Using a fuzzy approach to decision support in sports performance analysis

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Declaration:

I certify that I wrote the dissertation independently and that I included a list of all sources used in the bibliography.

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Contents

List of abbreviations

ANOVA	Analysis of variance
AI	Artificial intelligence
BSN	Badminton stroke networks
BWF	Badminton World Federation
CNN	Convolutional Neural Network
EAs	Evolutionary Algorithms
ESs	Evolution Strategies
Faster R-CNN	Faster Region Convolutional Neural Network
FIS	Fuzzy Inference System
FUT-SAT	System of tactical assessment in Soccer
GAs	Genetic Algorithms
GPS	Geographical Positioning System
HR	Human Resource
IMSs	Inertial Motion capture Systems
KP	Knowledge of Performance
KR	Knowledge of Results

LSTM	Long Short-Term Memory
MAFS	Mamdani–Assilan Fuzzy system
MANOVA	Multivariate Analysis of Variance
MD	Men's double
MF	Membership Function
MIMO	Multi-input-multi-output
MISO	Multi-input-single-output
MPW	Mutual Point-Winning probabilities
MS	Men's single
NOC	National Olympic Committee
OR	Odds Ratio
PART	Partial decision tree
PNN	Probabilistic Neural Network
RNN	Recurrent Neural Network
RMSE	Root Mean Square Error
RPE	Rated Perceived Exertion
RTK GNSS	Real-Time Kinematics Global Navigation Satellite System
RTLS	Real-Time Locating System
TSKFS	Tagaki–Sugeno–Kang Fuzzy system
uPATO	Ultimate Performance Analysis Tool
VTCS	Video Tracking Camera System
WD	Women's double
WS	Women's single
XD	Mixed double

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Abstract

This study discusses the design and implementation of decision-making performance analysis. First, it defines fuzzy inference systems, why advanced tools are required to analyse them in the given frameworks, and what technologies are suited for modelling them. The advantages of the proposed models and the circumstances under which they should be implemented are discussed, outlining the models based on these frameworks. Additionally, the potential for forecasting the performance of athletes using multi-sport modelling is discussed. The outputs from the mathematical models are based on athlete performance data from the 2012, 2016, and 2020 Summer Olympics.

This study aims to analyse and propose a method for the support of decision making as a part of the sports performance analysis. The mathematical methodology proposed uses the fuzzy approach based on the Mamdani–Assilan and Takagi–Sugeno–Kang fuzzy system theory. We created a fuzzy decision support system that can used in sports performance analysis. We similarly developed and optimised the fuzzy inference system for sport performance analysis in badminton using the Mamdani–Assilan and Takagi–Sugeno–Kang fuzzy approach.

Keywords:

performance analysis, annual planning, decision making in sport, Mamdani–Assilan fuzzy system, Takagi–Sugeno–Kang fuzzy system

1 Introduction

Until recently, the function of a performance analyst consisted mostly of filming a training session or game and creating video highlights to be distributed to management and players for in-depth evaluation. In most cases, video capturing and editing was time-consuming and labour-intensive. The role of performance analysts currently requires greater expertise in the use of tracking hardware and software that technological advancements have brought to the industry. This technology allows for more sophisticated data collection, storage, and coaching demands for data presentation. Because of the expanding phenomenon of 'big data', the vast amounts of data produced in the world of sport necessitate the hiring of analytical professionals to handle, disseminate, and generate insights.

Performance analysis has changed over the last decades as technology has become available to players in numerous sports. As a result, performance analysis has become an important part of the growth, coaching process, and competitive edge of athletes. While performance analysts might not use all available technologies to their full potential, they provide a consistent framework for assessing player interactions and skills. The goal of sports science analysis is to increase our understanding of game behaviour to improve future outcomes and performance. Coaching is less effective without performance analysis. Psychological fitness, psychological preparation, physical development, biomechanical competence, and tactical awareness are all thought to contribute to sports success.

Performance analysis is a specialised field that provides objective data to athletes and coaches to analyse their performance. This technique is supported by systematic observations, which provides reliable, trustworthy, and exact performance information. Performance analysis can enhance coaching by providing visual feedback (video analysis) and objective statistics (data analysis). Accurate data promotes more evidence-based decisions while minimising those based on guessing. Giving athletes evidence-based feedback enables them to understand precisely what they did to succeed or fail. Athletes and coaches may utilise this information to make the correct decisions at the right time and provide consistent outcomes. The following advantages are offered by performance analysis for athletes:

- Improved technical and tactical knowledge
- Improved decision making
- Improved confidence

Performance analysis provides the following advantages to coaches:

- Assists in understanding of the strengths and weaknesses of athletes
- Enhances their own development and coaching practice
- Enables in-depth performance review

1.1 Summary of the content of the dissertation

This dissertation presents the results of a fuzzy approach to decision support in sports performance analysis. The study aims at developing a decision support system model in MATLAB utilising the Mamdani-Assilan and Takagi-Sugeno-Kang in fuzzy inference system approaches for a specific sport - badminton. This thesis is divided into six major sections.

Chapter 3 provides an introduction to sports performance analysis, while sections 4.1 and 4.2 cover annual planning, in which performance analysis plays an important role. The introduction to racket sports is included in this chapter as this study makes use of data from badminton.

Chapter 4 presents a detailed overview of the technique used to create the annual plan (see part 4.3). In subsection 4.4, the fuzzy theory is described, covering fuzzy sets, operations, relations, and rules. The Mamdani-Assilan fuzzy system in part 4.5.1, Takagi-Sugeno-Kang fuzzy system in part 4.5.2, and Tsukamoto fuzzy system in subsection 4.5.3 are the three major fuzzy systems under evaluation. Section 4.5.4 discusses the various layouts of these fuzzy systems. The software used to generate the models is explained in section 4.6, including Fuzzy Logic *ToolboxTM*. The construction of fuzzy systems entails several processes detailed in section 4.7. The following section is dedicated to the membership function selection 4.7.1. The final section 4.7.3 is devoted to the data collecting procedure.

The systematic review includes a review of the literature on performance analysis, including which data are used during analysis (section 5.1), tools for data collection and automation analysis (section 5.2), methods of performance analysis (section 5.3), performance analysis software (section 5.4), and performance analysis used for sports prediction (section 5.5). Tables 5.1 and 5.2 depict a summary of the literature review. The final component of the literature review is dedicated to searching for keywords in primary sources.

Chapter 6 provides a thorough knowledge of how fuzzy theory may be used to aid decision-making in sports performance analysis by utilising the newly developed fuzzy inference system. First, the lists of decisions are defined in figure 6.1 as a component of the schematic layout for the plans for athletes. Those decisions are also depicted in Figure 6.2 with a temporal perspective. In the next section 6.1, how to create a FIS using source code samples is shown. Section 6.2 describes the results of selecting fuzzy inputs for both fuzzy inference systems. In each designated part, both fuzzy inference system solutions are described. Section 6.3 shows the Mamdani–Assilan fuzzy system, which includes the results of the membership function selection in section 6.3.1, fuzzy output in part 6.3.2, and the construction of IF-THEN rules in section 6.3.3. The output of the MATLAB ® platform is covered in sections 6.3.4 – 6.4. In section 6.5, the results of the Takagi–Sugeno–Kang fuzzy system are discussed. Section 6.6 presents important comparative findings.

Chapter 7 provides in-depth insights on how fuzzy theory aids decision making in sports performance analysis. This section also discusses, assesses, and underlines the significance and relevance of the findings. Future model adjustments, such as the integration of data from various sports or studies into competitive strength/weakness, are proposed. The problem of the misrepresentation of the analysis is evaluated. Finally, a discussion of a potential new sport that may soon be included in the Olympics is presented.

In chapter 8, a summary of the performance analysis background, the model building approach, systematic literature research, the results of the model, and the discussion is provided.

2

The work's objectives

This study aims to analyse and propose a method for supporting decision making as part of sports performance analysis. The objective is to create mathematical models using dynamic data of the performance of athletes in a particular sport.

In addition, the main objective is to develop a fuzzy decision support system to be used for sport performance analysis.

The following objectives are fulfilled in this dissertation:

1. The development of a fuzzy decision support system for sport performance analysis.
2. The development of the mathematical method using the fuzzy approach based on the Mamdani–Assilan fuzzy system theory.
3. The development of the mathematical method using the fuzzy approach based on the Takagi–Sugeno–Kang fuzzy system theory fuzzy system theory.
4. The development of a fuzzy inference system based on the Mamdani–Assilan fuzzy approach to be used for sport performance analysis in badminton.
5. The development of a fuzzy inference system based on the Takagi–Sugeno–Kang fuzzy approach to be used for sport performance analysis in badminton.
6. The optimisation of developed fuzzy inference systems for sport performance analysis in badminton.

3

Background

Traditionally, performance analysis can provide feedback to players and coaches to improve athletic performance. However, this is not always the case, as media coverage of sport frequently includes statistical information to educate the audience. In a world of uncertainty and change, it has never been more critical to stay ahead. Typically, when an athlete participates in a sport, the goal is to improve performance. Feedback is a crucial factor in learning a skill, where sensory information is obtained as a result of the performance. One type of feedback comes from the sensory channels of the athlete (i.e. sight, hearing, and touch), referred to as intrinsic or inherent feedback. While some information derived from intrinsic sources is self-evident (e.g. the ball missed the goal), more detailed information (e.g. coordination of joint activity, amount of force produced) frequently requires the assessment of the experience of the performer. The second source of feedback is typically provided by an external source, most often a coach, and is intended to supplement the intrinsic feedback. This information is referred to as extrinsic feedback, and it assists the athlete to compare their actions to their intended results. Extrinsic information is believed to accelerate the learning process for most complex skills and may be necessary to reach peak performance levels. Presumably, the experience and background of the coach enable them to provide helpful information about a particular movement, error detection, and correction mechanisms to aid in the development of that skill. Thus, extrinsic feedback can be viewed as a supplement to intrinsic feedback.

Knowledge of Results (KR) and Knowledge of Performance (KP) are the two basic types of extrinsic feedback that can be provided KP. When it comes to the outcome of an action, KR contains information about the outcome, whereas KP has information about the movement pattern that created the result. The vast bulk of feedback from the coach is KR, because KR is frequently intrinsically clear from the feedback provided to the athlete. The coach, on the other hand, still has various options when it comes to how and when the feedback is delivered. One factor to examine is the manner in which the information is presented. Although the vast majority of the feedback is given orally, coaches can also use demonstrations and modelling, video feedback, or even biofeedback, which involves information about bodily processes (i.e. heart rate, breathing, sweat rate, even brain activity). The coach must also consider the clarity of the feedback. Providing athletes with more specific feedback appears to be beneficial; however, the effectiveness may rely on the skill level of the athlete. As the skill level of an athlete grows, the precision of the feedback must proportionally increase as well as the amount of input, which is based on the skill level. Although receiving large quantities of input early in the learning process may be useful, receiving too much feedback too late may actually hinder performance. Because high frequency input may create a reliance on feedback, athletes may be unable to execute correctly when the extrinsic feedback is no longer available (i.e. during a competition). As a result, the error detection and repair mechanisms may develop more quickly if they receive less input that directs them to correction rather than just changing behaviours. The time of the presentation of feedback is another crucial element in the process of providing feedback to employees. In many cases, receiving input when performing a skill will impair performance since the attention will be split between the feedback source and skill being performed. Further, receiving feedback soon after a performance may not be the most beneficial, as athletes should be encouraged to evaluate his or her performance and then compare the intrinsic feedback received with the anticipated (or predicted) outcome. Providing feedback during this period of "self-reflection" may interfere with this process and, in certain situations, impede skill development, again by interfering with internal error detection and repair systems, as was the case with the previous example. As a result, the coach should consider several factors to guarantee that the feedback is delivered correctly and that the athlete gains the most benefit from it.

Performance analysis is an important part of the planning process to reach a specific goal. Planning is a critical aspect of an athlete's career. A well-planned season ensures the success and development of the players. On the other hand, an incorrectly peaked season can have a detrimental effect on previous results and preparations. The critical factor in planning is making the right decision and time it correctly, which is a complicated process. Decision-making in sport is a constantly evolving area, aided by technological advancements. Thus, the scientific component of these decisions becomes increasingly important, as it may be the only competitive advantage that an athlete has over the competition.

Athletes use annual planning to accomplish their objectives. Especially when society, and sport in particular, is goal-oriented. Nowadays, the ultimate focus of sports is to succeed, regardless of how this can be accomplished. Athletes are pushed to achieve their best results by their club, country, or sponsors, while the coach assist in executing training and achieving required goals by planning and adjusting the workouts. planning integrates the development of skills, bio-movement capabilities, and mental characteristics that can be tracked sequentially and logically.

3.1 Racket sports

Tennis, badminton, squash, and table tennis are the four major racket sports, amongst other racket sports played to a lesser extent. Racket sports can be played with a net separating the players or, as is the case with squash, with the players moving around a shared court area. The common feature of racket sports is that shots are exchanged between competitors, forming rallies. The major racket sports have singles and doubles competitions. Tennis was included in the 1896 Summer Olympic Games programme, followed by table tennis only in 1988 and badminton in 1992. Although squash was considered in the last three Summer Olympics, it was never included in the programme.

Qualifying for the Olympics is the pinnacle of the career of an athlete, which depends on the selected qualifying tournaments, critical for season planning and pacing peak performance to achieve the necessary results. The fuzzy model enables coaches to visualise rules for tournament planning based on designated pairs. Therefore, this study investigates performance analysis of sports and proposes a method for decision making.

The following research questions are discussed in this study:

1. How did the performance analysis methods change over time for the evaluation of racket sports?
2. Is the observation method the most frequently used in performance analysis?
3. Is there a correlation between the number of publications regarding performance analysis and the Summer Olympics?
4. Would a range of authors influence performance analysis research?
5. How can performance analysis be achieved using a Mamdani-Assilan or Takagi-Sugeno-Kang fuzzy approach?

6. What is the best optimisation strategy for performance analysis?
7. Are models transferable to open source software Octave Fuzzy Logic Toolkit?

4

Methodology

Creating a fitness regimen is systematic and scientific, enabling coaches to eliminate unpredictability and useless training. Appropriate planning considers the potential of an athlete, development of the player, and available facilities and equipment. To maximise performance, an annual training programme is required. This means that athletes may continuously train for a given period and significantly reduce their workload during the specific period. This work should be different from regular training to allow rest and regeneration of the physiological, psychological, and central nervous systems before the training period begins. Appropriate planning for an athlete is determined by the performance analysis (during competitions or tests), training factor progress, and competition schedule. This scheduling improves training organisation and enables the periodisation to be comprehensively conducted. Before athlete or coach planning cycles, a goal has to be established. Long term goals could be divided into multiple sub-goals (=short-term goals) for better measurements, determined by the vision or mission of the player. The goal has to be specific, measurable, and time-bound for players to evaluate them in every phase of the plan. Periodisation is the basis for planning. Scheduling improves training organisation and enables the periodisation to be conducted orderly and scientific. Before athletes or coaches plan cycles, they must establish a goal that can be set in both the long and short term. The vision or mission of the player determines the objective. The aim must be quantifiable and clearly defined, as this allows the plan to be evaluated by Bompa [7].

4.1 Periodisation in the annual planning

A key factor for annual planning is periodisation. This concept divides planning into two easy manageable segments called training phases as follows:

- preparatory;
- competitive.

The transition occurs between these two phases. In some publications, the transition phase between the preparatory and competitive phases is also included. The preparatory phase is divided into two components: general and specific preparation. The competitive phase is divided into two subcategories: pre-competitive and competitive. Two main phases are defined:

4.2 Cycle of the annual planning

Long term training cycle: A period of training, which ends with peak performance. The aim is usually to win or achieve a particular level of performance in that tournament. Long-term cycles can be from three months to four years in length depending on the level of the athlete.

Medium term training cycle: As was mentioned in the periodisation section, several phases exist. Each long-term cycle is split into medium cycle of transition, preparation, and competition.

Short term training cycle: The subsets of the medium-term cycles (between one and twelve weeks) are referred to as "short term cycles." The transition cycle is often short in duration and not usually broken down into short term blocks. The preparation cycle is usually split into short term cycles called “general preparation” and “specific preparation”. General preparation tends to put an emphasis on:

- Basic fitness (strength, flexibility, endurance, and speed)
- Technical development (in a tactical context)

Specific preparation involves a shift towards:

- Sports-specific fitness (e.g. elastic strength, speed-endurance, and agility)
- Tactics (employing new/refined technical skills)

Short-term cycles such as "competition development" and "priority competition" commonly divide the competition cycle into two parts. The following are the characteristics of activities that take place during the competitive cycle:

- Maintenance of fitness levels

- High intensity, short duration work
- Tactical emphasis

Short-term cycle consists of several weeks, where it may be necessary to split into more temporary blocks (e.g. 3 to 6 weeks). This can be useful to "refresh" the training, giving a different emphasis and potentially supporting greater training adaptation [192]. The example of an annual plan is shown in Figure 4.1.

