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Research Article

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# A fuzzy cognitive map-based algorithm for predicting water consumption in Spanish healthcare centres

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## Abstract

The management of water consumption in healthcare centres can have positive impacts on both the environmental performance and profitability of health systems. Computational tools assist in the decision-making process of managing the operation and maintenance of healthcare centres. This research aimed to integrate the empirical knowledge of experts in Healthcare Engineering and the historical data from 66 healthcare centres in a Fuzzy Cognitive Map. The outputs of the predictive model included water consumption, water cost, and $CO_2$ emissions in healthcare facilities, along with eleven variables to discover the causes and consequences of water consumption in healthcare centres. A healthcare centre with about 12 350 users, located in a city that experiences an average of 1100 heating degree days, whose facilities be moderately energy-efficient contributing over 50% with renewable energies is expected to consume 8.4 dam$^3$ of water with 32.1 k€ of cost, and contribute realising 30.8 ton $CO_2$eq emissions. The use of Fuzzy Cognitive Maps for prediction can provide a high level of effectiveness in identifying the factors that contribute to water consumption and in designing key performance indicators to manage the environmental performance of healthcare buildings. This tool is extremely effective in enhancing the performance of the management division of health systems.

## Keywords

water consumption
Fuzzy Cognitive Maps
healthcare centres
Healthcare Engineering
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## 1 Introduction

Water management in healthcare centres is a complex issue that entails the supply, treatment for human consumption, distribution to users and to equipment, and disposal of water to be safely discharged into the public water distribution system. Water is a scarce resource whose reserves are being bargained by today's excessive consumption (Deng et al. 2022). So, several challenges must be addressed by Health Systems managers in order to enhance water management performance in healthcare facilities. A comprehensive approach that sheds light on the causes and consequences of water consumption and its economic and environmental effects will be crucial in addressing this issue.

For medical care and support activities carried out in hospitals to be conducted properly, large quantities of water are required. Water consumption in a healthcare centre is used for toilets, domestic hot water (DHW), laundry, irrigation of green areas, therapy pools, kitchens, cleaning, cooling towers, laboratories, sterilization, and air conditioning, inter alia (WHO 2017).

In Spanish hospitals, between 196–263 m$^3$ per bed (Garcia-Sanz-Calcedo et al. 2017) and 54 m$^3$ per worker (González et al. 2016), are consumed annually, as well as 4 m$^3$ per surgery, 0.7 m$^3$ per hospitalisation, and 0.4 m$^3$ per emergency (Gómez-Chaparro et al. 2018). Batista et al. (2020) provided a systematic review of indicators to assess water consumption in hospitals around the world. They concluded that the services offered in each hospital, the intensity of care activity and the application of best practices infer variations across investigations. Different applications which use water in a hospital complicate its monitoring and

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control. This, and the lack of homogeneity in the indicators paves the way for exploring generalist models for predicting water consumption in healthcare facilities.

González et al. (2016) designed and validated indicators of water consumption with respect to functional parameters in hospitals in Spain. González et al. (2018) extended the scope of their earlier research on cold water for human consumption (CWHC) in hospitals in Germany. In both studies, they proposed a series of measurements to mitigate water consumption and quantified the energy and $CO_2$ emissions savings that these would entail.

García-Sanz-Calcedo et al. (2017) further developed their analysis in such a way that they obtained mathematical models to relate CWHC and DHW by using functional parameters of hospitals: number of beds and roof area. Gómez-Chaparro et al. (2018) extended the scope of regression models to relate CWHC to the medical activity carried out in a hospital. Zhou et al. (2014) developed a grey generalized forecasting model to predict water consumption for the hospitals in Wuhan City, using aggregate consumption data and making their prediction independent of both functional and operating parameters of hospitals.

Besides the above, also efficiency measures in grey water reuse, the attitude of the employees and the social awareness of the users have been shown to have a strong positive impact on the proper management of water consumption (D'Alessandro et al. 2016). However, these qualitative factors have not yet been considered in current models for predicting water consumption.

Until now, mathematical regression models have been developed to establish a direct relationship between functional parameters or medical activity as input variables and predicted water consumption in healthcare centres as output variables. The complexity of how a healthcare centre functions means that many factors might influence energy and water consumption (Batista et al. 2020). Although the degree of explanation of these models is adequate, it is possible to improve their predictions by incorporating intermediate factors, such as the efficiency of the distribution system, level of environmental awareness, etc., instead of imposing a direct mathematical relationship between consumption and functional parameters and/or health service activity. A broader range of possibilities to predict water consumption will be discovered, taking into account factors as yet not considered, such as degree of environmental awareness, efficiency of the water distribution system, contribution of renewable energy (RE), building occupancy level, etc.

The experts at the managerial level have in-depth knowledge based on their professional experience that create models with excellent predictive power about the outcome of a phenomenon, like the consumption of healthcare centres supplies, based on qualitative criteria. Therefore, a group of experts claim to provide adequate rules governing the interrelationships between the factors that influence a phenomenon, like water consumption, so that advancing this set of rules will lead to a proper prediction of that phenomenon under study (Bradley et al. 2006).

A fuzzy inference system such as Fuzzy Cognitive Maps (FCMs) can be used as a reasoning engine to project water consumption scenarios based on hospital buildings' operating and maintenance conditions (Glykas 2010). FCMs apply fuzzy logic to model a reasoning process in a complex decision environment (Zimmermann 2001). FCM can handle and represent tacit knowledge more effectively than other machine learning algorithms such as, artificial neural networks, adaptative neuro-FIS, random forest, etc. (Hsieh and Tang 1998). FCM can accommodate different levels of uncertainty and imprecision in the input data and the relationships between variables, which makes them a useful tool in domains where there is a high degree of ambiguity and uncertainty (Baker et al. 2018). Additionally, FCMs are more transparent and interpretable than neural networks, which can help in understanding the reasoning behind the decision-making process.

