Explainable Decision Support Modelling Based on Multi-Layer FCM with Multi-Objective Optimization Characteristics: The Case of the Microservices Adoption Problem

Andreas Christoforou[a] and Andreas S. Andreou[b]

Department of Electrical Engineering, Computer Engineering and Informatics, Cyprus University of Technology, Limassol, Cyprus

Keywords: Multi-Layer Fuzzy Cognitive Maps, Explainable Decision Support, Multi-Objective Optimization, Microservices Adoption.

Abstract: The tremendous progress in the field of artificial and computational intelligence has enabled the application of relevant techniques to a wide range of human life aspects. However, these techniques appear in their majority incompetent to allow users to explain and understand their decisions. This paper introduces an enhanced, explainable decision support approach using a promising graph-based computational intelligent model, namely Multi-Layer Fuzzy Cognitive Maps (MLFCM). MLFCM have evolved over the last two decades into a flexible and powerful tool that enables the execution of simulation scenarios to facilitate decision support in highly complex environments. The proposed enhancement of MLFCM revolves around their integration with Multi-Objective Evolutionary Algorithms that allows executing simulations with multiple conflicting targets and then analyzing the values and relationships of the participating nodes. The applicability of the enhanced MLFCM is demonstrated through a case-study on adopting microservices. Microservices have been considered as one of the most promising alternatives to software development nowadays. Nevertheless, their adoption often stumbles on various factors such as security, exit policy, effectiveness, etc. In this context, the factors contributing to Microservices adoption are assessed, analyzed and modeled via MLFCM using a series of real-world and synthetic scenarios that yielded quite promising results.

1 INTRODUCTION

Nowadays, the ever-increasing use of intelligent decision-making methods in complex problem domains plays a vital role in everyday human life. At the same time, trust and transparency are becoming essential for such kinds of approaches, and this underlines the importance and need for techniques that humans can interpret (Gunning and Aha, 2019). Models with enhanced explainable abilities can deliver results through a transparent process that allows one to understand how the system decides, predicts, and performs its operations.

While the models and techniques that aim to deliver predictions with high accuracy and support a decision efficiently become more complex, the development of transparent versions becomes more complex (Meske and Bunde, 2020). Towards delivering a sufficient model with enhanced explainable and analysis features, this work introduces a new computational intelligence process involving Multi-objective optimization characteristics. The applicability and performance of the proposed model are tested and demonstrated on a complex decision problem related to the adoption of microservices architecture.

Software microservice architectures are considered nowadays one of the most successful approaches for the development of cloud-native applications, offering a plethora of small, autonomous, and collaborative services, which are easy to understand, deploy, and scale. Nevertheless, there is yet no consensus between the industry and academia on the critical and decisive factors that would enable a global acceptance and adoption of this new paradigm (Wootton, 2014). In addition, since such architectures are highly complex and are described by multiple, often conflicting factors, the majority of the software development organizations are not ready to fully exploit the benefits of microservices, while adapting their pro-

[a] https://orcid.org/0000-0001-5598-8894
[b] https://orcid.org/0000-0001-7104-2097

Christoforou, A. and Andreou, A.
Explainable Decision Support Modelling Based on Multi-Layer FCM with Multi-Objective Optimization Characteristics: The Case of the Microservices Adoption Problem.
DOI: 10.5220/0011681000003393
In *Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART 2023) - Volume 3*, pages 413-420
ISBN: 978-989-758-623-1; ISSN: 2184-433X

cesses to this new environment is a tedious task (Balalaie et al., 2016). The present paper builds upon and extends previous works on the topic that utilized MLFCMs (Mateou and Andreou, 2005) and Genetically Evolved MLFCMs (Christoforou et al., 2022) to offer a novel decision and analysis model comprising the key factors to consider for adopting a microservice architecture using a multi-objective approach. So far the relevant literature reports hybrid MLFCM-GA forms and execution strategies that allow performing only single target optimization. This is considered as a weakness of the hybrid model as it is often desired that multiple factors are considered for optimization. This is addressed in this paper which proposes an extension of the MLFCM structure with Multi-Objective Evolutionary Algorithms (MOEA). The hybrid MOEA-MLFCM model allows for the execution of simulations with multiple, often conflicting targets and the analysis of the activation levels and relationships of the participating nodes.

