A Fuzzy Cognitive Map (FCM) as a Learning Model for Early Prognosis of Seasonal Related Virus Diseases in Tropical Regions

Enrique Peláez
Facultad de Ingeniería en Electricidad y Computación
ESPOL Polytechnic University, Escuela Superior Politécnica del Litoral, ESPOL
Campus Gustavo Galindo Km. 30.5 Vía Perimetral, P.O. Box 09-01-5863, Guayaquil, Ecuador
epelaez@espol.edu.ec

***Abstract*—Fuzzy Cognitive Maps (FCMs) and current developments in Machine Learning have been contributing in capturing human behaviors through data and learning models, which focus on predicting, interpreting or identifying behavioral patterns on systems and their relationships. In recent years seasonal diseases caused by vectors that transport viral pathogens in tropical regions, such as the Aedes Aegypti mosquito, have caused noticeable impacts both on public health and country's economies in Latin America. This work proposes a model for early prognosis based on FCMs for making a risk assessment of potential presence of seasonal virus-related diseases in a specific region of the Ecuadorian coast. The FCM is used as a knowledge representation strategy for the cause-effect relationships; and, learning models for gaining the identification of the underlying cause of symptoms. The model aims to improve the chances of proper prognosis of seasonal diseases, which could impact not only the prescription and correct decisions, but also the actions taken for preventing the spread of seasonal diseases.**

***Index Terms*—Fuzzy Cognitive Maps, Causal Complex Systems, Machine Learning, Knowledge Representation, Tropical Seasonal Diseases, Dengue Fever**

I. Introduction

Fuzzy cognitive maps (FCMs) as a cause-effect representation scheme are fuzzy feedback dynamical representations of knowledge. Bart Kosko [1] introduced them in 1986, as an extension of Cognitive Maps [2]. Cognitive maps are represented with a set of nodes linked by directed and signed edges; nodes represent concepts or events relevant to a given problem; when a concept or event is present or not, the node is in an on or off state respectively; and, the directed and signed edges, between these nodes, represent the direction of the causal influence and the excitatory or inhibitory effect from one node to another. When these maps are defined as Fuzzy Cognitive Maps, the causal relationships, as directed and signed edges, are represented by fuzzy numbers, and the state of a node is not only on an off/on state, but in a fuzzy state, represented by an activation function with outputs in the range of [0, +1]. A fuzzy number is a quantity whose value is a real number also in the range of [0, +1]. The dynamic representation of knowledge involves feedback; updating a node could affect other nodes, which in turn the affected nodes could affect the node initiating the update.

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In recent years the seasonal diseases caused by vectors that transport viral pathogens in tropical regions, such as the Aedes Aegypti mosquito, have caused noticeable impacts both on public health and country's economies [3]. In Latin America, on average, 1.5 million cases of Dengue fever per year were reported from 2010 to 2015, with an average cost of US$ 472 per person in outpatient treatments, and US$ 1227 for hospitalized cases, which for the case of the Dengue fever it represents, an approximate cost of US$ 2.5 billion per year [4].

Early prognosis tools embedded in Decision Support Systems and the provision of eHealthcare services based on machine learning techniques for disease management, could help mitigate the effects of seasonal virus related diseases and help reduce the negative impacts on public health administration. The aim of this research is to explore the potential of unsupervised learning techniques in FCMs as a model for prognosis and help establish early course of actions; we claim the possibility of learning the parameters from the initial identified cause-effect relationships from historical data and expertise, which in turn can be used to improve the effectiveness or effects of past decisions.

This work proposes a model for representing early prognosis based on FCMs, as a dynamic network with learning capabilities, which can be used for making a risk assessment of potential presence of viral seasonal diseases in a specific region of the Ecuadorian coast. The FCM is used as a knowledge representation strategy for the cause-effect relationship between symptoms, environmental conditions, observations and historical facts recorded in previous related events in this region; and the learning capabilities for gaining the identification of the underlying cause of symptoms. This model aims to improve the chances of proper diagnosis of seasonal diseases, which could impact not only the prescription and correct decisions, but also the actions taken for preventing the spread of seasonal diseases.

