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THE INTERSECTION OF AGENT BASED MODELS AND FUZZY COGNITIVE MAPS: A REVIEW OF AN EMERGING HYBRID MODELING PRACTICE

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ABSTRACT

Agent Based Modeling (ABMs) and Fuzzy Cognitive Mapping (FCM) are complementary modeling techniques: the former represents interacting agents across a landscape over time but does not specify how to encapsulate subjective behaviors in agents, whereas the latter can model a subjective behavior but lacks the ability to scale it to a population or do it over time. These techniques are increasingly used together, particularly as hybrid models. We propose the first review of this emerging practice and identified 31 articles that combined the two techniques. Our analysis revealed three different high-level architectures to structure the combined use of ABMs and FCMs, such as using an interface or embedding an FCM into each agent. Our review provides a snapshot of an emerging field, thus assembling the evidence-base to identify potential areas for future work, such as consolidating and standardizing software development efforts in a currently fragmented field.

1 INTRODUCTION

Agent Based Modelling (ABM) has a rich history in representing complex interactions between multiple entities (known as "agents") and their environment. This individual-based model technique is particularly convenient to simulate a population with heterogeneous features, such as when agents need to be equipped with diverse income levels or age to match a target population. Decades of research have also resulted in a host of advanced features, such as detailed protocols for interactions (e.g., Agent Communications Language), hardware accelerators for computationally expensive ABMs (Xiao et al. 2019), and cognitive architectures such as belief-desire-intention (Ye et al. 2018) to specify an agent's decision-making process.

While ABM *can* represent heterogeneous decision-making processes to capture how agents might think differently, an ongoing challenge is to do it in a *transparent and systematic* manner. This is essential for applications such as participatory modeling (PM) in which stakeholders are involved in developing explicit, shared models. As recently stated by a large group of practitioners in PM, *"representing ideas through models affords individuals a structured means of explaining not only how we think about the world but also how we make decisions."* (Jordan et al. 2018). For instance, explicitly developing a model allows one to compare the perspectives that different groups of stakeholders (e.g., fishermen, ecological experts, managers) hold regarding a complex system such as the dynamics of a fish population in a lake (Lavin et al. 2018). Stakeholders are familiar with a problem-space, but not necessarily with advanced modeling techniques. Externalizing their perspectives through sophisticated cognitive architectures in an ABM may present a technical barrier, thus making it less evident that the simulated actions of virtual agents are the consequence of the ideas held by the stakeholders. There is thus a gap between the transparent and standardized ways in which stakeholders model their understanding of the problem-space, such as using maps (Giabbanelli et al. 2019), and the way those maps are represented using Agent-Based Models.

The aggregate-level simulation technique of Fuzzy Cognitive Maps (FCMs) faces the opposite problem. This technique is commonly employed in participatory modelling (Voinov et al. 2018) as a wealth of reviews document its easy-of-use by stakeholders (Jetter 2006; Papageorgiou 2013). Rooted in soft computing, Fuzzy Cognitive Mapping allows stakeholders to intuitively represent vagueness (e.g., a factor has a "very strong" impact onto another), can incorporate data through learning algorithms (Papageorgiou 2013), and can be built from text (Alibage et al. 2018; Alizadeh and Jetter 2017) such as transcripts of a stakeholder's interview (Pillutla and Giabbanelli 2019). While FCMs can thus provide a transparent and systematic approach to externalizing how stakeholders make decisions, they lack the expressive power of individual-level techniques such as ABMs: they do not account for dimensions such as space and time, and their focus on *one* model does not specify how individuals would interact. The later was summarized through a metaphor as "the FCM methodology can provide the agents' brains, but brains cannot directly interact: they must be placed insides bodies" (Giabbanelli et al. 2019).

Combining other Modeling and Simulation (M&S) methods with ABM is not new. Several other reviews have been conducted that look at hybrid modeling with other M&S techniques, for example by combining System Dynamics (SD) models into Agents (Swinerd and McNaught 2012) or combining ABM with SD and Discreet Event Simulation (DES) (Borshchev 2013). These reviews are useful in that they show the utility in combining M&S methods, but they do not address the combination of ABM and FCM specifically.

