Physical education and sport through the centuries
2026, 13(1), 113-128
ISSN 2335-0598

Original research article DOI:

A SOFT COMPUTING–BASED DECISION SUPPORT SYSTEM FOR MULTIDIMENSIONAL ASSESSMENT OF NON-LINEAR COORDINATIVE PERFORMANCE IN COMBAT SPORT ATHLETES USING A FUZZY INFERENCE SYSTEM

Ram Niwas[1], Monika Verma[2], Avnesh Verma[3]

[1]Dept of Physical Education Chaudhary Devi Lal University Sirsa Haryana India
[2]Department of Physical Education. Chaudhary Devi Lal University, Sirsa
[3]Department of Instrumentation (formerly USIC), Kurukshetra University, Kurukshetra, State Haryana

ABSTRACT

This research establishes a Fuzzy Inference System (FIS) aimed at modeling, analyzing, and forecasting the coordinative capabilities of male athletes in judo and wrestling, with an emphasis on non-linear variables such as balance, reaction time, and agility. These coordinative elements are intricate and qualitative, necessitating a fuzzy logic methodology for enhanced accuracy in evaluation, as conventional binary assessments (e.g., good/bad) frequently overlook the subtleties of performance. The FIS classifies athletes' capabilities into fuzzy categories (Low, Medium, High), facilitating a more detailed examination of their strengths and weaknesses. By incorporating all physical parameters, it is determined that factors such as LBM (Lean Body Mass), PBF% (Percent Body Fat), BMI (Body Mass Index), and BMR (Basal Metabolic Rate) indicate that the athletes are advancing in both physical conditioning and sport-specific skills. The results imply that the implemented training regimen has a beneficial effect on athletic performance, as shown by positive trends in these parameters. Additionally, the research investigates the incorporation of wearable sensors and biomarkers to improve the accuracy of performance assessments and offer more tailored training protocols. This fuzzy logic framework serves as a robust instrument for optimizing player profiling, talent identification, and training strategies in combat sports, aiding coaches in making better-informed decisions and enhancing overall athlete development.

Key words: Fuzzy Inference System (FIS), Wrestling, Judo, Combat Sport Athletes, Multidimensional Non-Linear Coordinative Performance

Corresponding author
Avnesh Verma
verma.avnesh@rediffmail.com

INTRODUCTION

Analyzing body composition and physiological profiles is crucial for improving performance in combat sports such as judo and wrestling. These demanding, intermittent, full-contact activities rely on neuromuscular effectiveness, skillful technique, and strategic execution. While the techniques vary between modalities (throws in judo vs. takedowns in wrestling), both sports require substantial strength, explosive power, and rapid responsiveness, supported by low body fat and higher amounts of lean muscle mass. Key measurements—including somatotype, height, weight, body fat percentage (PBF%), lean body mass (LBM), body mass index (BMI), total body water (TBW), mineral density, and basal metabolic rate (BMR) are essential for improving performance. Body composition is related to the ability to generate force, with judo emphasizing upper-body and core strength, while wrestling prioritizes lower-body power. Training programs utilize high-intensity interval training (HIIT), explosive actions, and compound movements. These disciplines demand a combination of high power-to-weight ratio, anaerobic endurance, explosive strength, and coordinative abilities such as balance, agility, and reaction time (Burke et al., 2006; Campa et al., 2021). Although both sports involve grappling, their biomechanical and physiological demands differ. Judo, characterized by the use of a jacket and belt, places greater emphasis on upper-body endurance and grip strength, whereas freestyle wrestling requires sustained whole-body endurance and dynamic strength (Khaithi & Pungding, 2023; Çağlar et al., 2024). Consequently, a multidimensional assessment framework is necessary for accurately evaluating athletic performance.

Body composition is a key determinant of success in combat sports. Elite athletes typically maintain low Percent Body Fat (PBF%) and high Lean Body Mass (LBM) to optimize strength, speed, and efficiency within specific weight categories (Marques et al., 2019; Carvalho de Moura et al., 2025). Male judokas, for example, often maintain body fat levels below 10%, while female athletes range between 19–24% (Giovanelli et al., 2024). Additionally, a mesomorphic somatotype, characterized by high muscularity and low fat, is commonly associated with superior performance (Franchini et al., 2012; Brito et al., 2012). Physiological variables such as maximal strength, anaerobic power, and cardiovascular capacity further influence competitive success (Ostojic et al., 2006; Zupan et al., 2019). Traditional practices, such as rapid weight reduction prior to competition, may compromise LBM and performance, highlighting the importance of continuous monitoring and optimization (Burke et al., 2006; Baker et al., 2009).

Conventional evaluation methods, including linear models and binary classifications, often fail to capture the complexity and non-linearity of coordinative abilities (Verma et al., 2019; Rani et al., 2025). Attributes such as balance, reaction time, and agility are multidimensional and interdependent, necessitating advanced analytical approaches capable of handling uncertainty and variability in performance data (Lafont & Balmat, 2002; Moura et al., 2004).

Recent developments in wearable sensors and Very Large Scale Integration (VLSI) technologies, including Field-Programmable Gate Arrays (FPGAs) and Insulated Gate Bipolar Transistors (IGBTs), allow real-time monitoring of internal and external training loads, muscle fatigue, and cardiovascular responses (Verma et al., 2009a, 2009b, 2009c; Singh et al., 2015; Sharma & Verma, 2018). When integrated with fuzzy inference systems (FIS), these tools enable nuanced assessment of complex, high-dimensional athlete data. FIS models utilize rule-based reasoning to classify performance into graded categories, generate adaptive training prescriptions, and optimize decision-making (Verma & Tiwari, 2013, 2019; Rani et al., 2025).

