ISSN 2658-5014 (Print)
2021. Т. 3, № 3 (7). С. 5–16
СИИТ
СИСТЕМНАЯ ИНЖЕНЕРИЯ И ИНФОРМАЦИОННЫЕ ТЕХНОЛОГИИ
ISSN 2686-7044 (Online)
http://siit.ugatu.su

УДК 578.834

FUZZY COGNITIVE MAPS: A NEW MODELLING APPROACH IN TACKLING COVID-19

PETER P. GROUMPOS

groumpos@ece.upatras.gr

University of Patras, Greece

Поступила в редакцию 13 сентября 2021 г.

Abstract. Coronavirus disease, first detected in late 2019 the COVID-19 pandemic has considerably affected lives of all people around the globe. The health discipline has been using extensively mathematical models to address difficult medical problems. Mathematical models cannot be useful to anyone without specific theories. The crucial and important difference between correlation and causation is analyzed and discussed. There is uncertainty and ambiguity on several aspects of the COVID-19 pandemic. The symptoms are many and vary from person to person and from geographical region to geographical region. Challenging issues of the COVID-19 pandemic are analyzed. Recently new mutations of COVID-19 have shown us how rapidly a new disease can take new roots and spread. Such events are accompanied by an explosion of clinical and epidemiological information and research. Billions of data are provided every day. Many theories are summoned to battle COVID-19 especially artificial intelligence (AI). Most techniques that are being used in the detection, diagnosis and epidemiological predictions, forecasting and social control for combating COVID-19 are using statistical theories and the correlation coefficient. The recent theories of Fuzzy Cognitive Maps (FCM) are used to model and study COVID-19. Simulation results using real data are provided and discussed. The use of Fuzzy Cognitive Maps (FCM) prove to be an effective and useful approach in studying COVID-19. Many future research directions are highlighted with concrete applications of FCM in tackling COVID-19.

Key words: COVID-19; pandemic; correlation; ausation, artificial intelligence (AI); fuzzy logic; fuzzy cognitive maps; biomedical informatics.

INTRODUCTION

Coronavirus disease, the COVID-19 pandemic, has spread fast throughout the world since its appear late in 2019 [1–3]. It has considerably affected lives of all people around the globe and the number of deaths related to the pandemic keeps increasing worldwide. With some delay the World Health Organization accepted on March 11th, COVID-19 as a world pandemic disease [4]. The coronavirus disease (COVID-19) has created tremendous chaos around the world, affecting people's lives and causing a large number of deaths [5–9]. The deadly coronavirus continues to spread across the globe with mutations, [10, 11] and especially the latest one of DELTA to complicate the pandemic problem even more [12, 13]. Medical doctors and Researchers still do not know many issues regarding COVID-19. Thus they have turned to mathematical models [14, 15].

A mathematical model is an abstract model that uses mathematical language to describe the behavior of a system. Mathematical models are used particularly in the natural sciences and engineering disciplines (such as physics, biology, and electrical engineering) but also in the social sciences (such as economics, sociology and political science); physicists, engineers, computer scientists, and economists use mathematical models most extensively. The last couple of decades the health discipline has been using extensively mathematical models. Mathematical models can take many forms, including but not limited to dynamical systems, statistical models, differential equations, or game theoretic models. However mathematical models cannot be useful to anyone without a specific theory.

Research in tackling COVID-19 with scientific methods have been reported by the thousands the last 18 months. However, all reported research is centered around Artificial Intelligence (AI) [16–18]. Reference [18] has more than 650 references most of them using AI. In this paper an effort is made to address the modelling of COVID-19 using the very new scientific approach of Fuzzy Cognitive Maps (FCM), [19–21]. With the progress of the pandemic and rising number of the confirmed cases and patients who experience severe respiratory failure and cardiovascular complications, there are solid reasons to be tremendously concerned about the consequences of this viral infection [22]. An early report [57], provided some interesting and useful information about COVID-19 with clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus – infected pneumonia in Wuhan, China.

Determining appropriate approaches to reach solutions for the COVID-19 related problems have received a great deal of attention. From the outbreak of the COVID-19 pandemic, many scientists but primarily physicians look upon different scientific areas searching for promising approaches to investigate all aspects of COVID-19. We have just started this difficult health journey. The generation of a large volume of data, known as Big Data Driven World (BDDW) is a fact that complicates even further the problem in finding solutions in the process on fighting the pandemic. However, this BDDW of COVID-19 provides an excellent opportunity to health physicians and scientists to search solutions based on theories of Artificial Intelligence (AI) [16, 17]. Methods that use correlation as the basis for hypothesis tests for causality, including the Granger causality test and convergent cross mapping have been used extensively in the past [23]. However, the results are not satisfactory since it uses only statistical methods. This brings up the serious problem of confusing statistical correlation and causal relationship between variables and especially in the case of medical problems. Correlation does not imply causation; even though the research question at hand involves causality. A mathematical model that provides information on the causality of a dynamic complex system is the Fuzzy Cognitive Map (FCM) [19–21]. Thus, FCM is proposed in this study for the first time to model the early stages of patients with COVID-19 without using statistical models or probability density function. This paper is outline as follows after the introductory remarks on this section. In section 2 the important difference of correlation vs causation is presented and their importance in studying health care systems is outlined. Section 3 presents a short but informative mathematical description of the new scientific approach of Fuzzy Cognitive Maps (FCM). In section 4 the difficult problem of mathematical modelling of COVID-19 using FCM is provided while section 5 presents simulation studies and the obtained very encouraging results. Finally, section 6 draws the conclusions of the study and utlines a number of promising future research directions.

CORRELATION VS CAUSATION: WHY ARE THEY IMPORTANT IN HEALTH CARE SYSTEMS?