Given the complementarities between FCM and ABM there have been several independent efforts to combine the two methods. These combinations come in very different ways: some are focused on externalizing the mental models of stakeholders and 'plugging' them into the decision-making processes of agents (Giabbanelli et al. 2019), while methods such as Fuzzy Cognitive Agents regulate the interactions of agents through an FCM (Borrie et al. 2006a). Although both ABM and FCM have been the subjects of numerous reviews, there is currently no review covering their intersection. Our work contributes to addressing this knowledge gap by reviewing published articles with a focus on two questions:

- Q1: Why do studies combine ABMs and FCM?
- Q2: Which architectures support the combination of ABMs and FCM?

The remainder of this paper is structured as follows. In section 2, we offer a background on the two modelling techniques of ABM and FCM. Since the Winter Simulation community regularly features work on ABM but fewer articles on FCM, we succinctly cover the former and provide more details on the latter. The methodology of this review is outlined in section 3, providing the steps to find relevant articles, the number of articles retained at each step, and Balaban's Method Formats (MF) on hybrid models. Building on this, section 4 analyzes the final set of articles with respect to our two research questions. Our findings are contextualized and discussed in section 5, and we conclude by summarizing the core implications.

2 BACKGROUND

2.1 Agent Based Models

Agent Based Models (ABMs) are programmatic experiments used to model interactions between individual actors (known as "agents") and their environment. ABMs are written in a variety of programming languages, from non-computer scientist interfaces such as Netlogo (Wilensky 1999) to Java and Python. Regardless of the language used, ABMs consist of an application where a user can define their agents, the landscape in which they live, and the rules that govern their existence and interactions. A well-known example is the Sugarscape where a few simple rules suffice to reproduce many traits of human society which we generally perceive as complex (Epstein and Axtell 1996). ABMs have been used for modelling a variety of systems across a large range of disciplines from electrical grids (Ringler et al. 2016) to social simulation (Conte et al. 2001; Gilbert 2008). Part of the power of ABMs is the ability to gain understanding of complex phenomena by breaking them down into simple rules to examine their fundamentals. This leads to the concept of *emergence* (Goldstein 1999), where macro-level patterns emerge through the micro-level interaction of agents in their environment.

2.2 Fuzzy Cognitive Maps

Similarly to ABM, Fuzzy Cognitive Maps (FCMs) have a history spanning several decades since their introduction in (Kosko 1986). They have been used in application contexts as varied as wind energy deployment (Amer et al. 2011), fishery management (Lavin et al. 2018), or engineering and technology management (Jetter 2006). Many reviews of FCMs highlight that the technique's popularity for aggregate modeling owns to its relative simplicity while retaining predictability (Glykas 2010; Papageorgiou et al. 2013; Papageorgiou 2013; Jetter and Kok 2014; Felix et al. 2017).

The typical elicitation of an FCM from a participant focuses on listing relevant factors (i.e. nodes), identifying which ones have an effect on others (i.e. directed edges), and categorizing the strength of these effects using linguistic variables such as 'very strong' or 'medium' (which are turned into numerical edge weights via fuzzy logic). The use of fuzzy constructs such as 'medium' contributes to positioning FCM as a suitable approach for modeling human decision making in the presence of vagueness. In other words, fuzzy constructs allow FCMs to reflect human perspective based on an uncertain context (Papageorgiou et al. 2017). This elicitation process is relatively intuitive as it requires neither modeling expertise nor hard data, particularly in comparison with other aggregate approaches such as System Dynamics. The process also limits the capabilities of an FCM: since participants are not asked to specify the temporal aspect of a model (e.g., time scales associated with edges or the presence of delays), an FCM cannot predict when specific outcomes are obtained, unlike a System Dynamics model. However, an FCM retains some predictive abilities, which places it in the class of computational models rather than conceptual models such as causal loop diagrams or mind maps (Voinov et al. 2018). In an FCM, dynamics are computed by updating the value of each node based on connected nodes and the strength of these connections. In other words, a factor's level can change across iterations based on the level of factors that influence it, mediated by the strength of the influences. Given the absence of a temporal dimension, an FCM does not typically perform updates for a set number of iterations, unlike an ABM which may run for 52 steps because each represents a week and the model has a horizon of one year. An FCM thus updates the values of nodes until a subset of them (designated as model outputs) stabilizes, that is, converges to a fixed point. This convergence may not be guaranteed depending on the update function chosen for an FCM, as some produce a unique fixed point while others allow for a limit cycle or chaotic attractor (Knight et al. 2014).

