A Hierarchical Fuzzy Inference System for Evaluating Cyclist Training Performance

Miguel A. Wister, Fabricio Landero-Cristobal, Pablo Payró-Campos, and Pedro Iván Arias-Vázquez

***Abstract*—This paper proposes a method to obtain the quality of a cyclist's training session based on training zone, heart rate, and power. Our proposal is called FuCycling (Fuzzy and CYcling). We propose a hierarchical fuzzy inference system that is applied in two phases. The first phase evaluates three input variables: training zone, heart rate, and power; the output variable is performance. In the second phase, the output variable performance will be an input variable, adding a training zone and perceived exertion rating. The output in the second phase is the final output, called session quality. Using this proposed method, a sports coach can review the quality of the cyclist's session for further feedback on the training plan objectives. We also developed a web application to enable a sports coach to evaluate the dataset and visualize the quality rating of the session in a dashboard, training statistics, the time elapsed in the training zones, and a route map to show the training evaluation.**

***Index Terms*—Fuzzy Inference System, Heart Rate, Power, Cycling, Fuzzy rule-based System.**

I. Introduction

A wide range of commercial tools using GPS navigation and wearable technology to record cycling training performance data based on statistical analysis. For example, cheaper or more expensive devices, such as kilometer counters, cycle computers, smartwatches, smartphone apps, etc. Use their respective web pages to visualize data and graphs. There are free versions and web pages with PRO versions that pay monthly subscriptions.

Our proposal employs artificial intelligence techniques such as rule-based systems and fuzzy systems. Some values obtained from smartwatches and cycle computers are not reduced to simple numerical or categorical values but use qualitative linguistic variables, which could be subjective or ambiguous. Hence, we decided to use a fuzzy system model and a set of rules based on the experiences of a sports coach specializing in cycling and athletics.

Artificial intelligence has revolutionized our lives and facilitated some processes that were far away. Using algorithms to simulate human thinking, it has automated tasks such as decision making, problem solving, and learning.

Zadeh [1] introduced the concept of the fuzzy set; he proposes to use one or more membership functions ranging from 0 to 1 to subsequently evaluate the degree of membership of elements to a set.

Nowadays, research and applications using fuzzy logic have reached different fields. For example, in the field of health: [2] they implemented a mechanism for the detection of arthritis using a fuzzy hierarchical expert system, using 2 phases; the first phase has eight input variables and the second phase has four input variables to obtain as an output variable the condition of arthritis, is evaluated with the observations of experts from a hospital in Ireland, this expert system has an accuracy of 95.6%. In [3], an approach to the diagnosis of heart disease is proposed, taking six variables: age, chest pain, electrocardiogram, systolic blood pressure, diabetes, and cholesterol. The output will be a diagnosis of cardiac disease: negative, borderline, positive, and entirely positive; the proposed system has an accuracy of 94%.

Several health and sports applications employ artificial intelligence techniques, and more and more are making successful inroads into using them to support health, wellness, and sports activities.

In summary, the main contribution of our proposal is a hierarchical fuzzy logic system that combines heart rate and power with the variable perception of effort to evaluate the performance and quality of cycling training sessions. This approach allows us to handle the uncertainty and subjectivity inherent in human evaluations. Another contribution is a prototype web application called FuCycling, which facilitates the evaluation of cyclist training. The tool includes functionalities for a) Importing data from devices such as Garmin and Polar, b) Calculating heart rate and functional power thresholds based on user input data, and c) Visualizing performance metrics and training quality in interactive graphs. Finally, we validated with real data and expert opinion. Our system was validated using 81 training datasets from twelve cyclists and compared with evaluations from a sports medicine specialist, obtaining up to 94% similarity in some scenarios.

This paper is structured as follows: Section II reviews related works and highlights the gaps in existing evaluation methods for cycling performance. Section III presents the methodology, detailing the dataset, the preprocessing steps, and the hierarchical fuzzy inference system used for the performance assessment. Section IV introduces the computational

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F. Landero-Cristobal is with the Academic Division of Information Sciences and Technologies (DACYTI), Juarez Autonomous University of Tabasco (UJAT), Cunduacan, Mexico. M. A. Wister and P. Payró-Campos are with the DACYTI, UJAT, and P. I. Arias-Vázquez is with the Multidisciplinary Academic Division of Comalcalco, UJAT, Comalcalco, Mexico (e-mails: miguel.wister@ujat.mx, dccfabricio@gmail.com, pablo.payro@ujat.mx, and pivanav@gmail.com).

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complexity analysis and describes the implementation of the web-based application. Section V discusses the validation of the proposed system, including a comparison with expert evaluations and a discussion of its reliability. Section VI discusses results obtained in experiments. Section VII provides a detailed discussion of the findings, highlighting the system's strengths, limitations, and potential improvements. Finally, Section VIII concludes the paper with key takeaways and future research directions.

II. Related Work

Fuzzy logic in sports has aroused great interest in improving sports training, athlete selection, or strategy design as the following research:

[4] created a fuzzy decision support system that can be used in sports performance analysis. He developed and optimized the fuzzy inference system for the analysis of badminton sports performance using the Mamdani-Assilan and Takagi-Sugeno-Kang fuzzy approach.

[5] proposed a method to detect sports video scenes. With the help of fuzzy logic, it was combined with existing detection methods using macroblock information to transform the stage and the color model to extract image features.

[6] designed an intelligent model to identify volleyball talents based on human body measurements, analysis of the mechanics of the human body, physiological and technical input variables, and then categorize them into five different groups.

A study tested whether a monoexponential formula was appropriate to analyze and predict individual responses to the change of load bouts online during training. Therefore, 234 heart rate (HR) data sets obtained from extensive interval protocols of four participants during a twelve-week training intervention on a bike ergometer were analyzed [7].

A work [8] considered the parameter estimation problem formulated as an optimization one and solved it using Particle Swarm Optimization (PSO). This algorithm was used for the first time in this field. Achieved results and comparisons show better improvement for other estimation methods.

[9] presented an algorithm based on fuzzy logic for detecting jumps using accelerometer and GPS data in sports such as snowboarding and skiing.

A paper implements fuzzy control for human heart rate during aerobic endurance training. This device is tested and validated using two non-linear models of human treadmill use and presents uncertainties in model parameters and white noise. This proposal ensures the desired heart rate, finding its usefulness in supporting the training configuration process by specialized professionals [10].

In this paper, [11] uses devices that rely on models to recognize and classify current motion or activity patterns. Different methods and models, such as Support Vector Machines, Hidden Markov models, or Neural Networks, have proven to apply to this purpose.

Prototype feedback for monitoring, transmitting, and processing performance data in sports. Cyclists are equipped with a mobile device and wireless sensors using the ANT protocol to acquire biomechanical, physiological, and other sports-specific parameters [12].

In cycling, we found the following works that deal with artificial intelligence techniques or are close to the solution we propose: fuzzy inference or fuzzy logic.

