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Dynamic Membership Functions for Context-Based Fuzzy Systems

PABLO PANCARDO[1], JOSÉ ADÁN HERNÁNDEZ-NOLASCO[1], MIGUEL A. WISTER[1], AND MATIAS GARCIA-CONSTANTINO[2]
[1]Academic Division of Information Science and Technology, Juarez Autonomous University of Tabasco, Villahermosa 86690, Mexico
[2]School of Computing, Ulster University, Jordanstown BT37 0QB, U.K.

Corresponding author: José Adán Hernández-Nolasco (adan.hernandez@ujat.mx)

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ABSTRACT In fuzzy systems, membership functions determine the groups to which a variable can belong to, and these groups are static or only have one setting in some aspect. However, fuzzy systems typically require to model the dynamic environment they represent. Still, this behavior does not reflect the membership groups in a conventional way. Thus, conventional fuzzy systems are not capable of reflecting the dynamics of the real-time context. The approach presented consists of a fuzzy system where the membership functions can have dynamic transformations, according to contextual variables that influence them, to have a model that adjusts in real time. The membership functions' dynamism is achieved because the form in the sets can be transformed; the maximum degree of membership of a set is in a range of zero to one; and, the location of the sets in the discourse universe can vary dynamically. The results show the feasibility of a context-based fuzzy system with dynamic membership functions built-in real time, that has been influenced by contextual variables. Therefore, unlike other proposals, this approach allows modeling the influence of the context on a fuzzy system, making it more adjusted to reality. To illustrate our proposed approach, a case study is presented where a fuzzy system estimates the heat stress in a work environment that uses data acquired from wearable devices. This system automatically generates the following indicators: (i) energy level wasted while performing a physical activity, (ii) personalized measurement of workload level, and (iii) measurement of Occupational Heat Stress (OHS).

INDEX TERMS Dynamic membership functions, context based fuzzy systems, occupational heat stress.

I. INTRODUCTION

Fuzzy systems require a set of input variables assigned to a fuzzy set [1], built from a membership function, and with a certain degree of membership (fuzzification). An inference engine applies a set of knowledge-based rules (fuzzy inference) and produces a response to a decision problem (defuzzification). Typically, fuzzy sets are generated from the knowledge of experts in the field or by using information that is currently known, and they have no adjustments or adaptations once defined; thus, they are static sets. However, context variables (such as the elapsed time or the physical space where events occur) influence the fuzzy system. Consequently, membership functions should be dynamic in real time to reflect their adaptation to the domain of discourse.

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Some previous works have considered the need for dynamism in membership functions, but only to reflect a specific situation or time influence. For example, using a membership function scaled according to a criterion for an input variable [2], or scaling a Gaussian-shaped group from variations in the mean value and variance [3]. None of the cases refer to an approach where context influences the system variables in real time, so the question arises: how to reflect the context influence in a fuzzy system?

Therefore, we propose a fuzzy system approach where fuzzy sets are dynamic, based on the context that influences them in real time, and they adjust or adapt to model reality in a better way. We illustrate the dynamism in the membership function with three situations: (i) a decrease in the maximum degree of membership that a variable can have in a fuzzy set, (ii) changes in the form of the fuzzy set, and (iii) changes in the location of the fuzzy sets within the domain of discourse.

This proposed approach applies to a case study on the estimation of heat stress in a work environment, caused by continuous physical activity in an environment with high temperature and relative humidity values. The case study is relevant because it concerns the area of occupational health and safety. Specifically, the heat stress situation mainly affects developing countries located in tropical or hot geographical regions in the world.

This paper has two contributions. The first contribution is a new dynamic fuzzy system approach, where context imposes dynamism that influences the fuzzy system's variables and leads to dynamic membership functions in their form and location in the domain of discourse. The membership functions make real-time adaptations to reflect the influence of the context on the system. The second contribution is a new way of estimating heat stress. Following established occupational health and safety regulations, we applied our contextual dynamic fuzzy system approach, where personalization of the calculations and dynamism in the membership functions capture context and reflect how the same physical activity can impact different users in different ways. Therefore, when applying our approach, the calculation of heat stress presents heterogeneous results for the same physical activity due to the context, the diffuse values, and personal physiological data during the experiments' execution.

The remaining of the paper is organized as follows. Section II explains the background and related work. Section III introduces the proposed method and presents a detailed discussion about it. Sections IV and V present a description of the case study and a report of the obtained results from the proposed method applied to the case study, respectively. Section VI discusses the obtained results. Finally, conclusions and final remarks are presented in Section VII.

II. BACKGROUND AND RELATED WORK

Dynamic membership functions have their origin in the work of [4], who sought to understand the influence of different forms of membership functions in dynamic systems controlled by fuzzy logic. For this purpose, the author proposed an approach that employed four parameters. A membership function could change its form between triangular and Gaussian groups to reflect the control system's dynamism. The author of [4] showed how a slight change in the shape of the membership functions could induce a significant change in the system's steady state's qualitative behavior.

In contrast, in [5], they determined that the time variable must be considered in the fuzzy logic domain because, as in many domains, the fuzzy system's sets are dependent on time.

The following equation defines a conventional fuzzy set:

$$F = (x, \mu(x)) \tag{1}$$

where x is the element of the universe of discourse X, and $\mu(x)$ is the membership function of x to the fuzzy set F of the universe X.

Virant [5] made the first considerations so that fuzzy sets can change over time, and thus the membership functions are dynamic [3], so the following equation governs the representation of the membership functions F for a time-dependent fuzzy set $F(t)$.

$$F(t) = (x, \mu_{F(t)}(x)) \tag{2}$$

where x belongs to the universe of the fuzzy set F and $\mu_{F(t)}(x)$ in the membership function of F, the t domain can be continuous or discrete. The projection in the (μ, t) plane for a given x is called the dynamic membership function. In a time t_1 there is a set $F(t)_1$ and in a time t_2 there is another fuzzy set $F(t_2)$ and these sets could be different.

Virant shows how the degrees of membership of the elements of the discourse universe change over time. Therefore, the form or location of the functions of membership change. Cerrada [3] also investigated dynamism, which is exemplified by Gaussian membership functions, where dynamism is seen with changes in the mean and standard deviation of the functions, leading to changes in the width of the Gaussian function and shifts in the universe of discourse.

Later on, [6] considered that dynamism could be required in input variables, rules, output variables, or all of them simultaneously. In these works, the dynamic fuzzy system can adapt to changes in the temporal behavior of the system variables. The membership function of the fuzzy set can change according to the time t; these changes can be continuous or discrete.

Conversely, the fuzzy system proposed by [2] uses the concept of scalable membership functions for a company to select the most suitable supplier for its interests, based on an evaluation of the environmental performance of the supplier. Therefore, the authors used a scaled membership function (with values of 0.2, 0.4, 0.6, 0.8, and 1.0) for an input variable called environmental performance, following the priority level given by suppliers to the input. As it can be seen, this is a specific situation that does not require further changes once reflected in the system. These are not contextual variables (which can be very dynamic), so if the priorities of the company do not change, the membership functions will remain static.

The authors of [3] consider the adaptation of Gaussian-shaped groups over time. The adaptations come from changes in the mean value and variance of the group. Therefore, it only applies to Gaussian-shaped groups and does not consider the possible change in the group's shape towards trapezoidal or triangular.

In [7], the authors proposed a three-phase method to detect the local community to which a network node belongs, without requiring the global information of the network. In each phase, the dynamic membership function depends on the number of nodes from the local community, and which neighboring nodes belong to the community is determined by a formula.

This work [7] gives dynamism to the membership functions from a spatial criterion, since depending on the location of the node, it will belong to a local community. They do not consider the temporal variable. In [8], similar treatment is made, from the distances.