In this context, the present study proposes a soft computing–based decision support system to assess multidimensional, non-linear coordinative performance in judo and wrestling athletes. By integrating anthropometric, physiological, and sensor-based data, the model aims to provide individualized training recommendations, enhance athlete profiling, reduce injury risks, and support evidence-based decision-making by coaches and sports scientists (Verma et al., 2019; Khaithi & Pungding, 2023; Niwas et al., 2025). This approach represents a significant advancement over traditional evaluation techniques by combining real-time monitoring, predictive modeling, and fuzzy logic–based analysis to optimize combat sport performance.

REVIEW OF RELATED LITERATURE

Advancements in electronic, computational, and wearable technologies have significantly enhanced the precision and scope of sports science assessments. Early studies emphasized the importance of energy and carbohydrate management in training and recovery, establishing foundational knowledge for athlete monitoring (Burke et al., 2006). Contemporary developments in wearable sensors and field-programmable gate arrays (FPGAs) have facilitated real-time processing of physiological and biomechanical data, allowing objective evaluation of athletic performance (Verma et al., 2009a, 2009b, 2009c; Sharma & Verma, 2018). Optimized fuzzy logic systems have further improved the interpretation of non-linear and multidimensional performance metrics, enabling individualized feedback for combat athletes (Verma & Tiwari, 2013, 2019; Rani et al., 2025; Niwas et al., 2025). Research on combat sports emphasizes the relevance of anthropometry and body composition in performance optimization. Brazilian studies highlighted significant variations in body mass index (BMI), abdominal endurance, and vertical jump performance among young judokas and wrestlers (Marques et al., 2019), while comparative analyses noted differences in speed, agility, and strength endurance due to sport-specific demands (Khaithi & Pungding, 2023; Çağlar et al., 2024). However, some investigations report minimal differences in lean body mass, underscoring the need for multidimensional assessments (Giovanelli et al., 2024; Carvalho de Moura et al., 2025). Traditional BMI measures are limited in athletic populations because they do not differentiate between fat and lean mass (Durnin & Womersley, 1974; Wang et al., 1998, 1999). Advanced multi-component models, including two-, three-, and five-component analyses, allow for precise evaluation of fat, lean tissue, water, and mineral content, enhancing performance monitoring (Spady et al., 1987; Nelson et al., 1992). Modern techniques, such as bioelectrical impedance analysis (BIA) and dual-energy X-ray absorptiometry (DEXA), have gained prominence due to their non-invasive accuracy (Campa et al., 2021; Cataldi et al., 2024). These methods enable the assessment of fat-free mass, hydration, and sport-specific body composition standards (Giovanelli et al., 2024; Carvalho de Moura et al., 2025). High lean body mass is positively associated with enhanced performance, whereas excess fat mass reduces efficiency and increases metabolic risk (Wang et al., 1998, 1999; Helms et al., 2014). Research indicates that mesomorphic somatotypes and well-developed muscle architecture optimize judo and wrestling performance (Ostojic et al., 2006; Franchini et al., 2012; Brito et al., 2012; Zupan et al., 2019).

The integration of wearable sensors, fuzzy inference systems, and advanced body composition techniques provides a multidimensional approach to evaluating coordinative performance (Lafont & Balmat, 2002; Moura et al., 2004; Verma et al., 2019). Fuzzy logic models effectively classify performance outcomes into graded categories, accommodating variability in speed, strength, agility, and coordination (Verma & Tiwari, 2019; Rani et al., 2025). Combining physiological monitoring, anthropometric data, and neuromuscular testing enhances predictive accuracy for training adaptation, recovery, and performance optimization (Franchini & Takito, 2014; Nevill et al., 2014; Santos et al., 2015; Gobbo et al., 2019). Studies also emphasize nutritional, hydration, and weight management strategies to maximize performance and maintain health (Bridge & Jones, 2006; Maughan et al., 2007; Baker et al., 2009). Strength and power profiling, muscle architecture analysis, and body composition monitoring are critical for elite athletes in combat sports (Tan et al., 2009; Sayers et al., 2011; Loturco et al., 2017). Together, these technologies and analytical approaches provide a comprehensive framework for assessing, monitoring, and optimizing the non-linear coordinative performance of judo and wrestling athletes (Burke et al., 2006; Verma et al., 2009a, 2009b, 2009c; Campa et al., 2021; Khaithi & Pungding, 2023; Rani et al., 2025; Niwas et al., 2025).

METHODOLOGY

Data Collection and the body composition data of athletes.

Data on body composition were gathered from a group of 200 male athletes, all of whom are competitors at the district level, receiving professional coaching. This group consisted of 100 participants from judo and 100 from wrestling, all aged between 16 and 19 years. Each sport category included 50 athletes from rural backgrounds and 50 from urban settings.

The anthropometric and physiological parameters recorded included height (m), weight (kg), body type, Lean Body Mass (LBM, kg), mineral content (kg), protein mass (kg), Total Body Water (TBW, kg), Percentage Body Fat (PBF, %), Body Mass Index (BMI), fatness index, body fat mass (kg), and Basal Metabolic Rate (BMR). The experimental design and reporting structure are depicted in Fig. 1, and the dataset collected is summarized in Table 1.

Figure 1: *Test Conduction and reports on Combat Sport Athletes.*

Table 2 outlines the dependent (output) variables, which consist of ten indicators of body composition. Given the extensive volume of data and the associated uncertainty, traditional deterministic methods proved inadequate for thorough interpretation. Therefore, a fuzzy logic-based framework was implemented to model non-linear relationships and to simulate human reasoning in uncertain and ambiguous scenarios.