The work presented in [13] evaluates and compares the effectiveness of machine learning and time series algorithms to forecast bicycle demand from historical data. The study tested SARIMA, RF, and ARIMA algorithms by evaluating performance using MSE, RMSE, and MAE metrics.

[14] proposes a quality metric in bike lanes using fuzzy logic to model variables and, in turn, provide a quality level of safety and health.

The project in [15] applies and characterizes the measurement of the forces and mechanical power derived from the pedals and crankset of a road bicycle, analyzing its results with appropriate statistical methods. Its goal is to verify whether the measurements taken on the pedal are equivalent to the measurements taken on the crank.

The authors in [16] described a new approach to the measurement of cycling performance implemented using a three-input Adaptive Neuro-Fuzzy System, based on three parameters: the average mechanical power applied by the athlete to the pedal of the bicycle, the standard deviation of the power and the index of bilateral asymmetry of the effective force.

Cycling is one of the sports with more data available for analysis and competitive advantages over other athletes, using different devices attached to the human body and the bicycle. Here are some articles about using fuzzy logic to cycle. [17] developed a methodology to help cyclists select the most intelligent path to follow during their rides in a mobile application.

This paper [18] presented a new 3D instrumented crank prototype for characterization, analysis, and validation in race bikes. An experiment was designed with four controlled factors where data obtained followed a normal distribution. Symmetry and Cadence statistics (RMS, Mean, and Variance) were used in ANOVA, showing that symmetry in an outdoor environment was higher than in indoor tests.

In [19], collected datasets consist of the data produced by nine cyclists. Data were directly exported from Strava or Garmin devices. From each dataset, the information can be obtained: GPS location, elevation, duration, distance, average, and maximal heart rate, while some workouts also include data obtained from power meters.

A study [20] designs a load cell installed on the crank of a bicycle that can measure three-dimensional forces applied during pedaling. This device accurately analyzes a cyclist's force distribution and biomechanical efficiency with training, performance research, and equipment development applications.

Heart rate is an objective way of quantifying exercise intensity based on the stress generated by a given workload on the individual's cardiovascular system.

Outside of cycling-oriented research, we found a few more, such as [21], where researchers studied that modern data acquisition and processing techniques enable the development of advanced physical activity support systems with measurement data. They applied the Kalman filtering technique to estimate the speed of moving body parts since the most critical variable for physical activity monitoring is the velocity of a moving object.

Finally, authors in [22] proposed a fuzzy logic approach for evaluating strength training exercises. The conception considers gathered data from sensor-equipped machines and recommends suggestions and criteria for proper execution. This project integrates the designed procedures into a computer-based coaching framework, returning automated feedback on the performed technique.

In order to discuss the analyzed works, we include Table VIII that compares solutions close to fuzzy inference or artificial intelligence techniques applied to cycling and other similar areas.

Cycling-related work ranges from biomechanical approaches to artificial intelligence-based prediction and evaluation systems.

Some (such as [16] and [18]) are directly relevant to measuring cycling performance and efficiency, while others, such as [14], are more general or applied to urban contexts.

The paper's proposal complements these investigations by integrating objective and subjective variables (perception of effort), an approach missing in many previous studies.

III. Methods

A. Dataset and Participants

For this study, 81 training datasets from 12 cyclists were collected. The variables considered were Heart Rate (HR), Power, and the Subjective Perception of Effort or Scale of Rating Perceived Exertion (RPE). HR and Functional Threshold Power (FTP)[1] thresholds were determined using the Astrand and Karvonen methods for HR and stress tests for FTP.

We invited twelve cyclists to participate in the experiments; Table II shows the details. Aged from 22 to 58 years old; weights per cyclist are 58 to 90 kilograms, and there are competitive levels of amateur and professional.

B. Data Preprocessing

Data cleaning was performed by removing outliers and handling missing values. The data was normalized to ensure consistency in performance evaluation.

C. Fuzzy Inference Model

The model consists of two phases: the first evaluates objective variables (HR, Power, Training Zone) to determine performance, and the second incorporates the subjective perception of effort to assess session quality.

We developed a hierarchical fuzzy inference system using Mamdani's method [23], widely recognized for its interpretability. The model processes inputs in two stages:

- Phase 1: Evaluate objective variables (training zone, heart rate, and power) to determine performance.
- Phase 2: Integrates perceived exertion ratings with performance to assess overall session quality.

The system applies a set of *IF-THEN* rules, mimicking expert judgment by first analyzing physiological data and then incorporating perceived effort. Figure 1 illustrates this hierarchical approach.

We use linguistic labels to represent the input and output variables defined by triangular membership functions. The system uses IF-THEN fuzzy rules based on the knowledge of cycling-specialized sports coaches.

D. Computational Implementation

The model was implemented in R and MATLAB. A web application was developed to allow data upload and analysis in *.TCX format. The application enables the visualization of performance metrics and training quality through interactive graphs.

Below, we include the methodology used in the proposal, which includes data collection, preprocessing, fuzzy inference modeling, and validation.

E. Data Collection

We collected eighty-one training datasets from twelve cyclists, recording key performance indicators such as heart rate, power output, and perceived exertion. Data was acquired through smartwatches and cycling computers to ensure precision and consistency. Given accessibility limitations, we opted for convenience sampling [24], recognizing its limitations in representativeness.

Before training, cyclists established their Heart Rate Threshold (HRT)[2] and FTP. These values were derived using Astrand's formula [25] or through ergometer tests [26]. More detailed explanations of these calculations are given below.

F. Data Processing

To maintain data integrity, preprocessing was performed on all collected datasets. Missing power values were marked as *NA* where power meters were unavailable. Unusual heart rate and power fluctuations were filtered out based on predefined physiological constraints. The final dataset was structured and normalized before being fed into the fuzzy inference system.

For consistency in training evaluation, we categorized data into predefined training zones [27]. Key variables included time, heart rate, power, and perceived exertion, as outlined in Table V.

IV. Computational Complexity Analysis

To assess the computational efficiency of our hierarchical fuzzy inference system, we analyze the complexity of each phase.

A. Fuzzification Complexity

Each input variable is assigned a fuzzy membership function, requiring $O(n)$ operations, where n is the number of input data points.

[1]FTP indicates the highest average power a cyclist can maintain for one hour without fatigue.

[2]HRT represents the maximum heart rate a person can sustain over an extended period.

TABLE I
COMPARISON OF SOLUTIONS RELATED TO FUZZY INFERENCE OR ARTIFICIAL INTELLIGENCE TECHNIQUES APPLIED TO CYCLING AND OTHER AREAS.