In both approaches ([7] and [8]), the dynamism of the functions is a result of the increase in the community's nodes number and resolves communities' formation explicitly considering the spatial aspect. These are not context-based approaches.

Regarding the case study, few papers address the issue of occupational heat stress using fuzzy logic. For example, in [9], a fuzzy hierarchical analytical method is proposed to assess the safety and early warning in hot-humid work environments. Asghari *et al.* [10] used fuzzy logic to prioritize different criteria and evaluate different available indices to estimate heat stress. Both approaches ([9] and [10]) see the problem as a multi-criteria decision making; however, neither is for heat stress estimation in an automated way through wearable technology, personalized estimations, and within a fuzzy system with dynamic membership functions to represent the dynamics imposed by context variables.

III. FUZZY SYSTEM APPROACH

The real world is always changing. The population is growing, the temperature changes throughout the day; the currencies vary their values quickly. That is to say, practically everything changes. In this sense, intelligent systems must also adapt to changes. A fixed system will soon require modifications to adapt to changing parameters. A system that adapts in real time to the changes that occur will undoubtedly have better results.

Virant and Zimic [5] were the first to propose dynamic fuzzy systems. Dynamism can be in one or several points of the fuzzy system. The first point is the membership functions built from the input variables, the second point is the inference engine's rules, and the last point is the output functions [6].

Dynamic fuzzy systems have been modeled based on Equation 2, where a time-dependent function is in charge of modulating the membership functions of fuzzy sets. This function modulates the groups' membership degrees of the universe of discourse so that the membership degrees may be varying between 0 and 1. This modulation implies changes in the size, shape, or location of these functions in the universe of discourse. All these changes depend only on the passage of time.

We propose the membership functions to be dynamic not only as an effect of time, but also against situations or events of the context that cause the dynamism of the membership functions, representing the context's effects on the variables of the fuzzy system. Some examples of situations in the context that can cause dynamism are the health of a patient, the environmental temperature, the physical location, the volume of an object, etc.

For a fuzzy system to be adaptive, it is convenient that the context situations are only used as aspects that affect the input variables of the system, not as input variables themselves. It implies that changes in the context would not require adapting or modifying the design of the fuzzy system.

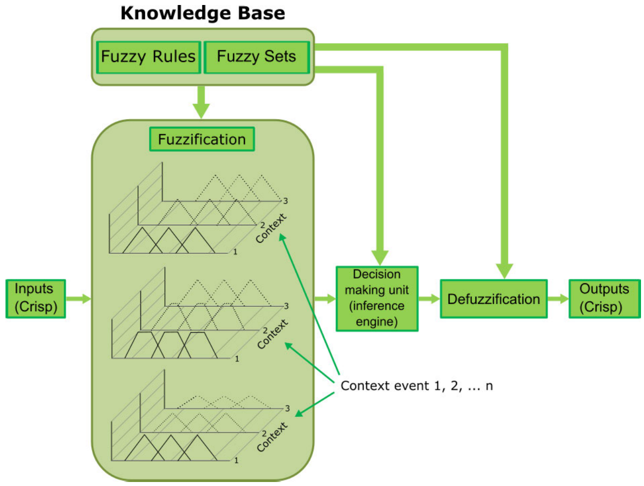

FIGURE 1. Context based Fuzzy System with Dynamic Membership Functions.

Contextual situations could change the membership grade from a given x to the fuzzy set function. Likewise, the context may require dynamism in the membership functions of the fuzzy set, requiring the function to move along the x axis depending on the context that affects it directly, i.e., the function is represented by:

$$F = (x, \mu(x \pm a(c))) \tag{3}$$

where $a(c)$ is a constant whose value depends on the criteria of change for this variable, for example, if we have membership functions for the thermal sensation of a person, the function will have a specific range. Still, if a person was in the sun, the membership function will move to the right (larger values), because the thermal sensation will be more significant. If the person is in the shade and the air is circulating, the function will move to the left on the x axis because the thermal sensation will be less. Figure 2 shows how a triangle membership function could shift a constant value to the right.

We propose a functional reference architecture representing a context-based fuzzy system where the membership functions are dynamic enough in form and location in the universe of discourse to reflect the system's environment in real time. Figure 1 shows the architecture.

In general, a fuzzy set offers the variables a maximum degree of membership equal to 1. We propose that there can be a decrease in the maximum degree of membership to a fuzzy set; therefore, a particular variable could reach, for example, a maximum degree of 0.7. It means the maximum degree is not necessarily 1 but can be in a range from 0 to 1. For example, a variable called temperature's impact can have a maximum degree of membership of 1 or 0.5 because a worker perceives a workload differently if it is a scenario with high temperatures due to the sun's intensity or an environment with pleasant temperatures (see Figure 2).

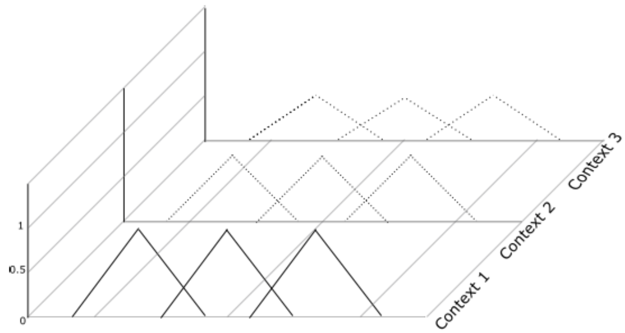

FIGURE 2. Dynamic function with variable maximum membership.

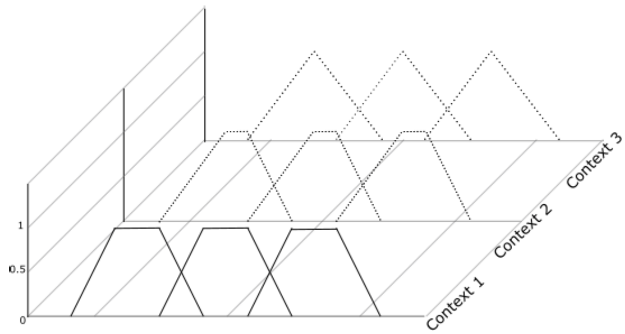

FIGURE 3. Changes in the form of the membership function.

In fuzzy systems, the groups' common forms are triangular, trapezoidal, and Gaussian, and they remain static once the system is built. However, many of the situations modeled with fuzzy systems are dynamic and require adaptations to reflect the context's impact during their life cycle. For example, if a group of values reaches the maximum membership degree to a set, then the shape of the set should be trapezoidal. Nevertheless, context-based variables can cause a group reduction, and just a single value meets the maximum membership degree, so it is necessary that the shape of the set changes to triangular (see Figure 3).

Usually, fuzzy sets occupy a fixed location in the universe of discourse; that is, the membership function exists for a range of values within the discourse universe, where it remains conserving its form and its maximum membership degree. However, the context may influence and it would be necessary to vary the discourse universe range. For example, a membership function ranging between 10 and 20 in the universe of discourse exists, but the context influences it. It can change its range to be between 15 and 25 to reflect the context (see Figure 4).

IV. CASE STUDY

Heat stress occurs when workers perform physical activities, from light to very demanding, in an environment with high temperature and relative humidity; consequently, people's thermal sensation becomes high. Thermal sensation causes reactions in workers that range from discomfort to possible severe health damage, leading to death in extreme cases. Due to the above, the ISO 7243 [11] standard of the occupational health and safety area determines within one working hour the percentage of time in which workers should carry out their activity and the percentage of time in which they should rest. The decisions on the percentage of physical activity and rest are taken based on evaluating the physical activity intensity (from light to very heavy). Consequently, the burden it represents for the worker and the environmental conditions prevailing in the workplace, which are mainly temperature and relative humidity. Generally, a labor supervisor monitors and controls heat stress levels.