Parameter Data

Table 1 shows the raw measurements of body composition for 200 athletes. Table 1 has been truncated from the full data to save space (Annexure 1 attached), and Table 2 organizes the output variables for the next analysis. Of the ten variables measured, height and weight were identified as inputs, and the other eight variables are outputs.

Table 1. Body composition Data of Athletes Collected

Sr. No	Height (m)	Weight (kg)	Body Type	LBM (kg)	Mineral (kg)	Protein (kg)	TBW (kg)	PBF (%)	BMI	Fatness	Body Fat (kg)	BMR
1	1.65	68	Athletic	52.5	4.2	3.1	60.5	22.1	24.9	0.23	15	1550
2	1.72	65	Lean	51	4	2.9	58	21.5	21.9	0.21	13.9	1600
3	1.66	63	Slim	48.5	3.9	2.8	55	23.5	22.9	0.22	14.8	1575
4	1.63	70	Athletic	54.5	4.3	3.3	61.5	24	26.3	0.26	16.8	1650
5	1.61	55	Slim	41.5	3.7	2.6	49.5	20.5	21.2	0.2	11.3	1500
6	1.7	69	Athletic	53	4.2	3.2	60	23.9	23.9	0.24	15.6	1625
7	1.62	60	Lean	44	3.8	2.7	51.5	22	22.9	0.21	13.2	1525
8	1.78	68	Slim	50.5	4	2.9	57.5	24.5	21.5	0.22	16.7	1680
9	1.8	70	Athletic	56	4.3	3.4	63	23.7	21.6	0.25	16.6	1700
10	1.68	60	Lean	45.6	3.9	2.7	54	23	21.3	0.23	13.8	1550
11	1.75	68	Athletic	52	---	---	---	---	---	---	---	---
12	1.6	55	Slim	40	3.5	---	---	---	---	---	---	---
13	1.7	65	Lean	49	4	2.9	58.5	---	---	---	---	---
14	1.82	70	Athletic	---	---	---	---	---	---	---	---	---
15	---	---	---	---	---	---	---	---	---	---	---	---
---	---	---	---	---	---	---	---	---	---	---	---	---
---	---	---	---	---	---	---	---	---	---	---	---	---
200	1.77	85	Lean	66	5.2	4.1	74	25.3	27.2	0.28	19	2050

Each variable was represented through three linguistic levels: low, medium, and high. The specific crisp ranges for these fuzzy sets are detailed in Table 3. These ranges were utilized to establish membership functions for the Fuzzy Inference System (FIS).

Table 2. Output Variables of Athletes' Parameters

S. No	Output Variables (Dependent Variables)
1.	Body Type - Classification based on body composition
2.	LBM (kg) – Lean Body Mass in kilograms
3.	Mineral (kg) - Mineral content in the body
4.	Protein (kg) - Protein weight in the body
5.	TBW (kg) - Total Body Water in kilograms
6.	PBF (%) - Percentage of Body Fat
7.	BMI - Body Mass Index
8.	Fatness - Fat classification level
9.	Body Fat (kg) - Total body fat weight in kilograms
10.	BMR– Basal Metabolic Rate (calories burned at rest)

Fuzzy Methodology

The fuzzy logic methodology emulates human reasoning by associating inputs with a degree of membership ranging from 0 to 1. In this context, linguistic variables are utilized to handle ambiguous data through the explanation of the fuzzy inference system (FIS), which encompasses fuzzification, rule evaluation, and defuzzification processes to transform vague inputs into clear, actionable outputs.

Identification of the Variables and Crisp Values:-

In this section, the complete set of 10 physical variable values is presented, with two variables (Height and Weight) chosen as inputs, while the remaining 8 variable values are treated as outputs. All input and output variables are classified into low, medium, and high value limits. The comprehensive body composition parameters are depicted in fuzzy crisp values in Table – 3.

Table 3 Possible crisp Values for Inputs and Outputs

S. No	INPUTs / OUTPUTs	Crisp Values (Inputs -2, Outputs -8)			
1.	Input-1	Height	0.8-1.1-1.25	1.2-1.5-1.8	1.6-1.85-2.1
2.	Input-2	Weight	0.95-1.25-1.55	1.30-1.60-1.85	1.5-1.75-2.05
3.	Output-1	LBM	35-60-85	45-70-95	76-108-130
4.	Output-2	Minerals	2-3-4	3-4-5	4-5.5-6.5
5.	Output-3	Protein	10-15-20	12-22-32	22-32-40
6.	Output-4	TBW	25-40-55	35-55-75	50-70-85
7.	Output-5	PBF (%)	3-10-17	6-13.5-20.5	12-18-24
8.	Output-6	BMI	18-25-32	22-30-38	30-36-42
9.	Output-7	Body Fat	3-10-17	6-15-23	10-20-30
10.	Output-8	BMR	1200-1700-2200	1600-2250-2900	2100-2650-3200