Month	May				Jun				Jul					Aug				Sep				Oct					Nov			
Week Commencing	7	14	21	28	4	11	18	25	2	9	16	23	30	6	13	20	27	3	10	17	24	1	8	15	22	29	5	12	19	26
Week Number	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Competition (a,b,c)																														
Training Camps																														
Test/ Review																														
Cycles — Long Term	LT1																													
Cycles — Medium Term				Preparation 1																Competition 1										
Cycles — Short Term				General Preparation 1.1						General Preparation 1.2					Specific Preparation 1					Competition Development 1						Priority Competition 1				
Cycles — Weekly	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Training Volume	6	6	6	7	9	11	12	12	13	13	13	14	14	13	13	13	13	13	13	13	11	13	11	13	10	10	10	10	10	10
Training Intensity	3	3	3	4	4	4	4	4	4	5	5	5	5	5	6	6	6	6	6	7	9	7	9	7	8	8	8	8	8	8
Training Load	18	18	18	28	36	44	48	48	52	65	65	70	70	65	78	78	78	78	78	91	99	91	99	91	80	80	80	80	80	80

Figure 4.1: Example of the long cycle term [195]

Tournament planning has always been challenging. The best option appears to be to enter a large number of tournaments; however, this is not practical, as you must achieve excellent results at each tournament, which requires extensive training. It is a difficult question for coaches to plan a season in order to accumulate enough points and earn a good ranking, especially when the Badminton World Federation (BWF) ranking system only counts the last 52 weeks. The Olympics are planned on a four-year cycle, but the crucial period is the 52 qualifying weeks, which include a large number of tournaments. Thus, the question becomes which tournament to enter and the accomplishments needed to secure a spot at the Olympics.

4.3 Methodology of the plan set-up

Weekly cycles: Usually the plan is organised into weekly sections.

Competitions: This section allows targeted competitions to be identified at the start of the season. Usually the tournaments are divided into three main categories. "A" tournaments are targeted, where athletes aim to play at their optimal level as they could win their event. On "B" tournaments, the player would hope to compete well, but would not be expected to be contesting the later stages of that event. On "C" tournaments, athletes test their strategies while the result is not important at all.

Training camps: This section allows for strategically placing training camps, thus the player develop their ability in the different training environment.

Testing/review: This section helps identify the timing of the tests, formal review, and evaluation.

Activity volume: This refers to the total amount of time spent each week in training and competition. It relates to the total quantity of work performed in the training session/phase. In sports like running and cycling, the volume can be represented as time or duration, or distance covered, whereas in the weight room volume or “volume load" can be reps $\times$ sets $\times$ weight lifted for each resistance exercise. For sprints, throws and lower body jumps can represent the number of repetitions, which can be increased by increasing the volume (method above) during the session or increasing the density (frequency) of training, or both.

Activity intensity: Intensity is a measure of how hard the activity or training and competition is. Intensity relates to power output, opposing force, or velocity of progression. It requires an increase in neuromuscular activation and can be expressed as meters per second (speed), kg (force), or Watts (power). The complexity of the badminton training and competition makes this very difficult to measure in reality. Borg defines the Rated Perceived Exertion (RPE) scale as is shown in table 4.1, which helps coach and players evaluate each sessions and plan each session with respect to their planned goal [8]. Two RPE scales are commonly used:

- The original Borg scale or category scale (6 to 20 scale)
- The revised category-ratio scale (0 to 10 scale)

The original scale was developed in healthy individuals to correlate with exercise heart rates (e.g. RPE 15 would approximate a Human Resource (HR) of 150 bpm), and to enable subjects to better understand terminology [8]. The category ratio scale was later developed and has since been modified to more specifically record symptomatic breathlessness (Modified Borg Dyspnoea Scale) shown in table 4.1. RPE scales are particularly valuable when HR measures of exercise intensity are inaccurate or dampened such as in patients using beta blocker medication. This is due to the ability to capture the perceived exertion from central cardiovascular, respiratory, and central nervous system functions.

Activity load: In order to calculate the activity load, the effective volume of activity and the intensity of activity needs to be multiplied. As a rule, an adult international player should have a maximum training load of 300 hours per week, which is equal to 30 hours per week multiplied by 10 on the intensity scale. Naturally, the actual figure is substantially lower because the maximal intensity could not be maintained for the whole 30-hour period.

Activity intensity	**Description of the difficulty of the training units**
0	Nothing at all
0.5	Very, very light
1	Very light
2	Fairly light
3	Moderate
4	Somewhat hard
5	Medium
6	Hard
7	Very hard
8	Very hard
9	Very, very hard
10	Maximal

Table 4.1: Borg Rating of Perceived Exertion Scale [8]

4.4 Fuzzy theory

The fuzzy theory has been widely applied to modelling decision-making processes that rely on imprecise and ambiguous information such as the judgement for decision makers. Qualitative aspects are represented by linguistic variables, which are qualitatively expressed through linguistic terms and quantitatively expressed through a fuzzy set in the discourse universe and its associated membership function [200]. Thus, when developing an annual plan using a fuzzy approach, coaches must define critical planning criteria and evaluate them in terms of their importance to the players. Sub-criteria and sub-sub-criteria are defined in the second step. The coaches must then structure the hierarchical model and prioritise the criteria order. Fitness, fatigue, intensity, volume, specificity, variation, strength, endurance, periodisation, and programming are just a few of the critical factors that influence decision making. Lotfi Askar Zadeh, as the founder of fuzzy theory, he published in 1965 a paper called "Fuzzy Sets" in which he introduced fuzzy theory. Instead of utilising a probabilistic model for information processing, Zadeh proposed fuzzy logic. When Lotfi Askar Zadeh introduced fuzzy sets for the first time, and represented a natural framework for resolving problems where the cause of imprecision was the absence of finely defined class membership criteria rather than the presence of random variables [199]. Fuzzy sets are utilised when the boundaries to which a given object belongs cannot be precisely specified. The sorites paradox is an excellent illustration (the paradox of the heap), which begins with an inquiry into the number of grains of sand contained in a heap of sand. Is that a single grain? No. Are there two grains? No. Are there three grains? No... and so forth. Thus, how many grains are required to form a heap? How many grains cannot be expressed mathematically. Additionally, which of these numbers is near to 0 or how many people constitute a throng are instances. In contrast to traditional set theory, where elements are classified as belonging or not belonging to a set, fuzzy set theory quantifies items in sets using a membership function. The membership value is the result of the membership function [36].

4.4.1 Fuzzy sets, operations, relations, and rules

A fuzzy set is composed of elements with variable degrees of membership in the set. It is defined by the membership function, which assigns each element a degree between zero and one [199]. Element x is in the universe U and is a member of fuzzy set A, it is visualised as $A = (x, \mu_A(x))|x \in U$. The degree of membership is symbolised by $\mu_A(x)$. The fuzzy theory works with three basic set operations – union, intersection, and complement. The fuzzy property sets are the same as the crisp property sets, which are commutativity, associativity, distributivity, idempotency, identivity, transitivity, and involution. In addition, fuzzy relations map one universe. If R and S are fuzzy relations on the Cartesian space $X \times Y$, then following operations can be applied to membership values for the various set operations: union, intersection, complement, and containment. The fuzzy rule 'IF antecedent THEN consequent' is important for the description of a fuzzy system. Both the antecedent and the consequent are expressed by fuzzy sets. Hence, the IF-THEN rule shows a fuzzy implication, which expresses the relationship between statements. The consequence is the result of a fuzzy implication. A fuzzy statement consists of two parts. The first is the input for fuzzy variables, and the second is the output, which is the fuzzy set. Statements can contain logical operators such as AND and OR. Thus, the obtained statements are called complex statements. Four types of fuzzy rules have been defined by Dubois and Prade [36] as following:

Certainty rules (implication-based fuzzy rule)

The first class of fuzzy rules corresponds to declarative expressions of the form "the more x is A, the more certain y lies in B". Interpreting the rule as $\forall u$, if $x = u$, it is at least $\mu_A(u)$ -certain that y lies in B", the degree $(1 - \mu_A(u))$ assesses, the possibility that y is outside of B when $x = u$, since the more x is A, the less possible y lies outside B, and the more certain y lies in B. Constraints for the conditional possibility distribution modelling the rule

$$\forall u \in U, \forall v \in V, \pi_{y|x}(v, u) \leq \max\left(1 - \mu_A(u), \mu_B(v)\right). \tag{4.1}$$

Gradual rules (implication-based fuzzy rule)

Gradual rules correspond to statements of the form "the more x is A, the more y is B". Statements involving "the less" in place of "the more" are easily obtained by changing A or B into their complements $\bar{A}$ and $\bar{B}$ due to the equivalence between "the more x is A" and "the less x is $\bar{A}$" (with $\mu_{\bar{A}} = 1 - \mu_A$). More precisely, the intended meaning of a gradual rule can be understood in the following way: "the greater the degree of membership of the value of x to the fuzzy set A and the more the value of y is considered to be in relation (in the sense of the rule) with the value of x, the greater the degree of membership to B should be for this value of y", i.e.

$$\forall u \in U, \min\left(\mu_A(u), \pi_{y|x}(v,u)\right) \leq \mu_B(v) \tag{4.2}$$

Possibility rules (conjunction-based fuzzy rule)

The fuzzy rule is equivalent to statements of the form "the more x is A, the more possible B is a range for y". If we interpret this rule as "$\forall u$, if $x = u$, it is at least $\mu_A(u)$-possible that B is a range for y". The following constraint on the conditional possibility distribution $\pi_y|x(,u)$ representing the rule when $x = u$

$$\forall u \in U, \forall v \in V, \min\left(\mu_A(u), \mu_B(v)\right) \leq \pi_{y|x}(v,u). \tag{4.3}$$

Anti-gradual rules (conjunction-based fuzzy rule)

Rule expresses that "the more X is A, the larger the set of possible values for Y is, around the core of B". Considering the inequality constraint obtained from equation 4.1 by exchanging $(\mu_B(v))$ and $(\pi_{y|x}(v,u))$ i.e.

$$\forall u \in U, \forall v \in V, \max\left(\pi_y|x(v,u), 1 - \mu_A(u)\right) \geq \mu_B(v).$$

This list of rules has been extended by Pedrycz et al. [125] with the functional rule, where the function f can be linear or non-linear. The rule is expressed as

$$\text{IF } X \text{ is } A_i \text{ THEN } y = f(x, a_i), \text{ where } f : X \to Y \text{and } x \in R_n. \tag{4.4}$$

4.5 Fuzzy systems

The fuzzy inference system is a widely used computing framework based on the fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning concepts. It has found widespread success in a variety of fields, including automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition. Due to the multidisciplinary nature of fuzzy inference, it is also known as a fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associative memory, fuzzy logic controller, and simply (and ambiguously) fuzzy system. The significance of a fuzzy system is demonstrated in circumstances where natural language to a binary logic-based intelligent machine is addressed. When probabilistic theory is applied to evaluate language, natural fuzziness in the text is removed, as are vague statements. As a result, the natural uniqueness of a language (uncertainty) will be lost [150]. Fuzzy sets, rules, and methods are used to specify the fuzzy system. In fuzzy systems, some variables (at least one, potentially) acquire values that are difficult to characterise in terms of real numbers. Fuzzy systems are extremely beneficial in two situations: when dealing with highly complex systems whose behaviour is unknown, and when an approximate but quick solution is desired [150]. Considering the size of their potential applications, numerous different types of fuzzy systems have been proposed in the literature [31, 152, 153]. However, novel solutions characterised by reduced computational complexity, enhanced model quality, or increased ease of linguistic understanding of inference results remain a study issue. E.H. Mamdani and S. Assilan's model [96] is widely recognised as the first fuzzy system to be published. At the moment, it can be considered the foundation of the fuzzy model family, which is built on if-then rules with fuzzy sets in both the antecedents and consequents.

4.5.1 Mamdani–Assilan fuzzy system

Mamdani–Assilan Fuzzy system (MAFS) employs a set of canonical conditional fuzzy rules that can be determined by a human expert. Each rule in a MAFS produces a fuzzy set as an output. MAFS has a more intuitive and easy-to-understand rule bases, system is well-suited for expert system applications involving the creation of rules from human expert knowledge such a diagnostics. The fuzzy inference is the process of using fuzzy logic to formulate a mapping from a given input to an output. The mapping then serves as a foundation for decision-making and pattern recognition. The process of fuzzy inference involves membership functions, logical operations, and If-Then Rules. A MF is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept. The only true constraint on a membership function is that it must vary between 0 and 1. The function itself can be any curve whose shape can be defined as a function that is simple, convenient, fast, and efficient. MF is defined as $A = x, \mu_A(x)|x \in X$, where $\mu_A(x)$ is called the MF of $x \in A$. The MF maps each element of X to a membership value between 0 and 1. In a broader sense, logical operations are the fuzzy intersection or conjunction (AND), the fuzzy union or the fuzzy union or disjunction (OR), and fuzzy complement (NOT). These functions are classically represented by the operators (AND) = minimum, (OR) = maximum, and (NOT) = additive complement. Typically, most fuzzy logic applications simply make use of these operations.

However, these functions are surprisingly arbitrary in general.

AND

A	B	min(A,B)
0	0	0
0	1	0
1	0	0
1	1	1

OR

A	B	max(A,B)
0	0	0
0	1	1
1	0	1
1	1	1

NOT

A	1 - A
0	1
1	0

Figure 4.2: Logical operations in a true table [130]

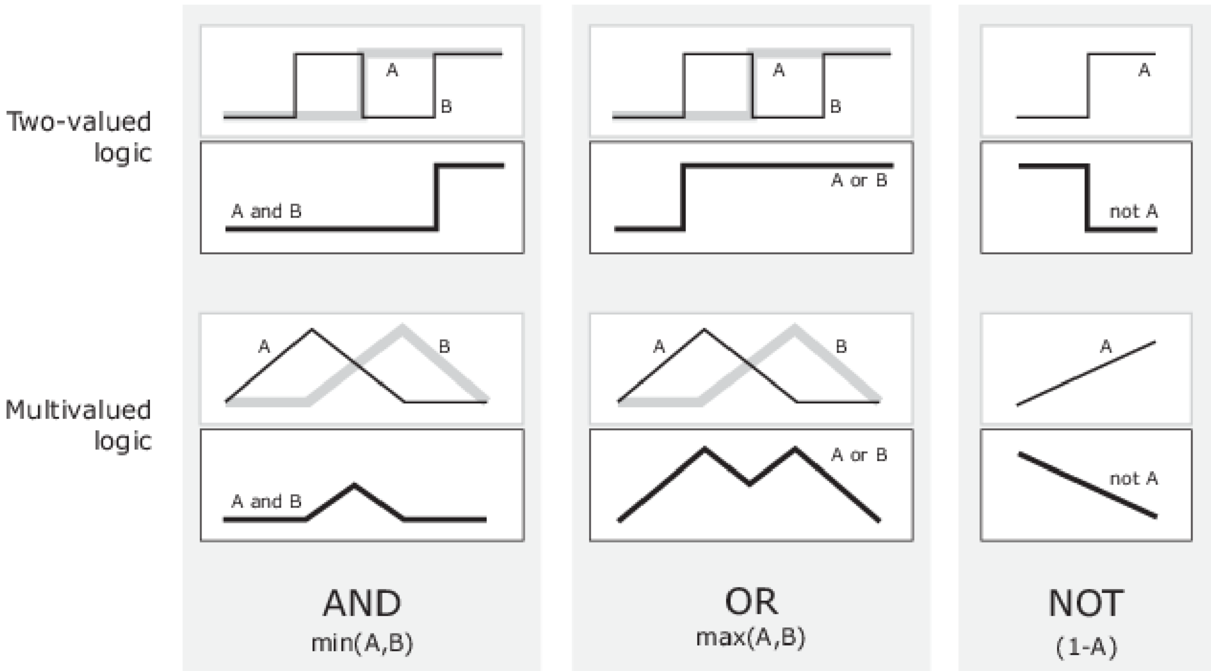


Figure 4.3: Logical operations converted to a plot [130]

Figure 4.3 display conversion of the truth table 4.2 to a plot of two fuzzy sets applied together to create one fuzzy set. The upper part of the figure displays plots corresponding to the preceding two-valued truth tables, while the lower part of the figure displays how the operations work over a continuously varying range of truth values for A and B according to the fuzzy operations you have defined. The subjects of fuzzy logic and verbs are fuzzy sets and operators. These if-then rule statements are used to construct the fuzzy logic conditional statements.