In order to better appreciate the usefulness of the new FCM methodology, in modelling health problems there is a need to clarify the difference between correlation and causality or also known as causation by Rohrer in a 2018 paper [24]. Without this clarification which will hopefully be done so thoroughly in this paper, for the first time for medical problems, it would not be clear why the FCM approach is not another statistical method. Why do we need to explore further and deeper the new scientific area of Fuzzy Cognitive Maps (FCMs)? Well, all this is important because of causation!! Which is confused with correlation!! Do causes have to precede their effects? Can causation be reduced mainly to the forces of physics? Do causes always produce their effects by guaranteeing them? Is causation related to correlation? Does causation depend solely on data? What is the integral role of correlation or causation that play in physics, biology, law, technology and science, geosciences and economics? These are only a small set of the many questions of correlation and causation that must be taking into consideration when medical problems are investigated. But, let us start with correlation which has been around many-many years before causation entered the scientific world. Correlation is any statistical relationship, whether causal or not, between two random variables or bivariate data. In the broadest sense, correlation is any statistical association, though it commonly refers to the degree to which a pair of variables are linearly related. In 1885, Sir Francis Galton first defined the term "regression" and completed the theory of bivariate correlation. Formally, random variables are dependent if they do not satisfy a mathematical property of probabilistic independence. In informal parlance, correlation is synonymous with dependence. However, when used in a technical sense, correlation refers to any of several specific types of mathematical operations between the tested variables and their respective expected values. In simple terms, correlation is the measure of how two or more dependent random variables are related to each other. There are several correlation coefficients, thirteen different ways to look at it is provided in reference [25]. In 1895, Karl Pearson developed the index that we still use to measure correlation, Pearson's r. Today the most familiar measure of dependence between two random quantities is the Pearson product-moment correlation coefficient (PPMCC), or "Pearson's correlation coefficient", commonly called simply "the correlation coefficient". Mathematically, it is defined as the quality of least squares fitting to the original data. It is obtained by taking the ratio of the covariance of the two variables in question of our numerical dataset, normalized to the square root of their variances. Mathematically, one simply divides the covariance of the two variables by the product of their standard deviations [26, 27, 58]. Correlations are useful because they can indicate a predictive relationship that can be exploited in practice. For example, an electrical utility may produce less power on a mild day based on the correlation between electricity demand and weather. In this example, there is a causal relationship, because extreme weather causes people to use more electricity for heating or cooling. In another example from the health science, the increase of the body weight of a person is related to drinking, eating and smoking. A person that is drinking, eating and smoking a lot usually gains a lot of weight. Furthermore, this body weight increase causes a number of health problems to the individual. Physicians and scientist believe that drinking especially alcohol, eating and smoking a lot is the cause for a number of medical problems of the individual. For example, the excessive smoking is the cause for developing lung cancer. Or eating a lot of meat is the cause for cancer of the large intestine or colon. Nevertheless, there is a correlation between drinking, eating and smoking (regardless little or a lot). However, in general, the presence of a correlation is not sufficient to infer the presence of a causal relationship thus, correlation does not imply causation-causality. Yet, conflating the two remains one of the most common errors in news reporting on scientific and health-related studies. This is especially the case for the COVID-19 pandemic. In theory, these are easy to distinguish – an action or occurrence can cause another (such as smoking causes lung cancer), or it can correlate with another (such as smoking is correlated with high alcohol consumption or drinking a lot of coffee). If one action causes another, then they are most certainly correlated. But just because two things occur together does not mean that one caused the other, even if it seems to make sense. However, causality always implies correlation while the reverse is not true. Correlations are useful because they can indicate a predictive relationship that can be exploited in practice [13, 58]. On the other hand, causation is a core area mainly of philosophy and one of the most fundamental connections in the universe! Without it, there is no moral responsibility: none of our thoughts would be connected with our actions and none of our actions with any consequences. Nor would we have a system of laws because blame resides only in someone having caused injury or damage. There would be no science and technology. Any intervention we make in the world around us is premised on there being causal connections that are to at least a degree predictable. It is causation that is the basis of this prediction and also of explanation. Causality (also referred to as causation, or cause and effect) is efficacy, by which one event, process or state, a cause, contributes to the production of another event, process or state, an effect, where the cause is partly responsible for the effect, and the effect is partly dependent on the cause. In general, a process has many causes, which are also said to be causal factors for it, and all lie in its past. An effect can in turn be a cause of, or causal factor for, many other effects, which all lie in its future. Some scientists have held that causality is metaphysically prior to notions of time and space. Although causality has appeared as a scientific term and used extensively just in the early 1960s the truth is slightly different. The same holds for the correlation concept. Here are some historical remarks for both correlation and causation. Years before 1885, when Sir Francis Galton first defined the term "regression" and completed the theory of bivariate correlation another British philosopher, John Stuart Mill first presented his "Five Canons of Experimental Inquiry" in 1843. Among those was included the method of concomitant variation: "Whatever phenomenon varies in any manner whenever another phenomenon varies in some particular manner, is either a cause or an effect of that phenomenon, or is connected with it through some fact of causation". Mill, first suggested three prerequisites for valid causal inference [27]. First, the cause must temporally precede the effect. Second, the cause and effect must be related. Third, other plausible explanations must be ruled out. Thus the separability of correlation and causation and the specification of the former as a necessary but not sufficient condition for the latter were being recognized almost simultaneously in the established discipline of philosophy and the fledgling discipline of biometry. By 1885 the stage was set for several important contributions [26]. During that year, Galton was the president of the Anthropological Section of the British Association. In his presidential address, he first referred to regression as an extension of the "law of reversion." a series of concentric and similar ellipses. The term correlation was officially accepted as a scientific statistical term for the first time in 1885 [26]. Nevertheless, the terms causation and causality officially are defined for the first time in the early 1960s.

