete because of the limits of decision-makers' expertise and capabilities or the complexity of the decision problems (Kou *et al.*, 2016). Inconsistency in expert judgment has been investigated, and demonstrated, in many research fields; one crucial finding is that there are considerable domain-specific differences (Grimstad and Jørgensen, 2007). In many multiple criteria decision-making (MCDM) models, inconsistency often arises from pairwise comparisons (Kou *et al.*, 2016). However, these are widely used because of being convenient tools to model the decision-makers' preference over sets of alternatives (Brunelli and Fedrizzi, 2015). Nevertheless, in making paired comparisons, it is well-known that people do not have the intrinsic logical ability always to be consistent (Brunelli *et al.*, 2013).

Like MCDM models, FCM make use of paired comparisons when establishing causal relationships between concepts. Hence, it becomes susceptible to inconsistency. In the current literature and practice, it is assumed that the dependability of the decision is related to the consistency of the decision-maker's pairwise judgment (Brunelli and Fedrizzi, 2015). Aside from being susceptible to inconsistencies, another drawback of FCMs is the difficulty in estimating strengths of causal relationships between variables (Osei-Bryson, 2004). While signs (positive or negative) are relatively more natural to determine, determination of the magnitude is often problematic; hence, in many cases, decision-makers vaguely specify the strength of relationship (Osei-Bryson, 2004). One of the properties of a converging FCM is the existence of a steady-state vector. The steady-state vector is the long-term value of a concept (i.e. once a concept converges, it does not change its value).

In scenario analysis for FCM, the concepts encoded in a vector change their values depending on an initial condition but approached a fixed attractor with increasing simulation steps (assuming the FCM does not cycle or approach a chaotic attractor) (Khan *et al.*, 2004). Hence, this paper proposes an algorithm for estimating a weight matrix for FCM without explicitly asking decision-maker input in establishing causal relationships. The only input needed is the steady-state target vector for a set of concepts. As such, the weight matrix provides the closest steady-state vector as the target steady-state vector will be evolved using GA. The proposed algorithm significantly fills the gap as it:

- reduces subjective bias by minimizing decision-maker judgment;
- removes inconsistency resulting from decision-makers' bias; and
- reduces effort in specifying the FCM.

The procedure for genetically evolving FCM is as follows:

- *Step 1. Obtain the target steady-state vector from decision-makers*. The target steady-state vector consists of the long-term expectation of each concept's activation degree. The target steady-state vector must be obtained from expert decision-makers, who will decide the potential long-term value of each involved concept. Because decision-makers may have different views and experiences on a topic, an FGD may be formed to facilitate the generation of a more well-rounded understanding of the topic. In this case, experts specify up to what degree a concept may be active in the long-run. For example, when using the hyperbolic tangent as an activation function, one can provide a value of −0.90 if a concept is perceived to be decreasing in a negatively high manner.