3 RESEARCH METHODS

We performed our search using Google Scholar in April 2019, without restricting the start date. Our initial results using "ABM" AND "FCM" as search terms were not satisfactory, as many publications use these acronyms with different meanings. We ensured that acronyms were used within the right application context by adding search terms: "ABM" AND "FCM" AND "fuzzy" AND "agent". This approach yielded 103 publications. We read each publication to ensure that it satisfied at least *one out of two* criteria, or it was removed from the results. Both criteria target publications that do not only *mention* ABM and FCM but *use* both. Such publications are the crux of the present review given our focus on combining these techniques.

The first criterion was to use ABM and FCM in creating a single model. This can lead to a tight integration of both techniques. Studies that did not meet this criterion included cases that mentioned the two methodologies without using both (Murungweni et al. 2011; Ghaderi et al. 2012; Dejam 2015), and a few studies that compared rather than integrated the two methodologies (Wildenberg et al. 2010; Gray et al. 2018). Studies that did not pass this criterion of a hybrid model were included if they satisfied the second criterion.

The second criterion for inclusion in this review is to use FCM to define some "agents" without having to incorporate them as part of an ABM (e.g., with social and/or environmental interactions). Although publications in this category do not explicitly involve both methods, the agents created through the FCM *could* have been added in an ABM as a minor extension. Such publications are thus relevant to assess possible uses of FCMs in respect with ABMs moving forward.

Given our two criteria, we specifically seek studies in *hybrid simulation*. As defined by Mustafee and Powell, these are studies in which two or more techniques are applied at the stages of model development or implementation (Mustafee and Powell 2018). It differs from the broader notion *of hybrid systems modeling*, in which various techniques may be used for conceptual modeling, validation, verification, or experimentation.

Finally, we categorize the results into the Method Formats (MF) proposed by (Balaban 2014) to relate these hybrid techniques back to the M&S literature. Although Balaban did not specifically include FCMs in his analysis, three of the six MFs that are proposed to generalize mixed-methods modelling pertain directly to the way FCM and ABM have been combined in the papers that we identified. Consequently, our findings will identify the specific MF to which each combination belongs.

4 RESULTS

4.1 Overview

The search process summarized in section 3 resulted in 31 publications. Although several themes appear across this corpus, our review focuses on *how* ABM and FCM are combined rather than whether some combinations are more prevalent in some fields or for some research groups. By dividing the corpus with respect to how the combination was operated, we assigned each of the 31 publications to one of two non-overlapping groups:

1. Works combining FCM and ABM. This is done *explicitly* in a group which we label "ABM+FCM" (n=16). It is done implicitly when authors use FCMs to design interacting agents (known as Fuzzy Cognitive Agents or "FCA") showing emergence but do not explicitly call out the use of ABM (n=11).
2. Other publications using ABM and FCM together in a novel way (n=4).

Figure 1 summarizes the results broken down by group, and over time. Besides a single paper in 1995, we observe that research in this area started in the mid 2000's and has increased going into 2010's.

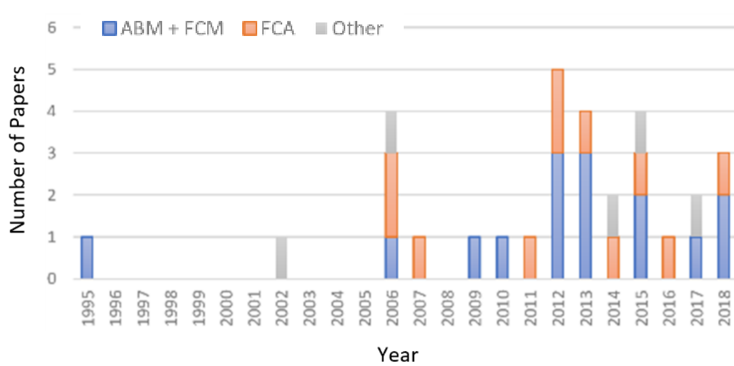

Figure 1: Number of selected publications, per group and over time.

The next subsection focuses on works combining FCM and ABM, which are organized into three categories based on how the hybrid is designed. The relation with Balaban's Method Format (MF) is highlighted in each category. We then briefly discuss the other publications and their unique take on the hybridization.

4.2 Group 1: ABM + FCM

Of all the papers we reviewed there were only 16 which truly combined and explicitly recognized the two methodologies, including a sufficient description of the approach taken and/or or results that reflected the strength of jointly using ABM and FCM.