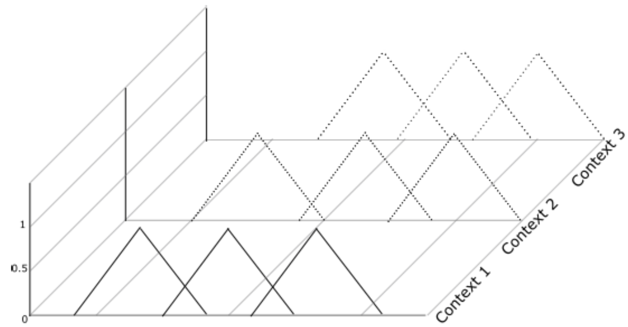

FIGURE 4. Membership function with changes in its position in the universe of discourse.

The process of estimating occupational heat stress is amenable to being treated as a context-based dynamic fuzzy system for two main reasons. The first reason is that conventionally, the workload is determined by assigning a static value in METs to the physical activity performed, based on generic tables. This makes the estimation imprecise and not personalized. Therefore, if we use a fuzzy system with a method based on heart rate for the estimation of workload that uses fuzzy ranges, together with other variables such as the measurement of the energy involved and whether there is habituation to the activity, we can have an estimate of workload that is more adjusted to reality and personalized.

The second reason is that the level of heat stress is calculated considering the workload and aspects of the context such as temperature and relative humidity present in the scenario, which may vary throughout the workday. As well as the possible effect of solar radiation, in the case of outdoor activities. The worker's acclimatization to the workplace climate also plays a role. Conventionally, the implications of all the above factors are obtained from generic tables. We propose a dynamic fuzzy system that can handle the inaccuracies of static ranges and therefore fuzzy ranges are used.

To our knowledge, there are no fully automated technological proposals for the evaluation and control of heat stress. The case study mentioned above represents an opportunity to implement the proposed approach of a fuzzy system with dynamic membership functions based on the context and through classification, to identify the level of stress presented to a worker in a specific place and time. Thus, to offer an automated technological solution using wearable devices and fuzzy logic.

As part of this research work, we included informed consent and a personal data protection policy. Before completing the experiments, we provided participants information about the research, including a brief explanation of its purpose. We assured them that their data would be kept confidential.

Our experiments consisted of three activities performed by the workers: (i) sweeping the floor using a broom, (ii) cleaning glass using a cloth and cleaning fluid, and (iii) stacking metal chairs in a classroom. The selected activities are those usually performed by university janitors. Volunteers carried out the activities freely; that is, they were not conditioned on the manner or intensity of acting. This free and uncontrolled manner is unlike other works found in the literature ([12], [13]), in which fully differentiated activities (walking, running, jumping, climbing stairs, etc.) were selected; in other words, participants had some form of control over the performance (for example, walking on an electric treadmill at a predefined intensity or controlled speed). Carrying out the uncontrolled activity reflects the personality of the user in the execution of the activity, and this supports our approach, which aims to have a personalized recognition.

The users that participated in the experiments were 20 workers: (i) 11 male with a mean age of 28.4 ± 8.5 years and BMI 26.26 ± 3.77, and (ii) 9 female with a mean age of 28.7 ± 5.97 years and BMI of 25.04 ± 4.45.

For this case study, the fuzzy system consists of three stages, where the output value of the first stage will be one of the input values for the second stage, and the output of the second stage will be an input value for the third stage. In the first stage, we automatically recognize the energy level used in physical activity; later, we estimate the second stage's personalized workload. Finally, we estimate the heat stress level in the third stage.

A. AUTOMATED RECOGNITION OF THE ENERGY LEVEL FOR PHYSICAL ACTIVITY

The first stage of the fuzzy system consists of automated recognition of the energy level involved in the physical activity of the worker, which was measured using non-invasive wearable devices worn by the workers. The input values of the fuzzy system are movement values obtained from a triaxial acceleration sensor placed and attached to the hip (near the body's center of mass) and another triaxial acceleration sensor placed on the wrist of the dominant hand.

Initially, we performed several tests with the participants, and we collected sensor data for each of the activities in the experiment. We used the collected sensor data above to identify and select the most relevant features to obtain the energy level from the sensors' x, y, and z values.

Regarding the fuzzy system to classify energy levels, statistical methods are an alternative for constructing the sets. The Gaussian Distribution is pertinent to represent the behavior of acceleration patterns [14].

The features obtained from the raw acceleration data from the sensor placed in the hip were: Root Mean Square (RMS), energy from vector sum, mean, standard deviation, maximum peak, minimum peak, correlation of the x-axis with the y-axis, and energy for each axis. The features obtained from the raw acceleration data from the sensor placed at the dominant hand's wrist were: RMS, mean, standard deviation, and energy. These features have been commonly used to recognize physical activities [15], [16]. RMS and energy have been used to calculate the energy level, and its calculation corresponds to the following formulas [14]:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{4}$$

$$E = \frac{1}{n}\sum_{i=1}^{n} |FFT_i|^2 \tag{5}$$

Various features were obtained from the raw data of the acceleration sensors. In the time domain, the features for each axis were the RMS, the mean, the standard deviation, the maximum peak, minimum peak and the correlations between the axes; and in the frequency domain, the feature was the energy. The features for the sensor placed in the dominant hand, in the time domain, and from the vector sum were: RMS, mean, standard deviation and maximum peak. The feature in the frequency domain was the energy.

Table 1 shows the mean and standard deviation for each selected feature to obtain the energy level.

TABLE 1. Features' media and standard deviation for each activity.

Feature	Activity	μ	σ
RMS	Cleaning windows	1.683	0.727
	Sweeping floors	1.466	0.492
	Stacking chairs	2.795	0.620
Hip Energy	Cleaning windows	15.288	5.487
	Sweeping floors	22.53	9.310
	Stacking chairs	129.535	43.295
Wrist Energy	Cleaning windows	1508.009	866.009
	Sweeping floors	1262.281	700.711
	Stacking chairs	233.974	132.244

Figure 5 presents the proposed fuzzy system that estimates the energy level used in each physical activity.

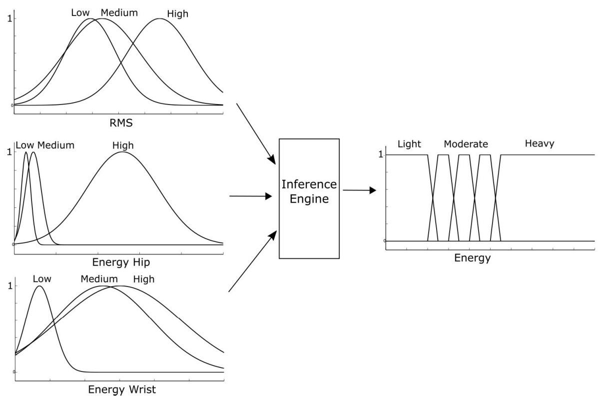

FIGURE 5. Recognition of the energy level.

B. PERSONALIZED WORKLOAD ASSESSMENT

The second stage consists of estimating the workload that the physical activity represents for the worker.

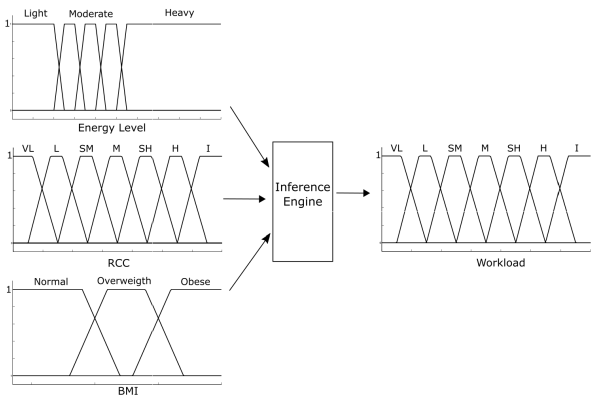

FIGURE 6. Personalized Workload Estimation.