- *Step 2. Setup an initial population of FCM matrices*. Randomly generate FCM matrices with size $n \times n$ for n concepts. The initial matrix may be optionally fine-tuned by the experts as well. To obtain the steady-state vector of each randomly generated FCM matrix, an inference rule (as presented in Table 5) must be selected. The choice of inference rule depends on the problem being modeled. For example, if experts believe that their current values only influence future values of concepts, then "Kosko's activation function" would be a suitable choice. Therefore, the choice of inference rules must be decided based on experts' knowledge of the problem being modeled. Similarly, benchmarking from related works in the literature may also aid in such a decision. The inference rule provides a way to derive the FCM steady-state vector from an initial state vector until it converges to a fixed-point attractor. For an FCM matrix that reaches steady state, the value of the initial state vector can be arbitrary because the matrix will still converge to a steady state regardless of the initial conditions. However, there may also be cases when FCMs do not converge to a steady state. In this case, the FCM is chaotic or approaches a limit cycle; refer Nápoles *et al.* (2016) for an in-depth discussion on such cases. To guarantee that the generated FCMs will converge, the choice of activation function must be given attention by users. For example, it has been shown in the literature (Nápoles *et al.*, 2016)) that the discrete activation functions (e.g. bivalent function) will always converge to a steady state. Moreover, Boutalis *et al.* (2009) showed that for the log-sigmoid and hyperbolic tangent functions, convergence is guaranteed for the FCM weight matrices. Thus, to ensure convergence of the generated FCMs, users must carefully choose an activation function. Moreover, users can also add constraints to the selection of candidate FCMs by including only those that converge up to a set number of max iterations. Although this would limit the search space of the algorithm, it eliminates the selection of a chaotic FCM or limit cycles and may help in speeding up the computation as well. Nevertheless, such concerns depend on the users' implementation goals.
- *Step 3. Obtain the best weight matrix using GA*. Using GA, the best matrix is selected on the basis of a particular loss function chosen by the decision-makers. Common loss functions used in literature are presented in Table 6.
- *Step 4. Construct the FCM graph using the best weight matrix*. With the values established in the best weight matrix, construct the digraph of the concepts to depict the causal relations visually. This step is optional, especially in cases when as many as 20 concepts are plotted.
- *Step 5a. Adjust the graph parameters if necessary using expert knowledge*. Expert decision-makers may opt to adjust the relationships established by the best decision-makers if some of the relationships do not clearly describe the actual scenario.
- *Step 5b. Establish the adjusted the FCM graph*. Finalize the FCM graph using the adjusted FCM matrix.

4. Computational results

FCMs provide a framework for analyzing a complex problem through the causal relationships of the involved factors. In this study, the relationship mapping of the strategies and adoption drivers of green computing is analyzed to understand how the adoption of green computing can be facilitated by initiatives/strategies that can be implemented by stakeholders. By obtaining a picture of such relationships, further model developments would be made easier. Hence, the establishment of the FCM is a crucial step in modeling. The inference function used for finding the steady-state vector is Kosko's inference function, as presented in Table 5, whereas the activation function used for mapping each concept values is the hyperbolic tangent as presented in Table 4. With limited knowledge in the current literature for selecting inference rules and activation functions, selecting the inference rule and activation function is agreed by the panel of experts. By considering the findings of Tsadiras (2008), Boutalis *et al.* (2009) and Nápoles *et al.* (2016), the hyperbolic tangent is selected as it was shown to always yield a unique solution and guarantee convergence. Moreover, the experts saw the hyperbolic tangent as naturally representing the potential increase (decrease) of each concept with the positive (negative) values taken by the selected activation function. Likewise, the panel of experts decided to adopt Kosko's inference function presented in Table 5 as it is the most widely used rule in many FCM applications. Thus, its convergence and usefulness are more extensively explored in the current literature to guarantee convergence as maintained by Nápoles *et al.* (2018). As such, the causal relationships between the factors were obtained by genetically evolving random FCM matrices with a target steady-state vector. According to the study's proposed algorithm, the decision-makers would only need to determine each concept's long-term values contrary to the traditional FCM and other learning FCMs in the current literature. The steady-state vector in Table 7 is then used as a target for the algorithm. This study uses the sum of squares error presented in Table 6 as a loss function by the expert panel's agreement. The experts agree that such loss function is desirable because it penalizes large deviations more than smaller deviations, making it more sensitive to larger differences from the target steady-state vector. Hence, the algorithm obtains the FCM matrix with a steady-state

Name	Mathematical form	Description
Bivalent function	$\sigma(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$	This function maps inputs to two discrete classes
Trivalent function	$\sigma(z) = \begin{cases} 1, & z > 0 \\ 0, & z = 0 \\ -1 & z < 0 \end{cases}$	This function maps inputs to three discrete classes. This extends the mapping of the bivalent function
Rectified linear unit (ReLU)	$\sigma(z) = z^+ = max(0, z)$	Defined as the positive part of its argument with z as input to the neuron
Logistic function	$\sigma(z) = \dfrac{1}{1 + e^{-z}}$	The logistic function (also termed as sigmoid) maps inputs in the interval [0,1]
Hyperbolic tangent	$\sigma(z) = tanh(z)$	The hyperbolic tangent function is also sigmoidal (shaped as an S-curve); unlike the logistic function, the hyperbolic tangent maps the inputs to the interval [−1,1]. It is useful in cases where positive and negative values make more sense in the analysis
Gaussian function	$\sigma(z) = e^{\dfrac{-(z-c)^2}{2\sigma^2}}$	The Gaussian function belongs to the class of radial basis functions (RBF) used in RBF networks. Here c is the function center and σ models the spread of the center