Solutions	Variables	Key Results	Advantages	Limitations
Fuzzy System for Strength Training. [22] Novatchkov and Baca (2013)	Data from sensor-equipped machines	Feedback on technical execution	Integration into an automated training framework	Limited to strength training, not applicable to sports like cycling
Crank Arm-Based Load Cell for 3D Force Analysis. [20] Balbinot et al. (2014)	3D force components during pedaling	Detailed biomechanical insights for cycling efficiency	Real-time force measurements, wireless data transmission	Requires custom equipment and calibration
Fuzzy Control of Heart Rate. [10] Patrascu et al. (2014)	Heart rate, nonlinear parameters	Robust control of heart rate during exercises	Precise control with significant model variations	Limited to treadmill aerobic training, excludes subjective effort perception
3D Load Cell for Measuring Force in a Bicycle Crank. [18] Casas et al. (2016)	3D force components during pedaling	Detailed biomechanical insights for cycling efficiency	Real-time force measurements, wireless data transmission	Requires custom equipment and calibration
Adaptive Neuro-Fuzzy System. [16] Pigatto and Balbinot (2018)	Mechanical power, power standard deviation, asymmetry index	Cycling performance metrics	Accurate analysis of applied force data	Does not consider subjective variables like perceived exertion
Instrumentation of Road Bike Pedals. [15] Hüsken and Balbinot (2019)	Force applied to pedals in multiple directions	Analysis of force components affecting pedaling efficiency	Precise measurement of pedaling dynamics	Requires specialized hardware and complex data processing
Fuzzy Metric for Bike Lanes. [14] Oliveira et al. (2020)	Safety, health, urban characteristics.	Qualitative evaluation of bike lane quality	Useful model for urban planning	Does not address sports performance metrics
AI-Based Demand Forecasting for Smart Cities. [13] Subramanian (2023)	Bike demand data, weather, traffic, public events	Accurate demand predictions for bike-sharing systems	Optimized bike distribution and resource allocation	Requires continuous data updates and substantial computational resources
Hierarchical Fuzzy Inference System. (Proposed System)	Training zone, heart rate, power, perceived exertion	Classification of performance and training quality	Combines objective and subjective variables, hierarchical approach reduces complexity	Depends on the quality of subjective data and limited data quantity

TABLE II
CYCLIST CHARACTERISTICS

Cyclist	Gender	Age	Weight	Height	BMI	Type of cycling	Cyclist level	Device
1	Female	22	62 Kg	161 cm	23.9	Rec	Am	Garmin
2	Male	52	78 Kg	170 cm	27	Rec*	Am*	Polar
3	Female	30	65 Kg	169 cm	22.8	Rec	Am	Garmin
4	Male	51	58 Kg	165 cm	21.3	Comp*	Pro*	Garmin
5	Female	50	70 Kg	170 cm	24.2	Rec	Am	Garmin
6	Male	58	67 Kg	170 cm	23.2	Rec	Am	Garmin
7	Female	56	67 Kg	168 cm	23.7	Rec	Am	Garmin
8	Male	43	90 Kg	180 cm	27.7	Comp	Am	Garmin
9	Female	47	61 Kg	165 cm	22.4	Rec	Am	Garmin
10	Male	31	78 Kg	174 cm	25.7	Comp	Pro	Polar
11	Male	35	85 Kg	184 cm	25.1	Comp	Pro	Garmin
12	Male	41	85 Kg	184 cm	27.4	Comp	Pro	Garmin

*Comp = Competitive, Rec = Recreational, Am = Amateur , Pro = Professional.

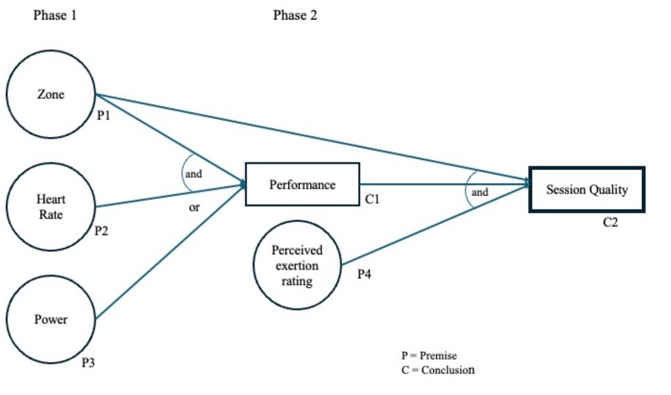

Fig. 1. Fuzzy Inference Tree

B. Rule Evaluation Complexity

Our fuzzy inference system applies m input variables to a rule base consisting of r rules. The worst-case complexity is $O(m \cdot r)$, as each rule must be evaluated for every input condition.

C. Defuzzification Complexity

The final crisp output is computed by aggregating fuzzy outputs, requiring $O(k)$ operations, where k is the number of membership functions used in defuzzification.

D. Web Application Performance

Our web-based implementation preprocesses TCX files and computes fuzzy outputs in real time. The response time for processing training session data is approximately X milliseconds, demonstrating efficient execution for real-world applications.

Finally, we have included a pseudocode algorithm to make the proposal feasible, practical, and replicable.

V. EXPERIMENTS AND VALIDATION

The system was validated by comparing its results with the evaluations of a sports medicine specialist. Five training sessions were analyzed, obtaining agreement rates of 91%, 94%, 83%, 85%, and 87%. To strengthen the validation, future work will focus on expanding the dataset with a more diverse range of cyclists.

We evaluated the system's accuracy by comparing its results with assessments from a sports medicine expert. Five training

Algorithm 1 Fuzzy Inference Process

```
Input: Training data (HR, Power, RPE)
Preprocess: Normalize data, clean outliers
Define fuzzy membership functions
for each training session do
    Compute fuzzy rules
    Apply inference mechanism
    Defuzzify output
end for
Output: Performance and session quality score
```

sessions were analyzed, showing alignment rates of 91%, 94%, 83%, 85%, and 87%. These findings suggest that the system closely mirrors expert evaluations. Nevertheless, broader validation with a more diverse dataset must confirm its general applicability.

A. Comparison with Existing Evaluation Systems

Traditional cycling performance evaluation systems such as Garmin[28], TrainingPeaks[29], and WKO5[30] primarily rely on numerical indicators such as Functional Threshold Power (FTP), VO_2 max, and heart rate variability. These approaches emphasize purely quantitative assessments. For example. Through the self-assessment function, Garmin allows users to manually record their subjective perception of effort and how they felt during an activity. Garmin analyzes multiple factors, such as sleep quality, stress level, and recovery, to determine how prepared the rider is for an intense training session at any given time. It provides a score to help plan workouts more effectively. There is no public information indicating that Garmin uses fuzzy logic to process or analyze these self-assessments.

Our approach integrates a hierarchical fuzzy inference model that blends numerical data like heart rate and power with qualitative insights like perceived exertion. This combination allows a more comprehensive assessment of a cyclist's training sessions.

Unlike other systems that rely on strictly fixed performance metrics, our approach considers individual differences because it incorporates subjective feedback. It makes a practical and flexible tool that adjusts and improves training based on objective performance and personal perception. In addition, validation against a sports medicine specialist's assessments revealed a strong level of agreement, further supporting the system's reliability.

Later in this section, we will discuss the following explanations:

In-depth descriptions of how HRT and FTP were calculated, including equations and testing protocols, are given.

In the following paragraphs, we include a Web Application Implementation and technical details regarding the web-based application, including data management, interface design, and system functionality.