While causation and correlation can exist at the same time, correlation does not imply causation. Causation explicitly applies to cases where action X causes outcome Y. On the other hand, correlation is simply a relationship. Action X relates to Action Y – but one event doesn't necessarily cause the other event to happen. Correlation and causation are often confused because the human mind likes to find patterns even when they do not exist. We often fabricate these patterns when two variables appear to be so closely associated that one is dependent on the other. That would imply a cause and effect relationship where the dependent event is the result of an independent event. The concept of causation and causality is fully explored and used in developing the scientific field of Fuzzy Cognitive Maps (FCM) [19, 20]. Due to this, the FCM approach is not another statistical method. It is the only scientific approach that tries to better understand and model the dynamic behavior of complex systems taking into consideration the causal phenomena of the system.

THE FUZZY COGNITIVE MAP (FCM) METHODOLOGY

Fuzzy Cognitive Maps (FCM) came as a combination of the methods of fuzzy logic and neural networks and were first introduced by Kosko in 1986 [19]. It is a very new method with less than 40 years of been used for modelling Complex Dynamic Systems (CDSs) with all their characteristics. A detailed presentation of FCM is provided by this author in [20]. This author, as early as 2011, provided in [21], basic theories of FCMs and their applications in many medical problems obtaining very encouraging results. FCM is capable of dealing with complex dynamic systems and is able to examine situations during which the human thinking process involves fuzzy or uncertain environments, using a reasoning process that can deal with uncertainty and ambiguity descriptions [20, 28, 29, 38].

In order to ensure the operation of the system, FCMs embody the accumulated knowledge and experience from experts who know how the system behaves in different circumstances. This knowledge is extracted using linguistic variables which then are transformed to numeric values using a defuzzification method. In other words, they recommend a modeling process consisting of an array of interconnected and interdependent nodes Ci (variables), as well as the relationships between them W (weights). Concepts take values in the interval [0, 1] and weights belong in the interval [–1, 1]. Fig. 1 shows a representative diagram of a FCM.

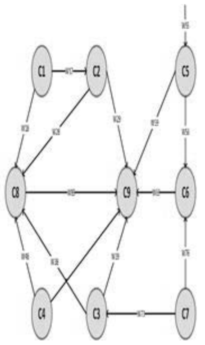

Fig. 1. A simple Fuzzy Cognitive Map (FCM)

The full procedure of the development of a FCM follows the steps below:

Step 1: Experts select the number and the kind of concepts Ci that constitute the Fuzzy Cognitive Map

Step 2: Each expert defines the relationship between the concepts

Step 3: They define the kind and the value of the relationship between the two nodes

Step 4: Experts describe the existing relationship firstly as negative” or “positive” and secondly, as a degree of influence using a linguistic variable, such as “low”, “medium”, “high” etc.

The sign of each weight represents the type of influence between concepts. There are three types of interconnections between two concepts Ci and Cj:

– wij>0, an increase or decrease in Ci causes the same result in concept Cj;

– wij<0, an increase or decrease in Ci causes the opposite result in Cj;

– wij=0, there is no interaction between concepts Ci and Cj.

The degree of influence between the two concepts is indicated by the absolute value of wij. During the simulation the value of each concept is calculated using the following rule:

$$A_i(k+1) = f\left(k_2 A_i(k) + k_1 \sum_{j=1,\, j\neq i}^{N} A_j(k) W_{ji}\right) \quad (1)$$

where N is the number of concepts; Ai(k + 1) is the value of the concept Ci at the iteration step k+1; Aj(k) is the value of the concept Cj at the iteration step k; Wji is the weight of interconnection from concept Cj to concept Ci and f is the sigmoid function. “k1” expresses the influence of the interconnected concepts on the configuration of the new value of the concept Ai and “k2” represents the proportion of the contribution of the previous value of the concept in computing the new value. The sigmoid function f is defined as:

$$f = \frac{1}{1+e^{-\lambda x}}. \quad (2)$$

Where λ>0 determines the steepness of function f. The FCM’s concepts are given some initial values which are then changed depending on the weights; the way the concepts affect each other. The calculations stop when a steady state is achieved, the concepts’ values become stable. A more comprehensive mathematical presentation of FCMs with application to real problems with very useful results is provided in [20, 21]. The NLH learning method has been studied since 2000 and a number of results have addressed this issue [28, 29]. In this learning algorithm the nodes are triggered simultaneously and interact in the same iteration step with their values to be updated through this process of interaction. The algorithm which modifies the initial weights defined by experts is described by the following relationship:

$$w_{ij}^{(k)} = g \cdot w_{ij}^{(k-1)} + h \cdot A_j^{(k-1)} \cdot \left(A_i^{(k-1)} - \mathrm{sgn}(w_{ij}) \cdot w_{ij}^{(k-1)} \cdot A_j^{(k-1)}\right) \quad (3)$$

where, the coefficient g called weight reduction learning parameter and the coefficient h is a very small positive scalar factor also called learning parameter. The “learning parameters” g and h of the above equation are very important and they usually take values between g ∍ [0.9, 1] and h ∍ [0, 0.1].

The weights wij are updated for each iteration step and they are used in equation (1) in order to compute the new values of concepts. Two stopping criteria terminate the procedure. The first one concerns the minimization of function F1 which is the sum of the square differences between each Desired Output Concept i (DOCi) and a target value Ti, which is defined as the mean value of the range of DOCi = [Timin, Timax].

$$F_1 = \sqrt{\sum_{i=1}^{m} (DOC_i - T_i)^2} \quad (4)$$

$$T_i = \frac{T_i^{\min} + T_i^{\max}}{2}. \quad (5)$$

The second criterion is the minimization of the variation of two subsequent values of Desired Output Concepts:

$$F_2 = \left| DOC_i^{(k+1)} - DOC_i^{(k)} \right| \quad (6)$$

when the termination conditions are met the new final weight matrix wij with the docs are returned. more on other drawbacks and proposed solutions of the up today theories of fcms are given in the next section. a more comprehensive mathematical presentation of fcms theories, methods and algorithms is provided in [19, 20], [28–30].