Table 4. List of common activation functions. In these functions, the variable $z = \beta_0 + \sum_{i=1}^{N} \beta_i x_i$ is a linear combination of parameters (β_i), features (x_i) and bias (β_0)

vector closest to the target steady-state vector, as presented in Table 8. The FCM derived by the algorithm obtains a minimal average error at only 0.042. By taking into account uncertainties in the estimation, a confidence interval is established in Table 7. The mean absolute deviation may take values within the confidence interval taking into account the uncertainty.

The proposed algorithm offers several advantages for building FCMs. First, it provides a tractable approach for establishing causal relationships. For instance, the traditional FCM requires a pairwise comparison between all concepts, which takes quadratic steps with respect to the number of concepts. On the contrary, the proposed algorithm takes only linear steps with respect to the number of concepts because decision-makers only have to establish each concept's value. Therefore, the proposed algorithm reduces the worst-case complexity of the estimation process from $O(n^2)$ to $O(n)$. Second, by minimizing the input from the decision-makers, inconsistencies resulting from subjective judgment are also minimized. The proposed algorithm, however, experiences a few limitations. With the FCM matrix estimated only from the target steady-state vector, the algorithm may become susceptible to:

- incorrect assignment of positive or negative signs; and
- assignment of a smaller or larger magnitude for the causal relationship contrary to what the experts would assign.

Table 5. List of inference rules for fuzzy cognitive maps (FCM) taken from Dikopoulou and Papageorgiou (2017)

Name	Mathematical form
Kosko's inference rule	$A_i^{k+1} = \sigma\left(\sum_{j=1, j\neq i}^{n} w_{ji} \times A_j^k\right)$
Modified Kosko's inference rule	$A_i^{k+1} = \sigma\left(A_i^k + \sum_{j=1, j\neq i}^{n} w_{ji} \times A_j^k\right)$
Rescale inference rule	$A_i^{k+1} = \sigma\left(2A_i^k - 1 + \sum_{j=1, j\neq i}^{n} w_{ji} \times \left(2A_j^k - 1\right)\right)$

Notes: The $\sigma(\cdot)$ is any activation function of choice, A_j^k is the value of concept C_j at simulation step k of the FCM and w_{ji} is the value of the interrelationship from C_j to C_i

Table 6. List of common loss functions for fuzzy cognitive mapping (FCM)

Name	Mathematical form	Description
L1 loss/mean absolute error	$L(\hat{y}, y) = \frac{\sum_{i=1}^{N} \lvert\hat{y}_i - y_i\rvert}{N}$	$\hat{y}_i$ is the predicted value, y_i is the target value, N is the number of targets
Sum of squares error	$L(\hat{y}, y) = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$	$\hat{y}_i$ is the predicted value, y_i is the target value, N is the number of targets
0–1 Loss function	$L(\hat{y}, y) = I(\hat{y} \neq y)$	$\hat{y}_i$ is the predicted value, y_i is the target value, $I(\cdot)$ is the indicator function
Mean bias error	$L(\hat{y}, y) = \frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)}{N}$	$\hat{y}_i$ is the predicted value, y_i is the target value, N is the number of targets
Hinge loss	$V(w, y) = max\{1 - w \cdot y, 0\}$	w is the predicted value, y is the target value
Logistic loss	$V(w, y) = \frac{ln(1 + e^{-w \cdot y})}{ln2}$	w is the predicted value, y is the target value