The main contributions of this paper are the following: (i) Extension and enhancement of the MLFCM model with multi-objective capabilities which opens new ground for the study and simulation of different scenarios that involve achieving simultaneously conflicting targets. This allows a deeper and more precise definition of the critical factors that affect the decision of microservices adoption, along with their importance and interrelationship. (ii) Revisit of the problem of supporting the decision for migrating to microservices architecture under a new, multi-objective prism. As will be shown later, the new multi-objective MLFCM model allows to define more than one objective reflecting the important factors affecting the final decision, set up different simulation scenaria with multiple objectives which relate to the major concerns or drivers against or in favor of adopting microservices respectively. (iii) Preliminary investigation and comparison between the results achieved when coupling MLFCM with known and widely used MOEA over the problem of adopting microservices as a new software development paradigm. The above contributions of this paper essentially constitute the most significant differences to similar attempts reported in literature in the past, which also differentiate the type of experiments executed and the results yielded and interpreted.

The rest of the paper is organised as follows: Section 2 outlines related work on the topic, while section 3 presents briefly the technical background behind FCM and MLFCM. Section4 describes the proposed approach for integrating MLFCM with MOEA, while Section 5 demonstrates its application on modeling the decision for adopting microservices as the architecture for developing software and discusses the results obtained. Finally, Section6 concludes the paper and suggests some future research steps.

2 RELATED WORK

The integration of FCM models with evolutionary techniques and methodologies has been used during the last two decades, mostly to address some FCM shortcomings and extend their application. The first attempt to use an evolutionary approach with a FCM and deliver a hybrid model is reported in (Koulouriotis et al., 2001). The authors in this work adopted an evolution strategy to estimate the cause-effect relationships among the concepts of the maps.

The authors in (Andreou et al., 2003) introduced a genetically evolved FCM model aiming to adjust the weights of the interrelations between the nodes to meet the objectives after a strategic change. A novel approach for the automatic construction of FCM models from historical data was introduced in (Stach et al., 2005). Through a comparative analysis, the authors in (Froelich and Juszczuk, 2009) showed how and to what extent evolutionary learning methods may outperform the corresponding adaptive ones. The research work of (Pedrycz, 2010) utilised Particle Swarm Optimization (PSO) to identify and calibrate the causal relationships between the nodes of the map. A decomposed learning scheme was proposed in (Chen et al., 2015) based on Swarm Intelligence to adjust gene regulatory networks. A new Structure Optimization Genetic Algorithm (SOGA) for FCMs learning is presented in (Poczeta et al., 2015) aiming to simplify complex FCM models and reduce their size by selecting the most important concepts and connections between them. The development of an evolutionary approach for FCM learning is introduced in (Poczeta et al., 2019) to reduce the number of concepts of the map, as well as to determine the weights of the connections between them.

One can easily observe that the majority of the relevant research uses evolutionary approaches to calculate the weights of the causal relationships between the concepts of the map under study targeting particular objectives. In addition, very few of them utilize evolutionary algorithms to identify the proper set of concepts and initial activation levels so that the model can deliver the best possible output. Although the approaches mentioned above exhibit high performance on the target they are designed for, by calculating the inter-correlations in a somewhat random way they practically remove the most significant advantages of the model, which are the transparency and the reasoning process. This weakness is tackled by the approach proposed in this paper through the evolution (optimization) of the model's initial activation levels, something that preserves its reasoning capabilities and explainability.