4.5.2 Takagi–Sugeno–Kang fuzzy system

The general class of Tagaki–Sugeno–Kang Fuzzy system (TSKFS) enabled the development of increasingly sophisticated complex rule-based systems, in which the rules are accompanied with conclusions derived by local regression models. While these models are appealing in terms of their basic topology (a modular fuzzy model composed of a series of rules), they still require formal solutions in terms of the structure optimisation of the model, such as a construction of the underlying fuzzy sets information granules, which are viewed as the fundamental building blocks of any fuzzy model. The creation of a fuzzy model can be viewed as a search problem in a multidimensional space, with each point representing a possible fuzzy model with a distinct rule structure, membership functions, and associated parameters. Due to their capacity to find irregular multidimensional solutions, Evolutionary Algorithms (EAs), such as Genetic Algorithms (GAs) and Evolution Strategies (ESs), have been extensively used in evolutionary fuzzy modelling [22, 146]. The TSKFS fundamental premise is that an arbitrarily complex system is composed of mutually connected subsystems. If K regions in the state space are defined to correspond distinct subsystems, the behaviour of the system in these regions can be characterised using simplified functional relationships. If the dependence is linear and each subsystem is allocated a single rule, the TSKFS is represented by the following K rules [196]:

$$\begin{aligned} R_i\text{: IF } X_1 \text{ is } A_{i_1} \text{ AND } X_2 \text{ is } A_{i_2} \text{ AND } \cdots \text{ AND } X_n \text{ is } A_{i_n}, \\ \text{THEN } y_i = a_{i_x} + b_i, \quad i = 1, 2, \cdots, K \end{aligned} \tag{4.5}$$

where R_i is the ith rule, and X_1, X_2,...,X_n are the input variables. $A_{i1}, A_{i2}, \cdots, A_{in}$ are the fuzzy sets assigned to corresponding input variables, variable y_i represents the value of the ith rule output, and a_i and b_i are parameters of the consequent function. The final output of the TSKFS $f(y)_k$ for an arbitrary x_k input sample is calculated using the following expression:

$$f(y)_k = \frac{\sum_{i=1}^{N}(\beta_i(x_k)y_i(x_k))}{\sum_{i=1}^{N}(\beta_i(x_k)S))} \quad , \qquad k = 1, 2, 3, \cdots, N \tag{4.6}$$

where $y_i(x_k)$ is output of ith rule for x_kth input sample, and β_i represents the firing strength of the ith rule.

The majority of approaches for training TSKFSs are global in nature, as the model parameters are calculated in one algorithmic step using all the samples. Assuming that the available samples cover the entire modelled problem, any of the techniques previously mentioned can produce a model with a high or acceptable level of accuracy. However, a global model developed in this manner cannot ensure a satisfactory representation of the actual system under other conditions. Regions may appear in the state space that are not adequately described by the created model. This condition may emerge as a result of a posteriori changes in the real system, as a result of the training set being incomplete or training set having an insufficient number of rules. As a result, it is desirable to update the model parameters using new samples received from the current operating system regime. In other words, this indicates that adjusting the parameters of the consequent component rules, which accounts for the firing strengths and the results of global learning, may have an effect on the final output quality of the model [79].

4.5.3 Tsukamoto fuzzy system

The result of a fuzzy if-then rule is represented in the Tsukamoto fuzzy inference system by a fuzzy set with a monotonic membership function. As a result, each output of a rule is defined as a crisp value. The aggregate output is calculated as the weighted average of each output. Consequently, the interference outputs of each rule are crisply presented in line with α-predicate (firestrength). The end result is obtained by a weighted average. Here, the consequent rules are fuzzy sets. The output of Tsukamoto fuzzy inference system is crisp even if the input is fuzzy [79]. However, the Tsukamoto fuzzy inference system is not frequently utilised in practise due to its lack of transparency compared to that of the MAFS and TSKFSs. Thus, only MAFS and TSKFS have been considered in this work.

4.5.4 Hierarchical fuzzy systems

The fuzzy trees are also known as hierarchical fuzzy systems because the fuzzy systems are arranged in hierarchical tree structures. The development of a fuzzy decision tree induction approach based on the elimination of classification ambiguity with fuzzy evidence. Fuzzy decision trees are more robust in tolerating imprecise, conflict, and missing information because they convey classification knowledge more naturally than the way humans think. Because the number of rules grows exponentially as the number of input variables grows, a rule explosion is a basic constraint of fuzzy systems. The number of rules in the normal fuzzy system is m^n if we have n inputs and m fuzzy sets established for each of them. A rule base with many input variables and a large number of rules tends to lose all of its positive characteristics such as transparency, generalizability, and accuracy. The technique to reduce the complexity of a fuzzy system and increase understanding into its behaviour is to organise fuzzy rule bases in a hierarchical manner. Design, transparency, and tuning, among other things, become easier for a system made out of smaller fuzzy systems.

A single monolithic $(n = 1)$ FIS with four inputs with three MFs $(m = 3)$ was created and then the system will have be 4.4. In the FIS of this figure, the total number of rules is

$nm^4 = 1 \times 3^4 = 81$. Thus, the total number of rules in an incremental fuzzy tree is linear with the number of input pairs. Implementation of a FIS as a tree of smaller interconnected FIS objects rather than as a single monolithic FIS object if preferred. In a tree structure, the outputs of the low-level fuzzy systems are used as inputs to the high-level fuzzy systems. There are two main fuzzy tree structures - aggregated (see figure 4.5) or cascaded (=combined) (see figure 4.6). At the lowest level of an aggregated structure, input values are included as groups, and each input group is fed into a FIS. The higher-level fuzzy systems mix (aggregate) the outputs of the lower level fuzzy systems.

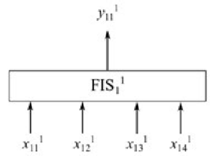


Figure 4.4: Example of the monolithic structure [173]

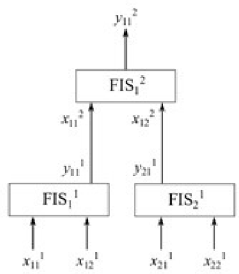


Figure 4.5: Example of aggregated fuzzy tree structure [173]

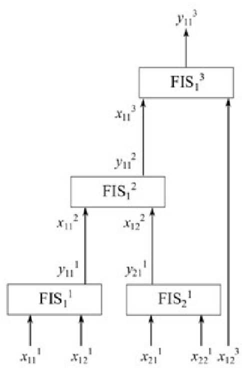


Figure 4.6: Example of cascaded (=combined) fuzzy tree structure [173]

The variation of the aggregated structure known as parallel structure 4.7 is implemented in the proposed FIS, the outputs of the lowest-level fuzzy systems are directly summed to generate the final output value. The following figure shows an example of a parallel fuzzy tree, where outputs of fis1 and fis2 are compared to the maximum final output.

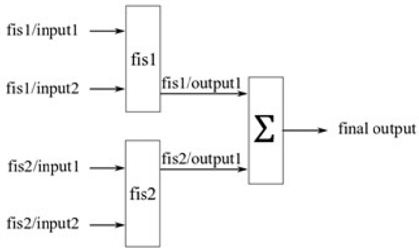


Figure 4.7: Example of the parallel fuzzy tree structure [173]

4.6 MATLAB platform

MATLAB® is a programming platform designed specifically to analyse and design systems. The Fuzzy Logic *Toolbox*^{TM} includes MATLAB® functions, applications, and a Simulink® block for analysing, designing, and simulating fuzzy logic-based systems. Numerous commonly used methods are supported, including fuzzy clustering and adaptive neuro-fuzzy learning. The Fuzzy Logic *Toolbox*^{TM} enables modelling complex system behaviours using straightforward logic rules and implementing them in a fuzzy inference system. It can be used independently as a fuzzy inference engine. Alternatively, you can use Simulink® fuzzy inference blocks to simulate the fuzzy systems as part of a broader model of the entire dynamic system. The Fuzzy Logic *Toolbox*^{TM} software supports two types of fuzzy inference systems: MAFS and TSKFS.

4.7 Development of the rule-based systems

In fuzzy modelling, there are two important milestones:

1. Determination of the overall structure. The information from experts is combined with personal expertise (general knowledge or previous experience as a professional athlete) at this point. After identifying suitable input and output variables, the following stages must be completed:

    - selecting the type of fuzzy inference system;
    - specifying the number of linguistic terms for input and output fuzzy variables;
    - constructing the set of if-then rules.

2. Definition of the architecture in greater detail. An in-depth description of linguistic words is provided, which includes:

    - selecting the family of membership functions;

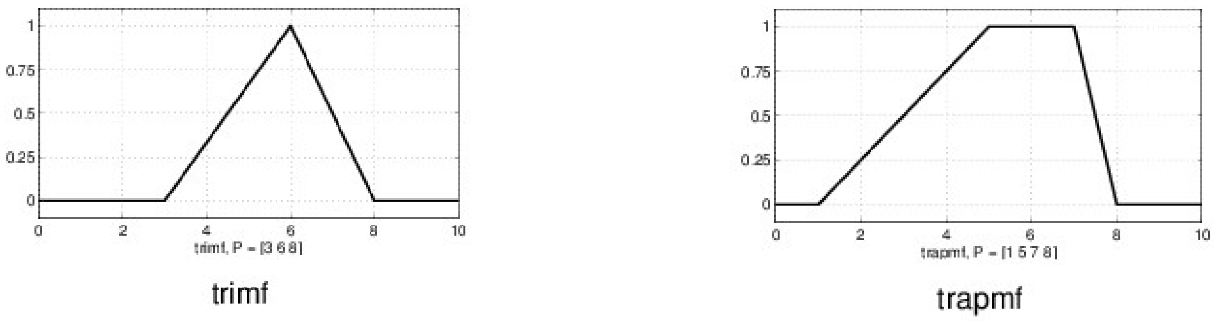
- selecting the parameter values for each of the membership functions;
- modifying the parameter values for each of the membership functions.

4.7.1 Membership Functions in Fuzzy Logic *Toolbox*^{TM} Software

The *Toolbox*^{TM} includes 11 built-in membership function types. These 11 functions are, in turn, built from the following basic functions:

- Piece-wise linear functions
- Gaussian distribution function
- Sigmoid curve
- Quadratic and cubic polynomial curves

Straight lines are used to create the simplest membership functions. The simplest of these is the triangular membership function, which is denoted by the function name `trimf` shown in Figure 4.8a. This function is simply a collection of three triangle-shaped points. The trapezoidal membership function, `trapmf` shown in Figure 4.8b, is a truncated triangle curve with a flat top. Straight line membership functions have the advantage of being straightforward.

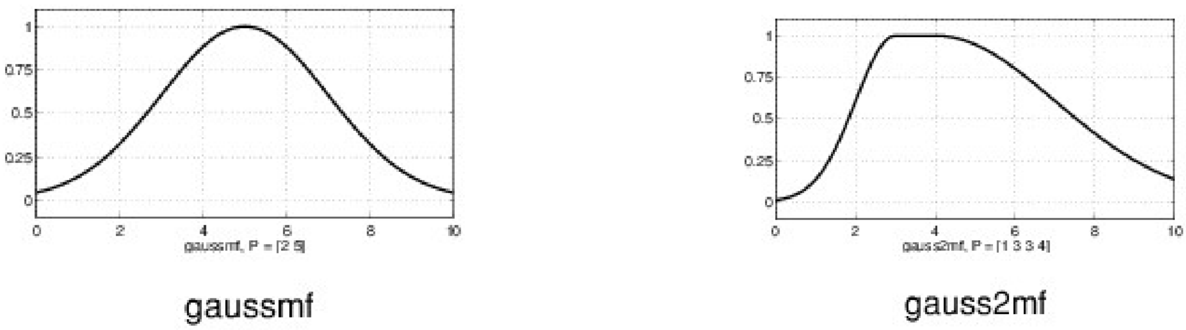


(a) Triangular membership function (b) Trapezoidal membership function

Figure 4.8: Membership function types [174]

On the basis of the Gaussian distribution curve, two membership functions are constructed: a simple Gaussian curve and a two-sided composite of two different Gaussian curves. `Gaussmf` shown in Figure 4.9a and `gauss2mf` shown in Figure 4.9b show the two functions.

Three parameters define the generalised bell membership function, which is denoted by the function name `gbellmf` shown in figure 4.10. Due to the fact that the bell membership function has one additional parameter compared to the Gaussian membership function, it can approximate a non-fuzzy set if the free parameter is tuned. Gaussian and bell membership functions are



(a) Gaussian membership function (b) Gaussian 2 membership function

Figure 4.9: Membership function types 2 [174]

popular methods for specifying fuzzy sets due to their smoothness and concise notation. Both of these curves have the advantage of being continuously smooth and nonzero.

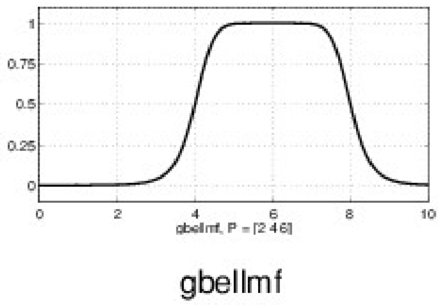
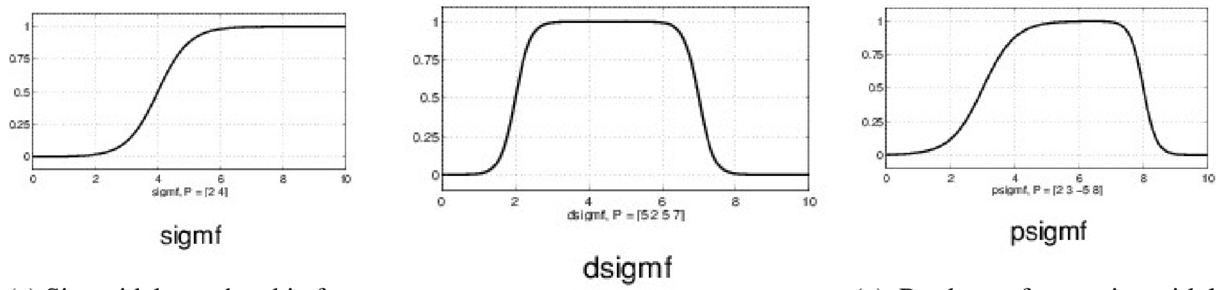


Figure 4.10: Generalised bell membership function [174]

While Gaussian and bell membership functions are both smooth, they are unable to specify asymmetric membership functions, which are necessary for certain applications. Following that, a sigmoidal membership function is defined, which can be left or right open. Asymmetric and closed (i.e. not open to the left or right) membership functions can be synthesised using two sigmoidal functions; thus, in addition to the fundamental `sigmf` shown in Figure 4.11a, the difference between two sigmoidal functions, `dsigmf` is shown in Figure 4.11b, and the product of two sigmoidal functions, `psigmf` is shown in Figure 4.11c.

Numerous membership functions in the $Toolbox^{TM}$ are based on polynomial curves. The Z, S, and Pi curves are three related membership functions named after their shape. The asymmetrical polynomial curve `zmf` shown in figure 4.12a is open to the left, the mirror-image membership function `smf` shown in figure 4.12b is open to the right, and `pimf` shown in figure 4.12c is zero at both extremes with a rise in the middle.

When it comes to selecting a membership function, there is an abundance of options. Additionally, unique membership functions can be created in the Fuzzy Logic *Toolbox*^{TM}. While

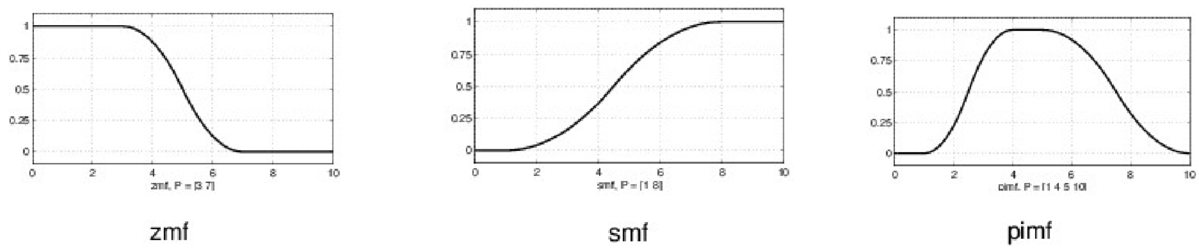


(a) Sigmoidal membership function

(b) Two sigmoidal functions

(c) Product of two sigmoidal functions

Figure 4.11: Membership function types 3 [174]



(a) Asymmetrical polynomial curve membership function

(b) Mirror-image membership function

(c) Membership function with a rise in the middle

Figure 4.12: Membership function types 4 [174]

there is a large selection for those interested in exploring the possibilities, expansive membership functions are not required for effective fuzzy inference systems.

Fuzzy Logic *Toolbox*^{TM} app allows the following processes:

- Design MAFS and TSKFS;
- Add or remove input and output variables;
- Specify input and output membership functions;
- Define fuzzy IF-THEN rules;
- Select fuzzy inference functions for AND operations, OR operations, Implication, Aggregation, and Defuzzification;
- Adjust input values and view associated fuzzy inference diagrams;
- View output surface maps for fuzzy inference systems;
- Export fuzzy inference systems to the MATLAB ® work-space.

4.7.2 Optimisation in MATLAB®

Optimisation is an important part of model development. MATLAB® work-space optimisation algorithm generates candidate FIS parameter sets during training. The fuzzy system is updated with each parameter set and evaluated using input training data. If input/output training data is available, the cost for each solution is computed based on the difference between the output of the fuzzy system and expected output values from the training data. There are two options to optimised the model as follows:

- Learn the rule base while keeping the input and output MF parameters constant.
- Tune the parameters of the input/output MFs and rules.