These limitations may prevent the algorithm from capturing the appropriate causal structure of the problems. Such problems are common in other learning approaches for FCM. However, no solution for overcoming such drawbacks has been well-studied in the literature yet. However, one can empirically analyze the algorithm's robustness by checking the probability that an incorrect sign is assigned and determining the average deviation of the causal relationships with respect to what an expert specifies. This study found a very low probability of incorrect assignments (or contradictions) and small average deviation, as presented in Table 9. The results imply that the proposed algorithm only has a 6.1% chance of assigning incorrect signs. Moreover, one would expect only a difference of 0.107 from an expert provided FCM on average. For example, if an expert would assign a value of 0.7 to the causal relationship between two factors, the algorithm may assign a value of 0.6. Such cases may be tolerable in many practical scenarios. Our results show that the proposed algorithm can estimate the FCM matrix with a high chance of capturing the problem's causal structure. Although the results do not achieve zero error, they may become beneficial in practice, especially when a vast number of concepts are involved, which becomes intractable for decision-makers.

There are 11 drivers and 15 strategies for the adoption of green computing in the current literature. Analyzing their relationships would require establishing the causality between the total 26 concepts (15 strategies and 11 drivers). For the traditional FCM, this would require 676 cells (in the matrix) to specify. As such, it would be cumbersome and intractable

Concepts	Target steady-state vector	FCM steady-state vector	Absolute deviation
S1	0.000	0.000	0.000
S2	0.000	0.000	0.000
S3	0.000	0.000	0.000
S4	0.000	0.000	0.000
S5	0.000	0.000	0.000
S6	0.000	0.000	0.000
S7	0.000	0.000	0.000
S8	0.000	0.000	0.000
S9	0.000	0.000	0.000
S10	0.000	0.000	0.000
S11	0.000	0.000	0.000
S12	0.000	0.000	0.000
S13	0.000	0.000	0.000
S14	0.000	0.000	0.000
S15	0.000	0.000	0.000
D1	−0.400	−0.724	0.324
D2	−0.200	−0.143	0.057
D3	0.500	0.504	0.004
D4	0.500	0.524	0.024
D5	1.000	0.940	0.060
D6	0.500	0.889	0.389
D7	1.000	0.947	0.053
D8	0.600	0.617	0.017
D9	1.000	0.986	0.014
D10	0.700	0.865	0.165
D11	1.000	0.997	0.003
Mean absolute deviation			*0.043*
Confidence interval			*0.004 to 0.081*

Table 7. Target steady-state vector contains the activation values assigned by the experts. The FCM steady-state vector is the steady-state vector attributed to the FCM matrix obtained using the proposed algorithm. The mean absolute deviation quantifies the average difference of the values established by the experts and the values obtained from the algorithm. The confidence interval depicts the possible values of the mean absolute deviation taking into account uncertainty in the estimation

