Research Square

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Fuzzy Logic Designer: A Proposed Model to Predict Performance Time of Sprinting Athletes

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Research Article

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Abstract

Background

A new model, called hereafter the Fuzzy Logic Designer, is presented that is capable to predict performance time of sprinting athletes. The proposed model employs Mamdani approach, one of the most popular fuzzy logic techniques.

Material and methods

As inputs the present model takes three important body composition parameters namely appendicular lean mass, body fat mass and skeletal muscle mass, and depicts performance timing of the sprinters as outputs. Each input has three Gaussian-type membership functions.

Results

As a test case the predicted results by our model are compared with the performance in 100m sprinting of university level athletes, and found a overall good agreement with the measured data. Our proposed model provides a smarter way to explore the interplay between body composition and performance timing of the sprinters.

Conclusions

These findings will contribute knowledge about sprinters body composition and may have implications for athlete-specific training, performance improvement and nutrition strategies.

Introduction

Sprinting ability is crucial for success in many sports. In athletics, there are two main sprinting events: the 100m and the 200m run. The 100m is widely regarded as the most impressive athletic event at major championships [1]. The sheer pace of the 100m race allows the winner to claim to be the fastest runner in the country or the globe [2]. The 100m sprint in the Olympics and World Championships, therefore, holds a special place in the hearts of sports fans throughout the world [3]. In the context of the 100m sprint, an athlete experiences different phases of speed. However, the sprinter's success is ultimately determined by the least time spent to complete the race [4]. Current breakthroughs in sports science suggest that there is a considerable correlation between an athlete's body composition and their performance time [5–7]. By evaluating the relationship between body composition and performance.

in 100m sprinters, we developed a new model, known as the fuzzy logic designer (FLD), for predicting athletes' performance times in sprinting.

The idea of fuzzy sets [8], introduced by Zadeh in 1965, has been successfully ap- plied such a wide range of fields as social modelling and simulation [9], agent-based simulations [10], and physical and engineering sciences [11]. Fuzzy logic offers a strong structure for managing the lack of clarity and imprecision in human thinking and decision-making procedures. Mamdani systems, one of the most prominent fuzzy logic techniques, have recently emerged as a powerful tool for function approximation and control. Mamdani inference is utilized in fuzzy control and other domains, including management and finance [12], economics [13], risk assessment [14], and education quality measurement [15].

Fuzzy logic's success is dependent on its capacity to represent and comprehend perceptions rather than measurements [16]. As opposed to conventional binary logic, which categorizes variables into distinct true or false states, fuzzy logic allows for varying degrees of truth, making it particularly useful in the analysis of complex, real- world phenomena such as the performance of athletes [17]. By utilizing a fuzzy logic methodology, researchers may enhance the modeling of these interactions and acquire deeper understanding into the influence of slight differences in body composition on sprinting performance [18]. This strategy improves the accuracy of performance pre- dictions and training optimizations, taking into account the individual diversity among athletes and connecting the divide between theoretical research and practical sports application [19, 20].

Our proposed model, FLC adopted Mamdani approach by employing three impor- tant body-composition parameters: appendicular lean mass (ALM), body fat mass (BFM), and skeletal muscle mass (SMM) as inputs. Physical fitness and athletic per- formance are intricately linked to the aforesaid parameters [21, 22]. The predicted model data are well tuned with the actual data measured for the champion team in the Bangladesh Inter University Athletic Championship 2022. To the best of our knowledge, this is the first time fuzzy logic has been used in Bangladesh to analyze athlete performance. We believe that this study will inspire further modeling research in sports science.

The paper is organized as follows. Section 2 describes the overall design of the fuzzy rules employed in our proposed model. Section 3 outlines the simulation approach, Section 4 displays some experimental data used to validate the model prediction, and Section 5 summarizes the work's conclusions and offers further work and outstanding topics.

FLD Model

The proposed FLD model is presented in Fig. 1. This model is designed to estimate the performance times of 100m sprinters. The model is built around four key modules: the rule base, the inference engine, fuzzification, and defuzzification [23]. Our model requires three inputs: ALM, SMM, and BFM. Each input is characterized by three linguistic variables: good, moderate, and poor. The output, or performance time, is also described by three linguistic variables: competent, average, and below average. Figure 2 depicts our FLD model's input and output variables, along with their membership functions. All linguistic variables are represented using Gaussian membership

functions. In this study, we adopt the Mamdani approach to develop our FLD for performance prediction. For the defuzzification process, we employ the centroid method to convert the fuzzy output into a crisp value [24].