Giabbanelli and colleagues gave two high-level ways to combine FCM and ABM (Giabbanelli et al. 2017): either as micro to macro, where FCMs are used as agents in an ABM (Figure 2 – Method A); or as macro to micro, which uses FCM to set the context of one or multiple ABMs (Figure 2 – Method B). A third way is evoked but not formally specified: the emergent values from agent interactions can be used to build an FCM (Figure 2 – Method C). We will refer to methods A, B, and C throughout this subsection. Intuitively, we can also think of them as "FCMs in an ABM" (Method A), "ABMs in an FCM" (Method B), or "FCM via ABM" (method C).

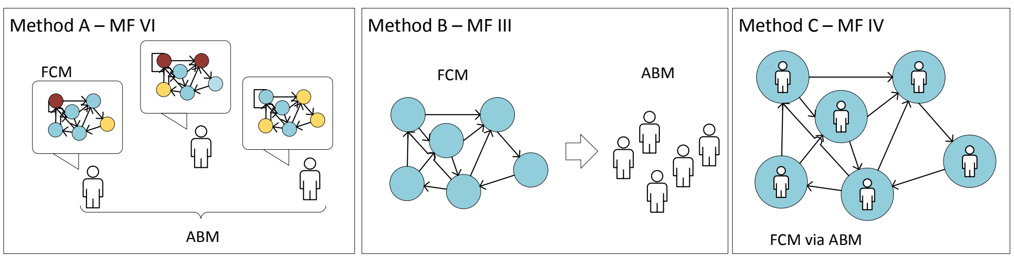

Figure 2. Potential combinations of FCM and ABM. Adapted from (Giabbanelli 2017) with added MF categorization (Balaban 2015).

4.2.1 Method A: Micro to Macro

Method A is by far the most popular approach in combining ABM and FCM, as several articles use FCM as decision models for agents. This is in line with MF VI, where one method is enclosed in another method (Balaban 2015). In this case FCM is enclosed in ABM, as the "brains" of the agents in the larger model.

The Method A approach is often driven by studies of decision-making through the lens of evolution in artificial life. In several articles, FCM serves to structure the decision-making process of agents in a predatory-prey ABM. Gras and colleagues created a model were predators and preys have their own FCMs, and can pass it to their offspring based on an evolutionary process (Gras et al. 2009). The second example builds on this research, where agents are given a genetic makeup represented by an FCM and the evolution is observed over time (Khater et al. 2012). The model of Khater and colleagues is called 'ecological simulations' (EcoSim). Finally Nachazel uses similar techniques, but replaces parts of the FCM in the agents with analytic hierarchy process (AHP) based models which are faster to execute (Nacházel 2015).

The next logical grouping of studies uses Method A in the context of social study. Several of these works articulate the case for representing mental models as FCM and leveraging them to program agents of an ABM. However, such models are not always created as part of the study. Ortolani *et. al* discussed the potential of combining FCM with ABM extensively in their analysis of farming policy in the EU (Ortolani 2010). The authors' contribution is primarily to outline the appeal of the method for future studies in policy analysis. Jackson followed a similar outline (Jackson 2013) by suggesting that the behavior of crowds can be modeled by equipping individuals with FCMs that interact through cellular automata (which is functionally equivalent to an ABM in this study). Similarly, several parts of (Giabbanelli 2014) conceptualized how FCMs could provide the 'brains' of agents representing people or places in an insurgency, but the study did not proceed to the simulation and experimentation stages.

While these three studies explain potential applications, the most detailed technical paper in this group studies the negotiation of ticket prices using FCM models in the context of an ABM (Lee et al. 2012b). The authors designed and implemented a framework for negotiation, which they called Multi-Agent based Mobile Negotiation Framework (MAMON). In this location-based negotiation framework, agents represent buyers and sellers (each with their own FCM-based mental model) and their interactions go through a coordinator agent serving as a broker. Simulations performed using NetLogo track the benefits of the buyer and seller agents, and the emergent behavior (across agents) serves to validate the ticket selling framework.

Although most studies were devoted to evolution in artificial life and social science, questions arising in other fields also motivated the development of a hybrid FCM-ABM with method A. Giabbanelli combined FCMs with complex networks (as simplified ABMs) to study health behaviors (Giabbanelli 2014). This study is closer to the work of Lee *et al.* in terms of touching on many stages of modeling and simulation, since Giabbanelli and colleagues also presented and implemented a framework which serves to generate simulation results. The final field represented is socio-ecological management. One study combined FCMs with ABM to better capture human decision-making activities as they shape socio-ecological systems (Elsawah et al. 2015).