Table 8.
Fuzzy cognitive map matrix

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
S1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.556	0.322	1	−0.252	−0.303	0.18	1	0	0.444	1
S2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−1	−0.974	−0.407	1	−0.899	0.734	1	−0.525	0.46	−0.735
S3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.865	−1	−0.178	−0.461	0.48	0.649	0.726	0.386	−0.597	−1	0
S4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0.332	0	−0.478	0.454	1	0.337	0	0.076
S5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.793	0.241	1	−0.378	0	0.18	0.494	0.119	1
S6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.989	1	−0.522	−1	−0.808	0.137	0.621	1	0.319
S7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.173	0.426	1	−1	−0.618	0	0.936	1	0.213	0.672	1
S8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.399	0	−0.102	−0.268	0	−1	0.644	0	0	1	0.613
S9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0.312	−0.208	0	0.626	0.786	0.232	0	0
S10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.453	0.461	−1	0.115	0	0	0.404	0.545	0.054	0	0.901
S11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.071	0	−0.896	0	0.768	0.091	0.722	0	0	0.161	1
S12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.55	1	−1	0	−0.212	1	0.822	0.118	−0.305	−0.155	0.122
S13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.748	1	−0.341	−0.606	−0.007	0.73	1	0.137	−0.555	1	0.194
S14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0.653	−1	−1	0.404	1	0.213	0	−0.62	0	0.844
S15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.485	0.619	−0.361	−0.778	0	1	1	0	0.257	0.805	0
D1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.686	1	0.026	0.866	−0.095	−0.618	1	0	0.095	−1
D2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0.146	−0.41	−0.548	0	−0.093	−1	−0.603	0.364
D3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0.06	1	−0.025	1	0.26	0	1	0.794
D4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−0.083	−1	0	0	0.202	−0.136	1	0.608	0.855	0	0.28
D5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0.438	0	−1	0	1	1	0.137	−0.109	1	0.67
D6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	−0.093	−1	0	0	0	1	0	0.441	−0.545
D7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.167	−1	1	0	0	1	0	−0.301	0	−0.596	1
D8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.735	0.922	0.02	0.047	0.829	0	−0.822	0	0.762	0	−0.253
D9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.626	0	−0.669	0	0	−0.662	0.716	0	0.565	1
D10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.901	−0.455	−1	−0.795	−0.212	1	0	0.523	0.734	0	0.275
D11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.518	1	0.054	1	1	0.179	0.022	1	1	0	0

for a decision-maker. With the proposed algorithm, the decision-makers would only specify 26 values in the worst-case, which significantly reduces the task. The characteristics of the FCM graph are shown in Table 10. It can be seen that drivers and strategies have different behaviors according to their indegree, outdegree and centrality measures. The in-degree measures the receiving power of a concept, whereas the outdegree measures the affective power. The centrality sums up the indegree and outdegree of a concept. These measures can be used to group concepts that share the same characteristics. It will be easier to cluster the concepts if there are only two characteristics to use. However, because there are three characteristics, it would be necessary to transform the data to project them on a 2D graph while retaining the three characteristics. In this study, a principal component analysis (PCA) is performed first to summarize such characteristics. Discussions on PCA can be found in Reris and Brooks (2015), Karamizadeh *et al.* (2013) and Shlens (2014). According to the PCA algorithm, two principal components are sufficient to explain the variability in the data. Using principal components, k-means clustering analysis is performed to cluster the concepts. A comprehensive discussion on k-means clustering can be found in Teknomo

Criteria	Statistics
Probability of contradictions	0.061
Average absolute deviation	0.107

Table 9.
Fuzzy cognitive map matrix statistics

Concepts	In degree	Out degree	Centrality	Density
S1	0	9	0.36	*0.338*
S2	0	11	0.44	
S3	0	10	0.4	
S4	0	9	0.36	
S5	0	9	0.36	
S6	0	9	0.36	
S7	0	10	0.4	
S8	0	7	0.28	
S9	0	6	0.24	
S10	0	8	0.32	
S11	0	7	0.28	
S12	0	10	0.4	
S13	0	11	0.44	
S14	0	9	0.36	
S15	0	8	0.32	
D1	18	9	1.08	
D2	22	8	1.2	
D3	20	8	1.12	
D4	22	8	1.2	
D5	18	9	1.08	
D6	20	6	1.04	
D7	21	7	1.12	
D8	21	8	1.16	
D9	18	6	0.96	
D10	18	9	1.08	
D11	22	9	1.24	