Because of the limited number of rule parameters, the first step is less computationally costly, and it quickly converges to a fuzzy rule base during training. The use of the rule base from the first step as a starting condition in the second step results in a rapid convergence of the parameter tuning process in the third phase. Defining tuning options with the `tunefisOptions` command is the first step. Because the FIS supports a high number of output MFs (which are utilised in rule consequents), a global optimisation approach should be implemented (genetic algorithm or particle swarm). Genetic algorithm and particle swarm perform better for large parameter tuning ranges since they are global optimisers. On the other hand, pattern search and simulation annealing perform better for small parameter ranges since they are local optimisers. If a FIS is generated from training data with the `genfis` command or a rule base is already added to a FIS using training data, then pattern search and simulation annealing may produce faster convergence as compared to genetic algorithm and particle swarm.

The genetic algorithm is a method for solving both constrained and unconstrained optimisation problems that are based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation [101]. Over successive generations, the population "evolves" towards an optimal solution. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population as follows:

- Selection rules select the individuals, called parents, that contribute to the population at the next generation

- Crossover rules combine two parents to form children for the next generation

- Mutation rules apply random changes to individual parents to form children

The simulated annealing is a method for solving unconstrained and bound-constrained optimisation problems. The method models the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimising the system energy. At each iteration of the simulated annealing algorithm, a new point is randomly generated. The distance of the new point from the current point, or the extent of the search, is based on a probability distribution with a scale proportional to the temperature. The algorithm accepts new points that lower the objective, but also, with a certain probability, to those that raise the objective. By accepting points that raise the objective, the algorithm avoids being trapped in local minima, and is able to explore for more possible solutions globally. An annealing schedule is selected to systematically decrease the temperature as the algorithm proceeds. As the temperature decreases, the algorithm reduces the extent of search to converge to a minimum [60].

The particle swarm algorithm begins by creating the initial particles, and assigning them initial velocities. It evaluates the objective function at each particle location, and determines the best (lowest) function value and location. It chooses new velocities, and based on the current velocity, the individual and neighbour best locations are selected. It then updates the particle locations iteractively (the new location is the old one plus the velocity, modified to keep particles within bounds), velocities, and neighbours. The command `particleswarm` is based on the algorithm described in [128], using modifications suggested in [109] and [124].

The pattern search method is divided into two parts: the first is the constraint criteria, and the second is the formation of an equidistant particle mesh between the constraints previously supplied. The evaluation of the particles in the function provides instructions for determining the directions in which the particles should begin searching for the full work area by providing previously specified leaps. The advantage of pattern search method is the global convergence as its main characteristic to not generate stagnation in local minimum presents an exhaustive search throughout the search range [87].

4.7.3 Data collection

The systematic review of the data collection identified in the literature is described in section 5.2, including the overview of already used methods in table 5.1. Previous studies have outlined three possible techniques that can be implemented for data collection. Table 5.1 provides a list of possible approaches, which are organised according to the sport. GPS tracking systems are the most extensively utilised data collection technology in sports.

Multiple sources of dynamic sports performance data for a given player have been included in this work. One dataset have been collected from expert interviews, with the input of open questions. Those experts have been selected based on the following criteria:

- Expert holds the highest coaching level of the country or at least a second highest coaching level issued by the Badminton World Federation.
- Expert has at least 5 years of experience in coaching juniors and adults
- Expert coaches (or have been coaching) player who won a medal at the international badminton tournament or won a gold medal at the national championship.

The reasoning behind those specifications are that experts have suitable experience to plan and evaluate the path of athletes to reach a specific goal. An specific goal based on experience includes a gold medal at the national championship. Ten experts have been interviewed from different countries (Czech Republic, Spain, Denmark, Finland, Poland). Data have been collected during training for coaches held in Oviedo, Spain from 16–22 October 2016. The result of this interview later informed the structure of the proposed system.

The second larger dataset was acquired from BWF website. BWF, which allows to see the evolution of the ranking for each week. This is helpful to track the ranking movement for the Olympic qualification as there is given criteria before the qualification starts. For further references, the Badminton World Federation Ranking can be evaluated.

5 Systematic review

The objectives of performance analysis can be captured in a variety of ways and for different sports. For example, we can mention the following. Identification of potential by: Arede et al. [2], Lago-Fuentes et al. [75], Waldron and Worsfold [182], Woods et al. [188, 189, 190]. Specific performance of young players has been evaluated by Brito et al. [9, 10], Gimenez-Egido et al. [49], Karakulak [66], Saphie et al. [161]. Analysis of technical skills (i.e. movement patterns) by: Challis et al. [19], Hökelmann and Richter [57], Mangan et al. [97], Nassis [115], Saavedra et al. [154], Santos et al. [160]. Performance analysis of players during the game (match analysis that includes stroke position, ball movement, match sequence, and substitutions) is covered in detail by: Belli et al. [6], Caballero et al. [13], Gal et al. [44], Michael et al. [110], Pereira et al. [126], Slawson et al. [166]. Some studies Tromp and Holmes [177], Monteiro et al. [111], Franchini et al. [42], Gimenez-Egido et al. [49], García-de Alcaraz et al. [47] and Ortega-Toro et al. [120] provided a solution for estimating the impact on performance after rule changes by using process model analysis an presenting a solution as an example. The approaches to team analysis are discussed in detail by.Young et al. [198], Ortega et al. [119], Travassos et al. [175], Korte and Lames [71], Clemente et al. [23] while Laporta et al. [77] discussed a social network analysis. Paulo et al. [122], Kusmakar et al. [74], Woods et al. [191], Araújo and Davids [1] and Vilar et al. [181] offered an ecological dynamics approach for team analysis.

5.1 Performance data

When it comes to performance evaluation, data collection and analysis are critical components of the process. It has an impact on the number of sources and databases available, depending on how popular sports are amongst people. The following sources of information were included in the selection:

- Amongst the authors who use match records and tournament statistics are the following: García-de Alcaraz and Usero [48], Laporta et al. [78], Marcelino et al. [98] and Drikos et al. [35];
- The following authors conducted an investigation into the official ranking analysis: Lemmer [82], Longo et al. [92], Mertz et al. [107], Russomanno et al. [151] and Hansen et al. [55].
- The following authors presented their findings on video/image observation: Raiola et al. [137], Tian [172] and Callaway [14];
- The data collected from wearable devices are used in the analysis described by Büthe et al. [12], Caporaso et al. [15], Goud et al. [52], Jahren et al. [62], Mahmoud et al. [95], Stetter et al. [168] and Yahya et al. [195].

5.2 Tools used for data collection/ automation analysis

The method used to collect data varies from sport to sport. Because of the public and scientific interest, studies on football use the most advanced tools and data collection techniques. Funding is also an important consideration for the development of tools.

Three viable approaches have been identified. Video/image tracking/recording, Geographical Positioning System (GPS) tracking, or wearable device tracking are all used to collect data. To accomplish this, only a few systems combine video tracking with wearable sensors. Table 5.1 contains a list of possible approaches organised by sport. GPS are the most widely used data collection techniques in sports.

The Video Tracking Camera System (VTCS) is a technology that captures two-dimensional position data (x and y) at high sampling rates (over $25Hz$). VTCS can collect technical and tactical parameters as well as external load variables. Reily et al. [144] demonstrated a system that uses a single Microsoft Kinect 2 camera to automatically evaluate the performance of a gymnast on the pommel horse apparatus, specifically the consistency of the timing and body angle. The depth of each pixel determined by the camera provides information not available to traditional sports analysis approaches based solely on RGB data. Amisco Pro, as described by Di Salvo et al. [32], is a multi-camera match performance analysis system. During the game, the movements of all 20 players (excluding the goalkeepers) are recorded. Amisco Pro tracks the distance travelled by the players, time spent in five different intensity categories, and time

Tools	**Sports**	**No. of articles**
Amisco Pro	football, running	2
Babolat Play	tennis	1
Digital Stadium®	football	1
Garmin™ Heart Rate Band	basketball	1
GPS	cycling, horse racing, sailing, running, surfing, tennis, basketball, football (13), handball (3), hockey, netball, rugby (6), volleyball	32
IMSs	cycling	1
Microsoft Kinect 2	gymnastics	1
Pliance™ electronic saddle mat, Casio high speed camera with Quintic™ biomechanical software	horse racing	1
Remote, RowX	rowing	1
RGB camera	skeleton, table tennis	2
RTLS	skiing	1
SAGIT	table tennis	1
Sony Smart Tennis	tennis	1
VERT™	volleyball	1
Vicon Motion Systems	football	1
Wimu™	basketball	1

Table 5.1: Data collection tools (author's work)

spent in various positions. Digital Stadium® is a performance analysis device defined by Beato et al. [5] as a video tracking multiple system with a semi-automatic performance analyst process. Ramón-Llin et al. [138] captured the data with two video cameras and analysed it with the SAGIT tracking system. The SAGIT algorithm is based on a movement/position analysis. The system recognised the posture from an RGB image, performed an overall evaluation, and returned the information in real time. Tamaki and Saito [171] proposed a system for reconstructing the 3D trajectories of table tennis balls using RGB camera data. The introduced method could be used for a match analysis because it can provide accurate information for service analysis.

Wearable devices provide an excellent opportunity not only to measure the motion and position of the player, but also to track the physical state in real time. Garmin™ Heart Rate Band and Wimu™ inertial devices have been used for data collection and real-time monitoring of physical activity and movement during training. Heart rate, player load, step count, and jumps are all outputs from these devices. Wimu™ was used by Poureghbali et al. [130] to collect external load and positional data for basketball performance analysis. The kinematic coupling algorithm of Inertial Motion capture Systems (IMSs) used by Cockcroft and Scheffer [24] can measure human kinematics both outdoors and in the laboratory. However, magnetic interference was a concern for the system. Swarén et al. [169] used a Real-Time Locating System (RTLS) to track cross-country skiers during a competition. Three RTLS tags were attached to the antenna of a Real-Time Kinematics Global Navigation Satellite System (RTK GNSS) carried by a skier who completed the course three times at three different intensities. Mahmoud et al. [95] used the VERT™ (Mayfonk Athletic Company) wearable sensing device to measure height jump in volleyball. Real-time data (i.e. last jump, best jump, jump average, and jump amounts) from these devices can be transmitted using bluetooth to a smartphone or tablet. Both the Babolat Play and Sony Smart Tennis Sensor evaluated by Büthe et al. [12] are used as wearable devices to track various types of tennis shots and provide a performance analysis to the player. The study by Llosa et al. [89] offered two different wearable devices for rowing (Remote and RowX). Both devices used sensors from the boat and a person on it. These sensors allowed the evaluation of the movement of the boat, individual rower performance, or performance in comparison to other crew members.

Hampson and Randle [54] used a combined approach to record trials and showed the influence of the rider on the horse by using a wearable device (Pliance™ electronic saddle mat) and Casio high speed camera with Quintic™ biomechanical software.

5.3 Methods of performance analysis

There are many different performance analysis methods that can be used depending on the variable being measured, data analysed, and sport investigated. The following techniques have been identified:

- Statistics methods including Analysis of variance (ANOVA), one-way ANOVA, two-way Multivariate Analysis of Variance (MANOVA), linear model, cluster analysis, k-means clustering, logistic regression, Chi-square analyses, Mann-Whitney U-test, discriminant analysis, Matched Paired t-test, mixed linear method and Markov chain: Castellano et al. [18], Conte et al. [25], Croft et al. [29], Douglas et al. [34], Escobar-Molina et al. [37], Francis et al. [43], García-de Alcaraz and Marcelino [46], Gómez et al. [50], Ibañez et al. [59], Iván Fernández-García et al. [61], Konings and Hettinga [70], Leicht et al. [81], Liu et al. [88], Pawista and Saphie [123], Saavedra et al. [154], Sarajärvi et al. [162], Torres-Luque et al. [173], Vencúrik et al. [180], Waldron and Worsfold [182], Wedding et al.

[184];

- Machine learning: García-Aliaga et al. [45], Khan et al. [67], Kusmakar et al. [74], Lai et al. [76], Metulini [108], Rangel et al. [142], Wang and Hsieh [183], Wenninger et al. [186];
- Neural networks, including Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM): Brock et al. [11], Fok et al. [40], Rahmad and As'ari [133], Rahmad et al. [134, 135], Xu and Yan [194];
- Decision tree, including Partial decision tree (PART) and random forest: James et al. [63], McIntosh et al. [102, 103, 103], Woods et al. [190];
- Social network analysis: Korte and Lames [71], McLean et al. [104], Ortega et al. [119], Ramos et al. [141], Travassos et al. [175];
- Notational analysis: Folgado et al. [41], Lupo et al. [93], Raiola et al. [136], Sampaio et al. [156], Saphie et al. [161], Van Maarseveen et al. [179], Winter and Pfeiffer [187]; and
- Self-organising maps: Chassy et al. [20], Croft et al. [28, 29];

5.4 Software used to analyse performance

As their primary data input, the following software video/image data collection, wearable devices, or GPS have been used. FRAMI®, a computer software for judo matches, was introduced by Sherwood et al. [163]. The system is used to analyse both technical and tactical behaviours of a recorded match. System of tactical assessment in Soccer (FUT-SAT) is a tactical assessment system designed specifically for football/soccer used by Moreira et al. [112] and Machado et al. [94]. The system investigates the movement progression of a player in the game across all age groups and levels. FUT-SAT analyses the actions of a player during the game, with ball possessions serving as the primary unit of analysis, followed by tactical action assessments. Bagadus is a real-time prototype of a sports analytic system described in Stensland et al. [167]. Using a video camera array, the system integrates a sensor system, soccer analytic annotations system, and video processing system. Legg et al. [80] presented visualisation software, Match-Pad that assisted coaches in examining actions and events in detail while maintaining a clear overview of the match, and to take decisions during the matches. It also enabled coaches to communicate critical information to players in a visually engaging manner, thereby improving their performance. Zhang et al. [201] outlined a computer vision technology to establish a sport detection and analysis system using an RGB camera and deep learning models. SportVU is an optical tracking technology used in basketball by Wu and Bornn [193]. The system enabled performance statistics by extracting coordinates of players and the ball using statistical algorithms to provide greater match insights and data for recent Artificial intelligence (AI) analysis software. Silva et al. [164] presented Ultimate Performance Analysis Tool (uPATO) allowing observation, codification, importation, visualisation, computational measures, and exportation of data from observed games. The tool enabled the introduction of data based on adjacency matrices and integration of various metrics used for team sports analysis. The ability to analyse GPS data is a significant advantage of this tool.

5.5 Performance prediction

Performance prediction is an extensively discussed topic in a number of articles and books. In this study, the authors describe the various approaches used, starting with standard statistical methods and progressing to sport-specific software. The following questions are addressed:

- Which performance indicator best predicts success?
- Can game statistics be used to forecast success?
- How can a successful player be identified?
- How much of an impact does travel/match location have on player/team performance?

Wei et al. [185] used Hawk-Eye ball and player tracking data to identify unique styles and predict within-point events. The study used spatial and temporal information to better characterise tactics and tendencies of each player, in addition to coarse match statistics (i.e. serves, winners, number of shots, and volleys). To model player behaviour, a probabilistic graphical model was used. Because player behaviour is affected by the opponent, model adaptation was used to improve our prediction. As a new measure for table tennis players, Ley et al. [83] proposed the Mutual Point-Winning probabilities (MPW) as server and receiver. The MPW quantify the chances of a player of winning a point against a given opponent and thus complement the traditional match statistics history between two players. These new quantities are based on a Bradley-Terry statistical model, which considers the significance of individual points. A random forest algorithm with parameters such as acceleration, rally duration, and time between rallies was used in a study by Dieu et al. [33] for prediction of conative stages with a prediction accuracy possibility for badminton. To demonstrate the potential impact of home vs away matches, Lo et al. [90] used general and generalised mixed linear models for rugby points difference and match won or lost prediction. Linthorne et al. [86] proposed a prediction method that combines the equation for the range of a projectile in free flight with the measured relationships between take-off speed, take-off height, and take-off angle of the athlete. The results of this method agreed well with competition take-off angle of the athlete.

5.5.1 Prediction of an athlete's career path

Kłys et al. [69] took an interesting approach to optimising sport skill level predictors for female judo athletes using Probabilistic Neural Network (PNN). In a research conducted by Lai et al. [76], network analysis and machine learning are used to estimate the contribution of the network of matches in predicting the success of an athlete. Li et al. [84] also discussed career path prediction. The introduced prediction method is based on thirty years of longitudinal data that included 82 top ten professional players between 2007 and 2017. The practical implications of the above-mentioned studies, specifically informing career planning, predicting professional success, monitoring, and assessing emerging tennis players, are discussed.

5.6 Classification by racket sport and methodology

The distribution of publications for each racket sport is listed in table 5.2 with tennis as the most widely represented racket sport.

We could divide the selected works into four broad categories:

- publications that use observation as the primary tool;
- publications that use a standard statistical approach;
- publications that use a combination of observation and statistics;
- non-statistic methods, primarily neural networks.

Observation: Despite technological advancements, the observation methodology remains an important tool for quick and cost-effective performance analysis across racket sports. Torres-Luque et al. [174] provided an example of technical and tactical analysis for badminton. The primary goal was to create, validate, and estimate the dependability of an observational instrument for analysing tactical and technical actions during single badminton. Aiken's V coefficient was used to calculate the validity.