Fuzzy Logic, Rule Structure and Rule Mapping:-

In accordance with the range established in Table 3, Table 4 has been constructed. The overall system comprises 10 elements (2 inputs + 8 outputs), leading to the calculation of possible combinations of 3 states (Low, Medium, High):

$$C\,(8,2)\ = \frac{10!}{8!.2!} = 45$$

Table 4 Possible Fuzzy Values for Inputs and Outputs

Input Height	Input Weight	Output LBM	Output Mineral	Output Protein	Output TBW	Output PBF (%)	Output BMI	Output Body Fat	Output BMR
L	L	L	M	M	M	M	M	M	M
L	M	L	L	M	M	M	M	M	M
L	H	L	L	L	M	M	M	M	M
M	L	L	L	L	L	M	M	M	M
M	M	L	L	L	L	L	M	M	M
M	H	L	L	L	L	L	L	M	M
H	L	L	L	L	L	L	L	L	M
H	M	L	L	L	L	L	L	L	L
H	H	M	L	L	L	L	L	L	L
L	L	M	M	L	L	L	L	L	L
L	M	M	M	M	L	L	L	L	L
L	H	M	M	M	M	L	L	L	L
M	L	M	M	M	M	M	L	L	L
M	M	M	M	M	M	M	M	L	L
M	H	M	M	M	M	M	M	M	L
H	L	M	M	M	M	M	M	M	M
H	M	H	L	L	L	L	L	L	L
H	H	H	H	L	L	L	L	L	L
L	L	H	H	H	L	L	L	L	L
L	M	H	H	H	H	L	L	L	L
L	H	H	H	H	H	H	L	L	L
M	L	H	H	H	H	H	H	L	L
M	M	H	H	H	H	H	H	H	L
M	H	H	H	H	H	H	H	H	H
H	L	H	M	M	M	M	M	M	M
H	M	H	H	M	M	M	M	M	M
H	H	H	H	H	M	M	M	M	M
L	L	H	H	H	H	M	M	M	M
L	M	H	H	H	H	H	M	M	M
L	H	H	H	H	H	H	H	M	M
M	L	H	H	H	H	H	H	H	M
M	M	L	L	L	L	L	L	L	H
M	H	L	L	L	L	L	L	H	H
H	L	L	L	L	L	L	H	H	H
H	M	L	L	L	L	H	H	H	H
H	H	L	L	L	H	H	H	H	H
L	L	L	L	H	H	H	H	H	H
L	M	L	H	H	H	H	H	H	H
L	H	M	M	M	M	M	M	M	H
M	L	M	M	M	M	M	M	H	H
M	M	M	M	M	M	M	H	H	H
M	H	M	M	M	M	H	H	H	H
H	L	M	M	M	H	H	H	H	H
H	M	M	M	H	H	H	H	H	H
H	H	M	H	H	H	H	H	H	H

Consequently, a total of 45 permutation combinations of 2 inputs and 8 outputs are also presented in Table 4. With 2 inputs each having 3 potential fuzzy states, this results in 3x3=9 fuzzy rules. The 9 potential input combinations are mapped as follows:

- (Input 1 is Low, Input 2 is Low)
- (Input 1 is Low, Input 2 is Medium)
- (Input 1 is Low, Input 2 is High)
- (Input 1 is Medium, Input 2 is Low)
- (Input 1 is Medium, Input 2 is Medium)
- (Input 1 is Medium, Input 2 is High)
- (Input 1 is High, Input 2 is Low)
- (Input 1 is High, Input 2 is Medium)
- (Input 1 is High, Input 2 is High)

Based on the aforementioned mapping, the fuzzy rules will be established. Each of these combinations corresponds to a fuzzy rule; while the 8 outputs add complexity to the system, they do not alter the number of input combinations or fuzzy rules. The 8 outputs will affect how the rules are assigned to the specific outputs, but they do not modify the 9 input combinations. The Fuzzy Inference System diagram illustrated in Figure 2 represents the Test on Combat Athletes, which summarizes and validates the data collection process depicted in Figure 1. The schematic representation outlines two input variables and eight output variables, organized to systematically accommodate and represent the crisp numerical values detailed in Table 3.

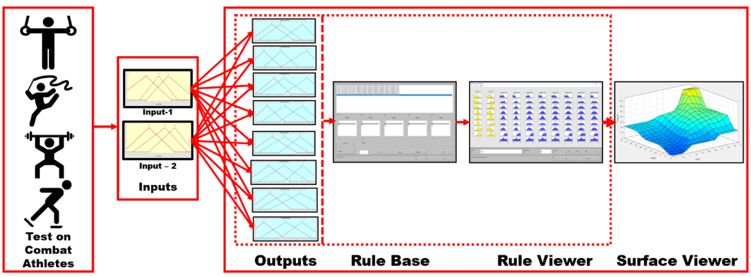


Fig. 2: *Fuzzy Set flow diagram with Membership Functions, Rule Base, Rule Viewer, and Surface Viewer.*

Combat sports are high-intensity, dyadic, full-contact systems characterized by complex, non-linear coordinative demands under rule-constrained conditions. Body composition is strongly associated with force-generation capacity; Judo athletes typically demonstrate superior upper-body and core strength, whereas wrestlers exhibit greater lower-limb power due to stance-specific biomechanics. Training in both modalities integrates HIIT, explosive lifts (e.g., power cleans), and compound resistance exercises to optimize neuromuscular output, with wrestling emphasizing aerobic endurance and Judo prioritizing grip strength (Uchikomi). These multidimensional performance attributes justify the application of a fuzzy inference–based decision support system for integrative assessment.