TABLE 2. RCC for each worker during activities.

Subject	BMI	Habituation	Sweeping floors	Cleaning windows	Stacking chairs
W1	29.62	Habituated	13	12	25
W2	21.98	Habituated	16	26	41
W3	20.95	Habituated	19	9	27
W4	24.72	Habituated	10	8	18
W5	28.27	Habituated	16	6	12
W6	20.03	Not Habituated	9	16	18
W7	19.27	Not Habituated	14	10	30
W8	31.24	Habituated	18	9	16
W9	21.68	Habituated	2	8	26
W10	28.44	Habituated	29	6	14
W11	28.33	Habituated	6	16	31
W12	24.38	Habituated	8	9	13
W13	33.64	Not Habituated	7	14	27
W14	29.36	Not Habituated	12	11	19
W15	23.63	Not Habituated	2	17	31
W16	24.35	Not Habituated	29	25	43
W17	24.68	Habituated	9	9	16
W18	26.29	Not Habituated	4	8	21
W19	30.44	Not Habituated	7	11	37
W20	23.12	Habituated	8	11	21

This individualized and personalized process gives added value to the calculation. Figure 6 represents the proposed fuzzy system for a personalized workload estimation.

We used the method proposed in [17], where an ergonomic method based on the heart rate of the individual is used, but with a personalized approach to make it more precise. The result represents the particular effort that an activity imposes on each worker.

One of the input variables of the fuzzy system is the estimated energy level for physical activity. This value results from the previous stage and constitutes an input variable for evaluating the personalized workload.

Another input variable is the individualized Relative Cardiac Cost (RCC), which is the result of the calculation of the personalized Chamoux defined in [17]. The RCC variable contributes to the personalization of the calculation since assigning a generic caloric consumption value to physical activity is not precise nor personalized [18]. Table 2 shows RCC values for participants when performing activities.

Based on its value, the RCC is stratified to assign a label that identifies the physical effort level during a work activity. Table 3 presents the correspondence between the RCC value and physical effort.

TABLE 3. Physical effort according to the RCC [19].

RCC	Physical Effort Level
0-9	Very Light
10-19	Light
20-29	Slightly moderate
30-39	Moderate
40-49	Slightly heavy
50-59	Heavy
60-69	Intense

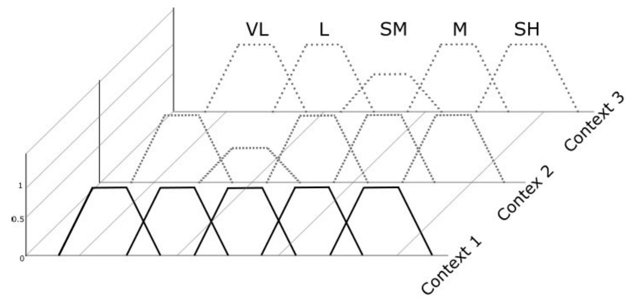

FIGURE 7. Dynamic RCC.

Habituation represents a temporal variable for this fuzzy system. Depending on the habituation time, the membership function is different for a habituated person with respect to a non-habituated person. There will be a transition of the membership function between non-habituated and habituated. Non-habituation may be due to the lack of experience of a worker in physical activity or the loss of physical condition when the worker stops the daily execution of the activity.

The membership function of the RCC variable is dynamic to reflect the impact of habituation on the workload. The maximum membership degree of the fuzzy set represents that the RCC variable must be adjusted dynamically in the range of 0 to 1, depending on the habituation level of the worker. Thus, the value of the workload obtained represents the particular condition of the worker. Figure 7 illustrates this dynamism.

The Body Mass Index (BMI) is also an input variable for the system; the BMI directly impacts the workload that a person perceives. For a given physical activity, the higher the BMI, the greater the impact on the workload.

The result of the system derives from the rules applied to the interaction between the activity's energy level, habituation, BMI, and RCC.

C. OCCUPATIONAL HEAT STRESS ESTIMATION

Heat stress occurs when a person executes a physical activity in an environment where the body produces or receives heat in excess, and it causes physiological impairment [20].

Heat stress estimation determines how physical activity, precisely the workload level, and environmental conditions (mainly temperature and relative humidity) impact the thermal sensation of the worker. Estimating the level of heat stress helps to define actions that protect the integrity of the worker, according to current worldwide regulations of occupational

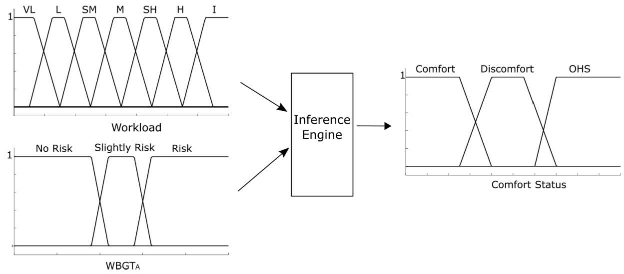

FIGURE 8. Personalized OHS Estimation.

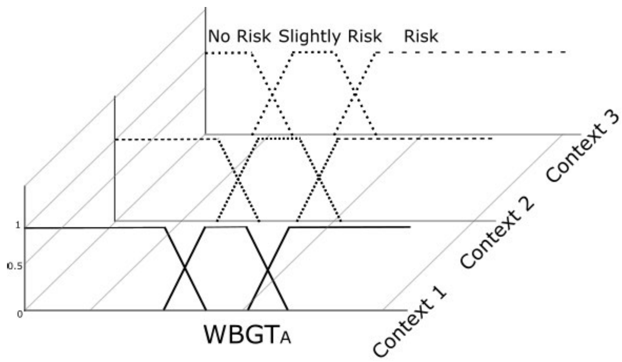

FIGURE 9. Dynamic $WBGT_A$.

safety and health. Figure 8 represents the proposed fuzzy system to estimate Occupational Heat Stress (OHS).

In ergonomics, the Wet Bulb Globe Thermometer (WBGT) proposed by ISO is a specialized device used to measure the effect of environmental temperature and relative humidity on workers performing physical activities. However, we can obtain the functionality of the WBGT using the temperature and humidity sensors of a smartphone and then apply the method proposed by [21]. A conventional thermometer is required to approximate the values obtained with a WBGT, which means a simple and automated solution that does not require specialized equipment. The Australian Bureau of Meteorology proposes this approach identified as $WBGT_A$. In [22], the authors demonstrated a high correlation between the results of the $WBGT_A$ and WBGT approaches.

In this third stage, the fuzzy system has two input variables: (i) the workload determined in stage two, and (ii) the estimation of the $WBGT_A$ from the temperature and relative humidity values prevailing when the worker performs the physical activity. However, the $WBGT_A$ is a variable influenced by a spatial context: the physical place where workers perform the activity. We classified the physical areas into two types: (i) indoors, and (ii) outdoors (with solar radiation).

The spatial context causes that the membership functions of the variable $WBGT_A$ must be dynamic to reflect the influence of the context on $WBGT_A$ (see Figure 9). The $WBGT_A$ membership functions will have a dynamic shift on the x-axis to reflect this dynamism; that is, we obtain the mean value of each membership function, and its value will be subjected to the type of physical area where the worker is performing the physical activity.

TABLE 4. Energy level for cleaning windows.