FCM was used by Salmeron and Lopez (2012) to predict the impact of maintaining an Enterprise Resource Planning software package, by Papageorgiou and Poczęta (2015) to propose a predictive model of electricity consumption in a house, and by Salmeron et al. (2016) to forecast short-term urban water demand. Prediction by a Fuzzy Inference System (FIS) was proposed by Papageorgiou et al. (2020) for gas demand in Greece, by Jallal et al. (2020) for the energy consumption of a public building, and by Al-Shanableh and Evcil (2022) and Nie et al. (2022) for the consumption in a residential building. Varghese et al. (2022) proposed a fuzzy cognitive approach for the prediction of crowd behaviour. Han et al. (2020) validated an FCM as a credit risk assessment model in lending platforms. Kuang et al. (2020) incorporated human decision factors into the technical criteria to assist in switched power supply design based on FCM. Firmansyah et al. (2019) addressed the challenge of clarifying the interrelationships among aspects of a smart city with the use of FCMs.

Concerning health systems, FCMs have been used to predict pathologies by capturing the reasoning followed by healthcare professionals (Andersson and Silver 2019). Shoaip et al. (2021) constructed a decision support system for Alzheimer's diagnosis based on FCM. Specifically, in the field of Healthcare Engineering, Martinez de Salazar and García Sanz-Calcedo (2019) validated an FCM predicting how maintenance operations influence healthcare centres' energy consumption. Dogu et al. (2021) used an FCM as support to predict the length of hospital stays for selected patients. Additionally, Izadikhah (2022) proposed a stochastic-based FIS to define performance evaluation criteria for the quality of services in hospitals.

However, no state-of-the-art research studies can be found which applied FCM to predict the causes and effects of water consumption in complex systems such as healthcare centres. Mathematical regression models that involve a large number of interrelated variables have been applied to the question of water consumption in hospitals. Prediction through the use of FCM will increase such models' level of explanation of the system, for which reason the present research study is novel and fills a gap in knowledge in the literature.

This research aimed to build and validate a computational tool for predicting water consumption in healthcare centres, along with its associated costs and environmental impact, uncovering the underlying causes and effects. This tool will be useful to support the operation and maintenance management of healthcare centres, as well as improve their sustainability and economic efficiency.

## 2 Material and methods

### 2.1 Overview

Based on the water consumption history of a representative sample of 66 healthcare centres—almost 60%—out of 111 throughout the region of Extremadura (Spain) (Ministry of Health 2021), a panel of five experts assembled relationships among the variables that influence the phenomenon of water consumption. These causal relationships among variables were transferred to an FCM through the adjacency matrix that was validated in a controlled experiment. This FCM then served to consistently predict water consumption in healthcare centres under any working conditions. Figure 1 shows the general method that we followed in the research.

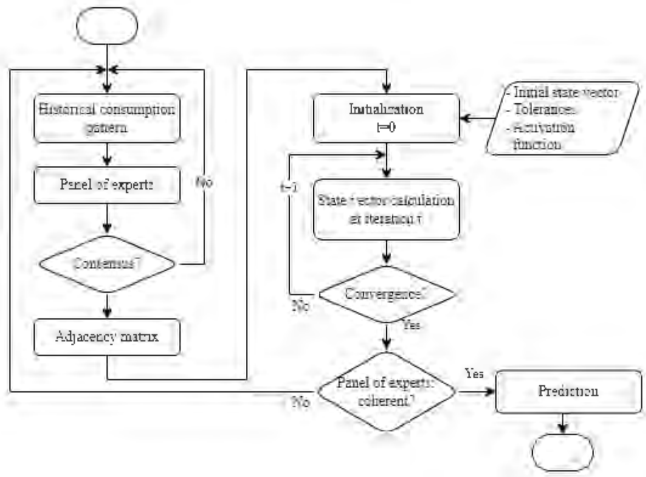


Fig. 1 The general method proposed for the research

More specifically, water consumption data were collected from 66 healthcare centres in eight health districts in a Spanish region from 2016 to 2020 for 14 variables, resulting in a dataset of 4620 records. These buildings had floor areas between 425 m$^2$ and 2582 m$^2$ and were built between 1984 and 2005. The buildings were characterized not only by their functional parameters, but also by the severity of weather conditions of their location (town's climate), the amount of use and the capacity of care to users, the level of energy and maintenance management, and the efficiency of their water installations. Therefore, a sufficiently representative sample of water consumption in healthcare centres was considered for robust water consumption management models.

The operating parameters for the healthcare facilities that will later be selected for inclusion in the FCM were provided by the Health System management (users, workers, basic care units, support units, and consumption). However, additional factors will also be taken into account in subsequent assessments, but they need to be quantified. The energy management level was quantified based on the energy label of equipment and the passive elements of each building. The level of maintenance management was evaluated using the overall equipment effectiveness (OEE) metric, which considers the available time, productive time, and working time of the water distribution system and its components. To assess the efficiency of the water distribution system, a volume balance was performed over a one-year period, considering the volume of water supplied to the system as an input and the desired output (volume of water delivered to users and facilities) and undesirable output (volume of leaked water) as outputs. Finally, the annual $CO_2$ emissions were estimated following The Greenhouse Gas Protocol accounting framework (WBCSD and WRI 2011). Specifically, the GHG emissions inventory was limited to Scope 1, which measures the emissions derived exclusively from the primary energy consumption for the operation of the healthcare centre. As all buildings have a heat pump for air-conditioning, annual $CO_2$ emissions were estimated using the Spanish energy consumption conversion factor (Ministry of Ecological Transition and Demographic Challenge 2020).

### 2.2 Topology of the Fuzzy Cognitive Map

Five health system managers made up the panel of experts in Healthcare Engineering. Three experts are employed within the regional healthcare system, while the remaining two are affiliated with a different healthcare system within Spain. All experts possess comparable educational backgrounds, as well as comparable capabilities, and collectively boast over 100 years of experience managing the operations and maintenance of healthcare facilities in Spain which results in a well-balanced expert panel. This group was provided with this systematic collection of information about water consumption in healthcare centres and other information about the functional parameters of those buildings. Based on this information and their own professional experience, they identified a series of factors that influence water consumption in healthcare centres (Stach et al. 2010).

The range of values of each factor that influences water consumption was fuzzified into the interval [−1,1] using a hyperbolic tangent function (Bueno and Salmeron 2009). In fuzzy linguistics, the activation level −1 represented the lowest value of the range of a factor, +1 represented the highest value of the said range, and 0 represented the average value of this interval of real values according to the fuzzy interpretation (Nahmias 1978). The values of the nodes in the equilibrium state after the simulation were defuzzified to translate the linguistic fuzzy back into numerical values.

