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Predicting Intravenous Fluid Resuscitation Rate for Burn Patients Through Type-1 Mamdani Fuzzy Inference System Modeling

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Abstract

Clinical decision-making, in most of the cases, is convoluted, perplexing, and critical, and becomes more delicate in case of burn patients where specialized healthcare services are required. In an emergency situation, various factors are needed to be considered within a limited time bound to take pivotal decision, such as the rate of replacement of the bodily lost fluid due to burn. In such circumstances, a computer-aided intelligent clinical support system is doubtlessly useful to make intuitive decisions in a shortest possible time, where a fuzzy inference model (FIS) may lead to the solution. In this study, an improved FIS-based fluid resuscitation model is proposed for burn patients, where the rate of required fluid revitalization is determined intelligently. The goal of this study is to suggest an assistive model for the physician in making a quick decision for intravenous fluid rate (IFR) adjustment depending on the percentage of total body surface area (%TBSA) burned and hourly urine output (HUO) measurements in burn patients. To attain the objective, the proposed FIS model is introduced with the %TBSA and HUO as input variables and IFR as the output variable of the system. These two inputs are considered in this research due to their foundational role in classical calculations, as all existing formulas are derived from them. This study also conducts a comparative analysis among various defuzzification methods for various membership functions to determine the best possible model. The simulated results ensure the viability of proposed model for practical experimentation where centroid of area with Gaussian membership function is recommended. Furthermore, the problems of traditional estimation of IFR such as discrete rate of fluid injection and abrupt shift (≈ ±20%) of IFR level depending on the variations of HUO would be resolved by the proposed FIS model, resulting in a smooth and continuous adjustment of IFR. Nevertheless, the proposed design shows significant improvements in determining IFR, as validated through benchmarking.

Categories: AI/ML-based decision support systems, Fuzzy Logic, Medical recommender system
Keywords: decision support system, fuzzy inference system, fis, fluid resuscitation, burn patient, %tbsa, huo

Introduction

Nowadays, digital technologies and artificial intelligence (AI) are empowering the clinical research, applied sciences, cognitive medical devices, assistive systems, and decision support intelligence [1-5]. Clinical decision-making is considered a critical field of study as it typically involves complex trade-offs, uncertainties, information overload both in quantitative and qualitative, decisions on future consequences, interrelated behaviors, and statistical dependencies [6,7]. Thus, during an emergency, it can be extremely difficult for individuals to make critical decisions in the shortest possible time [8]. A computer-based intelligent clinical support system usually incorporates medical specialists' expertise with computer programs simultaneously to accumulate information automatically in assisting a clinician intelligently [8,9].

Administering intravenous (IV) fluids is a vital therapeutic intervention for restoring lost body fluids caused by various conditions, and it has become a nearly universal practice for critically ill patients [10]. Fluid therapy is regarded as crucial in managing cases with burns, hemorrhagic shock, sepsis, and other various life-threatening conditions; therefore, more than 30 million individuals get IV fluid per year [11]. Burn fluid resuscitation originated in 1921 through the administration of liquids and electrolytes in preventing fatalities from such injuries [12]. A patient with burn injury may experience the combination of hypovolemic and cellular tremor, due to the pathophysiological responses triggered by the trauma [9]. In such cases, the correct amount of fluid resuscitation is vital to maintain optimal fluid levels in the body, as both under-resuscitation and over-resuscitation can be life-threatening for burn patients, leading to conditions such as hypovolemic shock or fluid overload [9,13]. The current practice in hospitals generally involves manual fluid resuscitation based on different formulas and standards, which may lead to human errors producing poor results in case of burn treatments [14,15]. To handle such situation, AI-enabled decision support for burn fluid resuscitation could be very beneficial. Classical machine learning-based or deep learning-based solution requires historical data and involves training overheads and computational complexities. To overcome these problems, a fuzzy-based system would be a better choice [16]. This research develops a fuzzy model that uses two inputs, the percentage of total body surface area burned (%TBSA) and the victim's hourly urine output (HUO), to continuously and adaptively estimate the total intravenous fluid restoration rate (IFR) required within 24 hours of burn injury.

Since the fuzzy system operates without the need for prior training, it minimizes computational overhead [17,18]. Most importantly, it imitates human reasoning demeanors of combining information from a range of partial facts to prepare corresponding results [1,19]. This research primarily aims to develop a fuzzy model that reliably predicts IFR, aiming to solve the problem of over-resuscitation or under-resuscitation. The two parameters, %TBSA and HUO, are the fuzzy input variables, where the system incorporates various design of membership functions (MFs) with knowledge base to determine the required IFR. The improved design of the MFs has significant effect in predicting the appropriate rate of resuscitation as demonstrated through benchmarking. The proposed design also has potentials in developing a computer-aided support system to enhance the error free decisions-making.

Materials And Methods

Background of the study

IV fluid restoration in critically ill patients is a routine procedure, where patient survival largely depends on the accurate regulation of the IFR [20]. Fluid resuscitation can be employed in various conditions, like a patient having severe sepsis or septic shock with severe kidney injury, where stabilizing the fluid rate in the body is essential [21]. Fluid resuscitation therapy is another widely practiced and common treatment for managing burn shock. The primary cause of burn shock is the loss of red blood cells and plasma through the injury area. In treating and preventing burn shock, the logical approach involves replenishing lost fluids in adequate amounts to maintain optimal blood flow to the kidneys, liver, and importantly the brain [22]. There is substantial clinical evidence showing that with a stable IV fluid intervention, a patient can successfully be revived from the trauma associated with extreme burns [23]. Conversely, fluid underload or overload due to skewed IV fluid therapy may lead to various organ dysfunctions, such as cerebral edema and hepatic congestion. To minimize the risk of complications associated with this potentially life-saving treatment, it is essential to accurately maintain the rate of IV fluids [13].