MODELLING COVID-19 WITH FCM METHODOLOGIES

The COVID-19 pandemic has sparked an unprecedented wave of research, data sharing and open science as the scientific world seeks to understand the disease, track its spread and analyze the SARS virus that causes COVID-19 or called more medically correct, SARS-CoV-2. Existing Medical Decision Support Systems (MDSS) methods are complex, difficult and insufficient to address the new emerged pandemic [58]. Mathematical models have drawn from many scientific fields with the Artificial Intelligence (AI) been the one most often been used [36, 37, 42–51, 55]. References [21] and [53] provide an extensive review of using FCMs in medical applications. The pandemic COVID-19 is an acute resolved disease, but it can also be deadly, with a not easily determined case fatality rate. Severe disease onset might result in death due to massive alveolar damage and progressive respiratory failure or due to other chronic diseases of the patient that are been further deteriorating from COVID-19. First, the early and automatic diagnosis of COVID-19 would be extremely beneficial to the patient and his/her relatives. It will also be beneficial to any state and private health system. In addition, it would be beneficial for countries for timely referral of the patient to quarantine, rapid incubation of serious cases in specialized hospitals, and monitoring of the spread of the disease. Although the diagnosis has become a relatively fast process, the financial issues arising from the cost of diagnostic tests concern both states and patients, especially in countries with private health systems, or restricted access health systems due to prohibitive prices. The symptoms reported have been growing since the first detection of COVID-19. These symptoms may appear 3–14 days after exposure. In order to develop an FCM model following the methodology been outlined in section 4 the first step is to determine the number and the kind of concepts Ci that constitute the Fuzzy Cognitive Map (FCM). Not been a physician but an engineer and from today's available literature, talking to MD doctors of the Patras University hospital and other relevant data by official organizations, the following twelve (12) concepts have been selected, see Table 1.

Table 1

Concepts of COVID-19

Concepts and Symptom description
C1: Fever-body temperature
C2: Cough
C3: Shortness of breath-breathing problems
C4: Headache
C5: Persistent pain or pressure in the chest
C6: Bluish lips or face
C7: Feeling weak
C8: heart rate
C9: loosing sense of smell
C10: Diarrhea
C11:Contact with confirmed case
C12: outcome of test: positive or negative

The next steps are:

1. Each expert defines the relationship between the concepts: 1) as "positive" or "negative" or "zero".

2. Their degree of influence using a linguistic variable, such as: “zero-NP” “very low-VL”, “Low-L”, “Medium-M”, “High-H”, “very high-VH”.

3. The FCM schematic diagram is developed similar to fig. 1.

4. The table of weights Wij is determined (same for the Wij).

5. Run simulations with equations 1 and 2.

6. Report the obtained results.

These steps must be further developed to an algorithm. The output concept C12, is referred to as positive if the patient has COVID-19 and negative if the patient does not have COVID-19. Of course, when running the simulations, the positive and negative interpretations will be defined by thresholds been determined by the physicians, as will become obvious in the next section. For this study the physicians agreed to a FCM COVID-19 model.

Important remark: the symptoms of the COVID-19 pandemic are certainly not only the twelve (12) provided in Table 1. Three months after the breakout of COVID-17 this author performed a theoretical study using FCM for the first time, to model the behavior of patient suspected having COBID-19 [31]. Later early in 2021 he also presented results [32], for the same approach using real data from the Patras University Hospital. Both reported studies used 17 symptoms-concepts and all were directly affecting the output concept. In this study 12 symptoms-concepts are used and some of them are affecting some other ones and makes this study the first one for using in a systematic way the FCM approach modelling COVID-19. Present studies carried by the research team of the Laboratory or Automation and Robotics (LAR) of the University of Patras in close collaboration team of the physicians of the Patras University Hospital, includes up to 20 symptoms-concepts such as, inability to communicate with doctor, swelling in the legs, shivering-cold and other relevant variables such as: age, gender, pregnant ladies, overweight patients, some chronic diseases, vaccinated or not and others. These research studies will soon be reported.

SIMULATIONS AND DISUSSION OF RESULTS

Using the Fuzzy Cognitive Map (FCM) methodologies a number of simulations were conducted. An example given here using the following basic assumption for the COVID-19 for running simulation studies based on real data of more than 150 patients.

– NP: Not present=0.0;
– VL: Very low=0.1;
– L: Low =0.3;
– M: Medium=0.5;
– H: High=0.7;
– VH: Very High=0.9.

CASE WITH REAL DATA

Using the above values for 150 patients and having secured enough medical data and in consultation with the physicians, an FCM COVID-19, is developed. Then using fuzzification and defuzzification methods, the weight matrix Wij needed for equation 1 for the FCM COVID-19 model is developed. Each of the weight matrix Wij a 12×12 matrix is determined. Using FCM theories simulations were conducted for all 150 patients. Out of the 150 cases (real data), 4 patients-cases were selected for conducting more extensive simulations, using the FCM methodologies. Table 2 provides the linguistic variables for the 11 concepts for the COVID-19 disease. Simulation results are given in Fig. 2.

Table 2

Linguistic variables for the concepts of COVID-19 for four (4) patients

Concepts	*Case 1*	*Case 2*	*Case 3*	*Case 4*
C1: Fever-body temperature	VH	VH	H	H
C2: Cough	VH	H	M	L
C3: Shortness of breathing problems	VH	H	M	M
C4: Headache	VH	H	VH	H
C5: Persistent pain or pressure in the chest	VH	H	M	L
C6: Bluish lips or face	M	M	NP	NP
C7: Feeling weak	M	NP	M	M
C8: heart rate	M	NP	M	VL
C9: loosing sense of smell	H	NP	H	NP
C10: diarrhea	M	NP	M	NP
C11: contact with confirmed case	H	M	H	NP
C12: Outcome- Positive or negative	?????	?????	?????	?????