3 TECHNICAL BACKGROUND

Fuzzy Cognitive Maps (FCMs) are computationally intelligent, soft computing tools that combine elements of fuzzy logic and neural networks (Kosko, 1992). FCMs are easy to construct and comprehend, and straightforward to execute. In essence, a FCM is a directed graph with nodes that represent concepts in a domain and weighted edges that describe the various causal relationships that exist among these concepts – either positive or negative. The capabilities of FCMs are enhanced by fuzzy logic, which defines both the type of representation of the causal relationships between the concepts and the strength of presence of each concept in the problem dealt. Causal relationships are defined as numerical values in the interval $[-1,+1]$. A value $w_{ij} > 0$ means that a positive interrelation exists between concepts C_i and C_j, that is, an increase or decrease of the C_i value causes an increase or decrease of C_j respectively. Inversely, when $w_{ij} < 0$ there is a negative interrelation between concepts C_i and C_j. Finally, if $w_{ij} = 0$ then there is no relationship between concepts C_i and C_j. Naturally, the higher the number of nodes and relationships, the higher the complexity of the resulting map. A numeric *activation level* AL (or *activation value*) per concept denotes the strength of its presence in the problem domain. Activation levels are represented as a vector the elements of which take values in the interval $[-1,1]$ or $[0,1]$, depending on the modelling scheme followed. The map is initialized with a set of activation levels which represent a particular situation or problem in hand, and then it is executed on a series of discrete steps. Equation 1 describes the update rule initially proposed by Kosko, which calculates the total causal input for node A_i at a given iteration $(t+1)$ based on the influence it receives from all other nodes A_j^t that are connected to it (also known as feeders or sources) at the previous iteration.

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

Similarly to neural networks, four transfer functions are widely used in FCMs (Bueno and Salmeron, 2009): (a) sigmoid, (b) hyperbolic tangent, (c) step and (d) threshold linear. Generally, most of the studies that use FCMs for decision making (including ours) use the unipolar sigmoid function, which exhibits the highest predictive capacity among all. FCMs that use sigmoid functions are also called sigmoid FCMs.

The iterative execution of the map (i.e., the application of the transfer function over the concepts) is terminated when the model for a number of iterations: (1) is stabilised at an equilibrium state, (2) exhibits oscillating behavior, or (3) exhibits chaotic behavior. The former two cases allow for inference, while the third case suggests that the model should be revisited. For inference purposes, the final activation value of the central concept of the model is interpreted in the context of the problem.

In the case of complex and multifaceted concepts then it comes into the picture the notion of Multi-Layer Fuzzy Cognitive Maps (MLFCM) (Mateou and Andreou, 2005). A MLFCM is essentially a hierarchical tree structure, with the upper levels (parents) being composed of other nodes at the lower level (children). Thus, several "local" sub-FCMs are formed. The traversing algorithm of the MLFCM adopted in this paper is the one proposed in (Mateou et al., 2008) which starts from the root FCM and follows a depth-first search approach, computes the activation level of a leaf sub-FCM for only one iteration and transfers its value back to the parent sub-FCM. Then the execution of this sub-FCM is performed for one iteration and its activation level is transferred again back to its parent FCM and so on. The process for one iteration ends when the root sub-FCM completes the calculation of the new activation level of all of the nodes it comprises.

4 MULTI-OBJECTIVE OPTIMIZATION IN MLFCM

As previously mentioned, this paper addresses a significant challenge in modeling problems with the use of MLFCM, that is, the inability to execute what-if scenarios with multiple, conflicting objectives. These scenarios essentially reflect hypothetical cases investigated in a simulated environment which focus on multiple concepts of the map at different levels of the hierarchy and with different impact on the final output. Therefore, the main contribution of this paper may be summarized to the integration of MLFCM with different Multi-Objective approaches. In this context, a multi-objective engine is developed to serve the dynamic analysis of MLFCM, that is, the analysis of the model's behavior under execution, which utilizes various well-known Multi-Objective Evolutionary Algorithms (MOEA), such as the NSGAII, GDE3, OMOPSO and SPEA2, that are then used to execute scenarios with multi-objective targets and compare the outputs of the map. The results are assessed in terms of demonstrating the applicability of the MOEA and proving the significant enhancement of MLFCM models.

Problems that require the optimization of multiple criteria at the same time, need to use multi-objective evolutionary algorithms where the goal is to find the best solution by optimizing a set of objective functions. In case of conflicting or competing objectives, a multi-objective evolutionary algorithm typically delivers a set of optimal solutions instead of a single one. This set of optimal solutions is called Pareto optimal set (or Pareto front) and contains those solutions that are not dominated by any other solution yielded during evolution. Each optimal solution constitutes a specific balance between the objectives under optimization, where any improvement in one of them leads to worsening the other. Therefore, a decision-maker is provided with the set of optimal solutions and is supported to decide which values of the decision variables are most suited based on the targets and the requirements of his application.