As aforementioned, some publications served as position papers detailing *why* a combination should be done (Ortolani et al. 2010; Jackson 2013), others explained *how* to do it only in algorithmic terms (Gras et al. 2009; Giabbanelli 2014), and three discussed the implementation. Given that ABM and FCM are ultimately executed through software, researchers have important architectural choices to make in an implementation that combines them. One paper was noteworthy in detailing the process through a framework called ICTAM (Interviews, Cognitive mapping, Time sequence UML, All-encompassing framework, and numerical agent-based Models), shown in Figure 3 (Elsawah et al. 2015). An FCM is first constructed, then turned into a UML diagram or pseudocode, and finally implemented in an ABM program such as NetLogo. The authors give a concrete case and walk the reader through the entire process, including code examples.

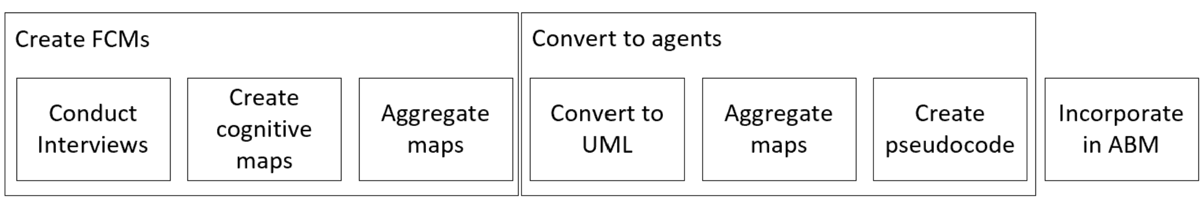

Figure 3: ICTAM methodology (Elsawah et al. 2015).

A more implicit type of hybrid models is provided by Fuzzy Cognitive Agents (FCA), which are designed to be used as autonomous agents that interact in an ABM. For example, an FCM would be used to define an AI-based agent or set of agents, and those agents are then used as building blocks in a larger simulation. The key idea of FCAs is that an agent interacts with other agents in an environment and the basis of the interaction is defined with FCM. While this is another example of method A (Figure 2), authors using FCA have *explicitly* recognized FCM based agents as FCAs and hence we examined their work separately.

Borrie and colleagues introduced FCAs in 2006 (Borrie et al. 2006a). FCAs typically use Method A, and can be applied to many problems from making software more adaptable in the face of poor or lacking requirements (Sinha et al. 2016), to estimating software development costs (Kazemifard et al. 2011), to exploring change management in product development (Beroule et al. 2014). One particularly detailed study using FCAs in Method A is the APIC platform (Agents for Product Integrated Communication) by Ostrosi *et al.*, which uses multiple levels of Fuzzy agents to form "communities" based on expert feedback

(Ostrosi et al. 2012). Another example, with details on the architecture, includes the work of Borrie *et al.* following on their introduction of FCAs (Borrie et al. 2007). In this follow-up, the authors modeled electrical resource trading by defining agents in MATLAB, then used a commercial ABM software (JACK) to program their agents to work in an ABM (Borrie et al. 2006b). Their examples include methodology and code similar to the article by Elsawah *et al*. While FCAs typically employ Method A, they occasionally use Method B (discussed in the next subsection), for instance to model the spread of the Human Immunodeficiency Virus (HIV) across injection drug users (Mago et al. 2012).

Fougères *et al.* have provided several works on the methodology of FCAs. In their 2013 article, they reflected on what a fuzzy agent is and why it is relevant (Fougères et al. 2013). This article includes a pseudocode representation of the behavioral functions of a fuzzy agent, which can help researchers envision a system but does not detail which software solutions or implementations to use. Later works describe not only the methodology but also results in a product configuration example (Beroule et al. 2015) and again in the context of product design by an autonomous manufacturing team (Ostrosi et al. 2018). In the former, the authors create FCM-based agents that interact across different ‘communities’ representing different mind frames or sets of FCMs. In the latter, the authors focus on autonomous interdisciplinary teams whose interactions between members are modelled via fuzzy agents. Fougeres’ recent work in the space of intelligent agents includes testing the concept of ‘quantum agents’, that is, agents that make decisions based on quantum computing theory (Fougères et al. 2016).