This panel of experts interrelated the factors and reported on the intensity of the influence of antecedent factors (pre-synaptic, cause) on the consequent ones (post-synaptic, effect) to build the adjacency matrix, [$\boldsymbol{A}$].

$$\boldsymbol{A} = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix} \tag{1}$$

where $w_{ij}$ represents the intensity with which the factors $i$ and $j$ are related.

An FCM was drawn whose topology follows the provisions of the group of experts for the adjacency matrix. Designated as source nodes were N01, N02, N03, and N04; in the graph, they are the ones which receive no edges. Designated as sink nodes were N12, N13, and N14; these are the ones which receive edges but from which no edge originates.

The relationship between a node $i$ and a node $j$ was represented by an edge with weight $w_{ij}$ that represented the intensity of the relationship between the two factors (Felix et al 2019). Positive causality between factors was represented by $w_{ij} > 0$ which means that the factor $j$ is potentiated by the factor $i$ (pre-synaptic, cause). The contrary is the case when $w_{ij} < 0$. The direction of the arrow indicated the direction in which the calculation evolves.

### 2.3 Calculation process and what-if analysis

Once the topology of the FCM had been defined, the calculation process (Salmeron 2012) began by setting the initialization state vector of the simulation following the general form of Eq. (2).

$$\vec{C}^0 = \begin{pmatrix} c_1^0 & c_2^0 & \cdots & c_n^0 \end{pmatrix} \tag{2}$$

where $c_i^0$ is the state assigned to the $i^{\text{th}}$ factor at time $t = 0$. Specifically, several initial vectors with values of the source nodes were proposed and the state of the rest of the nodes of the network was set to 0 to carry out a what-if analysis.

Due to the dynamic nature of the FCM, the process of iterative calculation caused the values of the non-source nodes in the network to evolve at each iteration according to Eq. (3):

$$c_i^{t+1} = f\left(c_i^t + \sum_{j=i}^{n} w_{ji} \cdot c_j^t\right) \tag{3}$$

where $c_i^{t+1}$ is the new value of node $i$ at time $t + 1$, obtained by $f(\ldots)$ as membership function, from $c_i^t$ as the value of the node $i$ at time $t$, from $w_{ji}$ as the intensity of influence of node $j$ on node $i$ and from $c_j^t$ as the value of node $j$ at time $t$.

The hyperbolic tangent (Bueno and Salmeron 2009) was used as the membership function to calculate the component $i$ of the state vector $c_i^{t+1}$ as shown in Eq. (4), although other membership functions were tested as shown in the validation section.

$$c_i^{t+1} = \frac{e^{\lambda\cdot\left(c_i^t + \sum_{j=1}^{n} w_{ji}\cdot c_j^t\right)} - e^{-\lambda\cdot\left(c_i^t + \sum_{j=1}^{n} w_{ji}\cdot c_j^t\right)}}{e^{\lambda\cdot\left(c_i^t + \sum_{j=1}^{n} w_{ji}\cdot c_j^t\right)} + e^{-\lambda\cdot\left(c_i^t + \sum_{j=1}^{n} w_{ji}\cdot c_j^t\right)}} \tag{4}$$

An error-driven approach was applied as the optimizer to adjust the developed model parameters. So, the values of the factors—states of the nodes—changed at each iteration until those changes were negligible concerning the previous iteration, meaning that they had converged to a state of equilibrium (Felix et al. 2019). The variation of state values between consecutive iterations was calculated from Eq. (5) to determine the evolution of the error on the system's dynamics:

$$E^{t+1} = \max_i \left| C_i^{t+1} - C_i^t \right| \tag{5}$$

where $E^{t+1}$ is the variation of states between two consecutive iterations, $C_i^{t+1}$ is the present state vector, and $C_i^t$ is the state vector of the previous iteration.

The value of the source nodes marked different configuration states of the graph, with that value kept constant for all the iterations of a simulation. The rest of the nodes influence other nodes and are in turn influenced by other nodes, so they are how the network will evolve from the source nodes to the sink nodes (Glykas 2010). This progress through the network nodes will continue until static or cyclic equilibrium is reached.

Finally, a what-if analysis was conducted to determine the prediction of the rest of the possible scenarios. All the possible options of input variable activation were considered in order to know their predictions. Assuming all input variables as null does not lead to any results since the network would not evolve, so this option was discarded (Jetter 2006).

### 2.4 Validation of the Fuzzy Cognitive Map

Out of the total 111 healthcare centres present within the region, a sample of 66 centres was taken. From the sampled cohort, 61 centres were utilized for model training purposes, while the remaining five centres were reserved for validation purposes. The model was subsequently tested using an additional 10 health centres selected from the remaining population.

Five forward simulations were performed taking as initial state vectors the actual data from five representative healthcare centres in the sample. The items for validation were selected based on their FCM input variables exhibiting similarities to scenarios in which a single variable was at a heightened activation level, as defined by fuzzy linguistic terminology, the scenarios in question were represented by S01 (where N01 = 1), S03 (where N02 = 1), S05 (where N03 = 1), S09 (where N04 = 1), and S14 (where N01 = 1, N02 = 1, N03 = 1, and N04 = 1). From the iterative process, consistent equilibrium state values were determined. These predicted values were compared with the actual records to calculate the error of prediction. This validation stage was checked by the expert panel to ensure the robustness of the Fuzzy Cognitive Map.

Additionally, the assessment of the model's accuracy and precision involved two ways: firstly, graphically via boxplots, which contrasted the distribution of actual and predicted data (validation subset); and secondly, through numerical evaluation using statistical metrics (testing subset): mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE). In the knowledge of the satisfactory results obtained in the test, the FCM developed to predict the level of water consumption in healthcare centres was validated.

## 3 Results

### 3.1 Topology of the Fuzzy Cognitive Map

Table 1 presents the factors identified by the expert panel and their descriptions, as well as the range of values that these variables took as extracted from historical records. These values were transformed into fuzzy linguistics by assigning the lowest value of the range to the fuzzy value −1 and the highest to +1.

The experts established the connections between the variables identified and assigned them the weight as the intensity of the relationship between nodes to construct the adjacency matrix (Table 2).