This paper is organized as follows: Section 2 presents an overview of the FCM modeling technique and a representation of the map, which will be used as the bases for making the analysis and derived the learning models; section 3 discusses the unsupervised learning method known as the Hebbian Learning rule used in neural networks, and its mathematical formulation for training FCMs; section 4 presents the prognosis model, its data and the parameters used in the case of seasonal virus diseases in the coastal region of Ecuador. Section 5 presents a discussion of the results; and, in section 6 the conclusions are presented.

II. Overview of FCMs as a Modeling Technique

A. Fuzzy Cognitive Maps (FCMs)

FCM is a graph of concepts, which represents a fuzzy feedback dynamical system composed by nodes, capturing the state or a characteristic of the system under analysis. The nodes, as neurons in neural networks, can be considered as computational units, which can get activated or deactivated, depending upon the incoming signals into the node. State values of the nodes can change over time, based on the evaluation of the activation function in the node; the state values are in the interval [0, +1]. The cause-effect relationships between nodes are represented as directed and signed links. The direction of the links captures the effect one node can provoke to the other interconnected nodes, and the signed values or weights associated with them represent the causal strength, which can be positive to reflect an excitatory effect, or negative as the opposite or inhibitory effect; the weight values are in the interval [-1, +1]. A weight of -1 represents full inhibitory effect, +1 full excitatory and 0 denotes not relation, hence no effect. Other values or weights in the [-1, +1] range represent different degrees of the cause-effect relationship. The graphical representation of the cause-effect relationships is equivalent to a zero-diagonal symmetric matrix, called the connection matrix, which stores the corresponding weights associated with the directed links between nodes.

In feedback dynamical systems agents provoke changes to the system, which in turn it reflects the effects on other agents; in epidemiology, such systems have a mechanism that transmits an infection or infectious agent, from one affected individual to another, which is known as a vector, usually a living organism. Vectors are usually invertebrates or arthropods like mosquitoes; these agents or animated intermediaries transport disease-causing agents from one susceptible host to another [5].

According to [6] the World Health Organization (WHO) estimated about half of the population is infected with at least one type of pathogen transmitted by vectors. Among these pathogens we have the agents that cause the Plague and Typhus, as well as the Dengue, Zika and Chikungunya fever. Recent research carried out by [3, 4, 13, 14, 15, 16, 17] has shown the cause-effect relationships not only among these vectors and humans but also with the environment, social, cultural and professional practices that impacted directly on health and the economy of the infected communities.

Table 1 shows the main factors, extracted from these studies, involved in the Dengue outbreak and seasonal virus infections occurred in the south coastal region of Ecuador.

TABLE I
MAIN FACTORS INVOLVED IN THE DENGUE OUTBREAK AND SEASONAL VIRUS INFECTIONS OCCURRED IN THE SOUTH COASTAL REGION OF ECUADOR*

#	**Favorable conditions which contribute to the evolution of seasonal virus diseases**
1	Region of interest is the coast area
2	Presence of ammonia (present when there are mammals)
3	Presence of carbon dioxide (present with mammals)
4	Presence of lactic acid
5	Presence of octenol (present in the respiration and sweat of humans)
6	Temperature of environment is above the average
7	Rainy season of the year
8	Wet containers (wet pans, tires, bathroom floor, bathroom tanks), standing water
9	People frequent visitors of parks and recreation areas
10	Tourism (human movement during vacation)
11	Close livestock production
12	Close poultry production
13	Actions from a public health entity because of the season
14	Population susceptible of getting infected by contact with infected patients
15	Symptoms identified associated with Dengue
16	Surveillance activities (active or passive)
17	Surveillance sites (permanent sentinel)
18	Average age of detected cases (between 20-30)
19	There are abandoned properties
20	No access to or interruptions of piped water service inside the house
21	Properties have or shared a patio with shade
22	Have mosquito nets for beds
23	Fumigation within the property
24	Family head is man
25	Family head is woman
26	Family head is young and works
27	Level of education of affected people
28	Work (employee / self-employed)
29	Income level
30	Conditions of the property
31	Areas with high population density
32	People knowledgeable about dengue
33	Perception of risk of contamination
34	Season between February and May
35	Trash collection services
36	Prevention medical services
37	Housing in apartment / condominium
38	Housing in rural sector
39	Conditions favorable for the El Niño event
40	Poor cleaning habits in the community

* Sources: 1) The Dengue Net, http://www.denguevirusnet.com.
2) Dr. Félix E. Beltrán A., University UT Machala, Ecuador.
3) Dr. Anna M. Stewart. Center for Global Health and Translational Sciences, State University of New York (SUNY).