The current technique has 27 active rules. The total number of rules equals the product of number of functions accompanied by the input variables in their working range [25]. The inference engine contains eight AND operators that pick minimum value input for the output. This inference engine applies the min-max composition method to obtain the output values. The min-max inference method performs a min AND operation between the three inputs [26]. The eight fired rules are listed in Table 1.

Results and Discussion

We evaluated two distinct testing samples, ID-5 and ID-8 [27, 28], to illustrate the predictive power of our model. Fig. 3 illustrates the rule views for these two samples,

Table 1. Eight fired rules employed in our present FLD model.

Rule	ALM	SMM	BFM	Performance-time
Rule-1	good	good	good	competent
Rule-2	good	moderate	poor	below average
Rule-3	good	poor	good	competent
Rule-4	moderate	moderate	moderate	average
Rule-5	moderate	moderate	poor	average
Rule-6	poor	good	good	competent
Rule-7	poor	moderate	good	average
Rule-8	poor	poor	poor	below average

Abbreviation: ALM= appendicular lean mass; SMM= skeletal muscle mass; BFM= body fat mass

demonstrating how fuzzy logic rules are used to estimate their performance timings. Figs. 4 and 5 provide a comprehensive visual representation of the surface views for each testing sample. These figures display the three-dimensional relationships between the pairs of input variables and their output. By examining these surface views, we can see how changes in ALM, SMM, and BFM effect the expected performance time. The prediction of our fuzzy model, based on the ALM, SMM, and BFM of each participant presented in Table 2, corresponds closely to the original 100m sprints performance timings [28]. The sprinter's original performance time had a maximum difference of 16.22% and a lowest difference of 2.80% compared to the predicted performance time.

Conclusion

This research describes a new model, FLD, that uses the Mamdani technique to forecast sprinter performance times. This model makes use of three crucial body composition indicators, ALM, BFM, and SMM, which are inextricably linked to an athlete's fitness and performance level. Our proposed fuzzy approach offers a more

Table 2. Comparison of the performance-time predicted by our FLD model with those of measured data.

Sprinter	Sex	Measured [a]BCP [27]			Performance-time (sec)		Error
ID		ALM	SMM	BFM	Measured [28]	FLD predicted	(%)
1	Male	18.4	22.9	3.7	12.41	13.6	9.59
2	Male	23.8	27.4	11.2	12.39	14.4	16.22
3	Male	22.4	25.6	9.9	12.35	14.2	14.98
4	Male	23.4	27.1	9.8	12.26	14.2	15.82
5	Male	25.6	28.6	7.2	12.11	12.8	5.7
6	Female	15	17.7	11.4	15.37	15.8	2.8
7	Female	15.4	19.7	7.5	16.52	15	9.2
8	Female	15.7	18.6	9.9	16.02	15.4	3.87

Avriviation: [a]BCP=body composition parameter.

intelligent way to forecast sprinter performance time by investigating the relationship between body composition and athlete performance in the 100m sprint. The anticipated data is compared to the performance time measured for the winning team in the Inter University Athletic Championship 2022 in Bangladesh. With a few exceptions, the projected findings are in good agreement with the measured data. This simple model is designed to offer coaches, athletes, and researchers with a better knowledge of the precise relationship between body composition and sprinting efficacy, ultimately improving athletic outcomes and training approaches. More research is needed to determine the efficacy of our model. Our future objective is to generate more data while reducing error by increasing our model's logical inputs.

Abbreviations

FLD
Fuzzy logic designer
ALM
Appendicular lean mass
BFM
Body fat mass
SMM
Skeletal muscle mass
[a]BCP=body composition parameter

Declarations

Ethics Approval and Consent to Participate

The study protocol was approved by the ethical committee of the Institute of Biological Sciences, Rajshahi University, Bangladesh (No: 72(22)/320/IAMEBBC/IBSc). All procedures were conducted in accordance with the declaration of Helsinki for human studies of the World Medical Association.

Written informed consent was obtained from all participants prior to participation in the study.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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This research received no external funding.

Clinical trial number: Not applicable.

Authors' Contributions

Al Azim (AA) conceived and designed the study, conducted data collection and analysis, and drafted the manuscript. Jakir Hossain (JH) contributed to data collection and interpretation. Tamanna Tasnim Prova (TTP) assisted in data analysis and manuscript preparation. M M Haque (MMH) supervised the study and critically revised the manuscript. All authors read and approved the final manuscript.