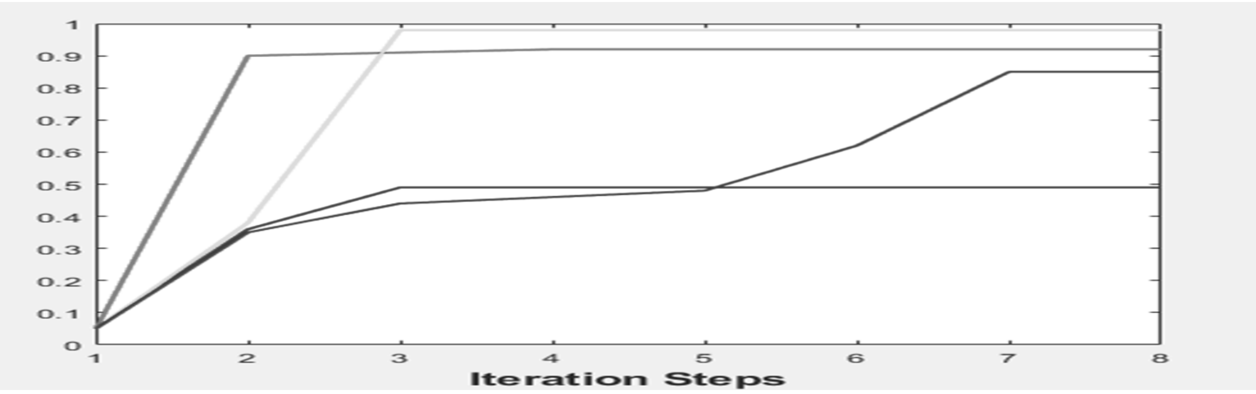

Fig. 2. Simulation results for Concept C12, using real data for the COVID-19 FCM model

DISCUSION OF RESULTS

Simulations were conducted using the classical FCM model, equations 1 and 2 and the FCM software tools been used by the research team of LAR, Univ. of Patras. The simulation results of Fig. 2 confirm the validity of the FCM methodology that provides satisfactory results for modelling COVID-19 with the FCM approach. This study is based on real data from the local Patras University Hospital and simulations for all 150 patients. In this paper using the same values for the linguistic variables, Table 2 provides us the necessary information to conduct simulations for the four cases (out of the 150-total data set). The iteration steps were chosen to be one full day (24 hours). If we want this can be changed and become an iteration step of one hour. This provides us with the capability to attend the health progress of a patient on a continuous basis. Different colors have been used for the outcome of concept C12. The threshold for the outcome concept C12 was set in consultation with the physicians to be 0.5. Below or slightly above it (but to remain constant), the patient was free of COVID-19, while above 0.6 a patient would be with COVID-19. From Fig. 2, the red, green and purple lines are for a patient having COVID-19 while the blue line is for a patient without COVID-19. Analyzing the results of Fig. 2 a number of useful remarks can be made. Please note that the blue line patient 4- case 4, starts with a jump lower to 0.4 after the first day and rises for the next two days to a value around 0.5 and remains constant. For patient 1-case 1, the C10 output, red line, rises with a steep slope and in less than a day reaches a value close to 1 (0.92). This result is considered as a positive result and thus the patient (case 1) is affected with COVID-19. The second case, green line the C10 output concept starts with a steep rise between the first and second day and then in the third day it reaches almost the value of 1 (0.98). Finally, case three (3), the third patient with COVID-19, the purple line follows the blue and the green line till the second day, then slows down between the third and the fifth days and it is below the non-COVID-19 threshold of 0.5. However, after the fifth day, it starts rising again passing the threshold point of 0.5 to reach the value of 0.85 after the seventh (7th) day, thus making patient case 3, also a positive case to COVID-19. These results have attracted the interest of the physicians asking more information for the FCM approach and methodologies. For this particular study of the four case-patients we were 100 % in agreement with the medical outputs. And we say this 100 % agreement since when we selected the four patient-cases we did not know the final condition of the patients after 6–7 days. A closer look at the table 2 with the linguistic variables for the concepts of COVID-19 for four (4) patients and the simulation results of figure 3 clearly show the validity and robustness of the FCM approach in tackling COVID-19. For example, the linguistic values for case 1 are so strong in favor for patient 1 to have the virus. Taking the values for cases 3 and 4, we see that these two cases have similar values. The FCM approach and simulation results of figure 3 also confirm the validity of the proposed use of FCM in tackling COVID-19. From just looking at the data (Table 2) and the simulation results (Fig. 2) if a decision as to if patients 3 and 4 have COVID-19 or not, was taken by a physician at the fourth day bot patients would be label as not having COVID-19. However, the FCM method which is easily can run for as many days as you wish, shows that the patient 3 has COVID-19, since after the 5th day concept C12 jumps and reaches the value of 0.85. This results to the decision that patient 3 also has COVID-19.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This paper has addressed COVID-19 from the mathematical modelling and reviewed the use of the very recent approach of Fuzzy Cognitive Maps (FCM) in tackling challenges of this pandemic. The important difference of correlation vs causation is presented and their importance in studying health care systems is highlighted. It must become very clear that correlation is a statistical measure (expressed as a number) that describes the size and direction of a linear relationship between two or more variables. A correlation between variables, however, does not automatically mean that the change in one variable is the cause of the change in the values of the other variable. Correlation does not imply causation. Causality shows that one variable directly effects a change in the other. This is the main characteristic and powerful tool of Fuzzy Cognitive Maps (FCMs). The COVID-19 pandemic remains one of the most significant crises in modern times. It is a global pandemic affecting all regions of the world, but more severe North America and Europe especially on the early times of the pandemic.

From the outbreak of the COVID-19 pandemic, many scientists but primarily physicians look upon different scientific areas searching for promising approaches to investigate all aspects of COVID-19. Mathematical models have drawn from many scientific fields with the AI been the one most often been used. We have just started this difficult health journey.