These factors reflect the inter-relationships among the vectors, environment, communities, health providers and official entities acting in prevention and mitigation of viral seasonal related diseases.

For this research the social, ecological and the effects of the preventive actions from seasonal virus events have been considered, as well as the climate conditions, which have contributed to the evolution of Dengue seasons in the past, and community perceptions about this fever.

TABLE II
MAIN FACTORS INVOLVED IN THE DENGUE OUTBREAK AND SEASONAL VIRUS INFECTIONS OCCURRED IN THE SOUTH COASTAL REGION OF ECUADOR

#	**Favorable conditions which contribute to the evolution of seasonal virus diseases**
n_1	Region of interest is the coast area
n_2	Temperature of environment is above the average
n_3	Rainy season of the year
n_4	Actions from a public health entity because of the season
n_5	Population susceptible of getting infected by contact with infected patients
n_6	Symptoms identified associated with Dengue
n_7	Average age of the identified cases between 20-30 years old
n_8	Areas with high population density
n_9	Trash collection services
n_{10}	Seasonal virus-related diseases

From Table I, we have selected ten conditions that in general represent the environment, attitudes and effects of practices regarding Dengue and the risk factors involved during the outbreaks and seasonal virus events from 2014 to 2016, as shown in Table II, these ten concepts will be used to represent the historical factors and captured in an FCM; as illustrated in Figure 1, nodes n_1 to n_9 will be considered as input variables, and n_{10} as output. The connection matrix equivalent to the FCM is shown later on Table III.

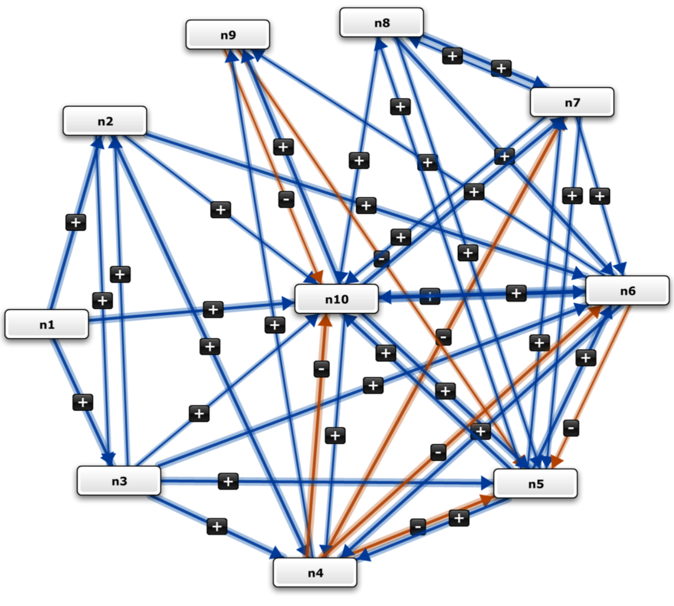

Fig. 1. FCM knowledge representation of conditions that contribute to the evolution of seasonal virus-related diseases in the south coastal region of Ecuador

The FCM in Figure 1 captures the context of the Dengue outbreak and seasonal virus infections occurred in the south coastal region of Ecuador, as a cause-effect map; nodes n_1 to n_{10}, as described in Table II, represent the main factors identified in the outbreak. In this map the excitatory effect, is represented as a (+) relationship and the inhibitory effect, is represented as a (-) relationship. For example, the presence of the event *"Population susceptible of getting infected by contact with infected patients"*, label as node n_5, increases the effect on node n_4 *"Actions from a public health entity because of the season"*, represented as a blue link in the map, which in turn also decreases the effect on node n_5, represented as a yellow link in the map. The degree to which the presence of a node affects other nodes, as capture from historical data, or from the experts, is captured in the connection matrix.