Table 10.
FCM graph measures

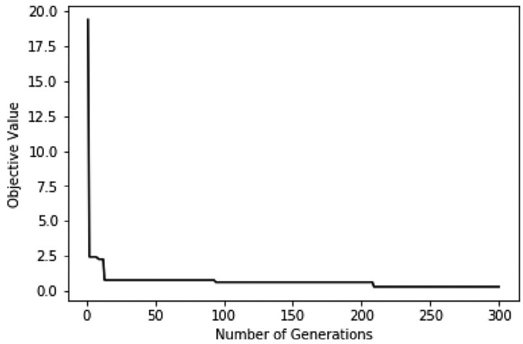
Code	Cluster name	Members	Group type
C1	Energy management strategy	Power and workload management (S2) Environmental awareness program (S13) Thermal load management (S3) IT governance (S7) Enabling power management features (S12) Energy conservation (S14)	Strategy
C2	Changes in the organizational conditions	Increasing cooling requirements for equipment (D2) Increasing equipment power density (D3) Increasing energy costs (D4) Organizational learning capabilities (D8)	Driver
C3	Process-oriented strategy	Process optimization (S8) Reducing energy consumption by PCs (S11)	Strategy
C4	Digitization strategy	Data center infrastructure (S1) Product design (S4) Virtualization (S5) Cloud computing and cloud services(S6)	Strategy
C5	Intrinsic innovation capability	Low utilization rates (D6) Innovation capabilities(D9)	Driver
C6	External environment pressures	The rapid growth of the internet and ICT usages (D1) Restrictions on energy supply access (D5) Institutional pressure (D10)	Driver
C7	Product-oriented strategy	Innovative end products and infrastructure solutions (S10) Eco-friendly design (S15)	Strategy
C8	Information and transparency	Information and transparency (S9)	Strategy
C9	Environmental awareness	Growing awareness of IT's impact on the environment (D7)	Driver
C10	Regulatory drivers	Policy, legal and government conditions (D11)	Driver

Table 11. Driver and strategy groups resulting from the clustering of drivers and strategies with similar characteristics

(2006), Neller and Brown (2016) and Károly *et al.* (2018). The k-means clustering algorithm was able to find 11 clusters to be optimal in describing patterns in the data, as shown in Figure 3. However, by doing content analysis, it is found that two of the clusters generated by the algorithm can be combined as they were only describing the same idea, which is on "energy management." Moreover, the energy conservation strategy (S14), which was categorized by the algorithm to belong to the digitization strategy (C4), was moved to the energy management strategy (C1) as it is more fit to be included in such cluster. These concepts are now merged into the energy management strategy (C1) cluster. The transfer of some concepts to C1 is reasonable because the involved concepts are also neighbors, as shown in Figure 3. The final clustering is presented in Table 11. Our results show that the 26 concepts can be grouped into ten clusters, composed of five driver groups and five strategy groups. The clustering approach based on the structural properties of the FCM helps streamline factors that would be useful in facilitating the adoption of green computing.

5. Discussion and implications

Green initiatives have constantly been receiving attention from scholars and practitioners across several domains because of society's growing environmental awareness. Green computing (also known as green IT) is the initiative for facilitating the environmental and



Notes: The test used 1,000 generations with a population size of 200. The computation was repeated 50 times to increase confidence of the results. In this paper, up to 300 generations of the best solution is shown for brevity. As such, the steady -state vector at Generation 1 has an objective value of 19.4. At Generation 209, the steady-state vector converged at an objective value of 0.294

Figure 2. Genetic algorithm convergence graph

eco-friendly use of computers and their resources. It is evident in the literature that green computing has received recognition by scholars and practitioners. For example, works such as Bokolo (2016), Raza *et al.* (2012) and Murugesan (2008) are notable for discussions of green and sustainable practices in computing. Despite the growing recognition of green computing, relatively fewer works have been made to understand how the adoption of green computing is carried out. However, it is crucial to understand such a process for green computing to be successfully implemented globally. In developed countries, green computing may have been implemented relatively quickly because of several organizations' receptiveness to green programs. However, this may not be the case for developing or emerging economies. The adoption of green computing in developing or emerging economies lag from developed ones, as can be seen in current works in the literature (Okewu *et al.*, 2017; Taruna *et al.*, 2014; Thongmak, 2012). Because developing countries play a significant role in the global supply chain, green computing adoption must also be facilitated in such countries. Moreover, with the sustainable development goals (SGD) set in these countries, green computing adoption may significantly impact achieving the SGD. This study shows that green computing drivers and strategies can be streamlined into five driver groups and five strategy groups. These groups are formed by looking into the structural characteristics of each strategy and driver. It can be observed from Table 10 that strategies and drivers vary in their *in degree*, *out degree* and *centrality*. These measures describe the structural characteristics of each concept. Hence, it enables us to group drivers or strategies that exhibit the same behaviors. As such, Figure 3 provides a snapshot of such behaviors. Looking into the generated clusters presented in Table 11, managers and other stakeholders can focus on a smaller set of factors For instance, strategies *S2*, *S13*, *S3*, *S7*, *S12* and *S14* can now be viewed as strategies pertaining to "energy management." These results complement the larger body of knowledge on green computing. While works in the current literature classify the drivers of green computing into *economic*, *ethical* and