Figure 2 shows the topology of the designed FCM and causal relationships among nodes. It includes the input layer which comprises four nodes (independent factors), an

**Table 1** Factors affecting water consumption in healthcare centres

| Code | Description | Definition | Range |
|---|---|---|---|
| N01 | Number of users | Average annual number of users assigned to a healthcare centre, expressed in units | 497–24 200 |
| N02 | Energy management level | Level of energy management in a healthcare centre, expressed as a percentage: low (≤25%); medium (25%–75%); high (≥75%) | 0–100 |
| N03 | Town's climate | Severity of weather conditions in the city where the healthcare centre is located, expressed in heating degree-days (HDDY): low (≤1500); middle (1500–1900); high (≥1900) | 1052–2250 |
| N04 | Contribution of renewable energies | Ratio between energy from renewable sources and the total energy used in a healthcare centre, expressed as a percentage: low (≤20%); medium (20%–40%); high (≥40%) | 0–52 |
| N05 | Number of workers | Average annual number of workers in a healthcare centre, expressed in units | 6–57 |
| N06 | Number of basic care units | Number of doctor-nurse teams per 1500 patients (±10%), expressed in units | 2–15 |
| N07 | Number of support units | Number of care services additional to primary care (rehabilitation, dental health, obstetrics, etc.), expressed in units | 0–6 |
| N08 | Domestic hot water system efficiency | Overall performance of the domestic hot water system, expressed as a percentage: low (≤60%); medium (60%–85%); high (≥85%) | 0–100 |
| N09 | Water distribution and pumping system efficiency | Overall performance of the water distribution and pumping system, expressed as a percentage: low (≤60%); medium (60%–85%); high (≥85%) | 0–100 |
| N10 | Environmental awareness level | Level of environmental awareness by healthcare centre staff, expressed as a percentage: low (≤30%); medium (30%–70%); high (≥70%) | 0–100 |
| N11 | Maintenance management level | Rate of annual corrective maintenance interventions to preventive, expressed as a percentage: low (≤25%); medium (25%–60%); high (≥60%) | 0–100 |
| N12 | Annual water consumption | Annual amount of water consumed in a healthcare centre, expressed in $m^3$ | 8184–271 270 |
| N13 | Annual $CO_2$ emissions | Annual amount of $CO_2$ emitted into the atmosphere by a healthcare centre, expressed in equivalent tons of $CO_2$ | 30–327 |
| N14 | Annual water cost | Annual cost of water consumed in a healthcare centre, expressed in euros (€) | 6629–219 728 |

**Table 2** Adjacency matrix between identified factors

| | N01 | N02 | N03 | N04 | N05 | N06 | N07 | N08 | N09 | N10 | N11 | N12 | N13 | N14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| N01 | 0 | 0 | 0 | 0 | 0.2 | 1 | 1 | 0 | 0 | 0.2 | 0.3 | 0 | 0 | 0 |
| N02 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | −0.5 | 0 | −0.4 |
| N03 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0.4 | −1 | 0 | 0 |
| N04 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6 | 0.5 | 0 | −1 | 0 |
| N05 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0.6 | 0 | 0 |
| N06 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0.3 | 0.5 | 0 | 0 |
| N07 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0.4 | 0.4 | 0 | 0 |
| N08 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | −1 | −0.5 | 0 |
| N09 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | −1 | −0.4 | 0 |
| N10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 | −0.4 | 0 | 0 |
| N11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.2 | 0 | −0.7 | −0.3 | 0 |
| N12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| N13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| N14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

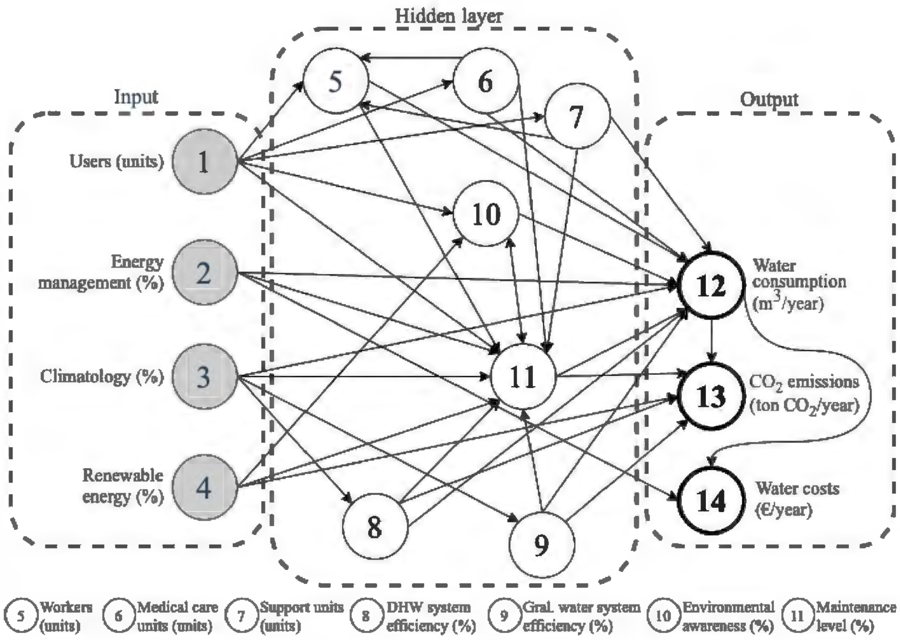


**Fig. 2** Topology of the Fuzzy Cognitive Map predicting water consumption

output layer with three nodes (dependent factors), and an intermediate (or hidden) layer that links the input with the output.

## 3.2 The output of what-if analysis

The outputs of the forward simulations are depicted in Figure 3, utilizing both fuzzy linguistic and deterministic values. This arrangement enables the ordered representation of the output values of all scenarios along intervals, facilitating a comprehensive visual representation of the what-if analysis.

The scenarios exhibiting the maximum values of water utilization, water expenditure, and greenhouse gas (GHG) emissions are S01, S08, and S02 respectively. Conversely, the scenarios demonstrating the minimal values of water utilization, GHG emissions, and water costs are in the following order: S13, S05, S12, and S04.

In particular, the deterministic values of the output variables—water consumption, $CO_2$ emissions, and cost of water consumption—are shown in Figure 4.