Hence, each node (concept) in the FCM has an activation value that reflects the degree to which the node is active at a particular iteration (discrete moment in time). Once the FCM has been created, the expert knowledge (or historical data) is captured and store in the connection matrix, and it is ready to receive data from its input nodes, learn, perform reasoning and infer decisions as values on its output nodes.

At a particular moment t the state of the map is represented by the state vector $S(t) = [S_1(t), S_2(t), ..., S_i(t), ..., S_n(t)]$; that is, the state value of a node n_i at time t is captured by the state vector value $S_i(t)$. The initial state refers to the system state at the first iteration or at time $t = 0$. Once the initial state, $S(0)$ of the entire system is defined, the model can be evaluated; that is, calculate the values of all nodes at discrete time points in the future, based on equation (1); where the value S_i of each node n_i at a time $t+1$ is calculated by the sum of the values S_i, at time t, and the sum of the product of the values S_j of the node n_j, at time t, with the signed value (weight) of the connecting link w_{ij} between nodes i and j:

$$S_i(t+1) = f\left(S_i(t) + \sum_{\substack{j=1 \\ j \neq i}}^{N} S_j(t) \cdot w_{ji}\right); \forall j \in \{1, \ldots, N\} \quad (1)$$

Where: N is the total number of nodes in the map and f is the activation function, which will be used to keep the state values within the range [-1, +1]. Given this expected output range, we use the Hyperbolic Tangent as the activation function, which is commonly used in neural networks, known as the *tanh* function of x and defined as:

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

The system state is then defined by all activation values of the nodes at a particular time t.

For example, consider the following initial state vector: $S(0) = [0.9, 0.9, 0.8, 0.0, 0.5, 0.5, 0.5, 0.3, 0.5, 0.0]$. In this vector the state values of nodes n_1, n_2 and n_3, $(0.9, 0.9$, and 0.8 respectively), indicate a strong presence of these concepts in this scenario; at the same time, a not so significant presence of nodes n_5, n_6, n_7 and n_9 (with a state value of 0.5); and, a weak presence of node n_8 (with a state value of 0.3). Figure 2 shows the results of the model after 12 iterations (time steps), starting from the defined initial state vector $S(0)$ and until the system reaches the stable state, as defined in section III; in this figure the target or output variable n_{10} is activated with a full degree, indicating that the event *"Seasonal virus-related diseases"* will definitely occur, with such conditions as defined in the initial state vector $S(0)$.

The values of all concepts N stabilize after a number of iterations, and they correspond to a stable state of the system; compared with the initial state some nodes increase, like nodes n_4, n_5, n_6, n_7 and n_9; others decrease, such as nodes n_1, n_2, n_3 and n_8; and yet there might be others which are not affected at all.

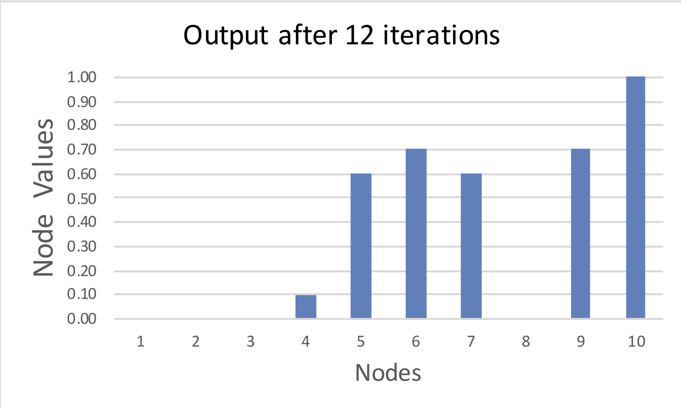

Fig. 2. System's output n_{10} after 12 iterations

III. Unsupervised Learning and the Non-Linear Hebbian Learning Rule

Construction of FCMs is based on the known cause-effect relationships, as identified in historical data or from past experiences; however, how much an event affects another depends on the expert's beliefs, expressed as a real number. As in neural networks, in FCMs the convergence to a steady state can be automated as an unsupervised learning methodology; the initial expert's beliefs in the map represent the initialization of the parameters, which will be used by the learning algorithm to adjust the link values of the FCM until a stable state is reached.