A Multi-objective optimization (MOO) problem can be mathematically expressed using the equation:

$$min/max f_1(x), f_2(x), ..., f_n(x), x \in U, \qquad (2)$$

where x is solution, n is the number of objective functions, U is feasible set, $f_n(x)$ is the $n_t h$ objective function and min/max is combined objects operations.

The proposed approach of integrating and executing an MOEA with an MLFCM model relies on a step-wise process as follows:

Step 1: Identify the decisive nodes in the map that were revealed through its static analysis; **Step 2:** Define the decisive nodes or nodes of interest after consulting domain experts and decision-makers; **Step 3:** Execute the resulting model utilizing a selected set of MOEA under different initial configurations; **Step 4:** Evaluate the resulting solutions and assess whether objectives are conflicting (set of solutions diverse) or synergistic (very few solutions); **Step 5:** Identify which algorithm provides the best values for the objectives-concepts.

In the context of the proposed approach, the candidate solutions, or the decision variables, are the activation values of all nodes participating in the MLFCM. The objectives reflect the final activation values of two or more nodes for which we target particular equilibrium values.

Four well-known and widespread MOEAs were selected, aiming to assess their ability to provide solutions coupled with an MLFCM: The Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002), the Generalized Differential Evolution 3 (GDE3) (Kukkonen and Lampinen, 2005), the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2001) and the Optimized Multi-Objective Particle Swarm Optimization (OMOPSO) (Sierra and Coello Coello, 2005).

5 MODELING THE MICROSERVICES ADOPTION DECISION PROBLEM WITH MO-MLFCM

As mentioned above, the case study used in this paper to demonstrate the applicability and efficiency of the Multi-Objective MLFCM is related to the adoption of microservices architecture as a paradigm for software development. This problem is quite complex and challenging, and was first addressed in (Christoforou et al., 2022) where the authors reported also the use of a framework introduced in (Christoforou and Andreou, 2017) to analyse the behavior of a MLFCM and reveal its hidden features and dynamics. This analysis is divided into two steps: The first provides information about the structure of the map and is called static analysis, while the second is called dynamic and it essentially executes the MLFCM model with different what-if scenarios (i.e. initial activation level values) and investigates the results produced. The dynamic analysis was extended in (Christoforou et al., 2022) with the integration of a Genetic Algorithm (GA) able to produce a set of near-optimal solutions in the form of initial activation values targeting particular final activation values. It should be noted that the GA integration targeted a single-objective optimization and therefore it was quite difficult, if not impossible, to reach to solutions involving more than one objective, and in particular when the objectives set are conflicting (see also (Christoforou et al., 2022)). This paper follows the same approach for the static and dynamic analysis of MLFCM, with the latter being enhanced with multi-objective (MO) optimization capabilities. In this context, the integration of MLFCM with known MO algorithms will be described in terms of traversing of the map and development of the solution space. Below we provide the main findings of the static and dynamic analysis performed on the MLFCM model depicted in Figure 1, which comprises the concepts listed in Table 1.

The static analysis uses notions and metrics from graph theory to draw meaningful conclusions about the structure of a MLFCM model. The results are

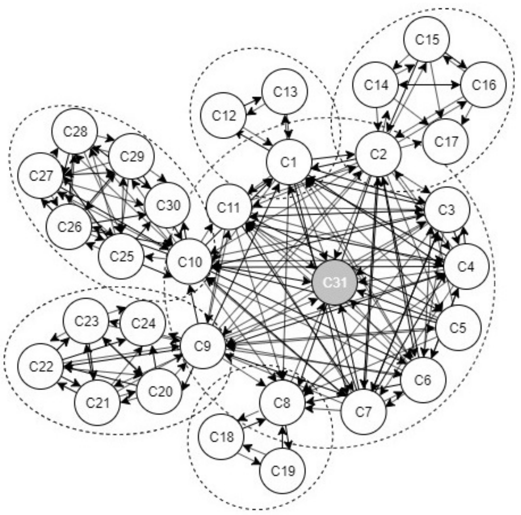

Figure 1: The MLFCM model for the Microservice Architecture adoption problem.

provided in Tables 2 and 3. Table 2 presents the corresponding metrics and measurements about the model's complexity and tendency for each subFCM. The *Complexity* indicator consists of *Density*, the number of nodes and interactions, and *Depth* the number of layers. The *Tendency* indicator takes into account the number of positive or negative cycles formed in a (sub)FCM and checks their balance; if the number of positive cycles is substantially higher compared to that of negative then the map exhibits a positive tendency (i.e. a small increase in any node leads the central concept of interest to increase as well) and vice-versa. Table 3 lists metrics and measurements that describe the impact of each participating node on the model (calculated incoming (*in-value*) and outgoing (*out-value*) weight, and number of incoming (*in-degree*) and outgoing (*out-degree*) edges).