Subject	RMS	Hip energy	Wrist energy	Energy level
W1	1.67	16.52	2746.39	Moderate
W2	0.97	15.57	417.83	Light
W3	1.77	21.24	2792.42	Moderate
W4	1.44	13.68	784.22	Slightly moderate
W5	3.32	17.35	1008.28	Moderate
W6	0.81	11.46	608.43	Light
W7	2.16	11.79	483.63	Slightly moderate
W8	1.43	9.08	1537.85	Slightly moderate
W9	1.11	11.97	2419.69	Slightly moderate
W10	1.37	11.46	2516.29	Slightly moderate
W11	0.92	13.47	1024.66	Slightly moderate
W12	3.23	8.49	2052.96	Moderate
W13	2.47	25.14	1691.43	Moderate
W14	2.07	16.62	347.61	Light
W15	1.50	8.55	1613.49	Slightly moderate
W16	0.91	13.07	1048.32	Slightly moderate
W17	1.66	22.60	2122.87	Moderate
W18	0.94	16.39	706.10	Light
W19	2.31	27.74	2729.71	Moderate
W20	1.64	14.86	1131.77	Slightly moderate

TABLE 5. Energy level for sweeping floors.

Subject	RMS	Hip energy	Wrist energy	Energy level
W1	1.17	21.76	778.61	Slightly moderate
W2	1.39	14.95	514.17	Light
W3	1.52	56.08	1936.10	Heavy
W4	2.04	24.36	1567.42	Moderate
W5	0.58	15.11	2357.07	Slightly moderate
W6	0.82	14.66	125.52	Light
W7	1.73	15.72	208.02	Light
W8	1.59	16.96	1342.00	Slightly moderate
W9	1.20	24.55	1070.79	Slightly moderate
W10	1.29	19.91	1660.09	Slightly moderate
W11	1.09	19.87	1419.41	Slightly moderate
W12	2.47	15.21	653.24	Slightly moderate
W13	1.79	27.18	895.32	Slightly moderate
W14	1.42	17.05	1285.19	Slightly moderate
W15	1.27	16.34	1778.27	Moderate
W16	1.19	24.76	1571.85	Slightly moderate
W17	1.60	27.51	1366.34	Slightly moderate
W18	1.18	22.41	641.12	Light
W19	2.61	26.42	2812.80	Moderate
W20	1.35	24.49	2231.19	Moderate

V. RESULTS

A. ENERGY LEVEL ASSESSMENT RESULTS

Tables 4, 5 and 6 show the results of the estimated energy levels for each of the participants during the performance of the activities. The tables show how a fuzzy system that classifies based on the acceleration values' features results in specific energy levels for different workers.

B. WORKLOAD ASSESSMENT RESULTS

A conventional, non-customized way to estimate the workload is to use its correspondence in METs (Metabolic Equivalent Task). In [23], the averages of caloric consumption for a wide variety of physical activities are listed: (i) the sweeping activity (code 05010) corresponds to 3.3 METs (equivalent to a slightly moderate workload), (ii) the window cleaning activity (code 05022) has an estimated consumption

TABLE 6. Energy level for stacking chairs.

Subject	RMS	Hip energy	Wrist energy	Energy level
W1	2.91	93.04	212.23	Heavy
W2	2.17	161.52	237.78	Slightly heavy
W3	3.23	174.19	458.92	Heavy
W4	3.73	112.71	120.39	Heavy
W5	2.78	184.72	215.40	Heavy
W6	1.71	57.27	97.69	Slightly heavy
W7	3.13	71.11	88.19	Heavy
W8	2.46	164.57	0.41	Heavy
W9	2.95	163.30	333.95	Heavy
W10	3.17	192.41	393.21	Heavy
W11	2.04	135.50	193.20	Slightly heavy
W12	3.36	54.16	82.32	Heavy
W13	3.44	111.34	204.90	Heavy
W14	3.60	148.03	245.44	Heavy
W15	2.10	97.57	211.25	Slightly heavy
W16	1.85	117.08	174.19	Slightly heavy
W17	3.30	182.81	489.26	Heavy
W18	2.28	146.79	374.12	Heavy
W19	3.30	137.61	312.66	Heavy
W20	2.37	103.45	163.29	Slightly heavy

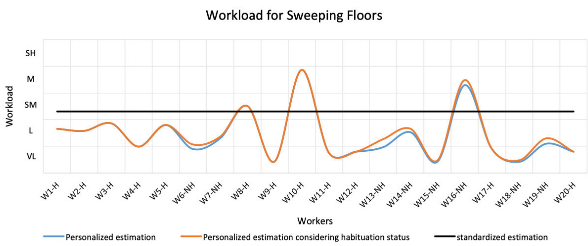

FIGURE 10. Workload for sweeping floors.

of 3.2 METs (equivalent to a slightly moderate workload), and (iii) the chair stacking activity (code 05121) 5.0 METs (equivalent to a slightly heavy workload).

However, generic solutions based on standard values (a typical person, e.g., male, normal BMI, 180cm height, etc.) do not allow the heterogeneity of the impact of variables on people to be reflected. Figures 10, 11, and 12 show a comparison of the generic estimation of the workload against a personalized assessment and a customized analysis considering the context (time of habituation to the activity).

Additionally, as seen in Figures 10, 11, and 12, the fuzzy system slightly increases the workload level for non-habituated participants to physical activity (W*-NH). This is the result of adapting the maximum membership degree in the RCC variable to reveal the lack of habituation. A non-habituated person increases their heart rate when performing demanding activities with respect to a habituated person.

Figure 10 shows how a conventional workload calculation method assigns a Slightly moderate workload to all workers sweeping (black line). However, if we use the customized fuzzy system approach (blue line), we obtain differentiated and individual workloads. This differentiation is because the energy level assessment applied to the activity (obtained with the acceleration and heart rate values) is an input variable.

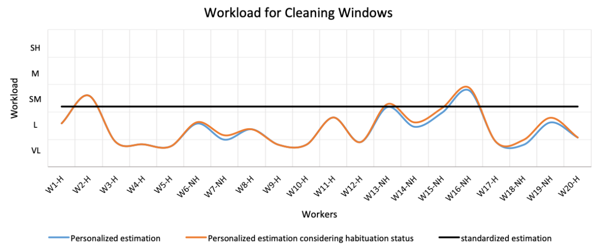

FIGURE 11. Workload for cleaning windows.

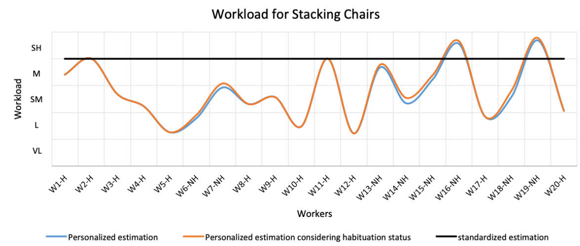

FIGURE 12. Workload for stacking chairs.

However, suppose we apply the contextual dynamic fuzzy system approach to calculate workload for considering the worker's habituation to the activity (orange line). In that case, a worker not habituated to the sweeping activity (for example, W6-NH) has an increase in the workload level, which even causes the workload level to rise from Very Light to Light. We can see another example with the non-habituated worker W13-NH. All of the above means that the contextual approach considers elements of the context that can influence the result.

Figures 11 and 12 show how the dynamic approach based on the fuzzy system's context produces results that reflect the fuzzy nature of the workload ranges and the context effect. That is the impact of activity's habituation on the worker's cardiac frequency, causing those who are not habituated to have a higher workload.

The proposal is adaptive since new factors that influence the system can be added, such as the worker's fatigue level. It is not the same to perform an activity in the early hours of the working day to perform it after several hours of physical activity. That is why the membership functions should be dynamic to reflect contextual situations or events.