Methods that use correlation as the basis for hypothesis tests for causality, including the Granger causality test and convergent cross mapping have been used extensively in the past. However, the results are not satisfactory since it uses statistical methods. A mathematical model that provides information on the causality of a dynamic complex system is the Fuzzy Cognitive Map (FCM) and is proposed in this study for the first time to model the COVID-19 without using statistical models or probability density function. The developed FCM COVID-19 model having 12 symptoms-concepts of COVID-19, has been used with real data from hospitals treating COVID-19 patients. An algorithm is proposed to investigate the problem of determining if a candidate patient is affected or not with the COVID-19 virus. The FCM approach seems to be an appropriate and very useful method in battling COVID-19. The references provided are the more recent ones and are very useful. The excellent results been obtained using FCMs and real data from clinical studies, having satisfying very much medical doctors and physicians have powered this author to dare in addressing further the COVID-19 pandemic using FCM theories.

The future research directions for the COVID-19 pandemic, are wide open. There are many questions related to this pandemic that need to considered and effective and realistic answers are needed immediately. What causes a coronavirus infection? Do humans first get a coronavirus from contact with animals? Then, how can it spread from human to human? How can we predict the spread of the Coronavirus? Do health officials comprehend and understand the COVID-19 pandemic? What are its symptoms? How is diagnosed? Which patients require an Intensive Care Unit (I.C.U.)? How is treated from medical point? Which of today's drugs are most effective? What might be the long-term effects of the disease for the people that recover from the disease and especially those who had severe symptoms and/or had the need of an I.C.U.? What might be the long-term effects of different vaccines? Do we have mathematical models that can address the many aspects of the pandemic and/or follow the patient for 24 hours a day? On a broader sense questions such how is spread throughout the populations? What are the consequences of all restricted measures imposed by governments on the economic and social life of the societies? On the financial markets? On specific industries such as: tourism, agriculture, auto, manufacture, energy, environment and so many other areas?

Therefore, future research directions are many when solutions are searched for all or some of the above questions. This paper is focusing on questions related to the questions if the today's mathematical models are adequate and sufficient to find solutions to this medical problem. In particular, it raises the need to pay more attention on the causality parameters and factors that are associated with all aspects of COVID-19. The use of FCMs which is the only mathematical approach that takes into consideration the causality factor when addressing medical problems and thus also COVID-19 seems to be an open field for future research efforts. This paper clearly demonstrates the FCM's usefulness in studying COVID-19. The proposed COVID-19 FCM model provides a good start for further studies. For example, to develop new models for studying the pandemic taking into consideration all related factors. FCM models can be used to track the patients progress in 24 hours and also to predict long term effects of the disease. In addition, the new state space Advanced FCM (AFCM) been proposed in [33, 34, 44] seem very promising to be applied in tackling problems of COVID-19. Both the Classical FCM and the AFCM approaches depend heavily on experts' knowledge and assistance. The process of experts' assistance plays a very important and crucial role in creating the Fuzzy Cognitive Maps. The physician experts determine the number and weight of each concept depending the individual case. Here the new theories of Big Data Driven World (BDDW) can play a role in determining the concepts of the FCM models, [54]. Another challenging future research direction is the new trend of cognitive modelling and specifically the creating of cognitive semantics that cannot be formalized and has to be taken into account by the indirect way (the inverse problem-solving method on topological space, quantum and relativistic semantics [56]. The book by Raikov [56] is bringing into the pharetra methods οφ the Artificial Intelligence (AI) in tackling COVID-19 problems with a good degree of success [16–18, 35]. These methods mainly are Machine and Deep learning and statistical methods [16–18, 41, 45].

With no dough all of them are promising potential methods to be used in the future research studies for COVID-19. Still the FCM theories hold a special promising opportunity in battling COVID-19.

REFERENCES

1. **World** Health Organization via http2. World Health Organization (2020) // WHO coronavirus disease (COVID19) dashboard. [Electronic resource]. URL: https://covid19.who.int/. (accessed 17 July 2020).

3. **World** Health Statistics 2019. World Health Organization. Geneva, 2019.

4. **WHO**, March 11, "announces COVID-19 outbreak a pandemic". Nature, 2020.

5. **Identifying** SARS-CoV-2-related coronaviruses in Malayan pangolins / T. T-Y. Lam, et al. // Nature. 2020. Vol. 583, no. 7815. Pp.282-285.

6. **Mahdy M. A. A., Younis W., Ewaida Z.** An Overview of SARS-CoV-2 and Animal Infection // Frontiers in Veterinary Science. 2020. Vol. 7. Article number 596391.

7. T**ransmission** of SARS-CoV-2 Lineage B.1.1.7 in England: insights from linking epidemiological and genetic data / E. Volz, et al. // Medrxiv. 2021

8. **Adaptation** of SARS-CoV-2 in BALB/c Mice for Testing Vaccine Efficacy / H. Gu, et al. // Science. 2020. Vol. 369, Iss. 6511. Pp.1603-1607.

9. **Deep** mutational scanning of SARS-CoV-2 receptor binding domain reveals constraints on folding and ACE2 binding / T. N. Starr, et al. // Cell. 2020. Vol. 182, Iss. 5. Pp.1295-1310.

10. **Major** new lineages of SARS-CoV-2 emerge and spread in South Africa during lockdown / H. Tegally, et al. // Medrxiv. 2020.

11. **Introduction** of Brazilian SARS-CoV-2 484K.V2 related variants into the UK / O. T. R. Toovey, et al. // Journal of Infection. 2021. Vol. 82, Iss. 5. Pp. 23-24.

12. **New** delta variant studies show the pandemic is far from over / T. H. Saey, et al. SCIENCE NEWS, 2021.

13. **How** Dangerous Is the Delta Variant (B.1.617.2)? American Society for Microbiology, 2021.

14. **Banks H. T., Tran H. T.** Mathematical and Experimental Modeling of Physical and Biological Processes. Textbooks in Mathematics. 1st Edition. New York: CRC Publication, 2009. 298 p.