A series of experimental runs (simulations) was then performed by setting different concepts of the model under study as objective functions (dynamic analysis). Each algorithm was run ten times for 5000 fitness evaluations (FE) and concluded with a Pareto near-optimal solution. For the performance comparison between the selected MOEAs, two indicators were utilized, the HyperVolume (HV) (Zitzler and Thiele, 1999) and the Inverted Generational Distance (IGD) (Van Veldhuizen and Lamont, 2000). These two quality indicators were selected to assist in comparing the four MOEAs with respect to performance and scalability, given the metrics' ability to assess both convergence and diversity (uniformity and spread) of the algorithms. Specifically, the HV indicator assesses the volume covered by the non-dominated solutions of a Pareto front in the objective space.

Table 1: Concepts related to the decision of adopting microservice architecture and their groupings (FCMs) - Central concept of each FCM in bold.

No.	FCM	Concept Name
C1	**1, 2**	**Governance**
C2	**1, 3**	**Infrastructure and Management Services**
C3	1	Maintainability and Evolvability
C4	1	Operational Complexity
C5	1	Business Complexity
C6	1	Reliability
C7	1	Security
C8	**1, 4**	**Cost**
C9	**1, 5**	**Design**
C10	**1, 6**	**DevOps**
C11	1	Data Migration
C12	2	Decentralized Governance
C13	2	Data Governance
C14	3	Containerization
C15	3	Scalability/Elasticity
C16	3	Monitoring
C17	3	Serverless Architecture
C18	4	Migration Cost
C19	4	Operations Cost
C20	5	Design For Failure
C21	5	Granularity and Bounded Context
C22	5	Service Contracts
C23	5	Communication Model
C24	5	Decentralization
C25	6	Organization Culture
C26	6	Skilled and Educated DevOps Teams
C27	6	Tool Support
C28	6	Continues Activities
C29	6	Automated Tasks
C30	6	Information Sharing
C31	**1**	**Microservices Adoption**

Table 2: Complexity static measurements.

FCM	Layer	Density	Cycles+	Cycles-
1	1	0.72	64642	65900
2	2	1	5	0
3	2	1	68	16
4	2	1	5	0
5	2	1	409	0
6	2	1	2365	0

Therefore, the larger the volume covered by the solutions generated in a run, the higher the HV value, which indicates a better performance. The IGD indicator assesses how far the elements of the true Pareto front (reference data in our case) are from the non-dominated points of an approximation Pareto front. Therefore, the greater the extent of the true Pareto

Table 3: Strength indicators for the top level FCM.

Node	$deg_{tot}(i)$	$val_{tot}(i)$	Cycles+	Cycles-
C1	18	8.4	56703	57479
C2	16	7.2	53897	54464
C3	18	8.5	56149	57610
C4	18	**8.7**	56724	57633
C5	9	4.5	30705	31338
C6	18	7	56355	58002
C7	18	7.8	56445	57912
C8	11	6.3	0	0
C9	18	**9.6**	**57279**	**58307**
C10	16	7.5	54070	55041
C11	**19**	5.6	**58390**	**59921**
C31	11	6.7	0	0

front that is covered by the non dominated points generated by a run in the objective space, the lower the IGD value, which denotes better performance.

All of the parameters in the algorithms used were selected considering that decision variables take real values ranging between 0 and 1. The overall implementation utilized the Platypus [1], a Python-based multi-objective optimization algorithms library.

Among a series of executions that were performed, two indicative simulations were selected and presented below. In the first case, consultation with domain experts and decision-makers indicated *Microservices adoption* and *Security* as the factors to take part in the objective functions. These concepts were considered interesting by the experts to study together and test how they may be related since security is a common concern of companies moving to developing software with microservices. Therefore, the model was executed targeting to identify solutions for maximizing both objectives. The resulting two dimensional Pareto fronts for each algorithm are depicted in Figure 2.