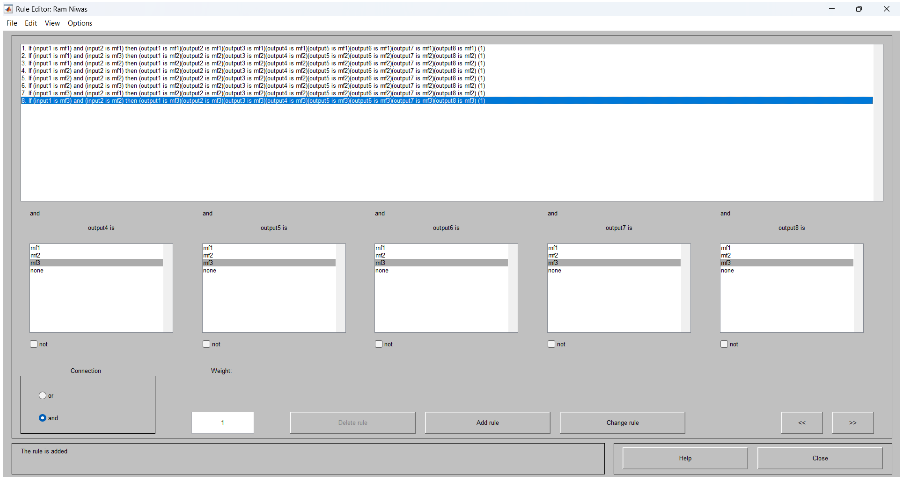


***Fig. 3**: Fuzzy Rule Sets in Fuzzy Editors.*

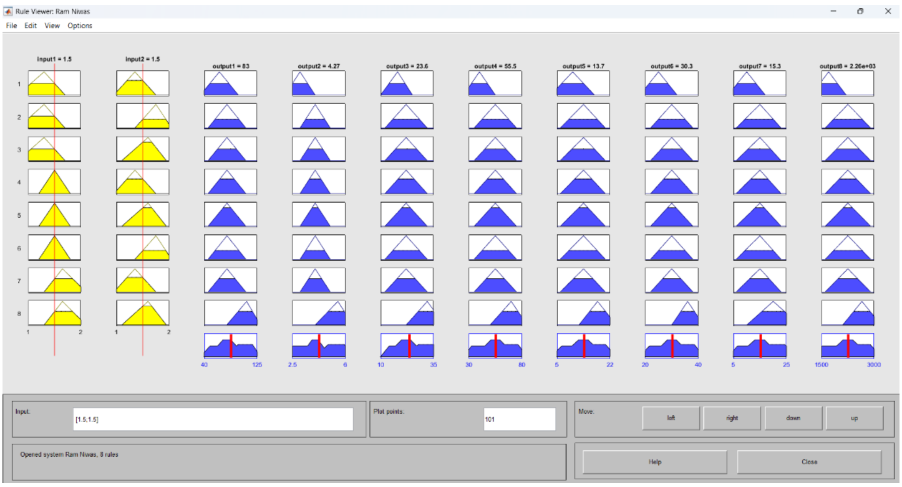


***Fig. 4**: Rule Viewer as per Fuzzy Rule Sets.*

Figure 3 provides a representative illustration of the Rule Editor interface; the complete set of 45 fuzzy rules is comprehensively presented in Table 4. The rules established for the combinations of inputs and outputs are represented in this figure through membership functions and linguistic rules aimed at enhancing the athlete's performance in a graphical format. Likewise, Figure 4 presents the Rule Viewer according to fuzzy rule sets, which facilitates the fuzzy interface by visualizing the membership functions corresponding to each rule's antecedent and consequent. The output dependence on the input is shown in Figure 4. Figure 5 showcases the Fuzzy Surface Viewer, which provides a micro-level visualization of rule interactions, delivering an innovative 3D representation of fuzzy logic reasoning.

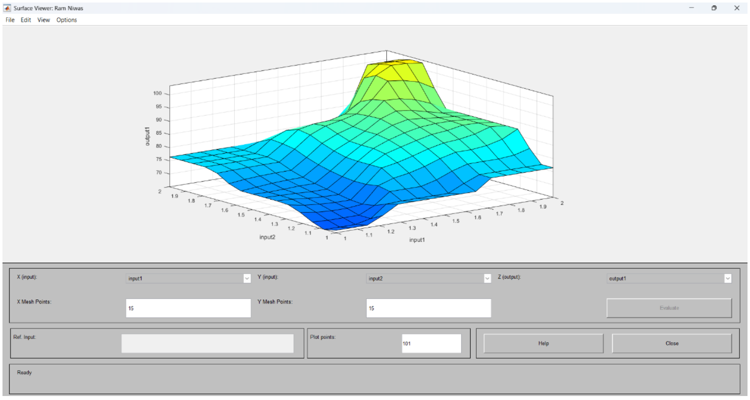


Fig. *5: Fuzzy Surface Viewer.*

It can be visualized that the surface viewer is isometric and uniform, with all axis orientations being harmonious, meaning that the X, Y, and Z axes are scaled equally. This consistency has ensured that measurements are reliable, maintaining a cubic angle of 120 degrees orientation, among other factors. Consequently, it has been visually demonstrated that the design is technically precise and specifically aligned, rather than merely realistic, thereby providing an impression of perspective-based depth.

Defuzzification*:-*

Defuzzification represents the final stage of the fuzzy logic system, wherein the processed and aggregated fuzzy output sets of athletes are converted back into a single, definitive numerical (crisp) value. At this juncture, the data from the fuzzy inference system will be reconciled with physical actions utilizing the centroid method (center of gravity method). In the initial step, employing the centroid method, the input values are adjusted based on the low values of 1/P1 and 1/P2 for the athletes. The corresponding outputs are recorded from 0/P1 to 0/P4 as LM - Low Medium, and from 0/P5 to 0/P8 as L - Low. The respective crisp values are as follows: 1/P1=1.13, 1/P2=1.14, 0/P1=66.4, 0/P2=3.28, 0/P8=18.5, 0/P4=44, 0/P5=10.7, 0/P6=26.1, 0/P7=11.1, and 0/P8=1910. These values are documented in Table 5, Sr. No. 1. In total, nine tests are conducted based on the nine possible input combinations and the previously established rules mapping, with their respective eight output values recorded after each test result. Table 5 contains all these values. Based on Table 5 and Figure 6, the Defuzzification Crisp Data Values derived from fuzzy set outputs indicate significant enhancements in parameters such as Lean Body Mass (LBM), Percentage Body Fat (PBF), Body Mass Index (BMI), and Basal Metabolic Rate (BMR), confirming that the athletes are making progress in both physical conditioning and sport-specific techniques. These findings suggest that the athletes are adhering to an appropriate training regimen. The observed changes reflect the athletes' capacity to improve their physical strength, power, and overall technique, which ultimately enhances their performance in the sport.