15. **Cessenat M.** Mathematical Modelling of Physical Systems. 1st Edition. Springer, 2018. 505 p.

16. **Artificial** Intelligence and COVID-19: Deep Learning Approaches for Diagnosis and Treatment / M. Jamshidi, et al. // IEEE Access. 2020. Vol. 8. Pp. 109581-109595.

17. **Application** of Machine Learn-ing in Diagnosis of COVID-19 Through X-Ray and CT Images: A Scoping Review / H. Mohammad-Rahimi, et al. // Front. Cardiovasc. Med. 2021. Vol. 8. Article number 638011.

18. **Tayarani N. M. H.** Applications of artificial intelligence in battling against covid-19: A literature review // Chaos, Solitons and Fractals. 2021. Vol. 142. Article number 110338.

19. **Kosko B.** Fuzzy cognitive maps // International journal of man-machine studies. 1986. Vol. 24, Iss. 1. Pp. 65-75.

20. **Groumpos P. P.** Fuzzy Cognitive Maps: Basic Theories and Their application to Complex Systems / M. Glykas (ed.) // Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications. Springer, 2010. Vol. 247. Pp. 1-22.

21. **Groumpos P. P.** Fuzzy cognitive maps: basic theories and their applications in medical problems // Proc. 19th Mediter-ranean Conference on Control & Automation (MED). 2011. Pp. 1490-1497.

22. **Cardiovascular** implications of fatal outcomes of patients with coronavirus disease 2019 (COVID-19) / T. Guoet, et al. // JAMA Cardiology. 2020. Vol. 5, no. 7. Pp. 811-818.

23. **Granger C. W. J.** Investigating Causal Relations by Economet-ric Models and Cross-spectral Methods // Econometrica. 1969. Vol. 37, no. 3. Pp. 424-438.

24. **Rohrer J. M.** Thinking Clearly About Correlations and Causa-tion: Graphical Causal Models for Observational Data // Advances in Methods and Practices in Psychological Sci-ence. 2018. Vol. 1, Iss. 1. Pp. 27-42. DOI: 10.1177/251524591774562 9.

25. **Rodgers J. L., Nicewander W. A.** Thirteen Ways to Look at the Correlation Coefficient // The American Statistician. 1988. Vol. 42, Iss. 1. Pp. 59-66.

26. **Sheldon M. Ross** Introduction to Probability and Statistics for Engineers and Scientists. 5th Edition. Elsevier: Academic Press, 2014. 60 p.

27. **Cook T. D., Campbell D. T.** Quasi Experimentation. Boston: Houghton Mifflin, 1979.

28. **Groumpos P. P., Stylios C. D.** Modeling supervisory control systems using fuzzy cognitive maps // Chaos Solitons & Fractals. 2000. Vol. 11, Iss. 1-3. Pp. 329-336.

29. **Papageorgiou E. I.**, **Stylios C. D.**, **Groumpos P. P.** Fuzzy Cognitive Map Learning based on Non-Linear Hebbian Rule // Advances in Artificial Intelligence Lecture Notes in Computer Science. 2003. Vol. 2903. Pp. 256-268.

30. **Papageorgiou E. I., Stylios C. D., Groumpos P. P.** Active Hebbian learning algorithm to train fuzzy cognitive maps // International Journal of Approximate Reasoning. 2004. Vol. 37, Iss. 3. Pp. 219-249.

31. **Groumpos P. P.** A new Mathematical Modell for COVID-19: A Fuzzy Cognitive Map Approach for Coronavirus Diseases // 11th International Conference on Information, Intelligence, Systems and Applications, (IISA, July 2020). 2020. Pp. 1-6.

32. **Groumpos P. P.** Modelling COVID-19 using Fuzzy Cognitive Maps (FCM) // EAI Endorsed on BEBI Transactions. 2021. Vol. 1, Iss. 2. Pp. 1-13.

33. **Groumpos P. P.** Intelligence and Fuzzy Cognitive Maps: Scientific Issues, Challenges and Opportunities // Studies in Informatics and Control. 2018. Vol. 27 (3). Pp. 247-264.

34. **Groumpos P. P.** Using Fuzzy Cognitive Maps in Analyzing and Studying International Economic and Political Stability // TECIS 2019, IFAC-PapersOnLine. 2019. Vol. 52, Iss. 25. Pp. 23-28.

35. **Nguyen T. N.** Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Directions // TechRxiv. 2020. DOI: 10.13140/RG.2.2.36491.23846/1.

36. **COVID-19** Prediction and Detection using Deep Learning / M. Alazab, et. al. // International Journal of Computer Information Systems and Industrial Management Applications. 2020. Vol. 12. Pp. 168-181.

37. **Abdulkareem M., Petersen S. E.** The Promise of AI in Detection, Diagnosis and Epidemiology for Combating COVID-19: Beyond the Hype // Frontiers in Artificial Intelligence. 2021. Vol. 4. Article number 652669.

38. **Groumpos P. P.** Deep Learning vs. Wise Learning: A Critical and Challenging Overview // IFAC-PapersOnLine. 2016. Vol. 49, Iss. 29. Pp. 180-189.

39. **Wohl W.** COVID-19 and Digital Transformation – Developing an Open Experimental Testbed for Sustainable and Innovative Environments (ETSIE) using Fuzzy Cognitive Maps // ArXiv preprint arXiv:2101.07509. 2021.

40. **Multi-faceted** impact and outcome of COVID-19 on smallholder agricultural systems: Integrating qualitative re-

search and fuzzy cognitive mapping to explore resilient strategies / R. Goswami, et. al. // Agricultural Systems. 2021. Vol. 189. Article number 103051.

41. **Abdulkareem M., Petersen S. E.** The Promise of AI in Detection, Diagnosis and Epidemiology for Combating COVID-19: Beyond the Hype // Frontiers in Artificial Intelligence. 2021. Vol. 4. Article number 652669.