Finally, we present further information on the experimental configurations, including adjustments in parameter tuning and additional observations.

B. Materials

The following materials and equipment were used to carry out all tests in our project. Of course, we must have bicycles; each participant who kindly collaborated and shared their training data with us has a bicycle.

Equipment:

1) A Smartphone - Huawei Y6 [31].
2) Polar A370, activity watch with continuous heart rate recording [32].
3) Garmin Dual Heart Rate Monitor, heart rate recording strap [33].
4) Garmin Edge 510 cyclocomputer records distance, speed, ascent/descent, and GPS position [34].
5) Garmin Edge 520 cyclocomputer records live tracking, sending and receiving routes, weather information[35].
6) Garmin Edge 830 cyclocomputer provides information on VO2 max, recovery, heat and altitude acclimatization, nutrition, and hydration[36].

Cycling computers require that at the end of a training session, these be connected to a mobile application installed on a smartphone to synchronize and store the training record on the device's platform.

Due to the nature of human responses, opinions, perceptions, and qualifications, which can be imprecise, ambiguous, subjective, inconsistent, blurred, and qualitative according to their particular way of feeling or giving their opinion on issues, we decided to use an artificial intelligence technique known as fuzzy logic. Helpful, in this case, to effectively manage subjective variables of feeling and opinion regarding perceived exertion rating, also known as Borg's scale of rating perceived exertion (RPE), responsible for measuring how hard the body works during sports or physical activities.

RPE has been used in previous studies as a valid indicator for training prescription in cycling, showing a strong correlation with heart rate and blood lactate in both alternated and continuous intensity exercises. In particular, in [37] "Relationships between the rating of perceived exertion, heart rate, and blood lactate during continuous and alternated-intensity cycling exercises" demonstrates that RPE can be employed together with heart rate and lactate to estimate exercise intensity in cycling. In this work, we use RPE as a key variable in our fuzzy inference system to evaluate the quality of the training session. This Borg's scale of rating perceived exertion uses numbers to rate an activity's effort and runs from 0 – 10. The rate of perceived exertion is subjective; we decide how hard we feel we are working during training.

Other physics and bio-metrics variables related to our performance are directly taken from vital signs obtained from different sensors, devices, smartwatches, and cycle computers. These measurements are quantitative variables, free of bias and subjective feelings.

Sports devices generate datasets at the end of a physical activity for further analysis. The variables that often (depending on the device purchased) appear in a dataset are time, latitude, longitude, altitude, distance, speed, heart rate, power, cadence, temperature, pace, calories, etc.

TABLE III
SCALE OF PERCEIVED EXERTION BY ZONE

Zone Description	Perceived Exertion Rating
Regenerative	3 - 4
Aerobic capacity	5 - 6
Aerobic power (anaerobic threshold level)	7 - 8
Maximum aerobic power at oxygen consumption level	9 - 10

TABLE IV
TRAINING ZONES

	Zone	Heart Rate/Power
1	Regenerative	50 - 60
2	Aerobic capacity	60 - 75
3	Aerobic power (anaerobic threshold level)	75 - 85
4	Maximum aerobic power at oxygen consumption level	90 - 105

However, in our case study, we apply the Center for Rehabilitation and Sports Medicine knowledge to our model; the variables to evaluate training are the training zone, heart rate, power, and Perceived exertion rating.

We programmed an R-based Web application prototype using the Shiny library[3] and Matlab to process data, obtain and calculate the results presented in Table III, Table IV, Table V, and Table VI. This web application will be explained in a subsequent section.

Perceived Exertion Rating measures the intensity of exercise based on the physical sensation that a person experiment during a sports activity [38]. The Center for Rehabilitation and Sports Medicine mentions that the proposed training zone should be the Borg's scale of rating perceived exertion (RPE). For example, if a cyclist trains in regenerative zone 1, his perception of action should be placed between three or four in the other zones, as shown in Table III.

Before starting a training session, a cyclist must know two things: 1. Heart Rate Threshold (HRT)[4] and 2. Functional Threshold Power (FTP)[5]. Hence, their trainer can create a training plan and establish the mesocycles and microcycles, with their respective training frequency, volume, and intensity, in addition to checking their fitness.

Some methods commonly used to determine the Heart Rate Threshold are as follows:

- Astrand's method [25]: subtract 220 from the person's age. For example, the maximum heart rate of a 36-year-old man is 184 beats per minute.
- Karvonen's method [39]: include the resting heart rate. The person must measure the heart rate upon waking up in the morning. For example, a 36-year-old man has 49 beats per minute resting heart rate. The operation is 220 - 36 = 184; the result subtracts the resting heart rate, resulting in 135 beats per minute.
- Perform a cycle ergometer test, with load increments of 50w every 2 minutes until reaching the fatigue.

A method commonly used to determine the Functional Threshold Power:

- Cycle for 60 minutes at maximum intensity on flat terrain.
- Cycle for 20 minutes at maximum intensity on flat terrain and multiply by 0.95 [26].
- To get an estimate, duplicate the person's current weight in pounds (2.2 pounds for every pound). Then, if the rider is over 35, subtract 0.5% for each year after 35[40].

Knowing the maximum heart rate, the trainer indicates the zone and the percentage to be worked over a given time according to Table IV [27].

The calculation to know the intensity of the training using heart rate or power is as follows:

$$HR = \frac{HRT \times HRZone}{100}$$

$$Power = \frac{FTP \times FTPZone}{100}$$

Mamdani [23] is the proposed type of fuzzy inference system. As we know, this method is possibly the most widely used and was proposed by Ebrahim Mamdani. The process is carried out in four steps: 1. Fuzzification of the input variables. 2. Evaluation of the rules. 3. Aggregation of the outputs of the rules. 4. Defuzzification.

Mamdani's method uses a set of fuzzy "IF-THEN" rules. It takes the fuzzification values as input and applies them to the antecedents of the fuzzy rules. If a rule has multiple antecedents, the AND or OR operator obtains a single number representing the evaluation result. This number (the truth value) is applied to the consequent.

This system is convenient because it applies a person's knowledge to the fuzzy logic model. The process follows: a numerical output of the inference system is calculated, and input information is given. First, we determined a set of fuzzy rules for the model; then, with the membership functions, we determined the inputs (premises). Next, the fuzzy inputs are combined according to the fuzzy rules to establish a forced rule. Afterward, we choose the output (the consequence of the rule) by combining the strength of the rule and the membership function to the output. Next, we combine the outputs to obtain a distribution of the output, and finally, if expected, a crisp result, we defuzzy the output distribution.

We used four input variables to create the proposed fuzzy logic system: Zone, Heart Rate, Power, and Rate of Perceived Effort Scale. Linguistic labels, membership function, and range for each variable are defined as shown in Table V. For the Heart Rate and Power input variables, the range parameter is calculated based on the age and weight of each cyclist.

C. Rule-based Engine

In the first phase, we process the objective variables (training zone, heart rate, and power) to determine performance;

[3]Shiny is an R package that facilitates the creation of Web applications and interactive graphics directly from within R.