Sports	Performance analysis method	Publications
badminton	combine approach (obser.+stat.)	[33]
	n/a	[127]
	neural network	[51, 133–135, 148]
	observation	[21, 121, 174, 178]
	statistical approach	[4, 132, 173, 197]
padel tennis	neural network	[65]
	observation	[27, 116, 140, 157, 158]
	observation (tracking software)	[138, 139]
	statistical approach	[26, 38, 147]
squash	observation (tracking software)	[170]
	statistical approach	[149]
table tennis	neural network	[76]
	observation	[118, 176]
	observation (tracking software)	[171]
	statistical approach	[83, 91, 165]
tennis	observation	[3, 6, 12, 49, 113, 143, 145, 155, 185]
	observation (tracking software)	[114]
	statistical approach	[16, 17, 30, 39, 53, 56, 58, 61, 68, 72, 84, 85, 99, 100, 105, 106, 129, 131, 159]

Table 5.2: Distribution of the performance methodology for each racket sport (author's work)

Roberts et al. [148] presented a frame-by-frame analysis to distinguish between skilled and less skilled athletes, using observing measures of anticipation in purely naturalistic match-play. The influence of skill level corresponded with empirically derived suggestions of skilled athletes accessing domain-specific knowledge for future event prediction.

Valldecabres et al. [178] created an ad hoc observational tool for badminton singles games that consisted of 13 criteria and 47 mutually exclusive categories. There were 287 actions from the 2015 Badminton World Championship studied. Cohen's Kappa and generalisability theory were used to evaluate the validity of the tool.

Yong and Tan [197] provided an example of the regression analysis method, to connect movement accuracy and heart rate data collected by the Microsoft Kinect tool.

Chiminazzo et al. [21] presented observational analyses of technical and timing variables to provide critical information for understanding the match. The technical and timing variables of badminton men's singles matches in the 2016 Olympic Games were examined and compared between groups and play-off stages. The findings are important for comprehending the game and providing information for training planning.

Statistical approach: Barreira et al. [4] illustrated the statistical approach. The purpose of that work is to calculate the point difference between winners and losers in badminton matches. To characterise the data collected from the tournament platform, the published analysis employed average, median, standard deviation, quartiles, minimum, and maximum values. The Shapiro-Wilk statistical test was used to confirm the data normality. The Mann-Whitney test was used to compare the maximum difference in points established by the winners and losers of the game.

In [132], the Crosstabs-Command and binomial logistic regression methods were used to determine the interactive effects of each contextual variable on challenge success (gender, requester player, next point winner, score-line, game, game interval, games in favour, challenges left per game, match-outcome, and international experience of the player). The request affected the success of a challenge with less efficiency than when the player requested the hawk-eye (Odds Ratio (OR) = 0.65) and when the player who requested the hawk-eye is the loser of the match (OR = 0.21). The identified trends enabled players to improve strategic plans that include determining the best time to request a Line Review.

Torres-Luque et al. [173] found statistical differences in a set of badminton competition matches across five competition levels (Group Phase vs. Eliminatory Phase). Non-parametric data were subjected to a descriptive analysis and a univariate test (Mann-Whitney U). The findings could assist players and coaches in planning and implementing various types of workouts or, more specifically, competition schedules tailored to the characteristics of badminton.

Combine approach: Dieu et al. [33] combined an observational approach (10 expert coaches) with a random forest algorithm. The study emphasised the benefits of performance analysis from the juxtaposition of subjective and objective data to design training plans based on the participants' level of expertise.

Neural networks: Gómez et al. [51] used bipartite networks for modelling racket sport performance. Non-linear and ecological approaches were associated with bipartite networks. Badminton stroke networks (BSN) were created by analysing the match activities of a player and their opponents. The model was able to recognise various playing patterns. The identification of the network of each player and its association with point outcomes, in particular, provided a better understanding of stroke performance and individual characteristics of world-class badminton players.

Rahmad et al. [135] focused on creating an automated system that used Faster Region Convolutional Neural Network (Faster R-CNN) to track the position of the badminton player from the sport broadcast video. Several different trained Faster R-CNN detectors were generated from the dataset before being tested on a variety of videos to assess detector performance. When the detector was fed a more generalised dataset, it successfully detected the player.

Rahmad et al. [134] used a pre-trained Convolutional Neural Network (CNN) method to create an automated system for badminton smash recognition on widely available broadcasted videos. The CNN models were built using smash and other badminton actions from the video such as clear, drop, lift, and net.

Most of the findings have been presented in *International Journal of Sports Science & Coaching* and *International Journal of Performance Analysis In Sport*. Interesting findings have been carried out by keyword analysis. Overall, there were 180 Keywords Plus in the examined documents, along with 158 Authors' Keywords.

5.7 Keyword analysis

Tableau Software generated a keyword word cloud, which is depicted in Figure 5.1. The size of the keywords represents how frequently authors use keywords. Not only are the keywords divided by size, but they are also divided by sport. The performance analysis phrase is the most commonly used in tennis. As a result, this phrase is the longest and greenest. Except for squash, performance analysis is the most frequently used keyword in the majority of racket sports, with the highest frequency of twenty-two for tennis. Tennis publications provide the most keywords (114), followed by badminton (62), padel tennis (49), table tennis (29), and squash (21). As more technology for in-game analysis becomes available, the keywords used in tennis publications become more specific. Surprisingly, the statistical approach was used first, followed by observation approach, which is simpler than any statistical analysis. In 2018, neural networks were introduced into the analysis, and more advanced methods and software became available. It is worth highlighting that the number of publications using the observation methodology has remained consistent over time, whereas the statistical approach may have shifted to more advanced methods such as neural networks.

Table 5.3 shows the most frequent words defined by authors and the most frequently used words in titles. Only 44 publications mention performance analysis as a keyword. Only eight of

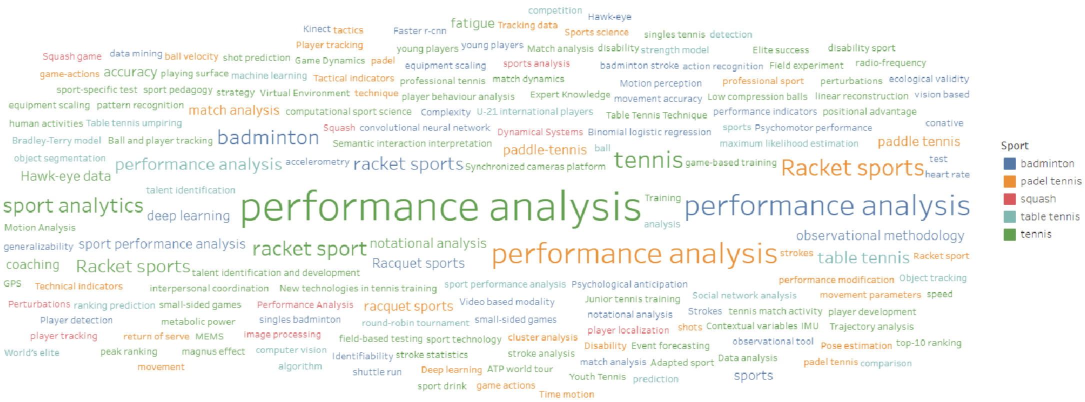


Figure 5.1: Keyword analysis based on the frequency for a specific racket sport (author's work)

the 25 tennis publications mention tennis, a similar ration could be found for badminton, where only five out of 15 publications mention badminton. When comparing those results with the keywords in the title, more than 50% of tennis publications define tennis, while all of the 15 badminton publications mention badminton in the title.

Author keywords	**Occurrences**	**Title Words**	**Occurrences**
performance analysis	44	tennis	35
racket sports	13	analysis	20
tennis	8	players	16
racket sport	7	badminton	15
badminton	5	performance	13
match analysis	5	padel	11
racquet sports	4	professional	9
sport analytics	4	elite	8
deep learning	3	match	8
notational analysis	3	table	8
sport performance analysis	3	serve	6
sports	3	success	6
table tennis	3	data	5
accuracy	2	game	5
coaching	2	network	5
disability	2	outcome	5
elite success	2	vision	5
equipment scaling	2	differences	4
fatigue	2	characteristics	4
hawk-eye data	2	player	4

Table 5.3: Most Frequently-used words - Author Keywords and Title Words (author's work)

Nevil et al. [117] noted that despite the many available research methods and techniques to model performance in sport (i.e. empirical modelling, stochastic modelling, dynamic systems, neural networks, and fuzzy logic), used singly or in combination, to date, the results have been disappointing practically. In fact, the recent use of computers and sophisticated software develops faster than the improvement of concepts and ideas about how to observe and learn from starting tactical game setting and its dynamical properties. Thus, further research on sports contests using various types of system descriptions is warranted. Performance analysis becomes useful whenever it corresponds to the progressive refinement and extension of observational variables, increasing its descriptive and explanatory potential according to the representative game events. The literature review was conducted using publications that have been indexed in Clarivate Analytics' Web of Science and Elsevier Inc.'s SCOPUS databases, and results highly depended on the keyword selection. A broad query (performance analysis AND sport) was used for the systematic review to ensure that broad categories were covered. More specific queries (fuzzy performance analysis in sport) search in Google Scholar yielded various results. Publications mentioned fuzzy theory as an option for future development [64], while others are missing fuzzy or sport after the first page of the results. Other queries have been examined (e.g. sport performance analysis, fuzzy) with a similar result.

6

Results

The aim of this chapter is to provide an understanding how fuzzy theory supports decisions in sport performance analysis.

Performance analysis in badminton covers many decisions, both on court and behind the scenes. Examples of these decisions are: when the player should use a specific shot to win the rally, which type of serve/receive the player should play, how the rules/score system affect the performance (how players should prepare for it), how many/which tournaments a player should attend to maintain a stable performance, personal development, and to secure a specific ranking, and how to plan each season to achieve specific goals. Each decision will need to consider the physiological aspects of the athlete including gender and handedness. Junior players have their own specific area for decision making as additional questions like will adjustments to the net height or court size help their development, or when to start with a specific skill development. The systematic literature review highlight that the correct evaluation of performance helps players reach the goal defined at the beginning of the planning process. This section provides a thorough explanation where fuzzy theory supports the decision-making in sport. The results from the expert interview are illustrated in figure 6.1 and defines the main stages of an athletes path as following:

1. Defining goals/ objectives for the athlete
2. Specifying the strategy (= planning the path) to reach their goals
3. Performing the strategy (= training & tournament)
4. Analysing the performance of the athlete (developed fuzzy inference systems are used in this stage)
5. Evaluation of reaching goals/ objectives based on performance analysis results
6. Adjusting the strategy or continuing with the same strategy

Figure 6.1: Schematic diagram for athletes plan (author's work)

Each stage contains thorough decision making. Some decisions can be easily made without implementing advanced technology, but most of the decisions will benefit from implementing a fuzzy theory methodology. The first stage can be defined by a coach or athlete based on the career objectives of the athlete. The second stage is designed when the coach uses experience and follows the scientific guidance for planning. While a coach is preparing an annual plan, there are numerous critical factors to consider, as well as numerous other factors that must be included but are frequently overlooked. These variables can distinguish between being a top national player and an international player. Typically, coaches create the plan in Excel based on the goals defined in stage one. The top international players who are aiming for Olympic medals typically have a four-year plan with multiple micro-cycles. International players aiming for a specific ranking position typically plan for one year according to the tournament calendar [192].

The example of an annual plan with two main peaks is shown in figure 6.2. During the season, in badminton, there are two separate competitive seasons such as the national and European championships. Because there are two distinct competitive phases, such a plan is called a bi-cycle. Figure 6.2 illustrates a bi-cycle that incorporates the following training phases:

- Preparatory phase I, which should be the longer preparatory phase

- Competitive phase I
- Short transition (12 weeks) linked with a preparatory phase II. The unloading transition phase is for recovery
- Competitive phase II
- Transition phase

Thus, this type of planning does not consider all of the variables that affect performance and is highly subjective, regardless of the experience and knowledge of the coach or athletes. The purpose of this study is to propose the use of fuzzy theory in order to create a more objective annual plan based on decision making with the goal of accomplishing goals.

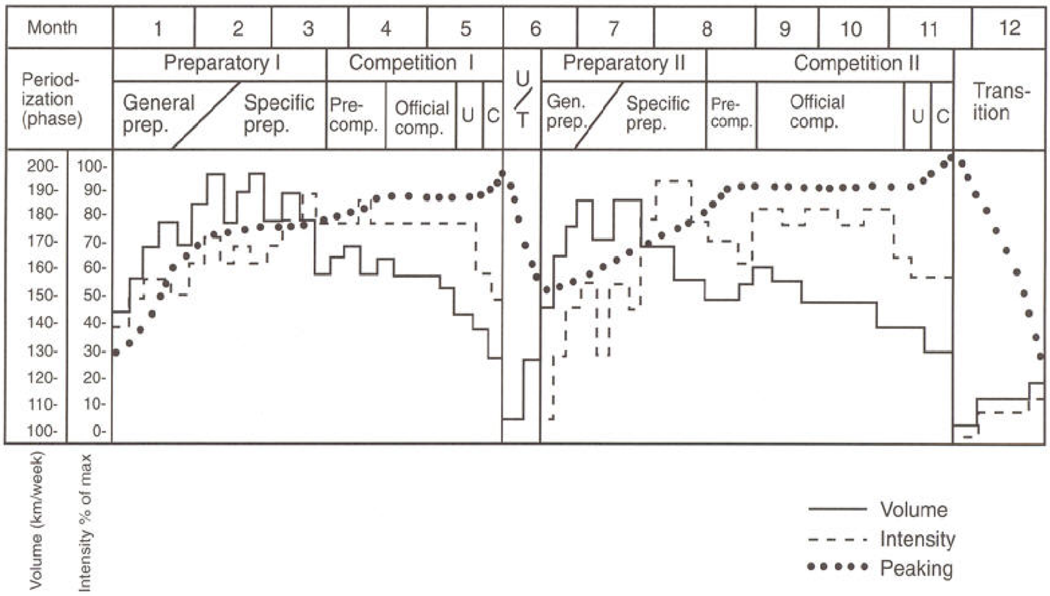


Figure 6.2: Example of a year plan [195]

There are numerous options for gathering the data such as video/image observation, ranking of players or results of physical tests to evaluate current status of the player through all phases. Physical tests and match analysis are great for in-depth analysis, but requires a lot of resources compared to that of ranking analysis. Ranking data could be easily obtained and they are updated weekly, thus progress could be monitored easily. Ranking analysis also contains a comparison with other players, which is an additional benefit. Multiple methodologies have been proposed in the literature 5.5, but fuzzy logic has not been broadly explored despite having a number of unique and advantageous characteristics making it an excellent alternative for solving a decision making problem.

6.1 Fuzzy models for athlete's performance analysis

This chapter presents the creation of FIS with source code samples. General fuzzy theory, specific settings, and the creation of fuzzy models are described in the relevant chapters of 4.4. MATLAB ® software and its packages were used to create the fuzzy models. The basis was to create a file with a fuzzy inference system, which is loaded by the appropriate startup script, and then executes its evaluation for each municipality in the input data file.

The aim of the proposed models is to examine the performance of an athlete using data obtained from the ranking. Mathematical models presented in this study used data from badminton. Badminton is an individual sport with a long history, including in the Olympic games, unlike squash which is not yet part of the Olympics. BWF is very open about each ranking, thus large datasets are available for the models, including head to head information about top players. There is a similar nomination procedure to the Continental Championships (Europe, Asia, Africa, PAN AM and Oceania), World Championship or the Olympics. Each player or coach, based on the level of the athlete, defines the tournaments they would like to participant in as a goal. Thus, their objective could be defined as a nomination to the Olympics for the presented models. Decisions of planning tournaments has always been difficult with the given goals. Initially, an athlete may think that the best option is to enter a high number of tournaments. However, this is not practical, as players need to achieve good results at each tournament, which require a lot of training to achieve those results. In addition, coaches are faced with tough decisions when planning a season to attain enough points and achieve a good ranking. Nomination ranking is created with results from the last 52 weeks by BWF. Although planning for the Olympics is a four-year cycle, the key weeks are the 52 qualification weeks involving a lot of tournaments. Thus, the question is which tournament to go for and which achievements have to be obtained to secure a qualifying spot. The final ranking for qualification to the Olympics in badminton have been collected and used for creating the fuzzy inference models. Ranking was considered across three Olympics - London 2012, Rio 2016, and Tokyo 2020(2021). There are five disciplines in badminton as follows:

- Men's single (MS)
- Women's single (WS)
- Men's double (MD)
- Women's double (WD)

- Mixed double (XD)

The individual model for each discipline has been created running the BWF rankings through MATLAB ® software and its packages. Multiple decisions such as which variables to include are significant, how fuzzy rules are created and how many players from the ranking are included have been made during the model creation and discussed with experts in coaching. Originally, multiple variables have been implemented into one fuzzy inference system, the results are displayed in [73]. The number of rules in a fuzzy system grew exponentially as the number of inputs rises. This extensive rule base degrades the computing efficiency of the fuzzy system. Additionally, it complicates the operation of the FIS and tuning of rules and MF parameters. Due to the limitation quantity of the training data, a large rule base decreases the general usability of the proposed fuzzy inference system. To overcome this limitation, a fuzzy inference system was implemented as a tree of smaller interconnected FIS objects rather than a single monolithic FIS object.