## 3.3 Causes analysis of the output of each scenario

The heat map shown in Figure 5 provides a view of the activation level of each FCM variable (intermediate and

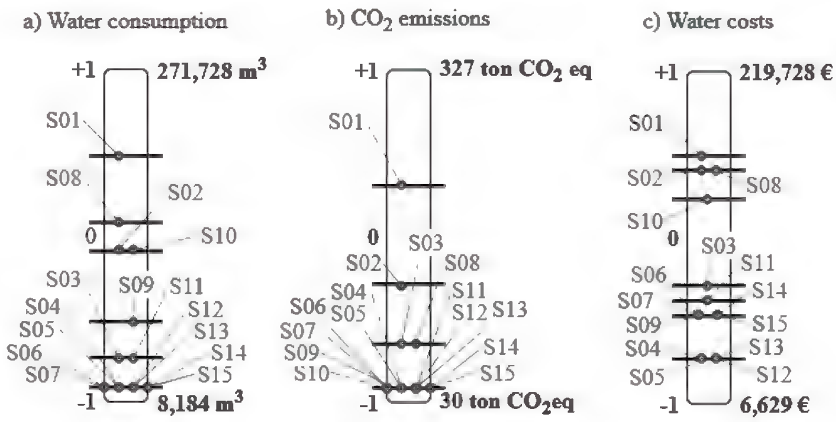


**Fig. 3** Output layer comparison between fuzzy linguistic and deterministic values

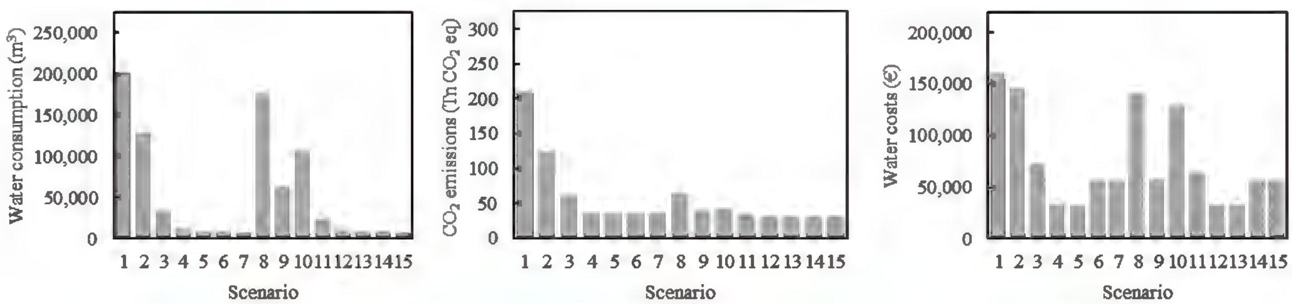


**Fig. 4** Deterministic values of the output variables: water consumption, $CO_2$ emissions, and water costs

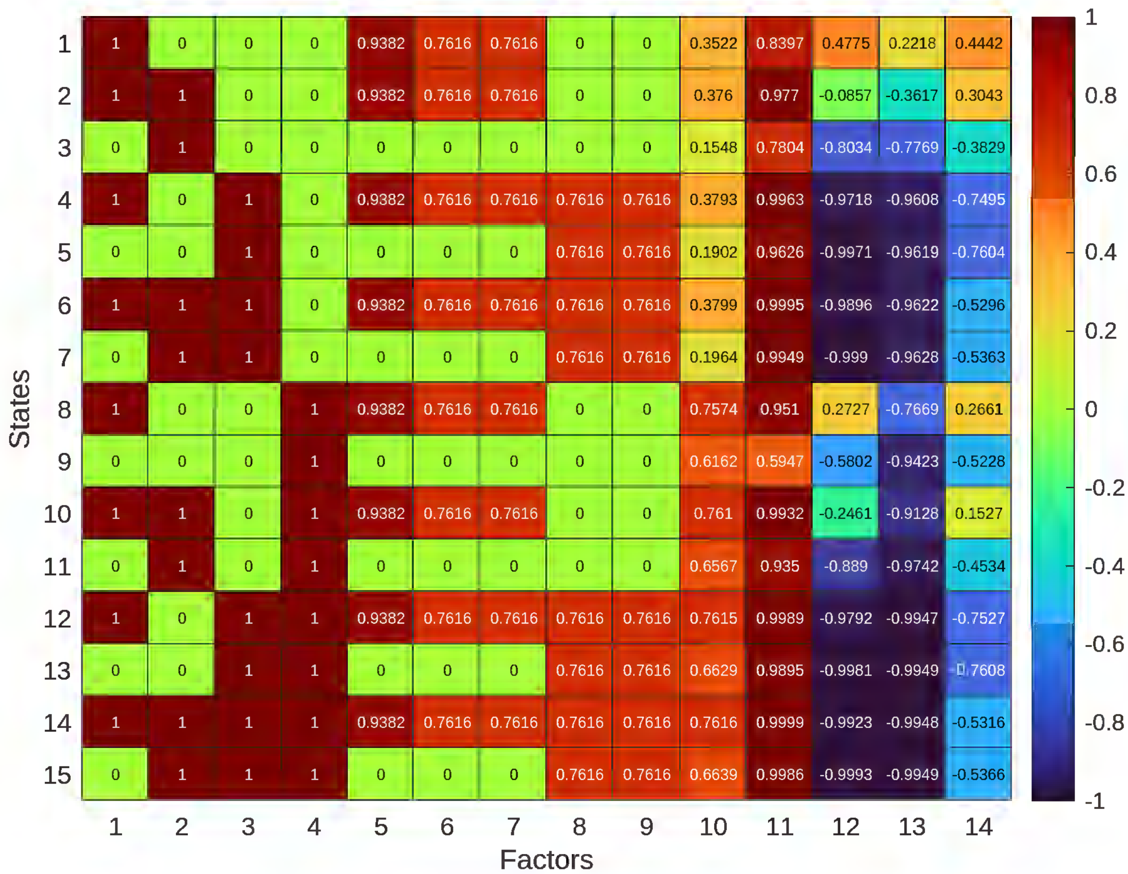


**Fig. 5** Heat map of equilibrium states according to each initial state

sink nodes), which are the equilibrium states of the forward simulations for each one of the initial state vectors—the level of activation of proposed scenarios—of the source nodes.

In the heat map, we can see that there are similarities in the output layer of several sets of scenarios, either in all three output variables or in at least two of them. Only scenario S02 does not comply with this pattern; however, S02 was compared to a similar pair. In order to highlight these patterns in the output layer of the FCM that help us identify common causes that lead to these consequences, the Venn diagrams in Figure 6 are provided, which also rank them from unfavourable (left) to favourable (right) scenarios.