[4]Heart Rate Threshold is a maximum heart rate that a person can maintain for a more extended period, such as 10 to 60 minutes, it depends on their ability and aerobic fitness level.

[5]Functional Threshold Power is the average maximum power sustained for 1 hour without fatigue.

TABLE V
VALUES INPUT VARIABLE.

Input Variable	Range	Linguistic terms
Zone	1 - 1.6 1.4 - 2.5 2.3 - 3.4 3.25 - 4	Regenerative Aerobic capacity Aerobic power Maximum aerobic power
Heart Rate	Calculated Min 50 Max 220	Inside of range Slightly out of range Moderately out of range Markedly out of range
Power	Calculated Min 0 Max 800	Inside of range Slightly out of range Moderately out of range Markedly out of range
Perceived exertion rating	3 - 4 .6 4.4 - 6.6 6.4 - 8.5 8.4 - 10	Light Moderate Intense Very intense

then, in the Second phase, we incorporate subjective perception (rating of perceived exertion) to assess the quality of the session. In this way, we emulate the style of expert decision-making, starting with the evaluation of physiological metrics and then the evaluation of perceived exertion.

Figure 1 shows an inference tree describing three input variables or premises indicated as P1, P2, and P3, corresponding to Zone, Heart Rate, and Power variables, whose conclusion or result is Performance (C1). Immediately, Performance (C1) becomes input for the next phase along with Zone (P1) and Perceived Exertion Rating (P4), which in turn outputs Session Quality (C2). Session Quality is the final result of the inferences; the arc connecting the lines indicates they have the operator ”and”.

Figure 2 describes the proposed system consisting of four components: Fuzzification Inference Unit, Decision-making Unit, Knowledge Base, and Defuzzification Inference Unit. The numbers for the training data measurements are precise, so they need to be translated into fuzzy sets to compute the Decision-making unit. With the knowledge base and the fuzzy input, the decision-making unit compares the input with the linguistic terms in the premise parts of the fuzzy rules and combines the results of the rules that match the input. The fuzzy output is defuzzified to produce a crisp output corresponding to the session performance and quality.

As mentioned above, the proposed system uses two fuzzy rule-based systems. The first phase consists of three input variables: Zone (training zone number), Heart Rate, and Power. The output variable is the Performance. The first phase's output will now be the input in the second phase. This phase consists of three input variables: Zone, Performance, and Perceived Exertion Rating (Scale of Perceived Exertion). Now, the output variable is Session Quality. (see Figure 2).

We created two output variables: session performance and session quality, defining a range from 1 to 10, and triangular membership functions (Figure 3) for each linguistic label, as shown in Table VI.

Figure 3 shows a graph after applying a triangular membership function and its outputs with their respective ranges, also shown in Table VI. Each triangle in the graph represents a

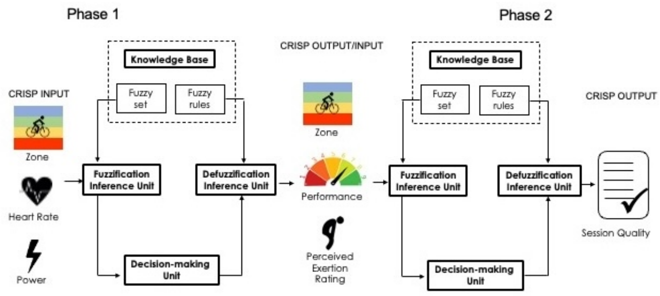

Fig. 2. Proposed system flow

TABLE VI
VALUES OUTPUT VARIABLE.

Output variable	Range	Linguistic terms
Performance	1 - 7.4 7.2 - 8.4 7.9 - 9.4 9 - 10	Low Regular Good Excellent
Session Quality	1 - 7.4 7.2 - 8.4 7.9 - 9.4 9 - 10	Low Regular Good Excellent

linguistic term or variable (Low, Regular, Good, and Excellent) for session performance and quality.

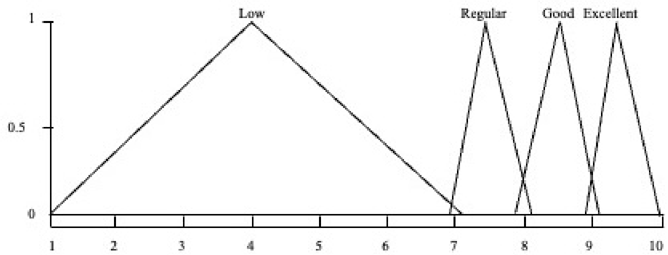

Fig. 3. Triangular membership function graph.

D. Protocol

All datasets available for experimentation and analysis of cycling performance data were convenience samples. We had datasets from twelve cyclists who voluntarily agreed to share them with us. It is worth mentioning that the data's anonymity, security, and privacy were always taken care of since cyclists' sensitive physiological and performance data are involved. Convenience sampling [24] was the non-probability sampling technique we used since subjects were selected due to their accessibility and proximity to us. However, it has limitations regarding representativeness, but for exploratory studies, it is useful because random selection is difficult or impossible.

As mentioned above, we collected eighty-one training datasets from twelve cyclists with data on power and heart rate; however, we used only one dataset per cyclist for model evaluation. Some rows do not have power data, and the cyclocomputer used did not register power because it did not have a power meter; hence, we wrote NA (not available) as

TABLE VII
TRAINING SUMMARY.

Cyclist	Max Speed Km/h	Avg Speed Km/h	Max HR Ppm	Avg HR Ppm	Max Power Watts	Avg Power Watts	Time min.	Distance Km
1	34.0	14.6	135	96	NA	NA	84	20.4
2	39.9	24.1	171	141	NA	NA	138.6	60.79
3	30.0	21.9	184	166	NA	NA	167	61.02
4	47.9	27.6	171	126	512	153	162	73.98
5	34.8	23.3	142	114	589	95	29	11.16
6	43.1	27.7	156	133	416	126	135	62.41
7	49.6	21.7	186	136	742	111	60	22.0
8	50.8	30.9	186	133	951	169	119	61.29
9	50.6	19.8	182	138	644	91	67	22.15
10	48.6	12.8	240	163	NA	NA	85	18.24
11	52.2	23.5	175	140	NA	NA	200	75.08
12	51.6	23.5	189	159	NA	NA	205	80.31

TABLE VIII
WEB APP COMPARATIVE.

App	Training summary	Time in zones	Route map	Charts	Training rating	Estimates THR/FTP thresholds
Garmin	Yes	Yes	Yes	Yes	No	No
Polar	Yes	Yes	Yes	Yes	No	No
Wahoo	Yes	No	Yes	Yes	No	No
FuCycling	Yes	Yes	Yes	Yes	Yes	Yes

a value. Therefore, this model was programmed with power data available.

All participants collected workout data by recording their activity using a cycle computer, a chest strap heart rate, or smartwatches. At the end of the training session, the participant synchronized their device with the sports app, uploaded to the cloud, and then shared the TCX files with us. The sports activities were collected from regular training rides, not competitions.