6.2 Fuzzy inputs

Both models include four major variables: the BWF rank, the number of tournaments attended, the amount of points received, and also BWF qualification rank. The number of tournaments a player needs to enter is difficult to predict, especially at the start of the qualification season. The proposed model enables rapid adjustment of selected variables. It is crucial to understand how changing inputs alters the model evaluation. This specific data shows the ranking for the Olympics; however, the inputs could be broadly used to evaluate the seasonal ranking of the athlete and transferred to tennis as the ranking system is similar across racket sports.

Looking at the input, multiple information needs to be considered. Qualification criteria varies for each Olympics, therefore unlike the previous Olympics, Rio 2016 and Tokyo 2020, each country could only enter a maximum of two players each in the singles (i.e. men and women), if both are ranked in the world's top 16; otherwise, one quota place until the roster of thirty-eight players has been completed. Similar regulations in the singles tournaments also apply to the players competing in doubles, as the National Olympic Committee (NOC) could only enter a maximum of two pairs if both are ranked in the top eight, while the remaining NOC is entitled to one until the quota of 16 highest-ranked pairs is filled. Qualification to the Olympics is based on the BWF Ranking list to be published at the beginning of May, providing a total of

16 pairs in each doubles event, and 38 players in each singles event using the following criteria:

- Singles:
  - Ranking 1-16: Players are taken in turn. A NOC may enter up to a maximum of 2 players, provided both are ranked in the top 16.
  - Ranking 17 and below: Players are taken in turn. A NOC may enter a maximum of 1 player.
- Doubles:
  - Rankings 1–8: Pairs are taken in turn. A NOC may enter up to a maximum of 2 pairs, provided both pairs are ranked in the top 8.
  - Rankings 9 and above: Pairs are taken in turn. A NOC may enter a maximum of 1 pair.

Each of the five continental confederations (i.e. Europe, Asia, Africa, PAN AM, and Oceania) will be guaranteed at least one entry in each singles and doubles event (this is called the Continental Representation Place system). If this has not been satisfied by the entry selection method described above, the highest ranked player or pair from the respective continent will qualify. A NOC can qualify players or pairs in a maximum of two events through the Continental Representation Place system; if a NOC qualifies for more than two events through the Continental Representation Place system, the NOC must choose which player will qualify, and the quota place declined will be offered to the next NOC eligible player or pair. For each player who qualifies in more than one discipline, an unused quota place will be allocated to the next best ranked eligible athlete of a respective gender in the singles on the BWF Ranking List.

The host nation is entitled to enter one male and one female badminton player in each of the singles tournaments, but more than two players may be permitted if they have achieved the qualifying regulations. Meanwhile, six quota places are made available to eligible NOC through the Tripartite Commission Invitation, with three each in each of the singles.

Thus, this task has been carefully discussed with the expert and allied with the dataset from the three Olympic qualification lists. The following variables have been identified as the most important ones:

- Ranking - Position of the athlete on the ranking

- Quality - The quality of the athlete is defined by the order in which the athlete qualified to the specific event.
- Earned points - How many points the athlete reached in the last 52 weeks, only the best ten results are accounted regardless if the athlete played in more than ten tournaments
- Number of tournaments - How many tournaments an athlete played in the last 52 weeks as only last 52 weeks is accounted in the ranking

6.3 Mamdani-Assilan Fuzzy Inference System creation in MATLAB

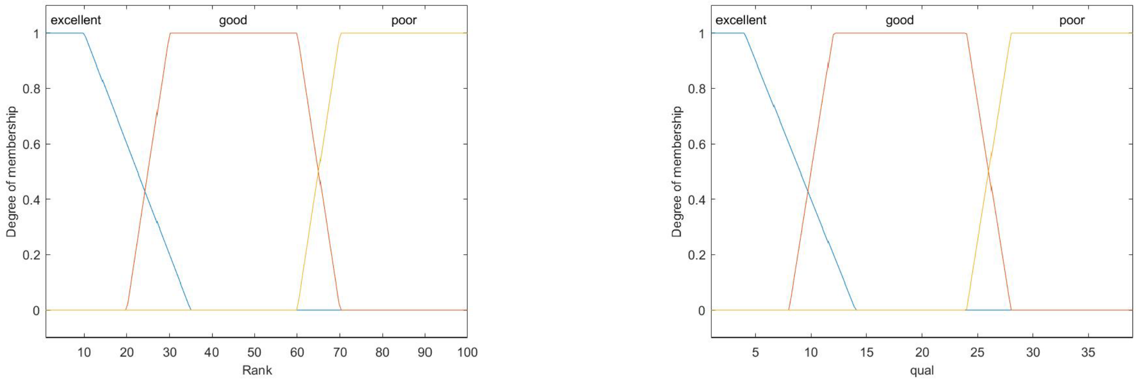
The fuzzy inference system for each discipline and Olympics consists of multiple steps. Below is an example of the system for the men's single in Tokyo 2020(2021). A FIS is implemented as a tree of two smaller interconnected FIS objects.

6.3.1 Selecting the family of membership functions

The MF for the inputs is defined according to the trend in the data. The MF is a curve that determines how each point in the input space is mapped to a membership value (or degree of membership) of 0 and 1. The input space is sometimes referred to as the universe of discourse. 0 and 1 is the value between which input function can vary. The curve of input function can be arbitrary, and the shape can be determined as a function that suits from the point of view of simplicity, convenience, speed, and efficiency. There are 11 built-in MFs. One of the simplest functions is the triangular MF, trimf, which is a combination of three points forming a triangle. The trapezoidal MF, trapmf, has a flat top and is a tilted elongated triangle curve. These straight line MFs has the advantage of simplicity. The 'trapmf' MF has been used to define MF in the presented fuzzy inference system, defined for each of these linguistic sets. Examples of the MF input plot are in figures 6.3a, 6.3b, 6.4a and 6.4b.

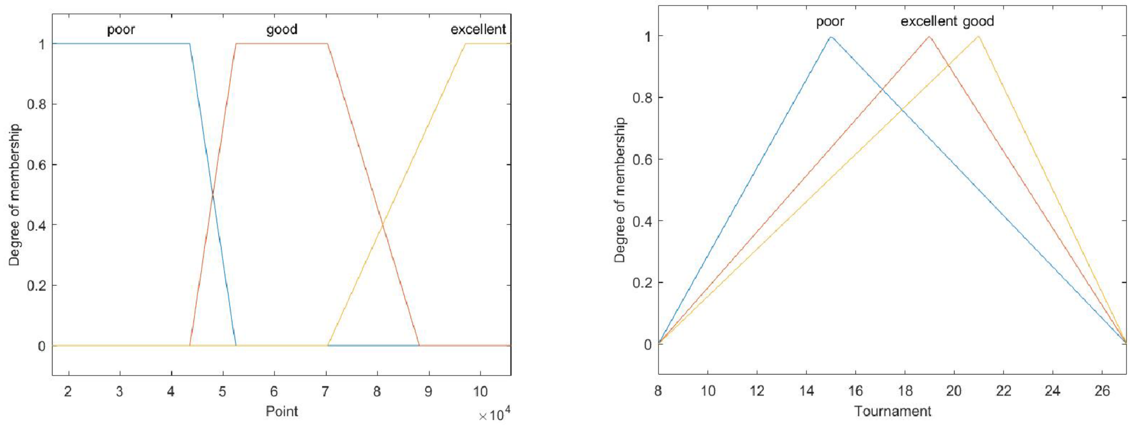
6.3.2 Fuzzy outputs

The dataset output has been defined as the chance of an athlete to reach a given goal. A specific output for the given dataset is the chance to qualify to the Olympics. The triangular MF is used to



(a) Example of the MF for ranking (b) Example of the MF for quality

Figure 6.3: Example of the MF (author's work)



(a) Example of the MF for earned points (b) Example of the MF for number of tournaments

Figure 6.4: Example of the MF 2 (author's work)

define the output MF. The 'trimmf' defines the outputs into several different fuzzy language sets: qualify is definitely no, qualify is no, qualify is less likely, qualify is yes, and rank is definitely yes. The MFs are defined for each of these linguistic sets. The results are shown in 6.5.

6.3.3 Constructing the set of if-then rules

Construction of the if-then rules is the next step while building the fuzzy inference system. MATLAB ® has been used to create IF-THEN rules. Four inputs and one output have been identified in the first step for the system. IF-THEN rules for each athlete was created using the data from the qualification for London 2012, Rio 2016, and Tokyo 2020, despite of the occasional alteration of the system qualification. The most important rules remain constant, like the maximum number of players from each country, qualification period (52 weeks), and ranking system. Analysing the data from all three qualification periods following IF-THEN rules has

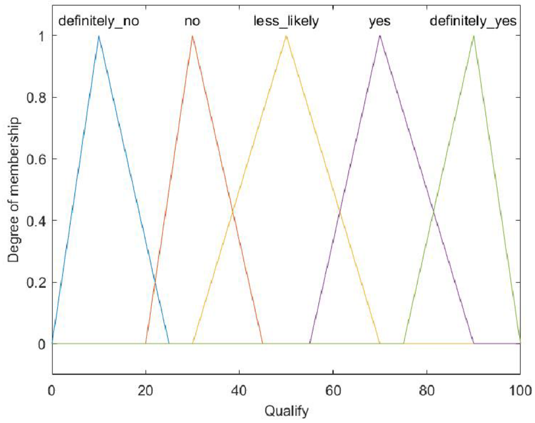


Figure 6.5: Example of the MF for qualification (author's work)

been established. For the qualification for one Olympics, there are more than 100 tournaments of various levels. The full list of tournaments is listed on the Badminton World Federation website. Two steps are included in order to find if-then rules:

- Calculation of the antecedent (fuzzyfying the inputs and use any necessary fuzzy operators)
- For consequent results applied

The second step is implication. For if-then rules, the antecedent P, implies the result, Q. In binary logic, if P is true then Q is also true $(P \rightarrow Q)$. In fuzzy logic, if P is true to some degree of membership, then Q is also true to the same degree of membership $(0.5\ P \rightarrow 0.5\ Q)$. If P is false, identify Q cannot be identified. The consequent is a fuzzy set assigned to the output. The implication function is used to modify that fuzzy set to the degree specified by the antecedent. Truncation is used to modify the output fuzzy set using the "min" function or scaling using the "prod" function.

Since decisions are based on testing all the rules in a FIS, the rule outputs must be combined in some manner. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation only occurs once for each output variable, which is before the final defuzzification step. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable. As long as the aggregation method is commutative, then the order in which the rules are executed is unimportant. Three built-in methods are supported:

1. max (maximum)

2. probor (probabilistic OR)
3. sum (sum of the rule output sets)

Following the display sections of the source codes to show real values of variables, membership functions, IF-THEN rules variations, which is important for understanding how systems have been created step by step, including various optimisations.

6.3.4 Creating the first FIS

The first input based on the ranking with three MFs is added to the fuzzy logic system. Three different MFs have different function ranges.

```
fis1 = mamfis('Name',"Qualifyer1");
fis1 = addInput(fis1,[1 100],'Name',"Rank");
fis1 = addMF(fis1,"Rank",'trapmf',[1 1 10 35],'Name',"excellent");
fis1 = addMF(fis1,"Rank",'trapmf',[20 30 60 70],'Name',"good");
fis1 = addMF(fis1,"Rank",'trapmf',[60 70 100 100],'Name',"poor");
```

The second input based on the quality of the athlete (which position the athlete qualifies for the Olympics) with three MFs is added to the fuzzy logic system. Three different MFs have different function ranges.

```
fis1 = addInput(fis1,[1 Qualmax],'Name',"qual");
fis1 = addMF(fis1,"qual",'trapmf',[1 1 ceil(Qualmax*0.1) ...
    ceil(Qualmax*0.35)],'Name',"excellent");
fis1 = addMF(fis1,"qual",'trapmf',[ceil(Qualmax*0.20) ...
    ceil(Qualmax*0.30) ceil(Qualmax*0.60) ...
    ceil(Qualmax*0.70)],'Name',"good");
fis1 = addMF(fis1,"qual",'trapmf',[ceil(Qualmax*0.60) ...
    ceil(Qualmax*0.70) Qualmax Qualmax],'Name',"poor");
```

The final output is added in the FIS with five MFs.

```
fis1 = addOutput(fis1,[0 100],'Name',"Qualify");
fis1 = addMF(fis1,"Qualify","trimf",[0 10 25],'Name',"definitely_no");
fis1 = addMF(fis1,"Qualify","trimf",[20 30 45],'Name',"no");
fis1 = addMF(fis1,"Qualify","trimf",[30 50 70],'Name',"less_likely");
fis1 = addMF(fis1,"Qualify","trimf",[55 70 90],'Name',"yes");
fis1 = addMF(fis1,"Qualify","trimf",[75 90 100],'Name',"definitely_yes");
```

IF-THEN rules are then defined and added to the system.

```
ruleList1 = ["If Rank is poor or qual is poor then Qualify is ...
    definitely_no";
            "If Rank is poor or qual is good then Qualify is no";
            "If Rank is poor or qual is excellent then Qualify is ...
                less_likely";
            "If Rank is good or qual is poor then Qualify is no";
            "If Rank is good or qual is good then Qualify is yes";
            "If Rank is good or qual is excellent then Qualify is yes";
            "If Rank is excellent or qual is poor then Qualify is ...
                less_likely";
            "If Rank is excellent or qual is good then Qualify is yes";
            "If Rank is excellent or qual is excellent then Qualify ...
                is definitely_yes"];
fis1=addRule(fis1,ruleList1);
```

6.3.5 Creating the second FIS

The first input based on the number of tournaments with three MFs is added to the fuzzy logic system. Three different MFs have different function ranges.

```
fis2 = mamfis('Name',"Qualifyer2");
fis2 = addInput(fis2,[Tourmin Tourmax],'Name',"Tournament");
difftour=Tourmax-Tourmin;
fis2 = addMF(fis2,"Tournament","trimf",[Tourmin ...
    (ceil(difftour*0.35)+Tourmin) Tourmax],'Name',"poor");
fis2 = addMF(fis2,"Tournament","trimf",[Tourmin difftour ...
    Tourmax],'Name',"excellent");
fis2 = addMF(fis2,"Tournament","trimf",[Tourmin ...
    (ceil(difftour*0.65)+Tourmin) Tourmax],'Name',"good");
```

The second input, based on the number of points with three MFs, is added to the fuzzy logic system. Three different MFs have different function ranges.

```
fis2 = addInput(fis2,[Pointmin Pointmax],'Name',"Point");
diffpoint=Pointmax-Pointmin;
```

```
fis2 = addMF(fis2,"Point",'trapmf',[Pointmin Pointmin ...
    (ceil(diffpoint*0.3)+Pointmin) ...
    (ceil(diffpoint*0.40)+Pointmin)],'Name',"poor");
fis2 = addMF(fis2,"Point",'trapmf',[(ceil(diffpoint*0.35)+Pointmin) ...
    (ceil(diffpoint*0.40)+Pointmin)   (ceil(diffpoint*0.50)+Pointmin) ...
      (ceil(diffpoint*0.65)+Pointmin)],'Name',"good");
fis2 = addMF(fis2,"Point",'trapmf',[(ceil(diffpoint*0.50)+Pointmin) ...
    (ceil(diffpoint*0.65)+Pointmin) Pointmax ...
    Pointmax],'Name',"excellent");
```

Finally, the output is added in the FIS with five MFs.

```
fis2 = addOutput(fis2,[0 100],'Name',"Qualify");
fis2 = addMF(fis2,"Qualify","trimf",[0 10 25],'Name',"definitely_no");
fis2 = addMF(fis2,"Qualify","trimf",[20 30 45],'Name',"no");
fis2 = addMF(fis2,"Qualify","trimf",[30 50 70],'Name',"less_likely");
fis2 = addMF(fis2,"Qualify","trimf",[55 70 80],'Name',"yes");
fis2 = addMF(fis2,"Qualify","trimf",[75 90 100],'Name',"definitely_yes");
```

IF-THEN rules are the defined and added to the system.

```
ruleList2 = ["If Tournament is poor or Point is poor then Qualify is ...
    definitely_no";
            "If Tournament is poor or Point is good then Qualify is no";
            "If Tournament is poor or Point is excellent then Qualify ...
                is less_likely";
            "If Tournament is good or Point is poor then Qualify is no";
            "If Tournament is good or Point is good then Qualify is yes";
            "If Tournament is good or Point is excellent then Qualify ...
                is yes";
            "If Tournament is excellent or Point is poor then Qualify ...
                is less_likely";
            "If Tournament is excellent or Point is good then Qualify ...
                is yes";
            "If Tournament is excellent or Point is excellent then ...
                Qualify is definitely_yes"];
fis2=addRule(fis2,ruleList2);
```

Both FISs have been created. Each structure is shown in figures 6.6 and 6.7.