Firstly, the highest prediction for water consumption (N12 = 202 538.8 $m^3$), GHG emissions (N13 = 211.4 ton $CO_2$eq), and water costs (N14 = 160 508.5 €) were observed in scenario S01. The second least favourable scenario (i.e., S08) showed a medium-high level of water consumption (N12 = 175 598.8 $m^3$), of water costs (N14 = 141 531.9 €), and a low level of GHG emissions (N13 = 64.6 ton $CO_2$eq). The third least favourable scenario was S02, which leads to 128 453.8 $m^3$ of water consumption (N12), 124.8 ton $CO_2$eq of GHG emissions (N13), and 145 602.2 € in water costs (N14). The three scenarios share a high number of users (N01) and a medium level of climate severity (N03). However, they differ in their levels of energy management (N02) and RE contribution (N04). In particular, scenario S08 incorporates a high level of RE contribution (N04), which leads to lower GHG emissions compared to the other two scenarios.

Secondly, the set of scenarios designated as S03, S06, S07, S11, S14, and S15, in their output layer exhibit a common characteristic of having a low level of water consumption (N12) and GHG emissions (N13), and a medium-low level of water cost (N14). The only input that is consistent across all scenarios is a high level of energy management (N02). It is noteworthy to mention the differences between the scenarios, including: (i) medium RE contribution (N04) in scenarios S03, S06, and S07, and high RE contribution in scenarios S11, S14, and S15; (ii) medium climate severity in scenarios S03 and S11 and high climate severity in the remaining scenarios; and (iii) a high number of users in scenarios S06 and S15 and a medium number of users in the other scenarios.

Then, in the output layer of the FCM, a similar pattern can be observed between scenarios S09 and S10. Both exhibit comparable levels of water consumption (63 405.8 $m^3$ and 107 354.3 $m^3$, respectively) and GHG emissions (38.6 ton $CO_2$eq and 42.9 ton $CO_2$eq, respectively). However, S09 displays a medium-low level of water cost (N14 = 57 474.7 €) while S10 has a medium level (N14 = 129 449.2 €). The similarities between these two scenarios can be attributed to their high user levels (N01), medium levels of energy management (N02) and climate severity (N03). The differences in their respective results are due to varying contributions of RE (N04), which is medium for S09 and high for S10.

Finally, the scenarios with the lowest values for water consumption (N12), GHG emissions (N13), and water costs (N14) are ranked as follows: S13, S05, S12, and S04. These four scenarios share a medium level of energy management (N02) and a high level of climatic severity (N03). Additionally, they are equal in pairs concerning the other two variables (N01 and N04). On one hand, while scenarios S05 and S13 demonstrate a medium level of users (N01), by contrast, scenarios S04 and S12 exhibit a high level of that variable (N01). On the other hand, while scenarios S12 and S13 exhibit a high level of RE contribution (N04), in contrast, scenarios S04 and S05 have a medium level of that variable (N04).

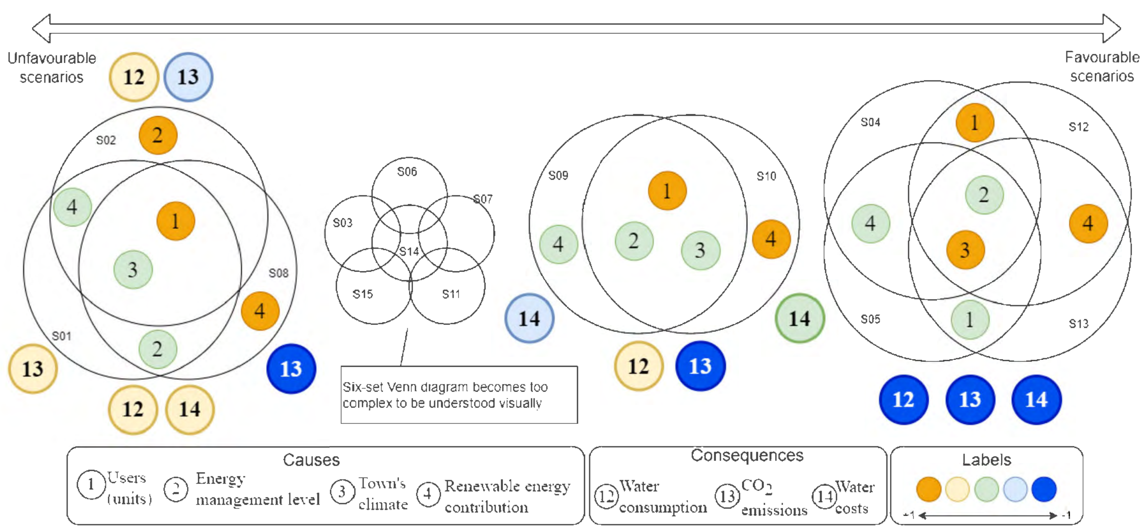


**Fig. 6** Venn diagrams of scenarios with similar patterns in the output layer of the Fuzzy Cognitive Map

### 3.4 Validation of the Fuzzy Cognitive Map

Table 3 shows the actual and predicted values for the FCM proposed. Absolute errors of less than 10% are obtained for the five healthcare centres, so this controlled experiment allows validation of the FCM developed.

Furthermore, Figure 7 illustrates the comparison of the distributions between the actual sample data and values obtained from the simulations. Notably, the actual data exhibits a narrower distribution compared to the predicted values, which display a slightly wider distribution. Despite this disparity, the pivotal features of the distributions, such as the quartiles, mean, and median, display comparable positioning. The discrepancy between the mean of the actual and predicted values is 8.21% for water consumption, 4.45% for GHG emissions, and 3.16% for water cost, what appears to be an adequate accuracy of the FCM model.

The accuracy of the model was tested with the statistical metrics (MAE, MAPE, and RMSE) shown in the Table 4. Additionally, statistical metrics indicate that the tangent hyperbolic membership function exhibits a lower error than the sigmoid function.

## 4 Discussion

The prediction of water consumption in a healthcare centre using FCM differs from conventional mathematical regression models in the state-of-the-art. FCMs take into account the comprehensive characteristics of a system, hereby, a healthcare centre. Specifically, FCMs consider causal relationships among various variables that define the dynamics of the water consumption phenomenon. The in-depth results that could be obtained from FCM provide valuable insights for decision-making in Healthcare Engineering management and are thus a very powerful tool for conducting what-if analyses (Jetter 2006).