The process of learning in neural networks consists of searching for the system's parameters that minimizes the error, which is defined by a cost or an objective function. This searching process can be supervised or unsupervised and Stochastic Gradient Descent has proven to be an effective local search technique to obtain these parameters [7]. The learning algorithm is defined as the mathematical model that determines these parameters until the system reaches the stable state. In an unsupervised learning the system expects an initial set of parameters with the initial state and an error function, expressed in terms of those initial parameters. The objective in the learning process is to reach the minimum error with the set of parameters found with the search technique; when the error is 0 or close enough, then stable state of the system is reached, and the corresponding parameters found will be used for running the system in the future, for interpreting the system's output based on new scenarios or inputs, which have not been seen before.

Learning in FCMs means updating the values of the connecting links, by fine-tuning the initial set of link values (weights) or w_{ji} parameters. In this work the Nonlinear Hebbian Learning Algorithm (NHL) is been used, which is based on a learning rule, expressed as follows [8]:

$$w_{ij}(t) = w_{ij}(t-1) + \alpha S_j(t-1) \cdot S_i(t-1) \quad (3)$$

Where: w_{ij}(t) is the weight or link value between nodes i and j at time t,

S_i and S_j are the current node values of nodes i and j, which were calculated using equation (1); and,

α is the learning rate.

The NHL algorithm, as proposed by [9, 10], takes the initial connection matrix known as $W(0)$ and iteratively updates the set of parameters, minimizing the error as expressed in (4) for all output nodes and until convergence; it consists of the following seven steps and termination conditions:

STEP 1. Obtain the initial node values $S(0)$, the initial connection matrix $W(0)$ and the conditions for the target variables or output nodes, defined as: $s_j^{min} \leq s_j \leq s_j^{max}$
STEP 2. For each iteration t
STEP 3. Update the weights according to equation (3)
STEP 4. Calculate $S(t)$, for each node according to equation (1)
STEP 5. Evaluate the two termination conditions, using $S(t)$ from STEP 4 and the connection matrices at steps t and $t-1$; e.g. $W(t)$ and $W(t-1)$
STEP 6. Until both termination conditions are met, go to STEP 2
STEP 7. Return the final connection matrix W

The first termination condition, as referred in STEP 6, has the objective of minimizing the cost function TC_1:

$$TC_1 = \sqrt{\sum_{n_{out_j}} \|n_j(t) - T_j\|^2} \quad (4)$$

Where: T_j is the mean target value of the output nodes S_j, which is determined as:

$$T_j = \frac{S_j^{max} - S_j^{min}}{2} \quad (5)$$

The second termination condition is based on the difference of subsequent values of the output node, which must be less than a constant value ϵ defined as a parameter of the algorithm, and it is expressed as:

$$TC_2 = \left| n_j(t+1) - n_j(t) \right| < \epsilon \quad (6)$$

Where: $n_j(t)$ is the state value of node n_j at time t.

The constant ϵ, is the minimum error calculated as the difference between subsequent node values.

TABLE III
CONNECTION MATRIX $W(0)$ OF THE FCM IN FIGURE 1, REPRESENTING THE CONDITIONS THAT CONTRIBUTE TO THE EVOLUTION OF SEASONAL VIRUS DISEASE IN THE SOUTH COASTAL REGION OF ECUADOR

	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}
n_1	0.0	0.7	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.6
n_2	0.0	0.0	0.4	0.5	0.0	0.6	0.0	0.0	0.0	0.4
n_3	0.0	0.4	0.0	0.5	0.4	0.6	0.0	0.0	0.0	0.7
n_4	0.0	0.0	0.0	0.0	-0.5	-0.5	-0.5	0.0	0.4	-0.7
n_5	0.0	0.0	0.0	0.5	0.0	0.7	0.4	0.3	0.0	0.6
n_6	0.0	0.0	0.0	0.6	-0.4	0.0	0.0	0.0	0.4	1.0
n_7	0.0	0.0	0.0	0.0	0.4	0.4	0.0	0.3	0.0	0.4
n_8	0.0	0.0	0.0	0.0	0.4	0.5	0.6	0.0	0.0	0.3
n_9	0.0	0.0	0.0	0.0	-0.3	0.0	0.0	0.0	0.0	-0.3
n_{10}	0.0	0.0	0.0	0.4	0.5	0.6	0.6	0.0	0.5	0.0

IV. Data set and setting the parameters

The following parameters have been used to train and evaluate the FCM, as expected in the generic NHL algorithm, as defined in [10]:

The connection matrix or data set is derived from the FCM and shows the link values between nodes. For example, node n_6 affects n_4 positively (exitatory effect) with a value of 0.6 and node n_4 affects n_5 negatively (inhibitory effect) with a value of 0.5.