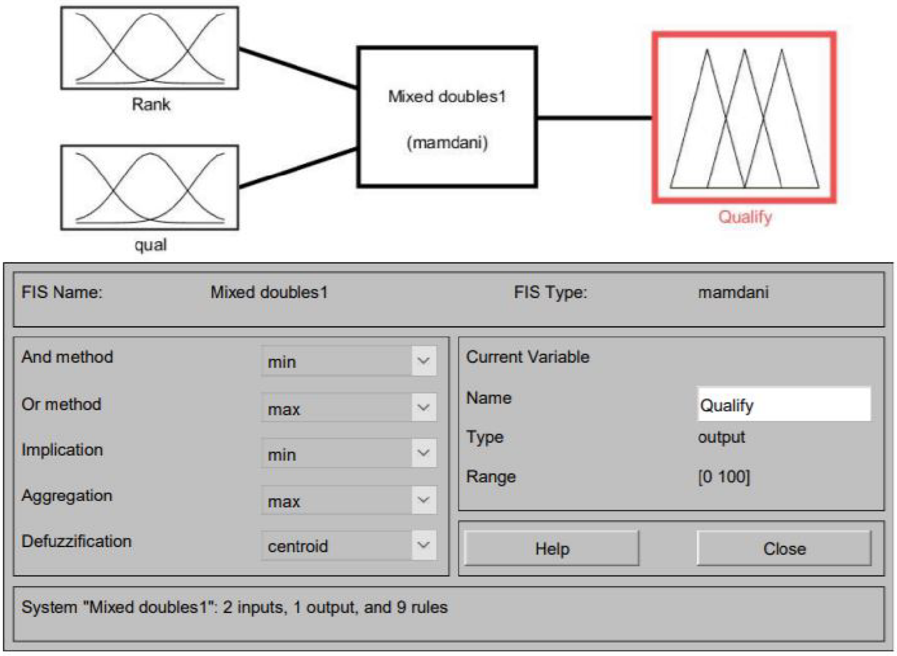


Figure 6.6: Example of the first FIS with ranking and quality as inputs (author's work)

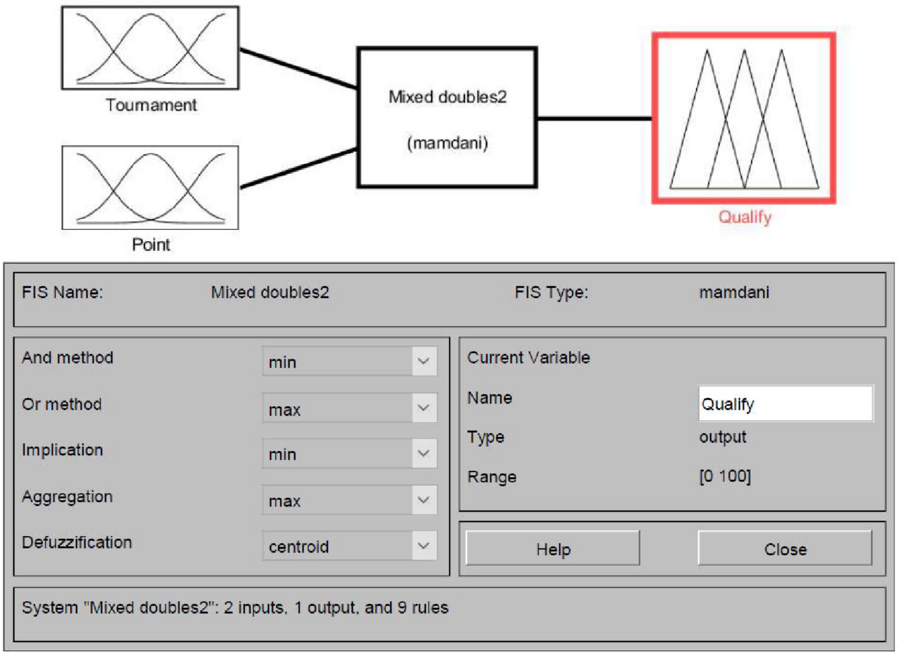


Figure 6.7: Example of the second FIS with tournament and points as inputs (author's work)

6.3.6 Fuzzy systems with a tree structure

Two FISs are used for creating the one FIS using the tree structure. Specific discipline needs to be revoked and both fis1 and fi2 need to be read for the FIS tree structure system to be created. One FIS is that all of the FIS objects are in parallel, there are no interconnections, and all the FIS outputs are FIS tree outputs.

```
name1="Mixed doubles1";
name2="Mixed doubles2";
fis1 = readfis(name1);
fis2 = readfis(name2);
Tree = fistree([fis1 fis2],[]);
```

6.4 Mamdani Fuzzy Inference System evaluation and optimisation in MATLAB

The system is then evaluated using the ‘evalfis’ by providing the fuzzy tree name and respective input crisp values. By running the command for test values, a crisp value is acquired at the output by getting the maximum of both the outputs. It is crucial for the performance of an athlete to obtain the results faster, for the coach to quickly run the code below the FIS and see the results in a command window.

```
output = evalfis(Tree,[2 2 15 97762]);
```

The first evaluation of the mixed doubles shows a result of 65.7849 for the second ranked pair, which qualified second, with 15 tournaments and 97,762 points. The system requires future optimisation based on these results, showing how the system output is a little less accurate with respect to the input provided, which could be solved by tuning and optimising FIS. The input and output parameter settings are extracted from the FIS. The parameter settings are represented by variable settings objects that include the FIS name, variable type, variable name, and MF parameter settings. For each parameter value of an input/output MF is specified if it is available for tuning its minimum and maximum values. By default, all MF parameters are free for tuning, and their ranges are set to [-Inf, Inf]. The default minimum and maximum range values of tune-able MF parameters are set to the corresponding input/output ranges in the tuning process.

```
[in1,out1] = getTunableSettings (fis1);
out = setTunable (out,false);
x = [1 1 11 105968;
     3 3 16 81312;
     12 12 18 53075;
     31 15 19 37807;
     45 21 21 30354;
     64 28 22 24002;
     78 33 16 21089;
     84 36 18 19475;
     89 37 23 18549;
     94 39 22 17894];
y = [97.5 97.5;
     94.2 94.2;
     85.3 85.3;
     68.3 68.3;
     58.4 58.4;
     40 40;
     30.9 30.9;
     17.6 17.6;
     13.3 13.3;
     5.6 5.6];
```

Four different methods, genetic algorithm, particle swarm optimisation, pattern search and simulation annealing were used for tuning.

```
options = tunefisOptions("Method","ga");
options.MethodOptions.MaxGenerations = 2000;
options.DistanceMetric = "norm1";
rng('default')
[fisout,optimout] = tunefis(parTree,[in;out1],x,y,options);
optimout
```

```
options = tunefisOptions("Method","particleswarm");
options.MethodOptions.MaxIterations = 2000;
options.DistanceMetric = "norm1";
rng('default')
[fisout,optimout] = tunefis(parTree,[in;out],x,y,options);
```

```
options = tunefisOptions("Method","patternsearch");
options.MethodOptions.MaxIterations = 2000;
options.DistanceMetric = "norm1";
rng('default')
[fisout,optimout] = tunefis(parTree,[in;out],x,y,options);
```

```
options = tunefisOptions("Method","simulannealbnd");
options.MethodOptions.MaxIterations = 2000;
options.DistanceMetric = "norm1";
rng('default')
[fisout,optimout] = tunefis(parTree,[in;out],x,y,options);
```

Four algorithms were chosen for tuning and optimisation as they are all available in MATLAB®. The maximum number of generations was specified for each method. The training of the fuzzy system takes time according to the maximum number of generations. `Fisout` includes the updated parameter values. `Optimout` provides additional outputs of the optimisation method and any error messages that are returned during the update process of the input fuzzy system using the optimised parameter values. The result of the training with 20 generations is shown in table 6.1. After the optimisation step, fuzzy inference system is optimal and can be implemented in the decision-making process.

The results of the fuzzy inference system were implemented in the decision-making procedure for the planning. When a coach evaluates a current stage, the latest ranking is downloaded from the badminton world, continental or national federations and implemented easily in the code. Another benefit alongside the optimised system is the ability to see the rules and the implication on the output. Those results allow the coach to assign the athlete a specific input such as the current ranking. Using Fuzzy Logic Designer rules could be displayed using option Rules. Examples of values for ranking and quality of the players are shown in figure 6.8.

The second option from Fuzzy Logic Designer, offering more in depth evaluation, is Surface Viewer. This option plots a graph with two inputs of their dependence on the exit area, as shown in figure 6.9. The core of the model was the evaluation of the inference system using the tree structure, which uses the cycle calculated for the qualification to the Olympics across five disciplines for three Olympics (Tokyo 2020, Rio 2016, and London 2012). The code creating the fuzzy inference system is described in detail in section 6.3. The script saves the defuzzified

Generation	Func-count	Best f(x)	Mean f(x)	Stall Generation
1	400	415.4	483.1	0
2	590	389	476	0
3	780	389	469.7	1
4	970	366.6	456.8	0
5	1160	366.6	447.5	1
6	1350	356.1	433.2	0
7	1540	353	420.8	0
8	1730	337.9	410.4	0
9	1920	332.3	401.8	0
10	2110	329.6	394.2	0
11	2300	305.8	384.4	0
12	2490	299.1	374.4	0
13	2680	299.1	363.7	1
14	2870	291.2	353.7	0
15	3060	280.9	339.1	0
16	3250	280.9	332.8	1
17	3440	270.7	317.3	0
18	3630	265.2	313.1	0
19	3820	257	304.7	0
20	4010	254.9	299.3	0

Table 6.1: Results of the training (author's work)

fuzzy output values in the output text file at the conclusion. After creating the fuzzy inference system with the tree structure, plotting the MFs and dependency graphs, the input is saved using the following commands.

```
writeFIS(fis1,'optimized1');
writeFIS(fis2,'optimized2');
```

The model is applicable to reach both short- and long-term objectives as it is easy to adjust variables based on given goals. The system was applied to specific data (qualification data for London 2010, Rio 2016, and Tokyo 2020 for all five disciplines - MS, WS, MD, WD and XD).

6.5 Takagi-Sugeno-Kang Fuzzy Inference System creation in MATLAB

TSKFS was created by converting current MAFS using the `convertToSugeno` function. The TSKFS created has a constant output MFs that corresponds to the centroids of the MAFS

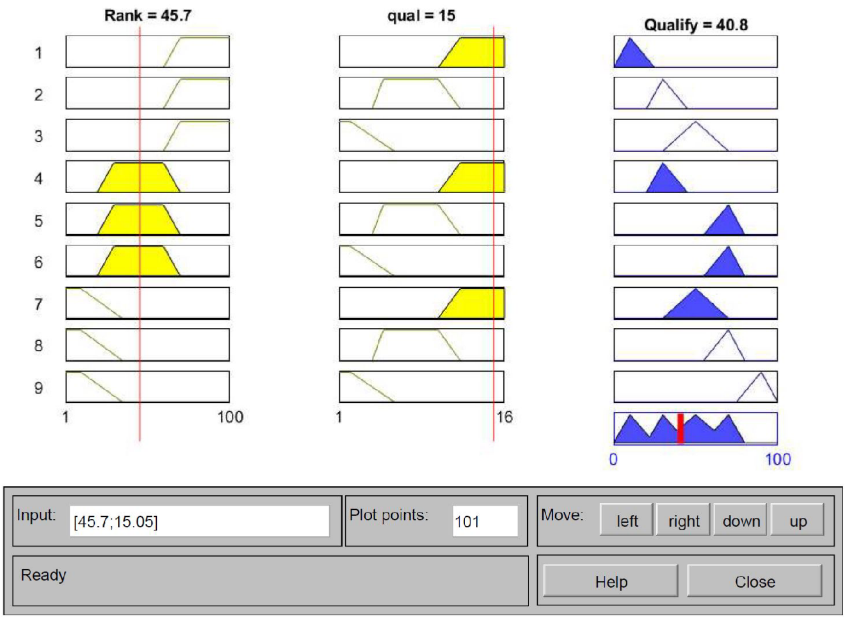


Figure 6.8: Example of the rule when the rank and quality values are 45.7 and 15, respectively (author's work)

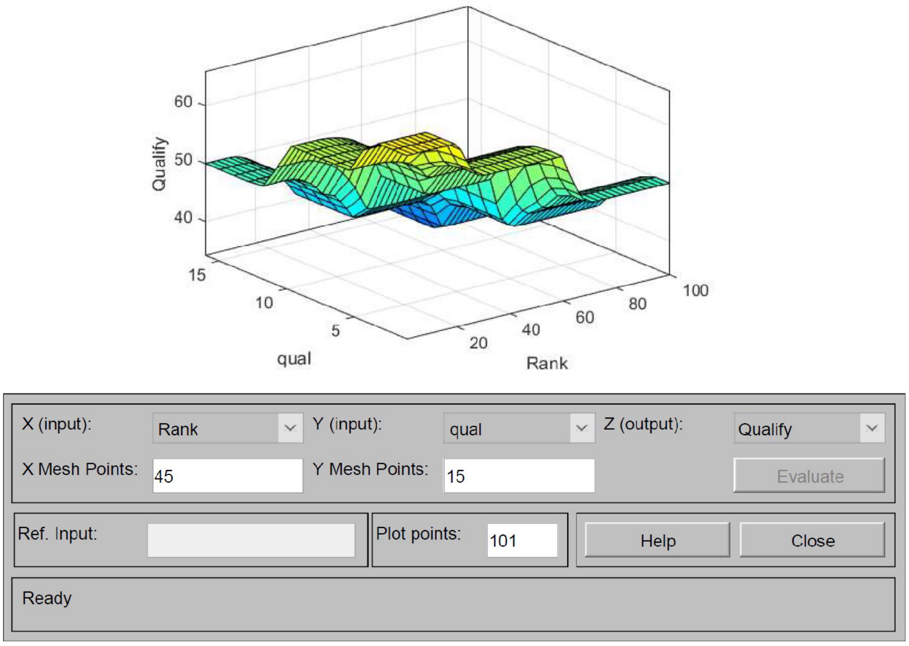


Figure 6.9: Example of the surface viewer when the rank and quality values are 45 and 15, respectively (author's work)

output MF which allows a fair comparison.

The development of the MAFS is described in detail in part 6.3, even when the system needs to include the following steps before it could be converted into the TSKFS:

- Creation of the first FIS for RANK and QUALITY input, including membership for both inputs and output

- Creation of the second FIS for TOURNAMENTS and POINTS input, including membership for both inputs and output

Once both FISs have been created, the conversion function could be implemented.

```
sug_fis1 = convertToSugeno(fis1);
sug_fis2 = convertToSugeno(fis2);
Tree = fistree([sug_fis1 sug_fis2],[]);
output = evalfis(Tree,[2 2 18 84328]);
max(output)
```

While creating the TSKFS, a similar process as for MAFS was taken to optimise TSKFS.

```
options = tunefisOptions("Method","ga");
options.MethodOptions.MaxGenerations = 20;
options.DistanceMetric = "norm1";
rng('default')
[fisout,optimout] = tunefis(parTree,[in;out],x,y,options);
optimout
```

6.6 Selecting the type of fuzzy inference system

Two fuzzy inference systems (MAFS and TSKFS) have been proposed for evaluating the performance of an athlete. MAFS is implemented using a tree structure for easier navigation and manipulation. MAFS broader usage benefits coaches as they would not need prior knowledge of this system. MAFS is compatible with the expert system applications where human expert knowledge is also used to create rules. The information from experts is combined with expertise (e.g. general knowledge or previous experience as a professional athlete) at this point. MAFS had many advantages over the TSKFS; however, TSKFS has less computational power demand. The TSKFS is faster to optimise and is therefore the main reason why it was considered in the system proposal. Multiple optimisation methods have been tested for both MAFS and TSKFS. Different iterations were also tested. RMSE is calculated as a part of the optimisation to help evaluate the process. The results of 60 and 2000 iterations are shown in table MAFS and TSKFS, respectively. Pattern search method showed the highest improvement with the increase in number of interactions.

Optimisation method	MAFS 60 iterations	MAFS 2000 iterations	TSKFS 60 iterations	TSKFS 2000 iterations
Non-optimised system	25.7628	25.7628	30.4196	30.4196
Genetic Algorithm	17.3577	16.7634	19.0441	17.3194
Particule Swarn Method	12.2475	8.4962	15.365	14.4886
Pattern Search Method	22.9110	6.7648	24.4159	11.2589
Simulated Annealing Algorithm	24.5418	22.6505	29.2932	27.5655

Table 6.2: RMSE value for each optimisation method (author's work)

Table 6.3 offers a comparison between MAFS and TSKFS. Description including the code could be found in sections 6.3 and 6.5.