Table 5 Fuzzy Input and Output with corresponding Crisp Values for Inputs and Outputs

S. No	I/P 1 (1-2)	I/P 2 (1-2)	O/P 1 (40-125)	O/P 2 (2.5-6)	O/P 3 (10-35)	O/P 4 (30-80)	O/P 5 (5-22)	O/P 6 (20-40)	O/P 7 (5-25)	O/P 8 (1500-3000)
1.	L-1.13	L-1.14	LM-66.4	LM-3.28	LM-18.5	LM-44	L-10.7	L-26.1	L-11.1	L-1910
2.	L-1.13	M-1.5	LM-71.1	LM-3.61	M-20.8	M-50.1	LM-12	M-28.2	LM13.2	LM-2110
3.	L-1.13	H-1.83	LM-76.4	LM-4	M-22	M-55	M-13.3	M-30	M-14.6	M-2250
4.	M-1.5	L-1.14	LM-73.4	LM-3.76	M-21.2	M-50.9	M-12.3	M-28.4	LM-13.4	LM-2140
5.	M-1.5	M-1.5	M-82.8	M-4.25	M-23.5	M-55.3	M-13.7	M-30.2	M-15.3	M-2250
6.	M-1.5	H-1.8	M-85.6	M-4.49	M-24	M-58.4	M-14.4	M-31.4	M-16.1	M-2340
7.	H-1.8	L-1.13	M-78.5	M-4.12	M-22.3	M-55.5	M-13.5	M-30.2	M-14.8	M-2260
8.	H-1.8	M-1.5	M-89.2	M-4.67	M-25.2	M-60.3	M-15	M-32.1	M-16.9	M-2390
9.	H-1.8	H-1.8	MH-103	MH-5.15	MH-29.5	MH-67	MH-17.6	MH-35.6	MH-18.5	MH-2600

L- Low, M- Medium, H-High, LM-Low Medium, MH-Medium High

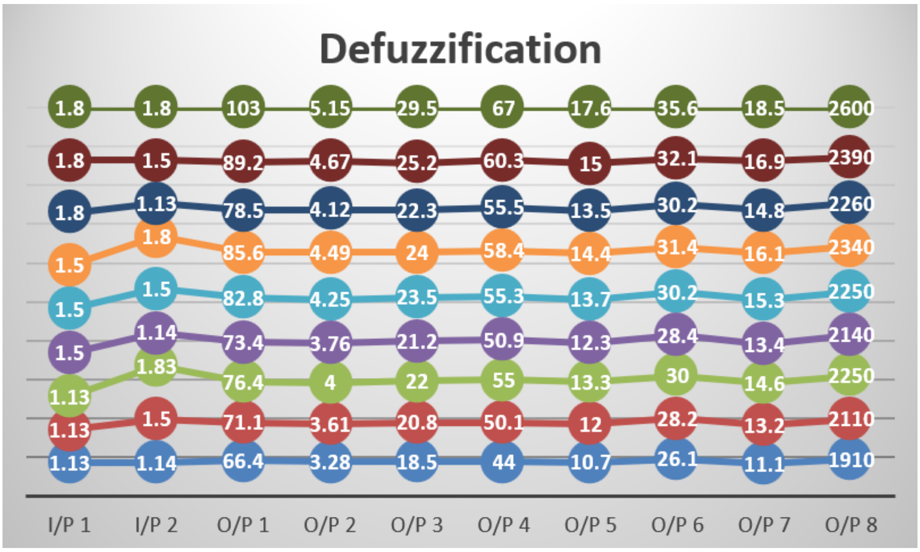
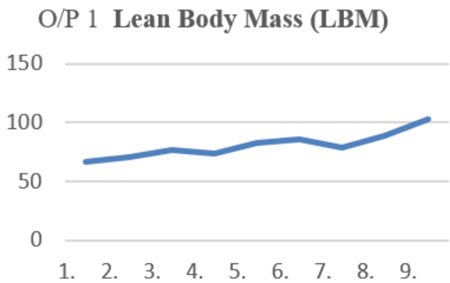


Fig. 6 *Defuzzification-Crisp Data Values from Fuzzy Set output.*

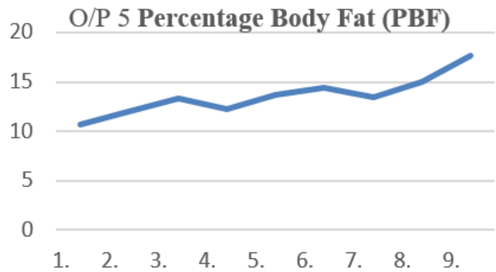
In the context of combat sports, Lean Body Mass (LBM) is essential for strength development. An increase in LBM is directly associated with greater muscle mass, which enhances an athlete's ability to exert force during critical actions such as throws or takedowns. Maintaining an optimal Percentage Body Fat (PBF%) is also crucial, as it allows the athlete to remain agile and explosive, preventing excess weight from hindering movement or stamina. Body Mass Index (BMI) serves as a general indicator of an athlete's body composition, providing insights into variations in muscle-to-fat ratios and their potential effects on performance. Despite its limitations, changes in BMI are a valuable metric for evaluating the success of training. Furthermore, a higher Basal Metabolic Rate (BMR) indicates an increase in muscle mass and elevated energy expenditure, which can offer deeper insights into an athlete's recovery and energy requirements, allowing coaches to more effectively customize nutrition and training programs.