4.2.2 Method B: Macro to Micro

The next two studies keep the ABM and FCM systems separate, allowing them to communicate through a software interface as shown in Figure 4. This is in line with MF III, where different methods are used in a two-step methodology (Balaban 2015). The first of these studies calls their architecture Fuzzy Agent Based Modelling (FABM) (Raoufi and Robertson2018). The authors seek to overcome the limitations of only using ABM to measure construction crew performance and motivation. FCM serves to equip agents with human-like subjective and behavioral rules in their interactions. This system uses a polyglot (i.e. multiple programming languages) architecture: the ABM system is built in AnyLogic, which runs on Java; the FCM-based agents are built with MATLAB; and AnyLogic provides the interface. The second paper with a similar architecture comes from the FP7 FUPOL Project (Aizstrauts et al. 2013), whose goal is to model complex outcomes in policy science (Ginters et al. 2013). The macro architecture is the same as Figure 4, but they use a service bus between the fuzzy platform (where agents are defined) and their modelling platform (which runs the simulations).

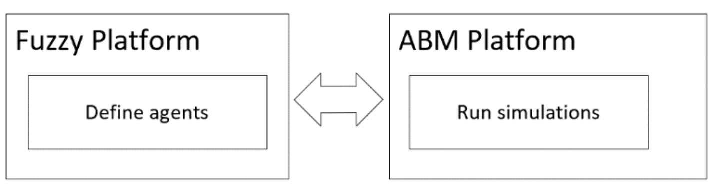

Figure 4: Generalized integration approach.

The final paper in this section is a capstone project that details a Java based system for ABM and proposes extensions to support FCM-based agents (Bahri 2018). This essentially would be a fully integrated system, where FCMs and ABMs can be defined together within the same Java based framework.

While papers in category A focus on the fusion of FCM and ABM, papers in category B (Aizstrauts et al. 2013; Raoufi and Robinson 2018; Elsawah et al. 2015) clearly separate FCM and ABM (Figures 3-4). They first define the macro model with their FCM, then use those results to inform the micro-ABM models.

4.2.3 Method C – Optimizing FCM with ABM

As explained in subsection 4.2.1, method A ("FCMs in an ABM") is an intuitive approach to making agents more lifelike by giving them decision-making models that can include loops and uncertainty. Method C is the opposite: the agents are used to define and optimize FCMs. This is in line with MF IV, where data is exchanged between models, and the output of one affects the other (Balaban 2015). Our review identified only three studies employing method C. In one study ABMs are used to optimize FCMs using a methodology called Multiple Agent-based Knowledge Integration Mechanism (MAKIM) (Lee et al. 2012a). The method uses ABM through Particle Swarm Optimization (PSO) (Kennedy 1995) to optimize an FCM. The FCM is first created through expert interviews (as is most common), then the authors break its components down into agents. Lastly, these agents participate in PSO: the particles/agents interact with each other by moving towards locations in their environment where they can achieve the best personal fitness and thus the best causal relationship values for the FCM. If there is a location that can improve their fitness they continue, otherwise they stop moving around.

In a follow up study, the same team used a framework they called MACOM, which used FCM to model industrial marketing plans and ABM to hone their FCMs over simulated time. The authors observed that industrial marketing planning could be modeled using FCM, but the models needed to account for dynamic relationships as they change over time. Lee et al created a more accurate model by using an FCM to define the decision making process, and run the interaction of nodes through an ABM (defined in NetLogo) to add the dimension of time (Lee et al. 2013). The authors introduced the concept of a coordinator agent that manages time and sets up the simulation for each node agent which represents a node in the FCM.

4.3 Group 2 - Other Related Work

Finally, several papers display a unique way of thinking about the intersection of these ABM and FCM, thus paving the way for innovative and relatively under-explored areas of research going forward.

A few of these studies apply FCM to create intelligent agents that interact with other entities in real or virtual systems. These range from bots used in ecommerce (Miao et al. 2002), to FCMs for agents in shared virtual worlds (Leong 2005), to individual robots in a swarm robotic system (Mendonça et al. 2017). The latter calls their system Dynamic FCM (DFCM) and observes the emergence of behavioral patterns among robots without using the framework of an ABM. While the authors do not go in depth on the techniques underlying the design and implementation of their system, the reader can get a glance at the mechanics through detailed data collected from their study.