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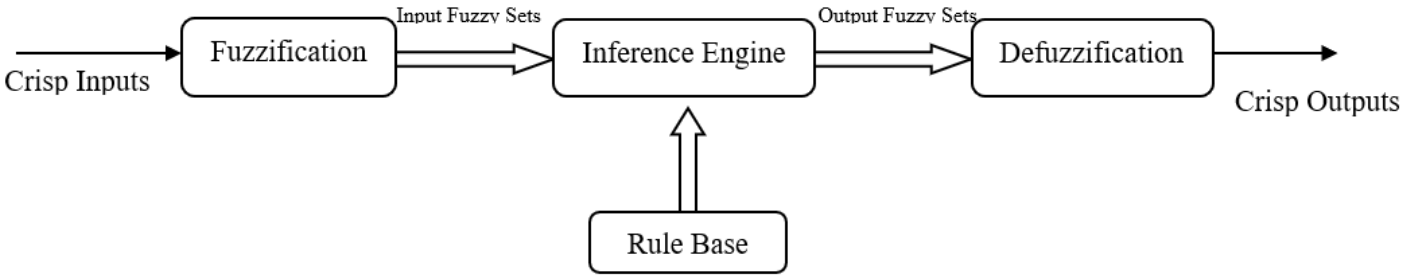
The authors sincerely thank all participants for their valuable contributions to this study, and special appreciation to the Department of Physical Education and Sports Science at the University of Rajshahi for their support.