Water scarcity and the environmental impact of its use, as well as its impact on public health, turns water management into an obligation (Rizzo et al. 2020). This research allows the most influential variables affecting the management of a healthcare centre's water consumption can be determined. The backwards and forwards tracking attributable to the FCMs makes the causes and consequences of the phenomenon under study recognizable (Nápoles et al. 2020). The FCM allows deviation to be detected, then the root causes of an adequate or inadequate level of water consumption to be identified, and it acknowledges the consequences of management decisions affecting the installation to be predicted by modifying the input variables.

Having about 24 200 users assigned to a healthcare centre, while keeping the rest of the input variables at a medium level, was seen to generate the worst scenario for water consumption, GHG emissions, and water costs. This FCM will enables to infer the demand for water based on the operational conditions of a healthcare centre, surpassing previous techniques that relied solely on the building's functional parameters. By incorporating additional input variables into the design, it becomes possible to prevent oversizing of water installations, thus reducing $CO_2$ emissions and the carbon embedded in the building installations (García-Sanz-Calcedo et al. 2021).

The distribution of users by healthcare centres is a

**Table 3** Comparison of actual and predicted values by the FCM

| Healthcare centre ID (scenario check) | | Water consumption | GHG emissions | Water costs |
|---|---|---|---|---|
| HC7 Scenario 01 | Actual | 210 437.21 $m^3$/yr | 212.70 ton $CO_2$ eq/yr | 172 039.20 €/yr |
| | Predicted | 202 538.78 $m^3$/yr | 211.44 ton $CO_2$ eq/yr | 160 508.51 €/yr |
| | Error | −3.75% | −0.60% | −6.70% |
| HC12 Scenario 03 | Actual | 32 068.30 $m^3$/yr | 62.90 ton $CO_2$ eq/yr | 78 329.34 €/yr |
| | Predicted | 34 045.35 $m^3$/yr | 63.13 ton $CO_2$ eq/yr | 72 381.01 €/yr |
| | Error | +6.17% | +0.37% | −7.59% |
| HC38 Scenario 05 | Actual | 8540.29 $m^3$/yr | 33.45 ton $CO_2$ eq/yr | 32 229.03 €/yr |
| | Predicted | 8565.47 $m^3$/yr | 35.66 ton $CO_2$ eq/yr | 32 158.38 €/yr |
| | Error | +0.29% | +6.60% | −0.22% |
| HC42 Scenario 09 | Actual | 64 823.23 $m^3$/yr | 39.12 ton $CO_2$ eq/yr | 59 309.93 €/yr |
| | Predicted | 63 405.75 $m^3$/yr | 38.57 ton $CO_2$ eq/yr | 57 474.66 €/yr |
| | Error | −2.19% | −1.41% | −3.09% |
| HC50 Scenario 14 | Actual | 9833.90 $m^3$/yr | 32.20 ton $CO_2$ eq/yr | 53 292.30 €/yr |
| | Predicted | 9196.88 $m^3$/yr | 30.77 ton $CO_2$ eq/yr | 56 537.02 €/yr |
| | Error | −6.48% | −4.43% | +6.09% |

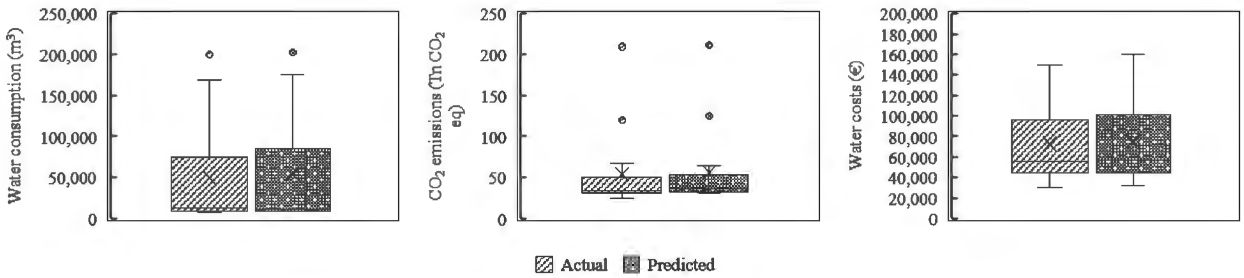


**Fig. 7** Comparison of actual data against FCM model predictions using boxplot

**Table 4** Model errors for predicted values compared to actual data

| Membership function | Error | Water consumption | Greenhouse gas emissions | Water costs |
|---|---|---|---|---|
| Hyperbolic tangent | MAE | 4426.65 $m^3$ | 2.79 ton $CO_2$eq | 2533.87 € |
| | MAPE | 8.88% | 5.17% | 3.48% |
| | RMSE | 8880.54 | 3.45 | 4068.00 |
| Sigmoid | MAE | 6659.74 $m^3$ | 4.33 ton $CO_2$eq | 6493.33 € |
| | MAPE | 12.33% | 14.38% | 12.23% |
| | RMSE | 14 049.38 | 9.42 | 10 938.32 |

result of the health system's strategic planning. Acting on this input variable is therefore neither direct nor immediate. However, we can take action by installing certain technologies and devices designed to reduce the unit consumption of water. These include electronic taps, aerators, misting shower systems, cisterns with optimized discharge, rainwater reuse systems, condensation from air conditioning installations, greywater, variable flow pumps, and intelligent control systems (Wei 2010; Attia et al. 2015).

Based on the scenario where about 12 350 users are assigned to a healthcare centre with high energy-efficient facilities in a low severity climatic location and a RE contribution greater than 50%, a total water consumption of 8.4 $dam^3$, 32.1 k€ in water costs, and about 30.8 ton $CO_2$eq of GHG emissions are estimated. Assuming a built surface area of around 1600 $m^2$, we would obtain an indicator of 5.25 $m^3/m^2$, compared to 1.65 $m^3$ per built surface area reported by Garcia-Sanz-Calcedo et al. (2017) for hospitals in the same region of Spain. However, the numbers are not similar as the hospital requires a much larger surface area for ancillary services to clinical practice than healthcare centres. Notwithstanding, a decline in this optimal scenario at the beginning of the paragraph is suggested by the FCM if the severity of the local climate demands almost 2250 heating degree days. This may be because too much RE installation would be required to meet the joint demand for DHW and heating (Atienza-Márquez et al. 2022).