For the experiments we have used historical data from three different scenarios: a) The Dengue outbreak occurred in 2010, b) the seasonal virus-related epidemic of 2014-2015, and c) the seasonal virus-related events of 2016. The initial activation vectors were defined from the data extracted from [3, 4, 13, 14, 15, 16, 17], and expressed as:

a) S(0) = [1.0, 0.8, 0.8, 0.4, 0.5, 0.6, 0.0, 0.5, 0.3, 0.0]
b) S(0) = [1.0, 1.0, 1.0, 0.0, 0.0, 0.2, 0.4, 0.0, 0.2, 0.0]
c) S(0) = [0.0, 0.0, 0.0, 0.0, 0.0, 0.7, 1.0, 1.0, 1.0, 0.0]

These activation vectors represent the following settings: In scenario a) we are interested in evaluating the coastal region (node n_1 is on with a degree of 1.0); as it was reported for the 2010 event, we know that the temperature was above the average (node n_2 is on with a degree of 0.8); and, the rainy season had started (node n_3 is on with a degree of 0.8). It was also reported that at the beginning of the event few actions, from the public health entity, such as field visits for vaccination were initiated (node n_4 is on with a degree of 0.4); some of the population was identified as susceptible of getting infected by contact with infected patients (node n_5 is on with a degree of 0.5); also some symptoms were reported as associated with Dengue (node n_6 is on with a degree of 0.6) in areas with more or less population density (node n_8 is on with a degree of 0.5); trash collection services were almost not present (node n_9 is on with a degree of 0.3).

In scenario b), as before we are interested in evaluating the coastal region (node n_1 is on with a degree of 1.0), during the epidemic of 2014-2015 it was reported that the temperature was high above the average (node n_2 is on with a degree of 1.0), and the rainy season was in full (node n_3 is on with a degree of 1.0). There were very few cases reported with symptoms associated with Dengue (node n_6 is on with a degree of 0.2), and some were males with ages between 20-30 years old (node n_7 is on with a degree of 0.4); trash collection services were almost not present (node n_9 is on with a degree of 0.2).

In scenario c) we are interested to explore the seasonal virus-related events of 2016, when several cases with symptoms associated with Dengue were reported in different parts of the country (node n_6 is on with a degree of 0.7), the cases were mainly among people between 20-30 years old (node n_7 is on with a degree of 1.0) in areas with high population density (node n_8 is on with a degree of 1.0); in this year the trash collection services were regularly present (node n_9 is on with a degree of 1.0).

In this problem domain we have nodes that inhibit the effect of other nodes; hence the "Hyperbolic Tangent" activation function will be used for all scenarios, and as defined in equation (2), it will keep the output values in the range [-1, +1].

For all scenarios the stop condition for the target variable or output node value, is set to: $0.6 \leq S_{10} \leq 1.0$, as the range of the desired confidence value for the output node. That is, a target value around 0.6 activates the output node.

The constant value ϵ, defined as the minimum error of the difference in subsequent node values is set to 0.002, as proposed by [10]. The learning rate α has been set to 0.01.

As part of the termination conditions we have also set a maximum number of iterations, which will be used to loop out if the 2 termination conditions are not met during the training process; this number has been set to 50.

With the knowledge captured in the connection matrix and the parameters defined as before, we have run the system for the different scenarios and compared the results against the events reported as the Dengue outbreak and other seasonal virus-related diseases as identified in [3, 4, 13, 14, 15, 16, 17].