42. **A review** of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications / A. Amirkhani, et al. // Computer methods and programs in biomedicine. 2017. Vol. 142. Pp. 129-145.

43. **Alon I., Farrell M., Li S.** Regime type and COVID-19 response // FIIB Business Review. 2020. Vol. 9, Iss. 3. Pp. 152-160.

44. **A New** Approach of Dynamic Fuzzy Cognitive Knowledge Networks in Modelling Diagnosing Process of Meniscus Injury / A. P. Anninou, et al. // Elsevier Journal, IFAC-PapersOnLine. 2017. Vol. 50, Iss. 1. Pp. 5861-5866.

45. **Apostolopoulos I. D.**, **Mpesiana T. A.** Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks // Phys. Eng. Sci. Med. 2020. Vol. 43, Iss. 2. Pp. 635-640.

46. **Epidemiological** and clinical characteristics of 99 cases of 2019 novel coronavirus in Wuhan, China: A descriptive study / N. Chen, et al. // Lancet. 2020. Vol. 395, Iss. 10223. Pp. 507-513.

47. **SARS** and MERS: recent insights into emerging coronaviruses / E. de Wit, et al. // Nature Reviews Microbiology. 2016. Vol. 14. Pp. 523-527.

48. **Hamet P., Tremblay J.** Artificial intelligence in medicine // Metabolism. 2017. Vol. 69. Pp. S36-S40.

49. **Online** health survey research during COVID-19 / T. G. Hlatshwako, et. al. // The Lancet Digital Health. 2021. Vol. 3, Iss. 2. Pp. e76-e77.

50. **Mintz Y., Brodie R.** Introduction to artificial intelligence in medicine // Minimally Invasive Therapy Allied Technology. 2019. Vol. 28, Iss. 2. Pp. 73-81.

51. **Mpelogianni V. G., Groumpos P. P.** Re-approaching fuzzy cognitive maps to increase the knowledge of a system // AI & Society. 2018. Vol. 33, Iss. 2. Pp. 175-188.

52. **Naudé W.** Artificial Intelligence against COVID-19: An early review // IZA Inst. Labor Econ. 2020. No. 13110. 14 p.

53. **Papageorgiou E. I.** A new methodology for decisions in medical informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques // Applied Soft Computing. 2011. Vol. 11, Iss. 1. Pp. 500-513.

54. **Raikov A. N., Avdeeva Z., Ermakov A**. Big Data Refining on the Base of Cognitive Modeling // Proceedings of the 1st IFAC Conference on Cyber-Physical &Human-Systems, (Florianopolis, Brazil, Dec. 7-9). 2016. Pp. 147-152.

55. **Raikov A., Ermakov A., Merkulov A.** Self-organizing cognitive model synthesis with deep learning support // International Journal of Engineering &Technology (IJET). Special issue on Computing, Engineering and Information Technologies. 2018. Vol. 7, no. 2.28. Pp. 168-172.

56. **Raikov A.** Cognitive Semantics of Artificial Intelligence: A New Perspective. Topics: Computational Intelligence XVII. Singapore: Springer, 2021. 128 p.

57. **Clinical** characteristics of 138 hospitalized patients with 2019 novel coronavirus-infected pneumonia in Wuhan, China / D. Wang, et al. // Jama. 2020. Vol. 323, no. 11. Pp. 1061-1069.

58. **Yan F., Robert M., Li Y.** Statistical methods and common problems in medical or biomedical science research // International Journal of physiology, pathophysiology and pharmacology. 2017. Vol. 9 (5). Pp. 157-163.

ABOUT AUTHOR

GROUMPOS Peter P., Emeritus Professor, University of Patras, Greece.

МЕТАДАННЫЕ

Заголовок: Нечеткие когнитивные карты: новый подход к моделированию в борьбе с COVID-19.

Автор: Питер П. Гроумпос

Принадлежность: Университет Патры

Эл. адрес: groumpos@ece.upatras.gr

Язык: Английский.

Источник: СИИТ (научный журнал Уфимского государственного авиационного технического университета), т. 3, № 3 (7), стр. 5–16, 2021. ISSN 2686-7044 (онлайн), ISSN 2658-5014 (печатный вариант).

Аннотация: Коронавирусная болезнь, впервые обнаруженная в конце 2019 года, пандемия COVID-19 значительно повлияла на жизни всех людей во всем мире. В области здравоохранения широко используются математические модели для решения сложных медицинских проблем. Математические модели никому не могут быть полезны без конкретных теорий. Анализируется и обсуждается решающее и важное различие между корреляцией и причинно-следственной связью. Существует неопределенность и двусмысленность по некоторым аспектам пандемии COVID-19. Симптомов много, и они варьируются от человека к человеку и от географического региона к географическому региону. Анализируются актуальные проблемы пандемии COVID-19. Недавно новые мутации COVID-19 показали нам, как быстро новое заболевание может пустить новые корни и распространиться. Такие события сопровождаются бурным потоком клинической и эпидемиологической информации и исследований. Ежедневно предоставляются миллиарды данных. Многие теории призваны бороться с COVID-19, особенно с искусственным интеллектом (ИИ). Большинство методов, которые используются для обнаружения, диагностики и эпидемиологического прогнозирования, прогнозирования и социального контроля для борьбы с COVID-19, используют статистические теории и коэффициент корреляции. Последние теории нечетких когнитивных карт (FCM) используются для моделирования и изучения COVID-19. Приводятся и обсуждаются результаты моделирования с использованием реальных данных. Использование нечетких когнитивных карт (FCM) оказалось эффективным и полезным подходом в изучении COVID-19. Многие направления будущих исследований освещаются конкретным применением FCM в борьбе с COVID-19.

Ключевые слова: COVID-19; пандемия; корреляция; аутация, искусственный интеллект (ИИ); нечеткая логика; нечеткие когнитивные карты; биомедицинская информатика.

Об авторе:

ГРОУМПОС, **Питер П.,** заслуженный проф. Университета Патры, Греция.