Values for maximum and average speed, maximum heart rate and average heart rate, maximum power, average power, elapsed time, and distance traveled were calculated in the workouts. Table VII shows the summary of these workouts.

E. Web Application Proposed

Different mobile and Web applications for sports (Garmin, Polar, and Wahoo) provide information to cyclists, including some variables such as statistics training, heart rate, power zones, speed graphs, altitude, power, and cadence. Table VIII shows variables such as training summary, time in zones, route map, charts, training rating, and HRT/FTP thresholds.

Amateur cyclists have different performances and maximum heart rate levels or power that they can maintain. However, they often need to learn because they do not have the economic solvency to pay a laboratory to obtain these results. Today's applications provide information that, in most cases, amateur cyclists need to learn the meaning and how they could use it to improve their performance.

To test our model described above, we programmed a Web application that uses fuzzy logic, similar to human reasoning, unlike the other applications mentioned above, provides the rating obtained in training according to the percentage of heart rate or power sustained in the training zone proposed by the trainer, as well as a final label of our overall performance. Figure 4 shows the Import Training Data tab for uploading training files collected from Garmin, Polar, Strava, etc. These files must have a .TCX[6] extension.

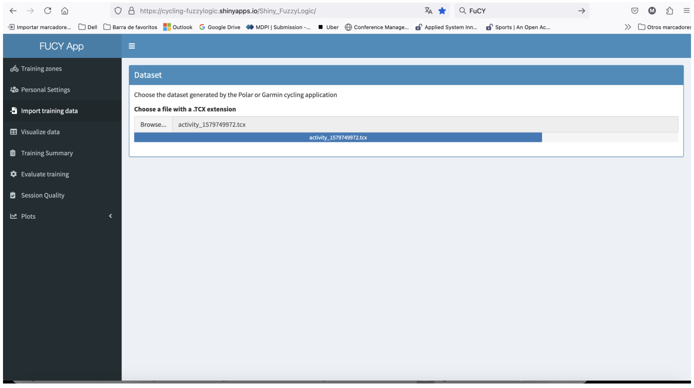

Fig. 4. Import Training Data Tab (view of the Web application)

It also allows cyclists to estimate the threshold or maximum level of Heart Rate based on age and the threshold or maximum level of functional power based on age and weight, as shown in Figure 5. This functionality generates a dynamic numerical matrix used in the ranges of the input variables: Heart Rate Threshold (HRT) and Functional Threshold Power (FTP) for phase 1. Users type their HRT value into the corresponding box in this tab and check the Heart Rate Threshold button. The user also introduces their FTP value into the corresponding box and checks the Functional Threshold Power button or introduces both values into the corresponding boxes and checks both buttons. If the user does not know their HRT, type his age into the box and check the Heart Rate Threshold button. If the user does not know his FTP, type his age and weight into the box and check the Functional Threshold Power button.

Subsequently, the cyclist or coach should import a training dataset from Garmin, Polar, or Wahoo devices into FuCycling and visualize a training summary, including measurements such as duration, distance, speed, pace, heart rate, cadence, and power, calculated by FuCycling.

We must select the number of training zones to evaluate the training dataset. FuCycling performs an internal process, cleans the data, and keeps only the heart rate and power variables, the input variable values for the fuzzy system. The result will show a graph (Figure 6) with the performance on a scale from 1 to 10, as defined in Table VI.

To continue with phase 2 in our hierarchical fuzzy system, we select the number of the training zone and the scale of perceived effort during that training, visualizing the quality of the session as shown in Figure 7.

[6]A TCX (Training Center XML) file is a data exchange format for sharing data between fitness devices. The Garmin brand of devices introduced it. TCX stores sports or physical activities. An activity comprises all the data from a workout, such as time, distance, lap time, ID, heart rate, intensity, cadence, tracking information, maps, altitude, etc. It also contains the position pairs and the time stamp for that position lat-long, similar to another format like GPX files.

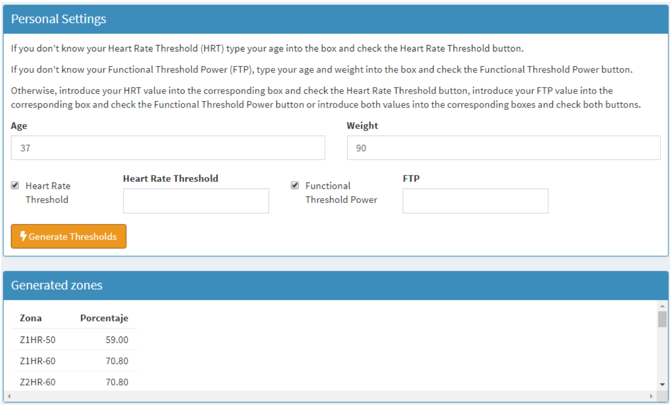

Fig. 5. Personal Settings Tab (view of the Web application)

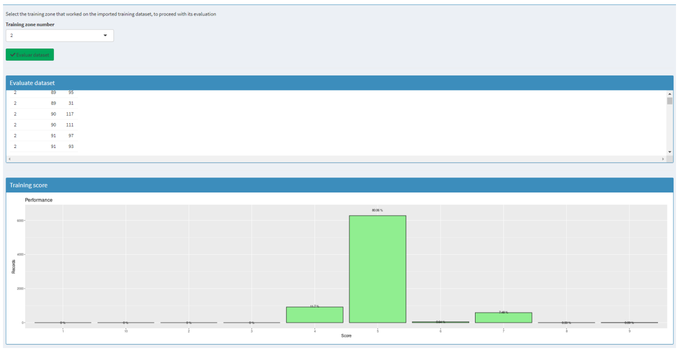

Fig. 6. Evaluate training (view of the Web application)

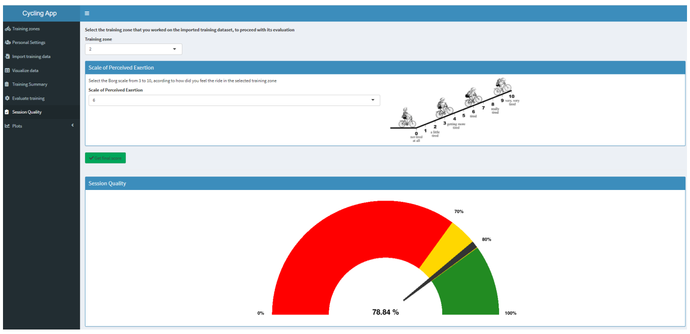

Fig. 7. Session quality (view of the Web application)

Figure 8 shows a flow chart explaining the general operation of FuCycling. A user enters a Web application and is asked if he knows his HRT and FTP; if he knows it, he clicks on the check box and loads the TCX file containing the training data. The HR, Power, and zone variables are obtained. The training is evaluated, and the performance is displayed. Again, the zone value and Perceived Exertion Rating are taken as input, and finally, the quality of the training session is produced and displayed.