References

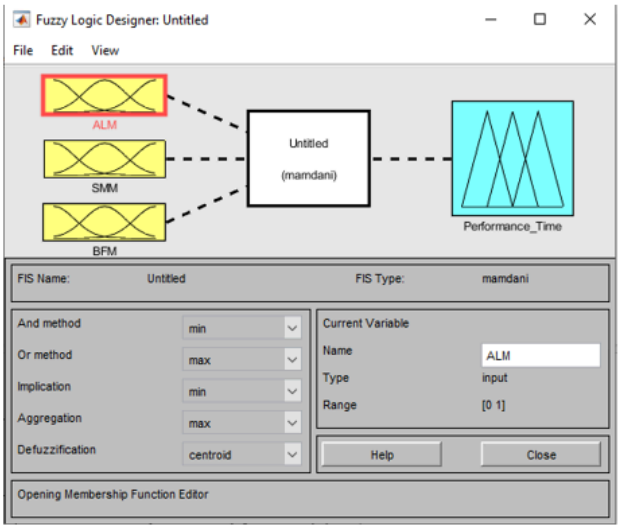
1. Majumdar, A. S. and Robergs, R. A. (2011). The science of speed: Determinants of performance in the 100 m sprint. International Journal of Sports Science & Coaching, 6(3), 479-493.
2. Bru¨ggeman GP, Koszewski D, Mu¨ller H. Biomechanical Research Project Athens 1997. Meyer and Meyer Sport, Oxford, 1997, 26.
3. Davis, J. A. (2012). The Olympic Games effect: How sports marketing builds strong brands. John Wiley & Sons.
4. Majumdar, A. S. and Robergs, R. A. (2011). The science of speed: Determinants of performance in the 100 m sprint. International Journal of Sports Science & Coaching, 6(3), 479-493.
5. Enroth, M. (2020). 100-meter sprint running: event analysis and programming of training and coaching.
6. Furrer, R., Hawley, J. A. and Handschin, C. (2023). The molecular athlete: exercise physiology from mechanisms to medals. Physiological Reviews.
7. Sauzier, R. F. E. G. (2022). Exploring discourses of masculinity within women track athletes' lives in South Africa (Master's thesis, Faculty of Humanities).
8. Feilich, K. (2015). Elite sprinters push forward. Journal of Experimental Biology, 218(21), 3350-3350.
9. Ragin, C. C. and Pennings, P. (2005). Fuzzy sets and social research. Sociological Methods & Research, 33(4), 423-430.
10. Izquierdo, L. R., Olaru, D., Izquierdo, S. S., Purchase, S. and Soutar, G. N. (2015). Fuzzy logic for social simulation using NetLogo. Journal of Artificial Societies and Social Simulation, 18(4), 1.
11. Arfi, B. (2010). Linguistic Fuzzy Logic Methods in Social Sciences. Berlin/Heidelberg: Springer.
12. Bojadziev, G. (2007). Fuzzy Logic for Business, Finance, and Management. River Edge, NJ: World Scientific.
13. Stoji´c, G. (2012). Using fuzzy logic for evaluating the level of countries' (regions') eco- nomic development. Panoeconomicus, 59(3), 293-310.
14. Nait-Said, R., Zidani, F. and Ouzraoui, N. (2008). Fuzzy risk graph model for determin- ing safety integrity level. International Journal of Quality, Statistics, and Reliability, (p. Article ID 263895)
15. Vald´es-Pasar´on, S., M´arquez, B. Y. and Gaxiola, L. (2011). Knowledge and data engineer- ing for analyzing the quality of education using fuzzy logic. In X. Wan (Ed.), Electrical Power Systems and Computers, (pp. 567-573). Berlin/Heidelberg: Springer.
16. L. A. Zadeh. From computing with numbers to computing with words - from manipulation of measurements to manipulation of perceptions. IEEE Transactions on Circuits and Systems - I: Fundamental theory and applications, 45(1):105–119, 1999.
17. Lim, C. H., Vats, E., and Chan, C. S. (2015). Fuzzy human motion analysis: A review. Pattern Recognition, 48(5), 1773-1796.
18. Afandi, M. A. M., Mohamad, N. I., Fazila, N., Malek, A., Chinnasee, C., and Nadza- lan, A. M. (2021). The Relationship between Core Strength Performance with Sprint Acceleration. In Journal of Physics: Conference Series (Vol. 1793, No. 1, p. 012056). IOP Publishing.
19. Guan, S., and Wang, X. (2022). Optimization analysis of football match prediction model based on neural network. Neural Computing and Applications, 34(4), 2525-2541.
20. Subramaniam, S., Shankar, M. R., Zazali, A. A., Swin, H. S., Muhamed, Z. et al. (2023). A Survey of Evolving Performance Analysis Technologies, Algorithms and Models for Sports. International Journal of Advanced Computer Science and Applications, 14(9).
21. Kumar, D., Nara, K. and Dhull, S. (2023). The advantage and disadvantage of body composition on athletic success: A kabaddi player perspective. Methods, 1, 19.
22. Almeida-Neto, P. F. D., de Medeiros, R. C. D. S. C., de Matos, D. G., Baxter-Jones, A. D., Aidar, F. J., de Assis, G. G. et al. (2021). Lean mass and biological maturation as predictors of muscle power and strength performance in young athletes. Plos one, 16(7), e0254552.
23. Sivanandam, S. N., Sumathi, S., Deepa, S.N., "Introduction to Fuzzy Logic using MAT- LAB", Springer, 2007.
24. Lu, S., Pei, J., Liu X. and Parados, M.P. (2020). Robust Parallel- batching scheduled with fuzzy deteriorating processing time and variable delivery time in smart manufacturing. Fuzzy Optimization and Decision Making, 19, 333-357.
25. Berthold, M., Hand, D. (2006), Intelligent Data Analysis, Second Edition, Springer-Verlag, Heidelberg.
26. D. K. Prathihar (2013). "Soft Computing:fundamentals and Applications"; Alpha Science International, Ltd;ISBN: 1842658638

27. Azim A, Hossain J, Ceylan HI, Muntean RI, Haque MM. Unlocking the Fast Track: Exploring the Interplay between Body Composition and Athletes' Performance in the 100 m Sprint. Motricidade. 2025 Oct 31;21:e40642-.
28. Jakir Hossain, Al Azim and MM Haque. Kinetics and kinematic analysis of different phases in 100m sprints. International Journal of Physical Education, Sports and Health 2024; 11(3): 183-190.