Fogel argued that (emphasis added) *"for an organism, or any system, to be intelligent, it must make decisions [and] without the existence of a goal, decision making is pointless"* (Fogel 2006). Leong *et al.* echoed this observation noticing that, while goal variables can be identified in an FCM (e.g., using them as sinks from which no causal edges leave), there may be a need to define a system-wide goal or paradigm. This was particularly important in the authors' context of a virtual environment, as Non-Playable Characters of massive multiplayer online games (MMOG) must feature goal-oriented behaviors. The authors propose Fuzzy Cognitive Goal Nets (FCGN) to model the goals of the agent rather than letting emergence occur. The influence of this paper on the field is perhaps more at the conceptual level, since the authors exemplify the idea but provide neither code nor the use of an ABM software for testing.

In a completely different vein, (Karavas et al. 2015) uses FCMs to define agents in a closed system. Their energy management system consists of different agent-based components that use FCMs for flexible computational processing. While the study does not have emergence (normally produced by an ABM), it does use FCM-based agents interacting in a system. The authors' implementation relies on MATLAB.

5 DISCUSSION

A panel at the 2018 Winter Simulation Conference recently explored hybrid simulation (Eldabi et al. 2018) as it pertains to three common approaches (discrete event simulation, system dynamics, agent based model) and their four possible combinations (DES+SD, DES+ABM, SD+ABM, DES+SD+ABM). The combination of these four methods is also well documented in previous research (Chahal 2010; Borshchev 2013; Balaban 2015). Although Fuzzy Cognitive Mapping is an established tool for participatory modeling as documented in many reviews (Jetter 2006; Glykas 2010; Papageorgiou 2013; Felix et al. 2017), its absence from recent conversations on hybrid simulations may be explained by the relative paucity of works using FCM at the Winter Simulation Conference (Lavin et al. 2018) and the relatively recent interest in hybrid models employing FCM. Our review aims to address this gap by specifically investigating the intersection between ABM and FCM.

We have found that researchers combine FCM and ABM for several reasons. Firstly, FCM creates much better transparency into the cognitive model of an Agent in ABMs, and researchers have enclosed FCMs into ABMs in line with hybrid modeling MF VI. FCMs are also used to inform the creation of ABMs in line with MF III, where one methodology is used to inform another. Finally, we see FCM and ABM being used together in a data exchange between models as detailed in MF IV.

Our study is the first to review why previous works combine ABM with FCM and what types of architectures support their combination. From a search performed in April 2019, and without restricting the start date, we have found 31 publications which we organized depending on how FCM and ABM were used. The most prominent architecture was the use of FCMs as the "brains" of agents in ABMs where they can interact with each other and their environment. We noted that ABMs and FCMs can be found in many areas of research, with examples ranging from socio-environmental management to social studies and industrial applications.

Although Google Scholar is noted for being able to tap into the "grey literature", our study is limited using a single search engine and language (English). Publications in other languages or that are not indexed via Google Scholar may still be relevant to studying the confluence of ABM and FCM. In addition, we used a target set of search terms to find research where authors articulated the use of FCM and ABM. There may be articles in which the work is *functionally* equivalent to FCM and ABM without being named this way.

Our review revealed that researchers wishing to use ABM and FCM together will face a lack of software support. Many publications are position papers, and others do not detail or provide access to their implementation. This issue may be partially alleviated as we observe (Giabbanelli et al. 2019) newer works which offer an open-access implementation, but they have not been applied to sizeable projects or subjected to extensive usability testing. The technical complexity for combining ABM and FCM thus remains one of the key obstacles in the field. Combining the various open-source FCM and ABM programs to create a holistic tool could be a useful option to facilitate the integration of FCM and ABM going forward.

6 CONCLUSION

We have provided the first review of Fuzzy Cognitive Mapping and Agent-Based Modelling, demonstrating that using them together can create richer simulations of complex and fuzzy scenarios across a variety of disciplines. The ability for FCMs to represent loops and uncertainty in human decision-making helps create richer agents in ABM, while the ability to simulate dynamics through space and time adds useful dimensions with which to hone FCMs. Our work identified three major groups in previous research: papers explicitly combining FCM and ABM, research focused on Fuzzy Cognitive Agents, and works making an innovative use of one while alluding to the other.

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