VI. Results

In Tables IX and X, we placed summaries of input and output data from datasets uploaded to the Web application. Although the output provided by the Web application proposed was shown by itself in Figure 7. Here, in two tables, we put

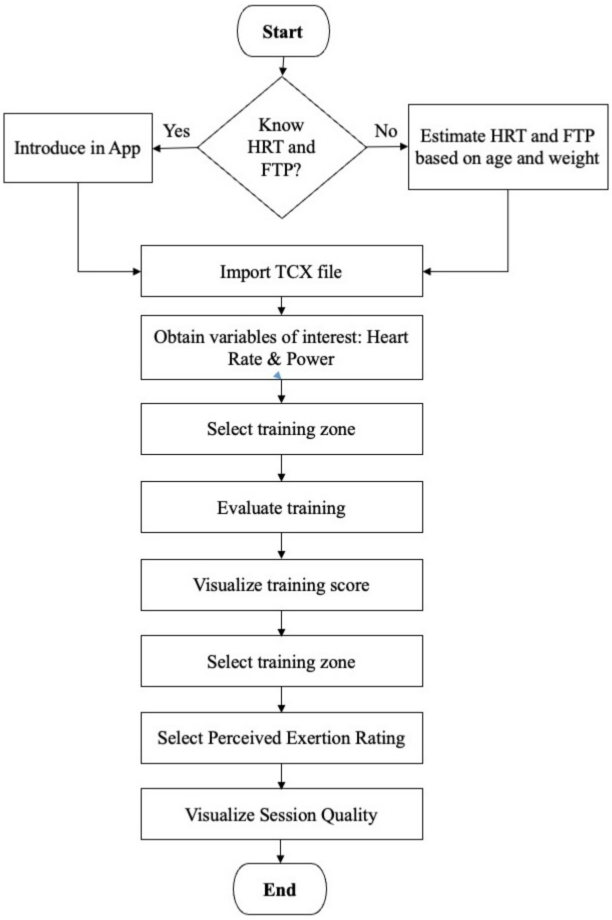

Fig. 8. Flow chart.

data so the reader can directly see incoming and resulting values.

Phase 1 and 2 evaluations were performed once per training zone for each cyclist. The model evaluated one record at a time until the total contained in each training dataset to get the results of phase 1, using the input variables: training zone, heart rate, and power. For example, cyclists 8, 10, and 11 scored nine points training in zone 4. Cyclists 9, 3, and 12 scored nine points working in zone 3; Cyclist 4 scored five points training in all zones. The total number of records for each dataset and the variables used are in Table IX.

In phase 2, to get the session quality, we used the performance rating received in phase 1, the training zone, and the cyclist's Perceived Exertion Rating, as shown in Table X. Working in zones 3 and 4, most cyclists obtained a fair and reasonable session quality.

Each input and output values are indicated in headers in Table IX and Table X.

In Table IX shows all results related to outputs in Zone 1, Zone 2, Zone 3, and in Zone 4. Whereas Table X applies the same sequence for inputs and outputs for Zone 1, Zone 2, Zone 3, and Zone 4.

A sports medicine specialist validated the results of our proposed model. First, we gave him five scenarios to obtain the rating in each one. Then, we evaluated the same datasets using

TABLE IX
RESULTS PHASE 1.

Cyclist	Total records	Input Heart Rate	Input Power	Output Score Zone 1	Output Score Zone 2	Output Score Zone 3	Output Score Zone 4
1	5140	✓	NA	5	5	5	5
2	3032	✓	NA	5	4	4	9
3	10052	✓	NA	5	7	9	8
4	9416	✓	✓	5	7	7	7
5	1864	✓	✓	5	5	5	4
6	7845	✓	✓	7	7	9	8
7	3635	✓	✓	5	7	5	4
8	7169	✓	✓	5	7	8	4
9	4041	✓	✓	5	7	8	4
10	3723	✓	NA	5	4	4	9
11	4058	✓	NA	5	7	9	4
12	3311	✓	NA	5	4	4	9

our algorithm to show the similarity percentage between our model and the rating provided by a human expert. As a result, we obtained the following percentages: 91%, 94%, 83%, 85%, and 87%, respectively.

VII. DISCUSSION

In this study, we employed training datasets from 3000 to 10000 records. The fuzzy system's hierarchy design reduces complexity by limiting the number of rules while maintaining accuracy and ensuring efficient data handling.

Defining the quality of the final training session according to the planned training plan is crucial for decision-making. Currently, we rely on the evaluation of a sports medicine specialist to assess and classify the performance of a cycling training session. However, different coaches may employ distinct evaluation methods, varying the number of training zones and percentage thresholds each cyclist must meet.

The scale of rating perceived exertion is key to training session classification. Cyclists may initially struggle to assess their exertion level accurately in each training zone, but their perception improves with continued training.

There is a lack of tools designed for daily performance evaluation relative to the training plan. Before training, cyclists must perform a stress test to obtain physiological measurements dictating exercise intensity. Training loads vary per microcycle within a training plan, and specialists verify an athlete's progress through periodic assessments.

Table XI summarizes the proposal's strengths and weaknesses. Some strengths and weaknesses highlight the following:

Our proposed system integrates hierarchical fuzzy logic into cycling performance evaluation, but it does not incorporate artificial intelligence techniques such as neural networks, which could enhance accuracy.

While the hierarchical fuzzy inference system effectively handles uncertainty and subjectivity, its dependence on predefined rules may introduce biases. Machine learning techniques could improve adaptability.

Combining objective (heart rate, power) and subjective (perceived exertion) variables offers a comprehensive assessment. However, the manual input of perceived exertion may introduce inconsistencies.

Although we achieved up to 94% similarity with a specialist's assessment, validation was based on only 81 training sessions from 12 cyclists, limiting generalization.

The FuCycling web application enhances usability but is restricted to TCX files, limiting users' adoption of other formats like GPX or FIT.

Although our system provides immediate feedback on performance, it does not fully replace expert evaluations, as it depends on user-entered data and external sensors.

Table XII compares popular commercial cycling tools with our fuzzy inference-based approach. It includes evaluation metrics, input data used, evaluation techniques, and results provided.

In the future, assessing training quality daily for a week and incorporating quality sessions each day to refine or continue training loads would be beneficial. This tool is particularly useful for specialists, as it enables more frequent monitoring of a cyclist's progress without requiring monthly evaluations.

VIII. CONCLUSION AND FUTURE WORKS

According to the objective mentioned above, we could quantify an indicator of cyclists' training quality: Heart Rate, Power, and Perceived Exertion Rating.

The algorithm presented in this paper successfully classified 88% of the training dataset, taking into account all scenarios and classes for each cyclist and demonstrating the strengths of the fuzzy rule-based system.

Performance improves because a cyclist can receive feedback from the fuzzy system. With this information, he can focus on another zone in another training session and improve his performance. The same happens with his perceived exertion rating; it increases.

Using hierarchical fuzzy inference systems to evaluate cycling performance is a novel approach in sports due to the use of subjective, personal, and ambiguous perceptions and opinions within the sports area. More literature is needed on handling cycling performance data with fuzzy inference systems. However, other artificial intelligence techniques could also be used, such as neural networks, expert systems, or machine learning approaches.