Figures



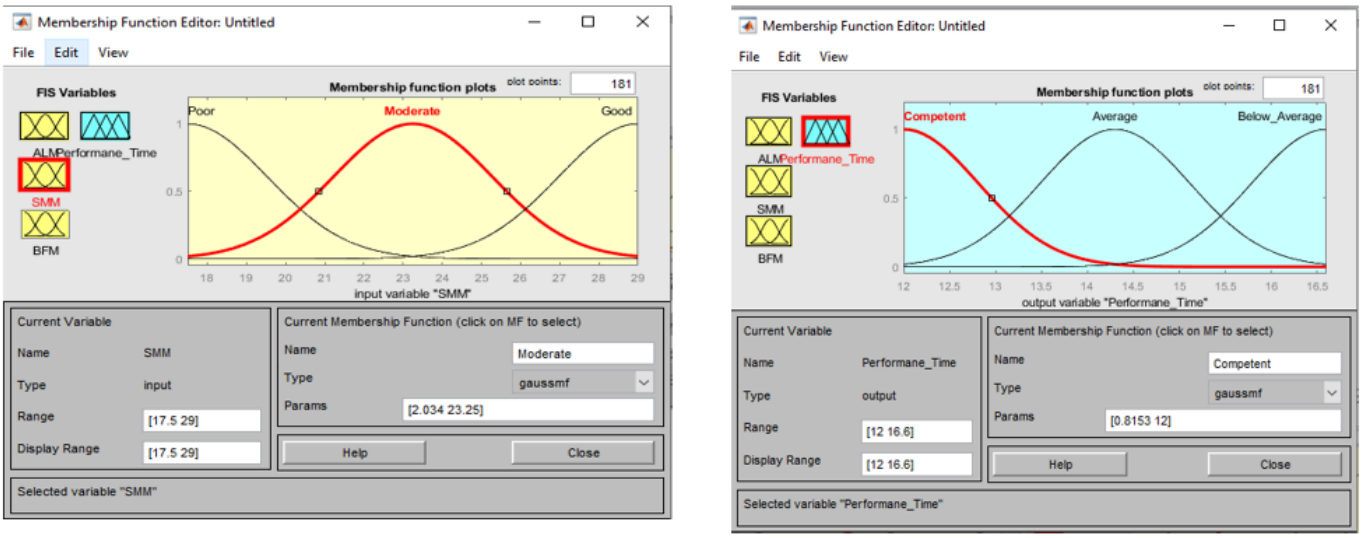
(a) Block diagram of our FLD model.



(b) Interference engine of our FLD model.

Figure 1

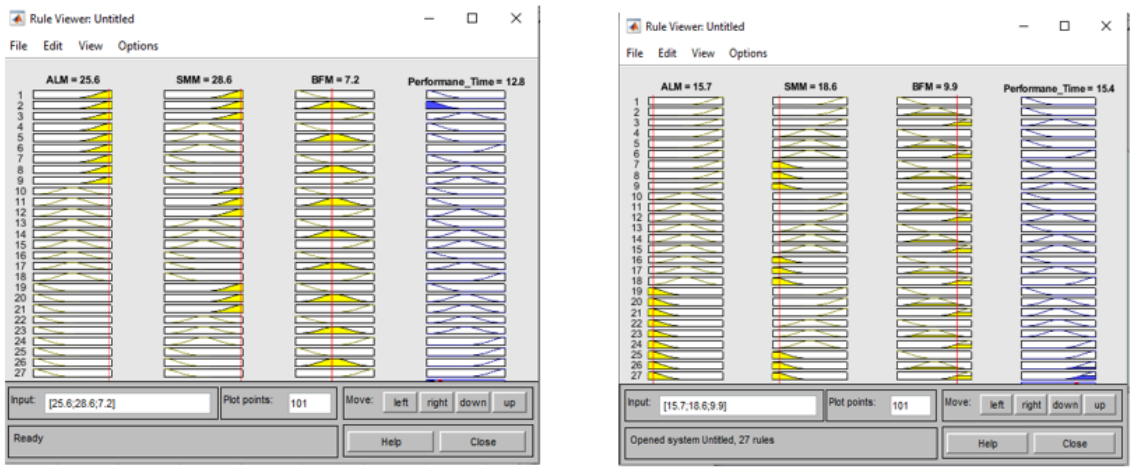
Proposed FLD model designed for predicting athlete's performance-time in 100m sprint.



(a)Input variables with its member- ship functions. (b)Output variables with its member- ship functions.

Figure 2

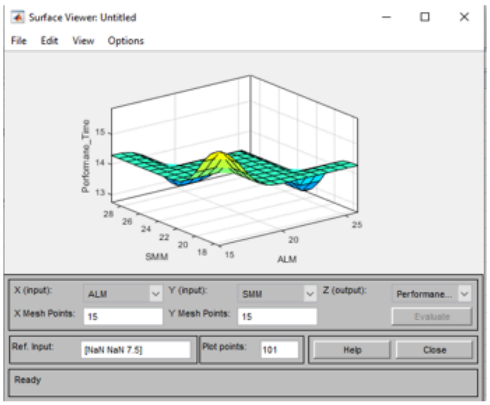
A typical input and output variables with its membership functions of our proposed FLD model.