The results indicate that adequate energy management leads to favourable results in terms of consumption, water costs, and GHG emissions. These results improve if RE contribution is also great than 50%. In this sense, GHG emissions are low if the contribution of RE is high, which is logical since it is not necessary to burn fossil fuels to obtain DHW (González-Domínguez et al. 2022).

Despite the above, it was found that having about 24 200 users together with a RE contribution greater than 50% do not by themselves lead to the minimum results in terms of water consumption, its cost, and GHG emissions, like scenario S08. Complementing the contribution of RE with appropriate energy management and energy-efficient installations will do so, like scenario S10. The difference between the two scenarios is almost 70 $dam^3$, more than 10 k€ in costs, and about 22 ton $CO_2$eq, which, when extended to a whole Health System of a country, would lead to incredible amounts of savings and efficiency. Similar findings were obtained by González et al. (2016) to deduce that they could save 34.24 $m^3$ per hospital bed and, consequently, would save 5600 $dam^3$ and about 22 400 ton $CO_2$eq in Spain.

With the prediction not only of water consumption but also of its cost and its GHG emissions, it is possible to adequately control the consumption of supplies and plan the operation and maintenance of the building and its facilities, as well as to take decisions on investment in renewable energies. Prognosis, i.e., the ability to forecast the most probable development of an event, is extremely worthwhile for those responsible for hospital management to be able to infer consumption, design helpful control indicators, and thus to manage the actual consumption.

On the long road towards healthcare sector sustainability, it is also crucial to introduce sector-based measurement systems to control the consumption segregated by areas of a hospital, and thus be able to implement specific measures to enhance consumption ratios. Future research should focus on extrapolating the FCM to hospitals with the incorporation of new variables, and on calibrations not only to greater building sizes and water installation complexity but also on including the specific water demands of certain medical treatments.

In this regard, the reduction of the complexity of our FCM model would pose a challenge for future endeavors, albeit the present study provides initial profound understanding of the phenomenon of water consumption in healthcare centres. In fact, the developed FCM is comprised of fourteen interdependent variables, wherein the instantaneous values of certain variables influence the remaining ones, while some of these influenced variables are further affected by others. It is feasible to curtail the number of variables and expert opinion's influence by conducting a smaller scale experiment that would enable the monitoring of continuous temporal evolution of magnitudes of interest, rather than discrete aggregate quantities.

### 4.1 Limitations

The primary limitation of this study is that the findings were derived from a simulated model and therefore, the input data uncertainty (aleatoric and/or epistemic) may impact the results if another sample of healthcare facilities is employed. The epistemic uncertainty affecting the phenomenon of water consumption in healthcare facilities has been mitigated through two efforts: (1) by taking a sufficient sample of buildings and (2) by incorporating a panel of experts with more than 100 years of experience in hospital management. Consequently, the methodology utilized in this investigation can be applied to other buildings and even to different geographic regions after incorporating managerial expertise.

Additionally, a limited number of experts involved in the study may introduce bias in the analysis due to their professional experiences. However, the extensive collective experience of the expert panel, totalling over 100 years in two diverse health systems, helps mitigate the uncertainty in the reliability of their opinions.

## 5 Conclusions

This research proposed an FCM to infer water consumption and its impacts on both economics and the environment while identifying the underlying causes. The management of healthcare centres often relies on the personal experience of managers. Consequently, some causes of weak hospital operation and maintenance performance may not be discovered. This study captured the expertise of Healthcare Engineering professionals to quantitatively determine the causes and consequences of the phenomenon in question. The FCM's weights of the causal relationships were obtained as a result of a quantitative diagnosis based on the qualitative opinion of experts. The robustness and accuracy of the predictions were verified through a controlled case study. Thus, the proposed FCM-based prediction algorithm was validated by a panel of experts in Healthcare Engineering.

The results indicate that 8.3 $dam^3$ of water was consumed and 30.7 ton $CO_2$eq of GHG emissions are generated in a healthcare centre with high energy-efficient facilities, or one that demands around 1100 heating degree days, or whose RE contribution exceeds 50% and the other input variables are at a medium level. Having nearly 24 200 registered users leads to the consumption of over 200 $dam^3$, a water cost of more than 160 k€, as well as more than 210 tons of $CO_2$ eq, with all other input variables remaining at a medium level.

For each target variable, the following conclusions were reached through analysis. Firstly, the lowest annual water consumption was observed to be 8.3 $dam^3$ for a healthcare centre that serves approximately 12 350 users and is equipped with high energy-efficient facilities, is located in a city that needs about 2250 heating degree days and a RE contribution of nearly 50%. Secondly, the minimum GHG emissions of 30.8 tons of $CO_2$eq were observed for a healthcare centre that boasts high energy-efficient facilities, or is located in a city with a demand for only 1100 heating-degree days, and has a RE contribution greater than 50%, and about 12 350 users. Finally, the lowest annual cost of water, estimated at 32.1 k€, occurs in a healthcare centre with medium energy-efficient installations and equipment and located in a town with a demand for only 1100 heating-degree days.

Conclusively, the type of healthcare centre with the lowest water consumption (8.4 $dam^3$), GHG emissions (30.8 ton $CO_2$ eq), and water cost (32.1 k€) will correspond to a healthcare centre with about 12350 assigned users and moderate energy-efficient facilities, whose climatic severity allows for about 1100 heating degree days, and more than 50% of the RE contribution.

The findings of this study show the capacity an FCM has to represent the functioning of a healthcare's water consumption system. From the above, it is demonstrated that FCMs are indeed effective in predicting a variable of interest in a complex system, such as water consumption in a healthcare centre. Moreover, they help to identify the factors that contribute to a phenomenon under study. Thus, FCMs actively serve health systems at the strategic level to design new health facilities, and also at the operational level of these organisations to control the operation and maintenance of healthcare centres. This computational tool is extremely effective in enhancing the performance of the management division of health systems.

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## Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

## Author contribution statement

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Gonzalo Sánchez-Barroso, Jaime González-Domínguez, Joao Paulo Almeida-Fernandes and Justo García-Sanz-Calcedo. The first draft of the manuscript was written by Gonzalo Sánchez-Barroso and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.



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