Finally, FuCycling provides cyclists with an adequate interpretation of how they performed their training based on the coach's plan. With this tool, it will be less complicated to integrate new cyclists, thus promoting an increase in the sport of cycling at the amateur level and helping to improve performance and avoid overtraining continuously.

Certainly, the datasets analyzed include a majority of male cyclists, only five females. The variables collected between men and women cyclists are practically the same. However, physiological differences between male and female cyclists could affect training responses related to perception.

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TABLE X
RESULTS PHASE 2.

Cyclist	Input Training Score Zone 1	Input Scale of Perceived Exertion	Output Quality Session	Input Training Score Zone 2	Input Scale of Perceived Exertion	Output Quality Session	Input Training Score Zone 3	Input Scale of Perceived Exertion	Output Quality Session	Input Training Score Zone 4	Input Scale of Perceived Exertion	Output Quality Session
1	5	4	Regular	5	6	Regular	5	8	Regular	5	10	Regular
2	5	4	Regular	4	6	Regular	4	8	Regular	9	10	Good
3	5	4	Good	7	6	Good	9	8	Regular	8	10	Regular
4	5	4	Regular	7	6	Regular	7	8	Regular	7	10	Regular
5	5	4	Regular	5	6	Regular	5	8	Regular	4	10	Regular
6	7	4	Regular	7	6	Regular	9	8	Good	8	10	Regular
7	5	4	Regular	7	6	Regular	5	8	Regular	4	10	Regular
8	5	4	Regular	7	6	Regular	8	8	Regular	4	10	Regular
9	5	4	Regular	7	6	Regular	8	8	Regular	4	10	Regular
10	5	4	Regular	4	6	Regular	4	8	Regular	9	10	Good
11	5	4	Regular	7	6	Regular	9	8	Good	4	10	Regular
12	5	4	Regular	4	6	Regular	4	8	Regular	9	10	Good

TABLE XI
STRENGTHS AND WEAKNESSES OF THE PROPOSED APPROACH.

Aspects	Strengths	Weaknesses
Innovation	First system to integrate a fuzzy hierarchical approach to cycling performance evaluation, combining rules based on expert knowledge.	Does not incorporate other artificial intelligence techniques, such as machine learning or neural networks, which could improve model performance.
Methodology	Use of a hierarchical fuzzy inference system to manage uncertainty and subjectivity in performance evaluation.	Reliance on subjective data, such as Borg's scale of rating perceived exertion (RPE), may introduce bias.
Variables	Considers both objective (heart rate, power) and subjective (perceived exertion) variables, providing a comprehensive performance assessment.	Requires cyclists to manually input perceived exertion, potentially leading to inconsistent and subjective evaluations.
Datasets	The model was tested on multiple datasets from cyclists.	Five female adult cyclists were included (one young female and four mature females).
Model Validation	Achieved up to 94% agreement with a sports medicine specialist's assessment, supporting its reliability.	Limited dataset (81 training sessions from 12 cyclists) may affect generalizability.
Practical Applicability	Development of a web application (FuCycling) to facilitate system use by coaches and cyclists.	The application supports only TCX file format, limiting compatibility with other formats such as GPX or FIT.
Impact on Training	Provides detailed training quality evaluations and valuable feedback for performance improvement.	Does not fully replace a coach's assessment, as it relies on manually entered data and external sensor readings.

TABLE XII
COMPARISON OF CYCLING PERFORMANCE EVALUATION SYSTEMS.

System	Input Data	Evaluation Metrics	Evaluation Techniques	Results Provided
Wahoo SYSTM[41]	Power, HR, Cadence	Training Load, 4DP, Neuromuscular Fatigue	Advanced Physiological Modeling	Weakness and Strengths Assessment, personalized recommendations
WKO5 [30]	Power, HR, HRV	mFTP, W'bal, Power Duration Model	Power modeling based on big data	Performance prediction, training optimization
Garmin Training Status[28]	HR, Power, HRV, Stress	VO_2 max, Training Load, Recovery Status	Physiological and Heuristic Algorithms	Fitness, Recovery Time
Polar Flow[32]	HR, Power, Duration	Recovery Status, Training Effect	Training Load and Recovery Algorithms	Fatigue Level, Cardiovascular Load, Rest Suggestions
TrainingPeaks[29]	Power, HR, Cadence, Duration, Intensity	Stress Score (TSS), Acute and chronic load, FTP, VO_2 max	Mathematical models (CTL, ATL, TSB)	Fatigue, fitness, performance trend
FuCycling (Proposal)	HR, Power, RPE, Training zone	Fuzzy inference based training quality	Hierarchical fuzzy inference system	Qualitative and quantitative performance assessment, subjective effort integration

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Fabricio Landero is a Ph.D. student in Computer Science with an MSc in Information Technologies Management, and a BSc in Administrative Computing at the Juarez Autonomous University of Tabasco (UJAT). He is also an ETL Developer. His research interests are fuzzy logic and pattern recognition.

Miguel A. Wister holds a BS in Computer Science from Juarez Autonomous University of Tabasco (UJAT) in 1993, a Master of Science in Information Technology from the Monterrey Institute of Technology (1997) and a PhD from the University of Murcia, Spain (2008). At the same university, he worked as a research assistant in the Department of Information Engineering and Communications intelligent systems group between 2005 and 2007. His professional career includes several important positions, such as Career Director of the Bachelor's Degree in Computer Systems and Informatics at Olmeca University (1997-2001). Since 1993, he has been a full-time professor at UJAT, where he teaches in the Computer Systems, Administrative Informatics, and Telematics degrees. He has been a research coordinator and has collaborated in the curricular design of graduate programs at DACYTI; since 2018, he coordinates the PhD in Computer Science.

Pablo Payró is Associate Professor at the Academic Division of Information Sciences and Technologies at Juarez Autonomous University of Tabasco (UJAT), Mexico. He has a BSc in Computer Sciences, an MSc in Management at UJAT, and a Ph.D. in Organizational Studies from Metropolitan Autonomous University (UAM), Mexico. His research interests include IT Management, Organizational Change, pattern recognition, classification, formal languages, and automata. He has authored/co-authored more than 25 scientific publications and has led/taken part in several research projects. Member of Mexico's National Researchers System.

Pedro Ivan Arias is Specialist in Rehabilitation Medicine (UNAM). Specialist in Sports Medicine (UADY), Master's in Physical Activity and Health (UEA). Master in Regenerative Medicine and Anti-Aging (UV). Professor - Researcher of the Department of Rehabilitation of the UJAT. Associate Professor in the specialty course in Rehabilitation Medicine CMN 20 de Noviembre /UNAM. Associate Professor in the postgraduate course of High Specialty in Clinical Physiology of Exercise CMN November 20th /UNAM. Professor of the Diploma in Rehabilitation in Sport. Professor of the Diploma in Complementary Therapeutic Methods in Rehabilitation.