The data trends illustrated from Fig 7 (a) to Fig 7 (d) demonstrate consistent advancements in LBM, PBF%, BMI, and BMR, respectively, confirming that the athletes are following a suitable training protocol. Coaches can interpret this upward trend as validation that the athletes are progressing appropriately with their training and technique development. Additionally, the clarity of the fuzzy logic model guarantees that these parameters are being effectively monitored and adjusted to optimize performance in judo and wrestling.



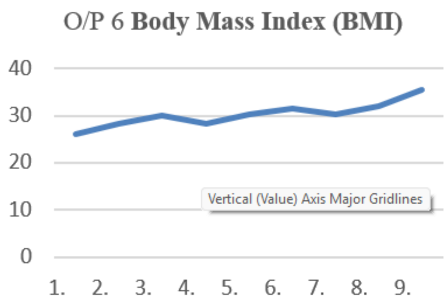
(a)

Fig. 7 *(a) O/P 1: Lean Body Mass (LBM)*



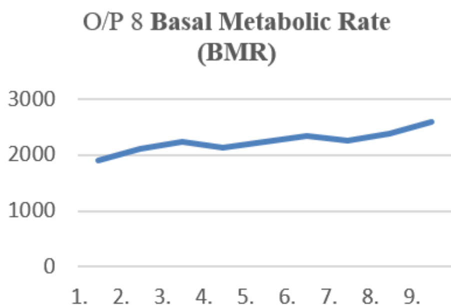
(b)

Fig. 7 *(b) O/P 5 Percentage Body Fat (PBF)*



(c)

Fig. 7 *(c) O/P 6: Body Mass Index (BMI);*



(d)

Fig. 7 *(d) O/P 5 Percentage Body Fat (PBF)*

CONCLUSION

In summary, LBM, PBF%, BMI, and BMR are vital metrics for monitoring and evaluating athletic development in judo and wrestling. These parameters offer significant insights into muscle mass, body composition, fat distribution, and energy expenditure, all of which are crucial for optimizing performance in these strength- and endurance-oriented sports.

FUTURE WORK

Subsequent research may investigate the incorporation of supplementary biomarkers or cutting-edge technologies, such as wearable sensors, to enhance performance metrics and tailor training protocols for combat athletes.

REFERENCES

1. Baker, D., et al. (2009). Physiological determinants of judo performance. *Journal of Strength and Conditioning Research, 23*(1), 60–65.
2. Bridge, C. A., & Jones, M. A. (2006). The effect of weight loss on judo-related performance. *Journal of Sports Science & Medicine, 5*(2), 125–131.
3. Brito, C. J., Marins, J. C. B., & Franchini, E. (2012). Physical performance and anthropometry of elite judo athletes. *Journal of Strength and Conditioning Research, 26*(6), 1664–1671.
4. Burke, L. M., Loucks, A. B., & Broad, N. (2006). Energy and carbohydrate for training and recovery. *Journal of Sports Sciences, 24*(7), 675–685. https://doi.org/10.1080/02640410500482602
5. Çağlar, E. Ç., Kutlu, M., & Taşkıran, C. (2024). Comparison of some physical characteristics of young judoka and wrestlers. *International Journal of Disability, Sports and Health Sciences, 7*(3), 615–620.
6. Campa, F., Toselli, S., Mazzilli, M., Gobbo, L. A., & Coratella, G. (2021). Assessment of body composition in athletes: A narrative review of available methods with special reference to quantitative and qualitative bioimpedance analysis. *Nutrients, 13*(5), 1620. https://doi.org/10.3390/nu13051620
7. Carvalho de Moura, R., de Moura Costa, C., Pinheiro Ferreira, C., et al. (2025). Body composition and physical performance of mountain bike athletes. *Scientific Reports, 15*, 3329. https://doi.org/10.1038/s41598-025-12345-6
8. Cataldi, D., Bennett, J. P., Wong, M. C., et al. (2024). Accuracy and precision of multiple body composition methods and associations with muscle strength in athletes of varying hydration: The Da Kine Study. *Clinical Nutrition, 43*(1), 284–294. https://doi.org/10.1016/j.clnu.2023.10.002
9. Durnin, J. V. G. A., & Womersley, J. (1974). Body fat assessed from total body density and its estimation from skinfold thickness. *British Journal of Nutrition, 32*(1), 77–97.
10. Franchini, E., Brito, C. J., & Artioli, G. G. (2012). Weight loss in combat sports: Physiological, psychological and performance effects. *Journal of the International Society of Sports Nutrition, 9*(1), 52.
11. Franchini, E., & Takito, M. Y. (2014). Physiological profiles of judo athletes. *Sports Medicine, 44*(3), 361–373.
12. Giovanelli, L., Biganzoli, G., Spataro, A., et al. (2024). Body composition assessment in Olympic athletes with different training loads. *Acta Diabetologica, 61*(3), 361–372.
13. Gobbo, L., et al. (2019). Use of wearable sensors for monitoring judo training loads. *Sensors, 19*(18), 3987.
14. Helms, E. R., Aragon, A. A., & Fitschen, P. J. (2014). Evidence-based recommendations for natural bodybuilding contest preparation: Nutrition and supplementation. *Journal of the International Society of Sports Nutrition, 11*, 20.
15. Khaithi, K., & Pungding, L. (2023). A comparative study of speed, agility and strength endurance between judo and wrestling players. *Journal of ReAttach Therapy and Developmental Diversities, 6*(1), 1987–1991.
16. Lafont, F., & Balmat, J. F. (2002). Optimized fuzzy control of a greenhouse. *Fuzzy Sets and Systems, 128*(1), 47–59.
17. Loturco, I., et al. (2017). Strength and power profiling of elite combat athletes. *Journal of Sports Sciences, 35*(12), 1180–1187.
18. Marques, V., Coswig, V., Viana, R., et al. (2019). Physical fitness and anthropometric measures of young Brazilian judo and wrestling athletes. *Sports, 7*(2), 38.