C. HEAT STRESS ASSESSMENT RESULTS

Tables 8, 9 and 10 show the final results of the heat stress estimation. The resulting values can be three: (i) comfort, (ii) discomfort, and (iii) occupational heat stress.

As mentioned in the method, the final value of comfort results mainly from the valuation of the workload and environmental conditions. One aspect to consider is the acclimatization level to the geographical area where a person performs their physical activity. In our case study, all participants were acclimatized. According to the workload, the maximum values of environmental temperature and humidity to avoid OHS are shown in the second column of Table 7.

TABLE 7. $WBGT_A$ limit related to workload [11].

Workload	Acclimatized Workers	Unacclimatized Workers
Light	30.0	29.0
Slightly moderate	29.0	27.5
Moderate	28.0	26.0
Slightly heavy	27.0	24.5
Heavy	26.0	23.0

TABLE 8. Heat stress for sweeping floors.

Subject	$WBGT_A$	Workload	Scenario	Comfort status
W1	28.01	Slightly moderate	Indoor	Discomfort
W2	26.90	Light	Indoor	Discomfort
W3	28.23	Heavy	Indoor	Discomfort
W4	31.08	Moderate	Indoor	OHS
W5	35.29	Slightly moderate	Outdoor	OHS
W6	38.09	Light	Indoor	OHS
W7	36.26	Light	Indoor	OHS
W8	35.68	Slightly moderate	Indoor	OHS
W9	31.52	Slightly moderate	Indoor	OHS
W10	35.06	Slightly moderate	Outdoor	OHS
W11	36.95	Slightly moderate	Outdoor	OHS
W12	26.49	Slightly moderate	Indoor	Discomfort
W13	33.13	Slightly moderate	Indoor	OHS
W14	30.73	Slightly moderate	Indoor	OHS
W15	32.54	Moderate	Indoor	OHS
W16	30.56	Slightly moderate	Indoor	OHS
W17	32.37	Slightly moderate	Indoor	OHS
W18	30.79	Light	Indoor	OHS
W19	31.87	Moderate	Indoor	OHS
W20	33.75	Moderate	Outdoor	OHS

TABLE 9. Heat stress for cleaning windows.

Subject	$WBGT_A$	Workload	Scenario	Comfort Status
W1	26.84	Moderate	Indoor	Discomfort
W2	27.22	Light	Indoor	Discomfort
W3	28.34	Moderate	Indoor	Discomfort
W4	32.24	Slightly moderate	Indoor	OHS
W5	36.13	Moderate	Outdoor	OHS
W6	36.47	Light	Indoor	OHS
W7	35.5	Slightly moderate	Indoor	OHS
W8	35.68	Slightly moderate	Indoor	OHS
W9	34.32	Slightly moderate	Indoor	OHS
W10	36.44	Slightly moderate	Outdoor	OHS
W11	35.07	Slightly moderate	Outdoor	OHS
W12	28.76	Moderate	Indoor	Discomfort
W13	33.84	Moderate	Indoor	OHS
W14	30.34	Light	Indoor	OHS
W15	33.5	Slightly moderate	Indoor	OHS
W16	31.32	Slightly moderate	Indoor	OHS
W17	32.96	Moderate	Indoor	OHS
W18	30.3	Light	Indoor	OHS
W19	31.92	Moderate	Indoor	OHS
W20	34.95	Slightly moderate	Outdoor	OHS

For this case study, high environmental values of temperature and relative humidity caused most participants to be under stress, even though physical activity was light.

Figures 13, 14, and 15 show clearly the value of comfort, discomfort or OHS for each participant. These figures are useful to appreciate that although several participants may have OHS as a final linguistic label, the level may be slightly different. This also applies to the final discomfort status.

TABLE 10. Heat stress for stacking chairs.

Subject	$WBGT_A$	Workload	Scenario	Comfort Status
W1	25.81	Heavy	Indoor	OHS
W2	27.76	Slightly heavy	Indoor	OHS
W3	28.07	Heavy	Indoor	Discomfort
W4	31.72	Heavy	Indoor	OHS
W5	34.86	Heavy	Outdoor	OHS
W6	37.55	Slightly heavy	Indoor	OHS
W7	36.33	Heavy	Indoor	OHS
W8	35.77	Heavy	Indoor	OHS
W9	35.30	Heavy	Indoor	OHS
W10	35.45	Heavy	Outdoor	OHS
W11	35.65	Slightly heavy	Outdoor	OHS
W12	27.29	Heavy	Indoor	Discomfort
W13	34.75	Heavy	Indoor	OHS
W14	30.41	Heavy	Indoor	OHS
W15	33.56	Slightly heavy	Indoor	OHS
W16	31.51	Slightly heavy	Indoor	OHS
W17	33.63	Heavy	Indoor	OHS
W18	29.43	Heavy	Indoor	OHS
W19	31.94	Heavy	Indoor	OHS
W20	33.39	Slightly heavy	Outdoor	OHS

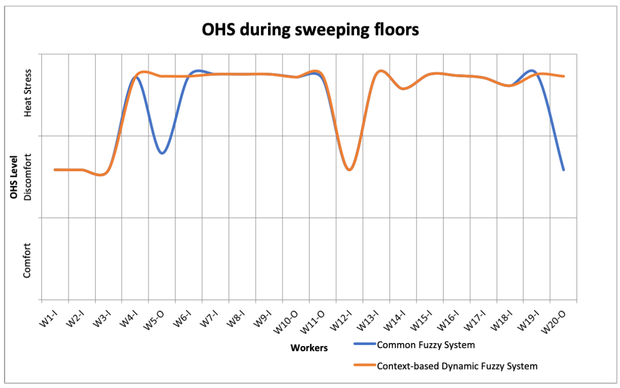

FIGURE 13. Comfort, discomfort or OHS status during sweeping floors.

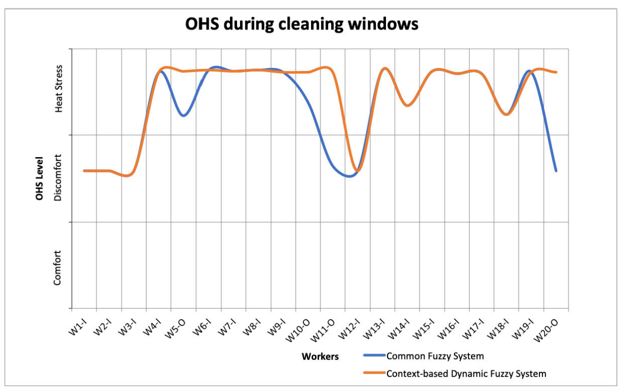

FIGURE 14. Comfort, discomfort or OHS status during cleaning windows.

Solar radiation significantly increases the thermal sensation of people [24], so a physical space with high solar radiation is part of the context to be considered when estimating heat stress. The blue lines show the results with a common fuzzy system and the orange lines show what is obtained when our proposed approach is applied. As we can see in the

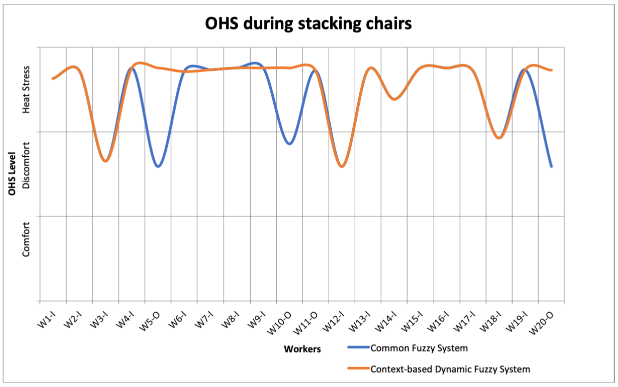

FIGURE 15. Comfort, discomfort or OHS status during stacking chairs.

graphs, the workers (W*-O) who performed the activities in sunny exteriors (Outdoor) presented an increase in heat stress, in most of the cases. To obtain the above, the proposed system performed a shift in the universe of discourse for the $WBGT_A$ variable, indicating that the risk increases when activities are performed outdoors and with solar radiation.