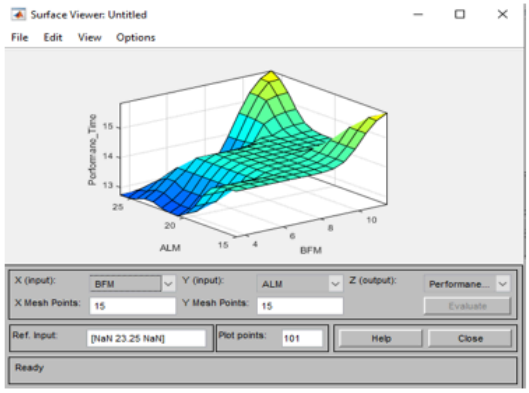
(a) For Sprinter ID-5. (b) For Sprinter ID-8.

Figure 3

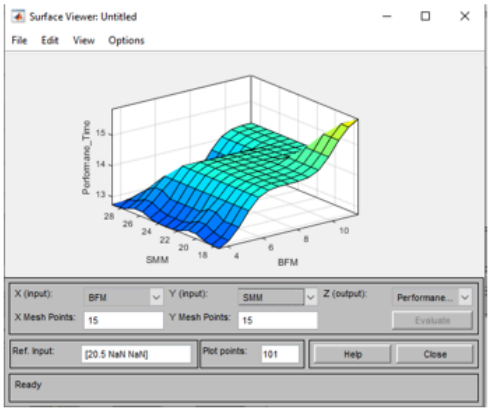
Fuzzy logic rules applied in our FLD model to predict sprinter's performance times.



(a) Surface View of ALM and SMM.



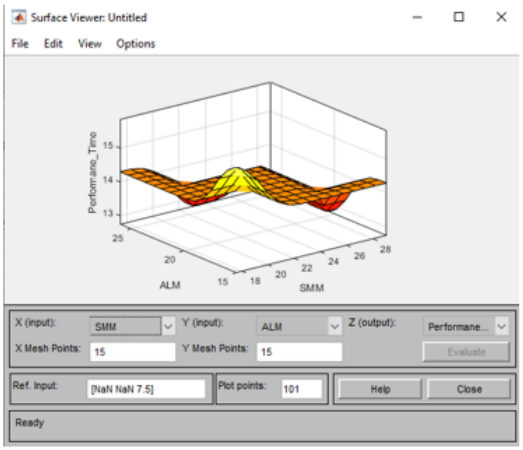
(b)Surface View of ALM and BFM.



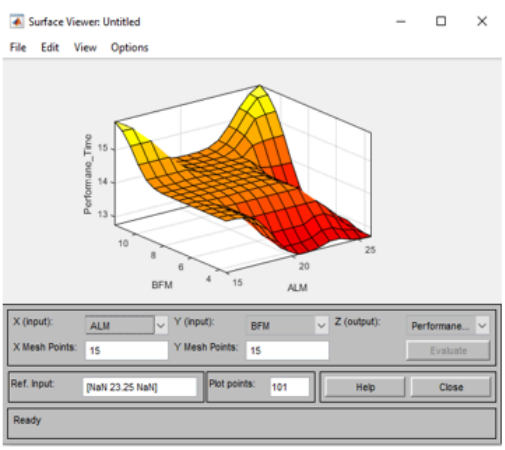
(c) Surface View of SMM and BFM.

Figure 4

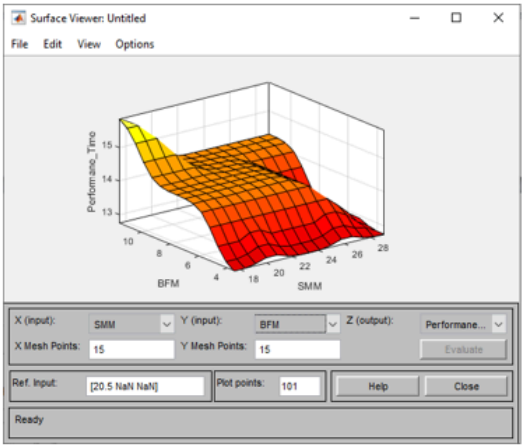
3D representation of relationships between the pairs of input variables simulated for sprinter ID-5.



(a) Surface View of ALM and SMM.



(b) Surface View of ALM and BFM.



(c) Surface View of SMM and BFM.

Figure 5

3D representation of relationships between the pairs of input variables simulated for sprinter ID-8.