Table 4: Hypervolume and IGD mean values from a series of 12 executions for the first optimization case.

	GDE3	NSGAII	OMOPSO	SPEA2
HV	0.8870	0.8856	0.8743	0.8803
IGD	0.5121	0.5189	0.7270	0.5134

The HV and IGD values of 12 executions (out of 100 repetitions) calculated for these series of simulations and their corresponding means are listed in Table 4. It is clear from HV and IGD that all algorithms perform quite well, with GDE3 appearing slightly superior than the rest in both metrics. It is also interesting to note that NSGAII and GDE3 reach multiple and diverse solutions, followed by SPEA2. OMOPSO, on

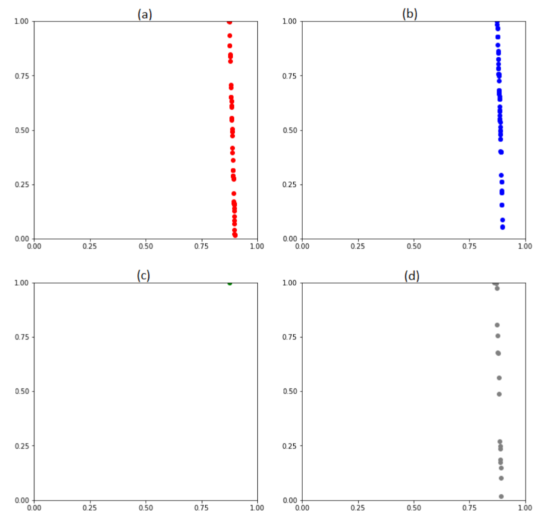

Figure 2: Pareto front for Microservices adoption (x-axes) and Security (y-axes) objectives. (a) NSGAII, (b) GDE3, (c) OMOPSO, (d) SPEA2.

the other hand, finds only one dominant solution with both objectives set to values very near to their desired maximums. We should also note here the existence of multiple solutions that span a range of values for the *Security* concept. This suggests that *Security* is not the most decisive factor contributing in favor or against *Microservices adoption* since the maximum values for the latter are also achieved with lower values of the former.

To check whether there is a statistically significant difference between the four algorithms, the Wilcoxon singed-rank test (Rey and Neuhäuser, 2011) was applied on both performance indicators HV and IGD. The null hypothesis (H0) initially set is that the two compared samples are equal. The calculation of the $p-value$, which indicates the level of significance, for HV and IGD is listed in Table 5. Based on the calculated $p-values$, in the case HV, the null hypothesis is rejected ($p < 0.05$) in all pairs of algorithms but NSGAII and OMOPSO. Similarly, when examining IGD it is not clear whether there is statistically significant difference between the algorithms except for the pairs GDE3-OMOPSO, NSGAII-OMOPSO and OMOPSO-SPEA2. Therefore, we may assume without loss of generalization that all algorithms perform well, but GDE3 stands out with significant statistical difference.

The second case explores the solutions delivered by the model considering three objectives, the *Microservices adoption*, which is the central concept of interest, the *Security* as the main concern of the decision-maker, and the *Operational Complexity* as one of the most decisive concepts based on the static

[1] https://github.com/Project-Platypus/Platypus

Table 5: Pairwise comparison for HV and IGD indicators for the first optimization case.

	NSGAII	OMOPSO	SPEA2
Hypervolume			
GDE3	**0.002**	**0.002**	**0.002**
NSGAII		0.770	**0.002**
OMOPSO			**0.002**
IGD			
GDE3	0.193	0.002	**0.131**
NSGAII		0.002	**0.160**
OMOPSO			**0.002**