VI. DISCUSSION

The findings of the approach presented demonstrate that a fuzzy system using dynamic membership functions can produce results that are expressed in a realistic way. It is an approach in which capturing the context, in real-time, modeled by adaptive membership functions allows to reflect the dynamic and fuzzy nature of real environments.

Other authors in the literature have studied the need to build fuzzy dynamic systems. However, the other approaches have partially addressed the aspect of the context in fuzzy system dynamics (dynamism of the degree of belonging, group's shape amplitude, displacement of functions in the X-axis, or the change of shape of belonging between triangular and trapezoidal; all this as a function of time).

None of the authors has proposed an approach to integrate the context in a fuzzy system, and therefore, to consider variables such as time, space, climatic conditions, groups' variability, etc. It means a system that presents dynamism and adaptability from the passage of time, physical location, time of day, type of scenario, people involved, etc.

As it can be seen, concerning dynamism, other authors have only considered those variables of a temporary nature, which are included as fuzzy system variables. Our approach considers the context impacting fuzzy system variables, which to our best knowledge has not yet been considered in other approaches in the literature.

Previous research works do not allow any combination of forms change among pyramidal, trapezoidal and Gaussian in membership functions. Our approach represents an advance in fuzzy systems concerning the current state of knowledge. It brings dynamism to the system through multiple adaptations in real time of the membership functions, based on changes in the context.

Although dynamic membership functions reflecting the context impact are significant, some limitations still need to be addressed. For example, the shape of membership functions may need to be even more diverse, including non-convex and even amorphous groups that could have a real-time evolution within a dynamic system.

We can appreciate the efficiency of the approach in the case study since heat stress estimation considers personalization and the dynamism imposed by real-time spatiotemporal variables. Therefore, heat stress estimation results are very heterogeneous and reflect that the same work and environmental conditions affect people differently.

In this sense, since our approach offers personalized results, the number of users who participated in the experiments is sufficient to exemplify the variations that can occur in the results when performing the same physical activity. We are not trying to reach generalized average values as proposed in the standards, rather an approach where the resulting values are for a specific person working in normal climate conditions.

This approach personalizes the results because it captures the physiological values of the workers in real time (movements and heart rate) and considers context variables such as time of habituation or changing physical space conditions where the workers perform their physical activities (indoors-shade, outdoors-sun). Consequently, these results are closer to real conditions than other proposals that do not include it.

Many authors have used fuzzy logic to estimate the risk derived from heat stress. Their solutions are static systems that do not have personalized estimations; they do not consider the dynamism imposed by contextual conditions (space-time) that occur in real time. The subject has only been addressed as a problem of multi-criteria decision making that presents ambiguous or imprecise situations, and therefore, fuzzy logic is used [25]. These are approaches based on past statistical data (not in real time) [26].

In the case study, no other approach considers the dynamism and personalization to be automated and as a real-time solution, which identifies the physical activity performed, the estimation of the personalized workload, and the calculation of the level of heat stress influence in real time of contextual variables. That makes it necessary for the membership functions of the fuzzy system to be dynamic and adaptable.

The main finding is that it was essential to personalize the estimations because although participants performed their tasks under the same instruction, they performed it in their own way. Consequently, there are different physiological responses to work activities. It means differences in work techniques influence how people use their muscles and the amount of strength when performing physical exercises. Also, the work tasks were performed at different intensity levels, as some workers were habituated, and others not. Specifically, when estimating physical stresses in real scenarios it must be considered that there are environmental aspects that have an influence, such as heat [27].

As these are personalized estimates, the approach applied to the use case allows identifying the work style of a person since the results reflect similar behavior in the various activities. For example, participant W12 carried out each experiment with low energy, as a characteristic of personality in physical work.

The limitations of the case study are that some factors related to people are not considered, for example, sick people, special feeding conditions, or tiredness derived from inadequate sleep, which could affect the worker's performance. As for the context, we do not consider scenarios such as cloudy or windy days. The above exemplifies that the context could consider an enormous amount of variables.

Performing experiments within an environment with lower ambient temperature values would result in a greater diversity of final status.

VII. CONCLUSIONS AND FUTURE WORK

A fuzzy system with dynamic membership functions is adaptive because it can reflect the context without being redesigned. The different forms of dynamism considered for the membership functions make the system evolutionary, unlike conventional fuzzy systems that are static. Therefore, it is necessary to include various types of dynamism so that the fuzzy system is context-aware.

Related to the case study, we can appreciate the benefits of an automated, personalized and dynamic heat stress evaluation, which reflects the diversity of the impact of the same physical activity on different people at any one time. Most workers were under occupational heat stress during the experiments. This was mainly due to the environmental conditions of the geographical location where the physical activities were performed. The selected scenario is useful because it allows evidencing the negative conditions to perform physical works in tropical climates (hot-humid), according to the international regulations of occupational health and safety.

This work impacts the field of fuzzy systems by making them adaptive to the context; that is, the approach considers that the membership functions are dynamic from contextual situations or events. The system design does not have to be modified to represent a change in the context.

Future work will consider the dynamism and adaptability of membership functions to have groups that better reflect the context, that is, the creation of forms different from the conventional ones (triangular, trapezoidal, and Gaussian), for example, non-convex or amorphous groups.

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REFERENCES

[1] L. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, 1965.

[2] P. Humphreys, A. McCloskey, R. McIvor, L. Maguire, and C. Glackin, "Employing dynamic fuzzy membership functions to assess environmental performance in the supplier selection process," *Int. J. Prod. Res.*, vol. 44, no. 12, pp. 2379–2419, Jun. 2006.

[3] M. Cerrada, J. Aguilar, E. Colina, and A. Titli, "Dynamical membership functions: An approach for adaptive fuzzy modelling," *Fuzzy Sets Syst.*, vol. 152, no. 3, pp. 513–533, Jun. 2005.

[4] P. Koprinkova, "Membership functions shape and its influence on the dynamical behaviour of fuzzy logic controller," *Cybern. Syst.*, vol. 31, no. 2, pp. 161–173, Mar. 2000.

[5] J. Virant and N. Zimic, "Attention to time in fuzzy logic," *Fuzzy Sets Syst.*, vol. 82, no. 1, pp. 39–49, Aug. 1996.

[6] E. Feng, H. Yang, and M. Rao, "Fuzzy expert system for real-time process condition monitoring and incident prevention," *Expert Syst. Appl.*, vol. 15, nos. 3–4, pp. 383–390, Oct. 1998.

[7] W. Luo, D. Zhang, H. Jiang, L. Ni, and Y. Hu, "Local community detection with the dynamic membership function," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 5, pp. 3136–3150, Oct. 2018.

[8] T. Meng, L. Cai, T. He, L. Chen, and Z. Deng, "Local higher-order community detection based on fuzzy membership functions," *IEEE Access*, vol. 7, pp. 128510–128525, 2019.

[9] G. Zheng, N. Zhu, Z. Tian, Y. Chen, and B. Sun, "Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments," *Saf. Sci.*, vol. 50, no. 2, pp. 228–239, Feb. 2012.

[10] M. Asghari, P. Nassiri, M. R. Monazzam, F. Golbabaei, H. Arabalibeik, A. Shamsipour, and A. Allahverdy, "Weighting criteria and prioritizing of heat stress indices in surface mining using a delphi technique and fuzzy AHP-TOPSIS method," *J. Environ. Health Sci. Eng.*, vol. 15, no. 1, pp. 1–11, Dec. 2017.