V. Results

For scenario a), after 5 iterations the node values converged with an $\epsilon \leq 0.002$, with a final stable state of the nodes' values set to:

S(5) = [0.98071, 0.76234, 0.73929, 0.725664, 0.96580, 0.77908, 0.76031, 0.56895, 0.29707, 0.99864]

Table IV shows the iterations for this scenario; as we can see the target value S_{10} of variable n_{10}, is activated with almost a full degree, indicating that the *"Seasonal virus-related diseases"* will definitely occur, as indeed did occur in the Dengue outbreak of 2010, giving the conditions as defined in $S(0)$ for scenario a).

From the historical data for this scenario weather conditions were within the main factors contributing to the evolution of the Dengue outbreak. During this event the public health entity started to take some actions on the field. As the number of infected cases increased, the population susceptible to get infected also increased, as well as the cases among males between 20 and 30 years old.

Results from this scenario suggest that there is consistency with what really happened in 2010. An interesting result, which also was reported in the historical records, is that garbage collection started to improve after the outbreak, which is also forecasted in the results of this scenario.

TABLE IV
ITERATIONS FOR SCENARIO A) THE DENGUE OUTBREAK OCCURRED IN 2010

Iter.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
1	1.00000	0.80000	0.80000	0.40000	0.50000	0.60000	0.00000	0.50000	0.30000	0.00000
2	0.94268	0.76770	0.76083	0.57066	0.67007	0.71920	0.03720	0.50042	0.29901	0.32067
3	0.91794	0.75935	0.74813	0.72177	0.83138	0.77899	0.53507	0.51639	0.29822	0.71077
4	0.98035	0.76212	0.74244	0.72540	0.96569	0.77931	0.76037	0.56885	0.29758	0.99727
5	0.98071	0.76234	0.73929	0.72564	0.96580	0.77908	0.76031	0.56895	0.29707	0.99864

For scenario b), after 8 iterations the node values converged with an $\epsilon \leq 0.002$, with a final stable state of the nodes' values set at:

S(8) = [0.99066, 0.98714, 0.94736, 0.35001, 0.53000, 0.33489, 0.38881, 0.08002, 0.19628, 0.62000]

Table V shows the iterations for this scenario, we can see that the target value S_{10} of variable n_{10}, gets activated with a degree of 0.62, indicating that *"Seasonal virus-related diseases"* can occur giving the conditions as defined in $S(0)$. In this scenario we can see that node n_4- *"Actions from a public health entity because of the season"*, node n_5- *"Population susceptible of getting infected by contact with infected patients"* and node n_8- *"Areas with high population density"* got activated; information elicited from this event has shown that in fact the public entity started real field actions once the season also started, as well as the first seasonal virus-related cases were reported; given the season environmental conditions, which favor the spread of viruses, the population susceptible to get infected increased, as well as the risk on areas of high population density.

TABLE V
ITERATIONS FOR SCENARIO B) SEASONAL VIRUS-RELATED EPIDEMIC OF 2014-2015

Iter.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
1	1.00000	1.00000	1.00000	0.00000	0.00000	0.20000	0.40000	0.00000	0.20000	0.00000
2	0.94268	0.96770	0.96083	0.17066	0.17007	0.31920	0.39628	0.00042	0.19901	0.32067
3	0.91794	0.95935	0.94813	0.32177	0.33138	0.37899	0.39330	0.01639	0.19822	0.32126
4	0.90385	0.95657	0.94244	0.32540	0.46569	0.37931	0.39091	0.06885	0.19758	0.36991
5	0.93348	0.97775	0.93929	0.32774	0.48684	0.37908	0.38898	0.06895	0.19707	0.42959
6	0.98382	0.98348	0.93736	0.33002	0.50807	0.36056	0.38743	0.07706	0.19665	0.60068
7	0.98724	0.98381	0.93605	0.34999	0.52938	0.34632	0.38756	0.07804	0.19631	0.61982
8	0.99066	0.98714	0.94736	0.35001	0.53000	0.33489	0.38881	0.08002	0.19628	0.62000

For scenario c), the system reached the stable state after 12 iterations, the node values converged with an $\epsilon \leq 0.002$, with a final stable state of the nodes' values set to:

S(12) = [0.00000, -0.00005, -0.00028, 0.14027, 0.41020, 0.00264, -0.00054, -0.00003, -0.00015, 0.74870]

Table VI shows the 12 iterations for this scenario; we can see that the target value S_{10} of variable n_{10}, gets activated with a degree of 0.7487, indicating that *"Seasonal virus-related diseases"* will probably occur giving the conditions as defined in $S(0)$ for this scenario.