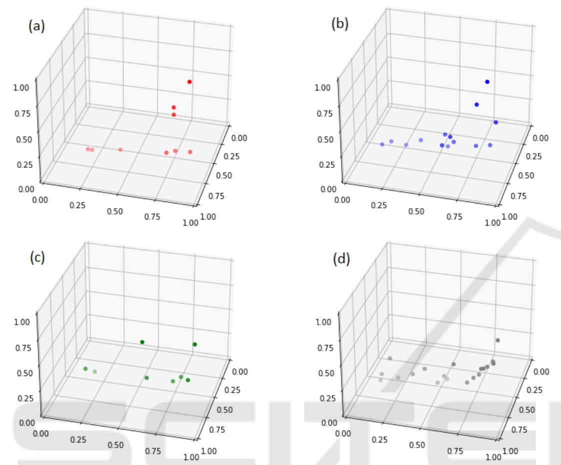

Figure 3: Pareto front for Microservices adoption (z-axes), Security (x-axes) and Operational complexity objectives (y-axes). (a) NSGAII, (b) GDE3, (c) OMOPSO, (d) SPEA2.

analysis (Table 3). The *Microservices adoption* and *Security* objectives were set to be maximized, while the *Operational complexity* was set to be minimized.

The three-dimensional Pareto fronts that emerged from the above executions are depicted in Figure 3. The calculations of the two performance indicators for the second series of simulations are listed in Table 6.

Table 6: Hypervolume and IGD mean values from a series of 12 executions for the second optimization case.

	GDE3	NSGAII	OMOPSO	SPEA2
HV	0.7880	0.7774	0.8012	0.6991
IGD	0.5121	0.5189	0.7270	0.5134

The results suggest again that the algorithms perform well and manage to find solutions despite the fact that the problem is now harder than the first case. The diversity of the solutions is now evident for all algorithms, while GDE3 seems again superior than the rest of the algorithms in terms of both the HV and the IGD metrics. According to the Wilcoxon test, the null hypothesis for the HV values may be rejected for all pairs of algorithms except for NSGAII-OMOPSO. In the case of IGD, the null hypothesis can not be rejected for the pairs NSGAII-OMOPSO, GDE3-NSGAII and GDE3-OMOPSO. Therefore, it seems that GDE3 again performs best, with slight differences compared to the rest of the algorithms.

Table 7: Pairwise comparison for HV and IGD indicators for the second optimization case.

	NSGAII	OMOPSO	SPEA2
Hypervolume			
GDE3	**0.002**	**0.002**	**0.002**
NSGAII		0.770	**0.002**
OMOPSO			**0.002**
IGD			
GDE3	0.084	0.084	**0.002**
NSGAII		0.084	**0.002**
OMOPSO			**0.004**

Overall, the experimental process described in this section demonstrated that all of the multi-objective algorithms utilized have managed to find good solutions and that GDE3 appears to be slightly superior. It should be noted that the theory of multi-objective optimization in the case of MLFCM is somewhat disturbed by the fact that the complexity of the relationships between the nodes does not allow for a clear separation of the conflicting nodes. This means that there are paths in the model that could be visited that are not easy to define a-priori and these alternative routes in some cases give birth to solutions that are not necessarily conflicting, as in the first case of the experimental process. Therefore, one thing that the model calls for further analysis and investigation is the number and type of individual solutions, as well as the different forms of conflicting or not objectives. This assessment reveals also the complexity of the optimization scenario in cases in which the set of solutions is not so rich and vice-versa.

6 CONCLUSIONS

This paper proposed an enhanced form of explainable decision support modelling based on Multi-Layer Fuzzy Cognitive Maps (MLFCM) and Multi-Objective Evolutionary Algorithms (MOEA). The case of a complex decision problem related to the adoption of microservices architecture was addressed to show the applicability and effectiveness of the proposed model using four well known and effective MO approaches, namely NSGAII, OMOPSO, GDE3 and SPEA2. Two MO scenarios were developed and tested, the first involving two and the second three objectives, which were formed with the aid of domain experts. The results suggested that the proposed integrated MOEA-MLFCM successfully managed to capture the dynamics behind the decision for migrating to microservices.

Future research will concentrate on the following: First, more objectives and scenarios will be investigated so as to form a more complete experimental picture in terms of factors and inter-dependencies. Second, automation of the selection of the most appropriate MOEA will be pursued for each multi-objective scenario formed in each problem dealt.

REFERENCES

Andreou, A., Mateou, N., and Zombanakis, G. A. (2003). Evolutionary fuzzy cognitive maps: A hybrid system for crisis management and political decision making.

Balalaie, A., Heydarnoori, A., and Jamshidi, P. (2016). Microservices architecture enables devops: Migration to a cloud-native architecture. *IEEE Software*, 33(3):42–52.