[11] *Ergonomics of the Thermal Environment-Assessment of Heat Stress Using the WBGT (Wet Bulb Globe Temperature) Index*, document ISO 7243:2017, Distributed through American National Standards Institute (ANSI), ISO, 2017.

[12] T. Tuncer, F. Ertam, S. Dogan, and A. Subasi, "An automated daily sports activities and gender recognition method based on novel multikernel local diamond pattern using sensor signals," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 12, pp. 9441–9448, Dec. 2020.

[13] I. Hammad and K. El-Sankary, "Using machine learning for person identification through physical activities," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, Seville, Spain, Oct. 2020, pp. 1–5.

[14] M. Fahim, I. Fatima, S. Lee, and Y.-T. Park, "EFM: Evolutionary fuzzy model for dynamic activities recognition using a smartphone accelerometer," *Int. J. Speech Technol.*, vol. 39, no. 3, pp. 475–488, Oct. 2013.

[15] Ó. D. Lara, A. J. Pérez, M. A. Labrador, and J. D. Posada, "Centinela: A human activity recognition system based on acceleration and vital sign data," *Pervasive Mobile Comput.*, vol. 8, no. 5, pp. 717–729, Oct. 2012.

[16] T.-P. Kao, C.-W. Lin, and J.-S. Wang, "Development of a portable activity detector for daily activity recognition," in *Proc. IEEE Int. Symp. Ind. Electron.*, Aug. 2009, pp. 115–120.

[17] P. Pancardo, J. A. Hernández-Nolasco, and F. Acosta-Escalante, "A fuzzy logic-based personalized method to classify perceived exertion in workplaces using a wearable heart rate sensor," *Mobile Inf. Syst.*, vol. 2018, pp. 1–17, 2018.

[18] M. D. A. Mendes, I. da Silva, V. Ramires, F. Reichert, R. Martins, R. Ferreira, and E. Tomasi, "Metabolic equivalent of task (METs) thresholds as an indicator of physical activity intensity," *PLoS ONE*, vol. 13, no. 7, pp. 1–10, Jul. 2018, doi: 10.1371/journal.pone.0200701.

[19] P. Frimat, M. Amphoux, and A. Chamoux, "Interprétation et mesure de la fréquence cardiaque," *Revue de Med. du Travail XV*, vol. 147, no. 4, p. 165, 1988.

[20] T. Kjellstrom, D. Briggs, C. Freyberg, B. Lemke, M. Otto, and O. Hyatt, "Heat, human performance, and occupational health: A key issue for the assessment of global climate change impacts," *Annu. Rev. Public Health*, vol. 37, no. 1, pp. 97–112, Mar. 2016.

[21] Thermal Comfort observations. (2017). *About the Approximation to the WBGT Used by the Bureau of Meteorology*. [Online]. Available: http://www.bom.gov.au/info/thermal_stress/#approximation

[22] G. Teimori, M. R. Monazzam, P. Nassiri, F. Golbabaei, S. F. Dehghan, M. J. Ghannadzadeh, and M. Asghari, "Applicability of the model presented by australian bureau of meteorology to determine WBGT in outdoor workplaces: A case study," *Urban Climate*, vol. 32, Jun. 2020, Art. no. 100609.

[23] B. Ainsworth, S. Herrmann, N. Meckes, D. Bassett, C. Tudor-Locke, J. Greer, J. Vezina, M. Whitt-Glover, and A. Leon, "2011 compendium of physical activities: A second update of codes and met values," *Med. Sci. sports exercise*, vol. 43, pp. 1575–1581, Jun. 2011.

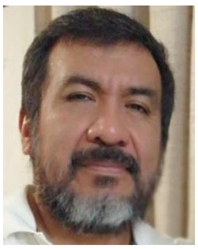
[24] Y. Xiao, Y. Gao, Y. Wang, and X. Meng, "Effects of solar radiation on thermal sensation and physical fatigue of the human body under heavy load exercise," *Indoor Built Environ.*, Dec. 2020, Art. no. 1420326X20974736, doi: 10.1177/1420326X20974736.

[25] E. Ilbahar, A. Karaşan, S. Cebi, and C. Kahraman, "A novel approach to risk assessment for occupational health and safety using pythagorean fuzzy AHP & fuzzy inference system," *Saf. Sci.*, vol. 103, pp. 124–136, Mar. 2018.

[26] J. Debnath, A. Biswas, P. Sivan, K. Sen, and S. Sahu, "Fuzzy inference model for assessing occupational risks in construction sites," *Int. J. Ind. Ergonom.*, vol. 55, pp. 114–128, Sep. 2016.

[27] L. Yang, K. Lu, M. Forsman, K. Lindecrantz, F. Seoane, Ö. Ekblom, and J. Eklund, "Evaluation of physiological workload assessment methods using heart rate and accelerometry for a smart wearable system," *Ergonomics*, vol. 62, no. 5, pp. 694–705, May 2019.

PABLO PANCARDO received the M.Sc. degree in information technology from the Monterrey Institute of Technology and Advanced Studies (ITESM), in 1998, and the Ph.D. degree in computer science from the Juarez Autonomous University of Tabasco (UJAT), in 2016. He is currently an Associate Professor and a Researcher with the Intelligent Data Sensing and Processing Group, UJAT. He has more than 40 publications in relevant international conferences and journals on *Ubiquitous Computing* and novel AmI applications related to welfare and healthcare. He has led/taken part in several research projects involving the adoption of mobile ubiquitous computing and sensor networks. His research interests include ambient intelligence, fuzzy logic, the IoT, and HCI.



JOSÉ ADÁN HERNÁNDEZ-NOLASCO received the bachelor's degree in electronic and communications engineering from the Autonomous University of Nuevo Leon, in 1996, the M.Sc. degree in electronic engineering (telecommunications) from the Monterrey Institute of Technology and Higher Education, in 2003, and the Ph.D. degree in optics from the National Institute for Astrophysics, Optics and Electronics, in 2012. He has been a Research Professor with the Universidad Juárez Autónoma de Tabasco, for 22 years. He has authored or coauthored over 25 publications in the areas of ambient intelligence and optics, and over 30 participations in conferences. His research interests include ambient intelligence, fuzzy logic, the IoT, and optics.

MIGUEL A. WISTER received the B.Sc. degree in informatics from Juarez Autonomous University of Tabasco (UJAT), Mexico, in 1993, the M.Sc. degree in informatics technology from the Monterrey Institute of Technology and Higher Education (ITESM), Mexico, in June 1997, and the Ph.D. degree in information technology and communications engineering from the University of Murcia (UM), Spain, in 2008. His research interests include ubiquitous computing with particular focus on ambient intelligence and the Internet of Things (IoT). He has tutored more than 40 B.Sc. and M.Sc. students both at the UJAT and Olmeca University. He has authored and coauthored 30 scientific articles published in national and international peer-reviewed conferences and journals. He is currently a member of the Researchers State System.

MATIAS GARCIA-CONSTANTINO received the bachelor's degree in computer engineering from the National Autonomous University of Mexico (UNAM), in 2007, and the Ph.D. degree in computer science from the University of Liverpool, in 2013. He has experience working in industry and in academia. He worked in Mexico City in two consulting companies as a Java Programmer and as a Data Analyst, respectively. He has worked as a Researcher of computer science at the universities of Liverpool, Newcastle, and Ulster, U.K. He is currently a Lecturer of computing science with the School of Computing, Ulster University. His research interests include data analysis, connected health, pervasive computing, and legal technology.