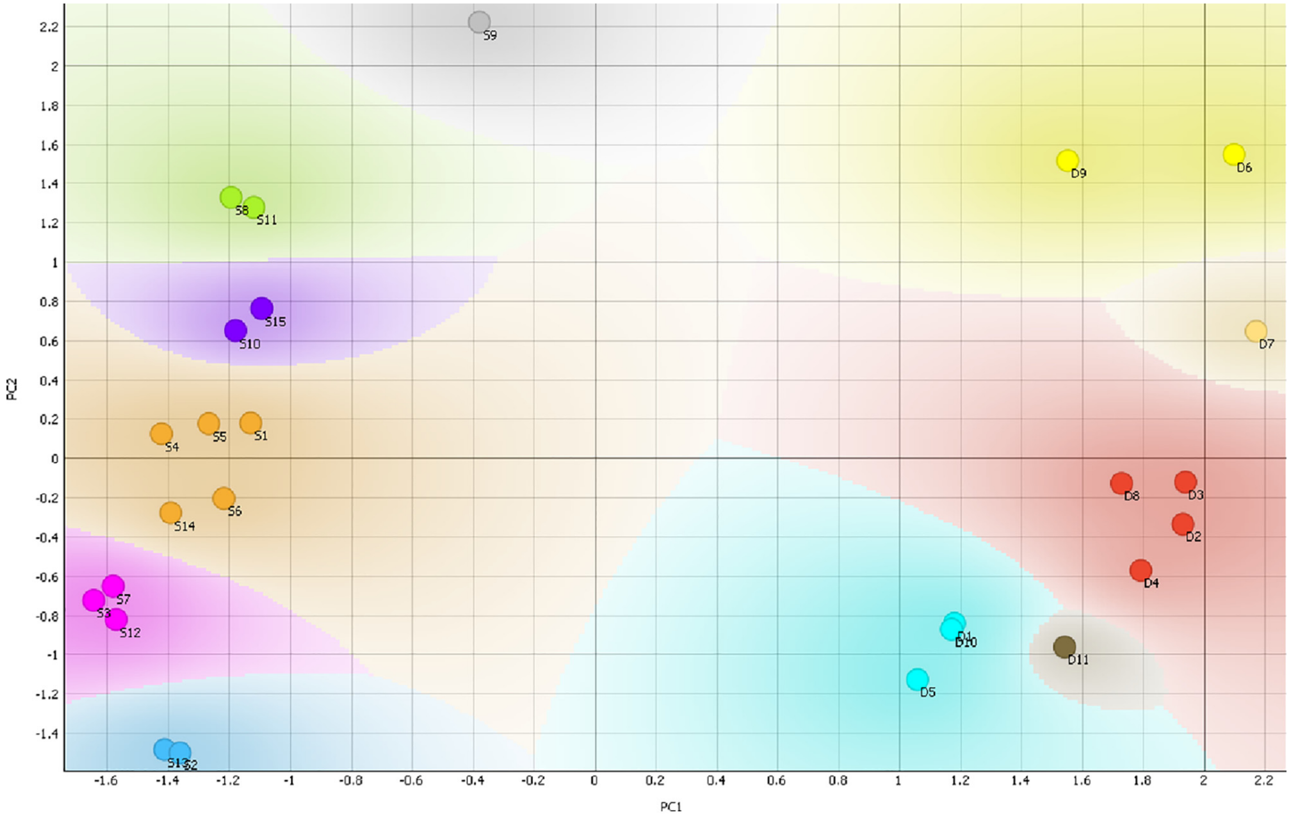


Figure 3.
K-means clustering result

Notes: The drivers and strategies are clustered into driver and strategy groups based on their in degree, out degree and centrality measures. To project the data points on a 2D plane, a principal component analysis (PCA) is performed to summarize the measures. Two principal components (PCs) have been generated. In the plot, PC1 is placed on the horizontal axis and PC2 on the vertical axis *regulatory drivers* (Molla, 2008), this study provides more granular classifications. Moreover, the clusters arrived in this study can also be placed in the classification used by Molla (2008). By providing a sufficiently finer set, benchmarking would be much easier for different stakeholders. For instance, if the adoption drivers and strategies provided are too general, stakeholders would have to exhaust drivers that fit their particular circumstances. Moreover, having too granular (as in Table 1), stakeholders would have to observe many factors. Hence, the clustering approach provided in Table 11 balances such trade-offs. Moreover, by clustering the drivers and strategies based on their structural characteristics, a more comprehensive evaluation is performed in contrast to plain content analysis.

The proposed algorithm provides a good avenue for arriving at such results. First, by reducing the time complexity of specifying the causal relationships, developing FCMs becomes tractable for many practical scenarios. Second, by specifying the causal relationships of the FCM using an evolutionary learning approach, bias and inconsistency resulting from human judgment is significantly reduced. Third, by establishing the FCM, the drivers and strategies' structural characteristics can be used as the basis for clustering similar drivers and strategies that provide a comprehensive set for stakeholders. This paper significantly contributes to the literature in two ways. First, it provides insights that would help shed light on the adoption of green computing, particularly in developing or emerging economies. Second, it provides an algorithm for establishing causal relationships between factors that can be used in many decision-making environments. The proposed algorithm serves as a decision support system. As such, drawing a picture regarding the structural relationships between factors helps stakeholders understand the mechanism of a certain phenomenon or complex system. Moreover, performing such operations in a compliant manner would become advantageous in many practical decision-making environments.

6. Conclusion