A selected system has been tested using data from a 52-week qualifications period to the Olympics in Tokyo 2021. The qualification journey of a Czech female single player is used as example. She started ranking at 142 at the beginning of the qualification period on the 29th of April 2019, then 125 spot at the 15th March 2020 when ranking was frozen, and finished at the 101 spot ranking spot. The results from the optimised model have been used to inform decision

Olympic year	Discipline	Qualification spot	Ranking	No. of tournaments	Points	MAFS	TSKFS	Optimised MAFS	Optimised TSKFS
London 2012	MS	3	3	18	84633	58.4023	53.1566	59.074	79.0947
	WS	3	4	17	76320	58.2061	52.8597	58.4196	74.1721
	MD	3	3	14	78257	57.9657	52.4638	57.0892	59.4879
	WD	3	3	11	76540	58.5625	52.7336	57.2316	76.5927
	XD	3	3	22	80990	58.0172	53.8946	62.5248	68.3968
Rio 2016	MS	3	3	19	75327	58.154	52.6004	58.2279	58.9163
	WS	3	3	17	78147	57.9695	52.126	58.7166	69.6853
	MD	3	3	14	72117	57.9374	52.1994	56.9873	63.2118
	WD	3	3	11	77369	58.0011	52.248	58.7509	58.5763
	XD	3	3	22	79190	59.2597	54.2732	59.7873	51.749
Tokyo 2020	MS	3	3	16	81312	58.154	52.1381	58.2405	58.7189
	WS	3	3	15	82676	57.974	52.5372	58.483	75.6927
	MD	3	3	17	78350	58.2691	53.7239	58.9167	60.7496
	WD	3	3	16	85653	57.9641	53.7318	59.2271	58.3364
	XD	3	3	15	80883	58.3081	53.2581	58.3914	54.9426

Table 6.3: Results for the selected input (author's work)

such as which tournament a player needs to attend to reach enough points to jump over the next spot (using rule viewer to see the target number of tournament and points). The player was able to adjust tournaments (one of the adjustment was to not visit low level tournament in Spain that offered less points and entered a high level tournament in India).

Both MAFS and TSKFS have a similar computational time around 60s. The computational time dramatically increased after optimisation, with only 20 iterations computational time up to 120s for MAFS and up to 287s for TSKFS. The computational time could be decreased by only running a selected part of the code. Two main factors - computational time and reliability - need to be considered for the final system recommendation. The optimised TSKFS is the most reliable system, even when it had the longest computational time. The used system needs to be selected considering the needs of the coach. When the coach needs to compare multiple athletes during a monthly planning session, MAFS could be used. However, for yearly performance evaluation, optimised TSKFS needs to be used.

Multiple research questions have been established at the start of the research.

How did the performance analysis methods change over time within racket sports? The first publications in 1997 only included a statistical approach. Observation was included as individual method later on. Neural network method was used in 2018, and a combine approach for analysis was introduced later. For racket sports, a significant alternative identified was machine learning, decision trees, and neural networks (particularly for tennis and squash, where no reviewed literature has used this method) for performance analysis (especially for tennis and squash). Neural network technique is showing some promising patterns. Greater participation of software technologies, such as automatic in-game movement recognition and evaluation and in-game wearable devices for badminton, table tennis, and squash should be considered in future research.

Is the observation method the most frequently used in performance analysis? Statistical approaches were the most used analysis methods, while observation methods became commonly used during the last decade when ranking, tournament statistics, and information of players become publicly available.

Is there a correlation between the number of publications regarding performance analysis and the Summer Olympics? The distribution of publications is influenced by major sporting events. The peak was recently recognised for the Olympic games. The following factors have been identified as driving factors:

- Data sets are easily accessible to large groups
- Data sets are collected in a more advanced manner
- More funding is available for performance analysis to achieve a gold medal
- Widespread public interest about performance analysis

Would a range of authors influence performance analysis research? The systematic review identified a total of 197 authors, with 257-fold that an author appeared in the database. There has been no separate publication from an author, with an average of 3.03 authors per document published.

How can performance analysis be achieved using MAFS and TSKFS? The results from the expert interviews highlight which phase of the proposed models are used. Figure 6.1 shows performance analysis using both MAFS and TSKFS implemented between data collection and results comparison. Developing both systems included data collection from a publicly available source (for higher transparency and wide transferability of the models), variables selection for both input and output, development of IF-THEN rules, MFs selection, and optimisation of the models. Section 4.6 describes the theory for MAFS and TSKFS development in MATLAB®. Sections 6.3 and 6.5 describe the in-depth development of both MAFS and TSKFS, including source code for better understanding which benefit systems are offered to coaches and players.

What is the best optimisation strategy for performance analysis? Four optimisation methods (i.e. genetic algorithm, particle swarm optimisation, pattern search, and simulation annealing) have been proposed. Pattern search method delivered the best results in the terms of RMSE for higher number of iterations (2000) for both MAFS with RMSE of 6.7648, and TSKFS with RMSE of 11.2589. Pattern search method was implemented into the proposed systems. Detailed results are in section 6.6.

Are models transferable to the open source software Octave Fuzzy Logic Toolkit? The Octave Fuzzy Logic Toolkit is an open-source toolkit for the Octave programming language that provides a significant MATLAB compatible portion of the functionality of the MATLAB Fuzzy Logic Toolbox, as well as many additional features and additions. Building, modifying, and evaluating FISs from the command line or from Octave scripts is made possible by the functions of the toolkit, which also allow the user to read and write FISs to and from files and generate graphical output of both MFs and FIS outputs. Future work will concentrate on the implementation of sophisticated fuzzy inference algorithms as well as graphical user interface tools. The Octave Fuzzy Logic Toolkit could be obtained for free via Octave-Forge and SourceForge. The Octave is a good second option, but as MATLAB ® offers a free trial, it is recommended to first use MATLAB ® due to better user experiences mainly with rules viewer, adjusting IF-THEN rules or variables adjustments.

7

Discussion

This section provides an explanation, evaluation, importance, and relevance of the results. Detailed results can be found in 6. The findings are shown in relation to the literature review 5 and research questions. The Mamdani approach was used to implement fuzzy logic in the problem of athlete performance, which results in the creation of the fuzzy inference system using the tree structure. The fuzzy inference system was created using the specific data (qualification data for London 2010, Rio 2016, and Tokyo 2020 for all five disciplines - MS, WS, MD, WD and XD). The FIS, including four independent inputs, each with a different membership function, were then combined to form a single output. The output of the FIS had five different membership functions, described in part 6.3.1. The FIS was developed for each category of the three different Olympic games held in the various years. The findings obtained by these un-tuned systems were unsatisfactory and unreliable due to their inaccuracy. The optimisation was carried out up to twenty generations utilising the available data derived from the dataset. The examination of the optimised FIS resulted in significant improvement. Further, the genetic algorithm was used while optimising and tuning of the FIS.

The advantages of the fuzzy logic, selection of the MAFS over TSKFS, number of variables included in the FIS, and scalability challenges are address below.

The optimised model could be adjusted by including different ranking in racket sports. While the optimised model demonstrated a significant improvement in terms of selecting tournaments and then incorporating them into the planning process, the model does have some limitations that must be considered. There are 52 weeks, which is a lengthy period for making accurate predictions, particularly when multiple tournaments take place on the same weekend. To begin, increasing the amount of data sets on which the system is trained or increasing the maximum number of generations for the optimisation process can both improve the performance of the system. The model benefits from publicly available datasets, which allows anyone to duplicate the proposed systems. Models have been proposed in this way to eliminate differences between large clubs, where funding for performance analysis is not an issue, and small clubs that may have only one coach, responsible not only for coaching but managing the club. Players benefit from this approach as well as they can analyse chances almost instantly. Data sets are regularly updated weekly, thus this time frame allows coaches/athletes to analyse the data on a regular basis. During the modelling, more variables were considered, but the output from the expert interviews show a demand for a fast and reliable system. As a result, four inputs have been chosen to mirror important qualification variables. Metrics will show how the ranking of players is trending or how many tournaments a player can consider entering in the next month. Models would benefit from additional metrics, even when this will cause additional computational time and interaction with the coach. Models allow some input changes, however, due to the scalability challenges, no more than eight variables are recommended. Different inputs such as the current physical stage using heart rate monitoring or physical tests could be included. Using this data may present disadvantages, because coaches cannot compare data to other players from different clubs or countries. On the other hand, ranking is publicly available as it provides true comparable results across all athletes.

The level of generality of fuzzy logic is far higher than that of bivalent logic. The generality of fuzzy logic is at the root of much of what fuzzy logic has to offer in terms of applications. Linguistic variables and ambiguous if–then rules are the main benefits. The formalism of linguistic variables with fuzzy if–then rules is, in effect, a sophisticated modelling language that is extensively utilised in fuzzy logic applications. Essentially, the formalism is used to summarise and compress information through the use of granulation. The main advantages are the FIS is capable of working with any type of input information, regardless of how imprecise, distorted, or loud the information is. The building of FIS is simple to comprehend, hence any changes to FIS are straightforward. Fuzzy logic is based on mathematical ideas of a set theory, and the rationale behind them is straightforward. The fact that it parallels human reasoning and decision-making means that it can provide an extremely efficient solution to complicated problems in all aspects of life. Despite the many advantages of using fuzzy logic, there are some less positive points to consider. When applying fuzzy logic to an issue, there is no systematic strategy that can be used, which results in ambiguity. A preliminary mathematical description is not always received, making it difficult or impossible to prove its properties in the majority of circumstances. Accuracy may be compromised as a result, because fuzzy logic can function with accurate and imprecise data. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth, truth values between "completely true" and "completely false".

The advantage of MAFS over TSKFS is that it can be used directly in both Multi-input-single-output (MISO) and multi-input-multi-output Multi-input-multi-output (MIMO) systems, whereas TSKFS can only be utilised in MISO systems. MAFS is a more widely used system, particularly in applications requiring decision assistance, owing to its intuitiveness, ease of interpretation of the rule base, and ability to produce understandable results. As the right system was selected, the quality of the rules also needs to be discussed. To define the rules, input from experts is required, but can coaches span all nuances of the rules? Thus, it is important to spend quality time when creating the FIS and test the system in different occasions. While creating the FIS two problems were encountered, dimensionality and scalability. Dimensionality refers to the fact that algorithms are more difficult to build in high dimensions and their running times are often exponentially proportional to the number of dimensions. Although a higher number of dimensions theoretically allows for more information to be saved, in practice it is rarely beneficial due to the high likelihood of noise and redundancy in real-world data. Scalability refers to the size of the FIS. Is it feasible to build a system which will cover all the different cases? In addition, financial aspects need to be taken into consideration in the final decision.

It is worth noting the importance of analysis bias which can occur when the coach analyses the performance with a formed hypothesis about the athlete and, therefore, could interpret the results to confirm the pre-made decision. There are several methods to avoid bias in the analysis when reviewing the data such as multiple coaches making the decisions together or using additional data from physical tests.

Future development of this model could include data from a different sport or multi-sport modelling including movement of athletes. The model could be extended by competitive studies of strength/weakness not only for a physical aspect, but to include the mental state of the athlete. Mental models may provide natural sequels of the performance analysis. Further, eye tracking of the athlete during video analysis could provide additional insights.

Finally, Esports are becoming more popular and will potentially be part of the Olympics. Esports offers a great opportunity from a data collection perspective, monitoring, and evaluating the players as they can be fully observed without having a physical impact on the player. Both

Esport and sport performance analysis could work together with a common analysis to uncover important performance factors in both fields.

8

Conclusion

The main objective of this study was to analyse the decision making method used to improve sport performance analysis and model layout by implementing fuzzy logic. The objective of developing fuzzy decision support systems was achieved. The mathematical methodology for the sport performance analysis in badminton used the fuzzy approach based on the Mamdani–Assilan and Takagi–Sugeno–Kang fuzzy system theory. Consequently, fuzzy inference systems for sport performance analysis in badminton were optimised.

This study aimed to answer the following research questions: How did the performance analysis methods change over time within racket sports 6? Is the observation method the most frequently used in performance analysis 6? Is there a correlation between the number of publications regarding performance analysis and the Summer Olympics 6? Would a variety of authors influence performance analysis research 6? How can performance analysis be achieved using Mamdani-Assilan 6.3 or Takagi-Sugeno-Kang 6.5 fuzzy approaches? What is the best optimisation strategy for performance analysis 6.6? Are models transferable to the open source software Octave Fuzzy Logic Toolkit 6?

A theoretical task was to create a comprehensive description of fuzzy inference systems, which uses a rule base to decide or make an inference from the output of the system. These systems are the core of appropriate type of fuzzy regulator, which is used as a replacement to expert knowledge of the relevant problem by inference system for data with uncertainty. Section 4 describes the methodology used to create the most common types MAFS and TSKFS including the full description of fuzzy theory, including a section on fuzzy system creation for both MAFS and TSKFS showing differences between them and the steps of processing data in fuzzy system – fuzzification, creation of the rule base, membership function, and defuzzification. Data collection is described in this section as well as the annual plan creation, including the decision-making process.

To analyse methods used for the analysis of athlete performance. The section 5 provides a deep analysis of the literature and highlights the gaps for development. Multiple topics such as which performance data are analysed, which tools are used for analysis, which methods are used for analysis, and which software is used for analysis are covered. Interestingly, only a few studies have evaluated performance prediction, including the career path of athletes. A summary of performance methods for selected sports is described in 5.2. Keyword analysis is provided as important addition to the theoretical section.

The findings are presented in 6. An schematic diagram 6.1 of a plan undertaken by athletes as a result of the discussion with coaches is provided. Section 6.1 describes a process of creating fuzzy inference systems, including the results of fuzzy input selection. The results of creating MAFS and TSKFSs are stated in 6.3 and 6.5, including the evaluation and optimisation section in 6.4. The advantages of fuzzy logic have been added into the decision of the analysis of athlete performance. The best results shown in chapter 6.6 were achieved using optimised TSKFS, which fulfil the coaching requirements of the analysis of athlete performance. Using this proposed strategy to inform tournament planning for an athlete is straightforward as the model allows dynamic changes. If a player is injured during the season, you can still adjust your strategy for selecting which tournaments to enter (entry deadlines are typically around a month before the tournament), allowing the player to recover. You can interact with the model in real time and modify the rules. It enables precise simulation of the conditions of the opponent and provides the coach with a realistic assessment of the situation. It enables coaches to make more precise decisions based on both historical and real-time data. The results will allow decision makers to express their judgements significantly more effectively when they use language rather than when they represent them in terms of precise numerical values. When there is a scarcity of evidence data or when the data values are rapidly changing as a result of changes in the environment, the fuzzy approach should be used to make decisions. The use of fuzzy logic can make the development and implementation of software much easier. It does not necessitate the use of complex mathematical models, but the application of actual knowledge to the entire system behaviour. Fuzzy logic mechanisms have thus the potential to improve accuracy while also providing smoother control.

Section 7 provides an evaluation and relevance of the proposed models, including potential extension using data from different sports or even Esports data. Numerous large-scale performance analysis challenges cannot be resolved with simple yes/no or black/white programming responses. Considering that responses can occasionally be ambiguous, fuzzy logic offers better application. The overall advantages of the proposed model are addressed in the discussion. The difference between MAFS and TSKFS is also discussed in this section. In summary, fuzzy logic deals with imprecision or uncertainty by associating multiple metrics of propositional credibility.

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Author’s publication in an IF or SJR journal

Karel Kolář, Rafael Doležal, Natálie Karásková, Nadezhda V Maltsevskaya, and Šárka Křížková. Molecular models in chemistry education at university and upper secondary school-structure of amides. *Chemistry-Didactics-Ecology-Metrology*, 24(1-2):45–51, 2019. ESCI, SJR = 0.13 (Q4).

Šárka Křížková, Hana Tomášková, and Erfan Babaee Tirkolaee. Sport performance analysis with a focus on racket sports: A review. *Applied Sciences*, 11(19):9212, 2021. IF = 2.679 (Q2/Q3), SJR = 0.435 (Q2).

Author's publication in the conference's indexed proceedings

Ondřej Doležal, Hana Tomášková, Šárka Křížková, and Martin Kopecký. Analysis and optimization of processes using process mining with a focus on sport. In *Conference proceedings of 22nd Conference of the International Federation of Operational Research Societies (EURO IFORS 2020), South Korea*, 2020 (accepted). Due to a pandemic, the conference has been canceled.

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Šárka Křížková and Martin Gavalec. Marketing campaign performance measurement by return of investment: A fuzzy set approach. In *Conference proceedings of the 30th European Conference on Operational Research. Ireland*, 2019.

Šárka Křížková and Martin Gavalec. Fuzzy performance analysis for determining marketing strategies. In *Conference proceedings of 22nd Conference of the International Federation of Operational Research Societies (EURO IFORS 2020), South Korea*, 2020 (accepted). Due to a pandemic, the conference has been canceled.

Šárka Křížková and Hana Tomášková. Fuzzy approach for evaluation bank's client. In *27th International Business Information Management Association Conference*. Int Business

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Hana Tomášková and Šárka Křížková. Process analysis in sport. In *Conference proceedings of 22nd Conference of the International Federation of Operational Research Societies (EURO IFORS 2020), South Korea*, 2020 (accepted). Due to a pandemic, the conference has been canceled.

A summary of the published works and project collaborations of the author

A summary of the author's published works:

	publications	h-index	Total number of citations
Scopus	3	1	6
WoS	5	1	5
Google Scholar	3	1	9

Participation in projects:

Grant Agency of Czech Republic

2015–2016

GA14-02424S	Member	Operational research methods for decision support in conditions of uncertainty

2017–2020

18-01246SS	Member	Non-standard optimisation and decision-making methods in management processes

Student specific research projects FIM UHK

2017	Member	Autonomous socio-economic systems
2018	Member	Socio-economic models and autonomous systems
2019	Member	Socio-economic models and autonomous systems 2
2020	Member	Socio-economic models and autonomous systems 3