Bueno, S. and Salmeron, J. L. (2009). Benchmarking main activation functions in fuzzy cognitive maps. *Expert Systems with Applications*, 36(3):5221–5229.

Chen, Y., Mazlack, L. J., Minai, A. A., and Lu, L. J. (2015). Inferring causal networks using fuzzy cognitive maps and evolutionary algorithms with application to gene regulatory network reconstruction. *Applied Soft Computing*, 37:667–679.

Christoforou, A. and Andreou, A. S. (2017). A framework for static and dynamic analysis of multi-layer fuzzy cognitive maps. *Neurocomputing*, 232:133–145.

Christoforou, A., Andreou, A. S., Garriga, M., and Baresi, L. (2022). Adopting microservice architecture: A decision support model based on genetically evolved multi-layer fcm. *Applied Soft Computing*, 114:108066.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197.

Froelich, W. and Juszczuk, P. (2009). Predictive capabilities of adaptive and evolutionary fuzzy cognitive maps-a comparative study. In *Intelligent systems for knowledge management*, pages 153–174. Springer.

Gunning, D. and Aha, D. (2019). Darpa's explainable artificial intelligence (xai) program. *AI magazine*, 40(2):44–58.

Kosko, B. (1992). Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence/book and disk. *Vol. 1Prentice hall*.

Koulouriotis, D., Diakoulakis, I., and Emiris, D. (2001). Learning fuzzy cognitive maps using evolution strategies: a novel schema for modeling and simulating high-level behavior. In *Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No. 01TH8546)*, volume 1, pages 364–371. IEEE.

Kukkonen, S. and Lampinen, J. (2005). Gde3: The third evolution step of generalized differential evolution. In *2005 IEEE congress on evolutionary computation*, volume 1, pages 443–450. IEEE.

Mateou, N., Andreou, A. S., and Stylianou, C. (2008). A new traversing and execution algorithm for multi-layered fuzzy cognitive maps. In *2008 IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence)*, pages 2216–2223. IEEE.

Mateou, N. H. and Andreou, A. S. (2005). Tree-structured multi-layer fuzzy cognitive maps for modelling large scale, complex problems. In *International Conference on Intelligent Agents, Web Technologies and Internet Commerce*, volume 2, pages 131–139. IEEE.

Meske, C. and Bunde, E. (2020). Transparency and trust in human-ai-interaction: The role of model-agnostic explanations in computer vision-based decision support. In *International Conference on Human-Computer Interaction*, pages 54–69. Springer.

Pedrycz, W. (2010). The design of cognitive maps: A study in synergy of granular computing and evolutionary optimization. *Expert systems with applications*, 37(10):7288–7294.

Poczeta, K., Kubuś, Ł., and Yastrebov, A. (2019). Analysis of an evolutionary algorithm for complex fuzzy cognitive map learning based on graph theory metrics and output concepts. *Biosystems*, 179:39–47.

Poczeta, K., Yastrebov, A., and Papageorgiou, E. I. (2015). Learning fuzzy cognitive maps using structure optimization genetic algorithm. In *2015 federated conference on computer science and information systems (FedCSIS)*, pages 547–554. IEEE.

Rey, D. and Neuhäuser, M. (2011). Wilcoxon-signed-rank test.

Sierra, M. R. and Coello Coello, C. A. (2005). Improving pso-based multi-objective optimization using crowding, mutation and dominance. In *International conference on evolutionary multi-criterion optimization*, pages 505–519. Springer.

Stach, W., Kurgan, L., Pedrycz, W., and Reformat, M. (2005). Genetic learning of fuzzy cognitive maps. *Fuzzy sets and systems*, 153(3):371–401.

Van Veldhuizen, D. A. and Lamont, G. B. (2000). Multiobjective evolutionary algorithms: Analyzing the state-of-the-art. *Evolutionary computation*, 8(2):125–147.

Wootton, B. (2014). Microservices: a definition of this new architectural term. Retrieved from:.

Zitzler, E., Laumanns, M., and Thiele, L. (2001). Spea2: Improving the strength pareto evolutionary algorithm. *TIK-report*, 103.

Zitzler, E. and Thiele, L. (1999). Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach. *IEEE transactions on Evolutionary Computation*, 3(4):257–271.