Green computing is a growing field of research in sustainability and computing. It has gained attention from scholars in the domain literature. Despite works in the current literature regarding green computing, relatively few efforts have been made to analyze the strategies and adoption drivers. Such analysis would provide insights that would help understand green computing adoption, particularly in emerging/developing economies that lag behind developed countries. To carry out such analysis, relationship mapping using structural modeling has been the benchmark in the domain, and relevant fields. However, with too many concepts involved in adopting green computing, current structural modeling techniques would be challenging to specify. This paper proposes a genetically evolved FCM. The proposed algorithm significantly reduces the computational complexity in obtaining the FCM contrary to the traditional FCM. Using the structural characteristics of the drivers and strategies derived from the FCM, a clustering approach was performed to group drivers or strategies with similar characteristics. As a result, this study finds that among the 26 factors extracted from the literature, five driver groups and five strategy groups are comprehensive to describe green computing adoption dynamics. These results complement and reinforce the findings in the current literature. First, the obtained driver and strategy groups can still be described by the existing classification used in the literature. Second, the obtained driver and strategy groups provide a more comprehensive and granular perspective than the current literature classification. Finally, this paper's clustering approach uses the drivers' structural characteristics and strategies in grouping them in contrast to straightforward content analysis. The proposed algorithm offers significant benefits to stakeholders. First, it provides an approach for establishing causal and structural relationships in a tractable manner. Second, it reduces the bias and subjectivity inherent in human decision-making. Moreover, this paper's results and findings would be valuable for stakeholders because it offers insights that would be useful in analyzing green computing adoption. For instance, the provided set of driver and strategy groups is comprehensive enough for benchmarking by stakeholders. As with other structural models, because the model's output is a causal map (and no predictions are made), comparing the results of the model with other causal models is currently a challenge in the literature. It would then be useful for future works to develop a framework for comparing these types of models. This would enable a more thorough model validation that would be useful in many decision-making scenarios.

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