19. Maughan, R. J., et al. (2007). Nutrition and hydration for combat sport athletes. *Journal of Sports Sciences, 25*(1), S3–S10.
20. Moura, D. J., Naas, I. A., Queiroz, M. P. G., & Amendola, E. (2004). Estimating thermal comfort and solar orientation in broiler housing using fuzzy logic. *Proceedings of the 6th Latin American and Caribbean Congress of Agricultural Engineering.*
21. Nelson, K. M., Weinsier, R. L., Long, C. L., & Schutz, Y. (1992). Prediction of resting energy expenditure from fat-free mass and fat mass. *American Journal of Clinical Nutrition, 56*(5), 848–856.
22. Nevill, M. E., et al. (2014). Muscle mass and performance relationships in combat athletes. *European Journal of Applied Physiology, 114*(8), 1687–1695.
23. Niwas, R., Verma, M., Verma, A., et al. (2025). Neuromotor adaptations and coordinative ability differences in judo and wrestling athletes from Haryana, India. *Journal of International Education and Practice, 8*(2).
24. Ostojic, S. M., Mazic, S., & Dikic, N. (2006). Profiling in Olympic judo athletes: Physical and physiological characteristics. *Journal of Sports Medicine and Physical Fitness, 46*(3), 364–371.
25. Rani, R., Verma, M., & Verma, A. (2025). Application of fuzzy inference system for interpreting physical fitness metrics of trainee athletes. *Journal of Electronic Information Systems, 7*(2), 13–24.
26. Santos, D. A., et al. (2015). Body composition and physical fitness in combat athletes. *European Journal of Sport Science, 15*(3), 263–272.
27. Sayers, S. P., et al. (2011). Predicting performance using lean body mass and neuromuscular tests in combat athletes. *Journal of Strength and Conditioning Research, 25*(5), 1353–1360.
28. Sharma, A., & Verma, A. (2018). An automated soil pH and EC indicator cum controller system for nutrigation adjustment. *AIRO International Research Journal, 4*(3), 182–189.
29. Singh, N., Devi, A., Kumar, S., et al. (2015). Response surface methodology for standardisation of lignocellulosic biomass saccharification efficiency of NSF-2 fungus isolate. *Journal of Environmental Biology, 36*(4), 903–908.
30. Spady, D. W., Schiff, D., & Szymanski, W. A. (1987). A description of the changing body composition of the growing premature infant. *Journal of Pediatric Gastroenterology and Nutrition, 6*(5), 730–738.
31. Tan, B., et al. (2009). Muscle architecture and performance in elite wrestlers. *Journal of Sports Sciences, 27*(6), 563–573.
32. Verma, A., Dhingra, S., & Soni, M. K. (2009a). VLSI-cell placement technique for architecture of field programmable gate array design. *Turkish Journal of Electrical Engineering & Computer Sciences, 17*(3), 327–336.
33. Verma, A., Dhingra, S., & Soni, M. K. (2009b). Design and synthesis of FPGA for speed control of induction motor. *International Journal of Physical Sciences, 4*(11), 645–650.
34. Verma, A., Dhingra, S., & Soni, M. K. (2009c). PID behavior of FPGA fed IGBT based inverter for induction motor in industrial applications. *International Journal of Computer Science & Systems Engineering Information Technology, 2*(2).
35. Verma, A., & Tiwari, V. A. (2013). Optimum fuzzy-based approach to improve instrument performance affected by environmental conditions. *Serbian Journal of Electrical Engineering, 10*(2), 309–318.
36. Verma, A., Kaur, G., & Nagpal, M. (2019). A fuzzy-based artificial intelligence approach to detect caries from digital X-ray data extracted through edge detection technique in pixel values. *International Journal of Research and Analytical Reviews, 6*(2), 253–261.

37. Verma, A., & Tiwari, V. A. (2019). A fuzzy logic controller to minimize the effect of input temperature fluctuations on the deviation of relative humidity to avoid instrument deterioration. *International Journal of Research in Advent Technology, 7*(6), 73–77.
38. Wang, Z. M., Deurenberg, P., Guo, S. S., et al. (1998). Six-compartment body composition model: Inter-method comparisons of total body fat measurement. *International Journal of Obesity, 22*(4), 329–337.
39. Wang, Z., Deurenberg, P., Wang, W., et al. (1999). Hydration of fat-free body mass: Review and critique of a classic body-composition constant. *American Journal of Clinical Nutrition, 69*(5), 833–841.
40. Zupan, M., et al. (2019). The impact of anthropometric factors on judo performance. *Journal of Sports Sciences, 37*(14), 1653–1661.

Received on 11.03.2026.
Accepted on 02.06.2026.