TABLE VI
ITERATIONS FOR SCENARIO C) SEASONAL VIRUS-RELATED EVENTS OF 2016

Iter.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.70000	1.00000	1.00000	1.00000	0.00000
2	-0.05732	-0.03230	-0.03917	0.01707	0.17007	0.81920	0.99628	1.00042	0.99901	0.32067
3	-0.03259	-0.01394	-0.05187	0.03218	0.33138	0.87899	0.99330	1.01639	0.99822	0.32126
4	-0.01850	0.01385	-0.05756	0.04581	0.34481	0.87931	0.99091	1.06885	0.99758	0.36991
5	-0.00040	0.00893	-0.06071	0.06815	0.34693	0.87908	0.98898	1.06895	0.99707	0.42959
6	0.00011	0.00321	-0.06264	0.07043	0.36815	0.86056	0.98743	1.07706	0.99665	0.60068
7	0.00011	0.00287	-0.06395	0.09040	0.38946	0.84632	0.98756	1.07804	0.99631	0.61982
8	0.00011	-0.00045	-0.05264	0.11037	0.39160	0.83489	0.98881	0.08002	0.99628	0.63895
9	0.00000	-0.00136	-0.00052	0.13034	0.39373	0.00520	-0.00102	-0.00005	-0.00028	0.66714
10	0.00000	0.00008	-0.00042	0.13733	0.40584	0.00413	-0.00083	-0.00004	-0.00022	0.69823
11	0.00000	-0.00007	-0.00034	0.13933	0.40882	0.00330	-0.00067	-0.00004	-0.00018	0.74737
12	0.00000	-0.00005	-0.00028	0.14027	0.41020	0.00264	-0.00054	-0.00003	-0.00015	0.74870

We can also see that nodes n_4- *"Actions from a public health entity because of the season"* and n_5- *"Population susceptible of getting infected by contact with infected patients"* got activated. Although, it can be interpreted as if the public entity started some field actions, the degree is rather small to draw some conclusions, and the records showed that there were several public entities taking preventive actions during the season. These results also show that risks of the population susceptible to get infected increases and it needs to be looked at, given the virus-related cases reported among the young population of males in high density areas.

In general, the results obtained from these cases show that "*what if...*" scenarios could help decision takers and health managers, make educated risk analysis and assert effective actions to prevent epidemic events before they occur. A reasonable set of actions, with practical implications for decision takers, could be taken to mitigate or eliminate the effects of the causes as represented in the map. For example, scenario a) showed that when trash collection services were not present, the effect on the epidemic outbreak was high; hence early garbage collection actions could have helped in mitigating this effect.

VI. CONCLUSIONS

The most significant weaknesses of the FCMs, is their dependence on the expert's beliefs, and the potential convergence to undesired steady states, which can be overcome by automated learning. An unsupervised learning methodology for FCMs training has been implemented and tested for seasonal virus-related diseases in a tropical region of Ecuador. The NHL algorithm adjusts and modifies the weights of FCMs accordingly and has shown to be effective for learning the parameters.

This paper proposes a mathematical analysis for seasonal virus-related diseases based on the Non-Linear Hebbian Learning algorithm for FCMs. The mathematical formulation and the implementation of the algorithm have been effectively investigated and the experimental results based on real historical data, which captured the expert knowledge, verify the effectiveness, validity and the expected behavior of the proposed prognosis alternative. The proposed solution, once it gets implemented is easy to used, it is flexible and can be set to test "*what if...*" scenarios.

This technique depends on a good knowledge of a given problem domain, the initial expert knowledge is fundamental for configuring the initial state and its parameters. The expert intervention is also relevant in evaluating the values of output nodes of the FCM model to make sure they are within the desired behavior.

Decision takers, health professionals assisting people and those making early prognosis of causes, can benefit from this technique; FCMs as a cause-effect knowledge representation and NHL as the learning algorithm, can improve Decision Support Systems and eHealthcare services based on historical data and the effects of past decisions, for supporting future educated course of actions.

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