Clinical treatment of revitalizing bodily lost fluids due to perspiration, bleeding, fluid changes, or other pathological processes with an aim to increase cardiac output with an improved organ mechanism is known as fluid replacement therapy or IV fluid resuscitation [24]. The IFR should be measured accurately, monitored carefully, and adjusted timely based on the necessities of the critically ill patients. The measurement and adjustment of IFR depend on various factors and methods of calculations. One of the recent approaches to IFR is the World Health Organization Technical Working Group on Burns (WHO-TWGB) method, which commends administering 100 ml/kg/24 hours (orally or intravenously), for adults with over 20% of surface burn [25]. The current consensus guidelines recommend 2-4 ml/kg/%TBSA (Evans and Brooke formula: 2 ml/kg/%TBSA; Parkland (Baxter) formula: 4 ml/kg/%TBSA) [25-28]. Another formula called the rule of 10 recommends 10 ml/h/%TBSA plus 100 ml/h for each 10 kg above 80 kg body weight [25]. For children, Galveston formula is commonly used that recommends 5000 ml/m^2 body surface area (BSA) burned per 24 h plus maintenance fluids 2,000 ml/m^2 BSA/24 h [25]. In continuous IFR, the calculated volume of fluids is used at the same rate for 24 hours. On the other hand, variable IFR such as Parkland formula says that 50% of the calculated fluid is required to be provided throughout the initial 8 hours post-burn and the residual fluids should be used within the rest 16 hours [25,28]. During the resuscitation or fluid infusion process, the targeted volume of urine output (0.5 ml/kg/h or 30-50 ml/h) should be achieved, otherwise a significant accumulation of fluid in the body can lead to fluid creep or scarcity of fluid inside the body may cause hypovolemic shock [28].

The mostly used parameters to determine the IFR for the fluid resuscitation of burn patients are %TBSA and HUO. To calculate the IFR, one of the available formulas is the Parkland Formula, established by Dr. Charles Baxter [29]. This formula suggests that most burn cases can be effectively resuscitated by administering 3.7-4.3 ml of Ringer's lactate (a solution containing calcium chloride, potassium chloride, sodium chloride, and sodium lactate in water for IV use) per kilogram of total body weight per percentage of body surface burned during the initial 24 hours following a severe burn injury [29,30]. On the other hand, the American Burn Association suggests using 2-4 ml per kilogram of patient's total body weight per percentage of total BSA to calculate the IFR with the consideration of patient's HUO [31]. In such cases, generally the half of the measured volume is injected in the initial 8 hours of post-burn, and the rest is injected during the next 16 hours. The MC Govern Medical School of the University of Texas suggests that the adult burn victims' resuscitation should be standardized with the careful analysis of the urine output along with %TBSA burn [26].

Recent research of fluid resuscitation focuses to improve the available formulas to elude the complications of over-resuscitation and under-resuscitation situations. This entails the development of innovative resuscitation approaches, such as computer-assisted clinical decision support systems (CDSS), to expedite decision-making on IFRs [4,13,32]. For instance, Salinas et al. [33] outlined a decision-aid protocols featuring a system with closed-loop feedback. This system uses computerized feedback mechanism to automate the IV fluid infusion management. The approach enables precise titration and improved regulation of urinary output.

Another study by Salinas et al. [34] applied the burn protocol algorithm in a computerized open-loop support system focusing on 35 patients having over 20% of surface area burned. The results indicated that using the automatic decision support for burn intervention in the critical care unit led to a better-quality fluid management for critically burned cases, achieving more consistent hourly urination target. Chen et al. [35] also demonstrated a decision support model using information systems that provides suggestions for the volume of injected fluid depending on assessed biological reaction. The results discovered that treatments using the proposed support system significantly lowered down the fatality rates, prolonged ventilation-free periods, and increased ICU-free days compared to those receiving conventional fluid therapy.

One study has experimented a fuzzy logic-based medical decision-making model related to fluid resuscitation in the ICU [36]. The developed model outputs the IFR based on the inputs as average blood pressure in arteries and hourly urination. Applying such AI-enabled system in critical decision-making would surely be beneficial as the dynamics of the disease and patient features with variety of data increase the challenges in identifying the exact needs for every imaginable combination in many cases [37].

Though a lot of research on CDSS for fluid resuscitation is being conducted recently in various perspectives, very few studies are found that consider both %TBSA and HUO as input parameters for predicting IFR of burn patients based on AI-enabled systems, especially the fuzzy inference model. So, it becomes apparent that the Fuzzy Inference System (FIS) model could be a notable strategy for such kind of decision support systems. Moreover, the majority of literature highlights the efficacy of the simple Mamdani FIS model, demonstrating acceptable prediction efficiency. Comparisons of some existing and relevant literatures are presented in Table *1*.

Ref.	Objectives	Testing	Methods used	Outcomes	Limitations
[15]	To design FL-based automated resuscitation model	For burn patients	Mamdani FIS with %TBSA and HUO as inputs and IFR as output	A controlled method for fluid resuscitation	Simplified design with moderate number of MFs affecting precise measurement
[33]	To investigate the pertinence of closed-loop control	Tested on animals (dog)	Classical control (PID)	Accurate monitoring of fluid in and urine output	No controlled trials on clinical application
[34]	To utilize an open-loop decision care system based on the burn protocol computation method	39 medical cases with >20% TBSA burns	Curve fitting algorithm applied on infusion and urine output	A better fluid management	Statistical method is applied considering a fixed value of HUO
[35]	To design a DSS using IT & decision support technology	Tested on burn patients	Model based on assessed biological reaction	A better fluid management	Single parameters and linear models do not meet the scientific treatment requirement
[36]	To design FL-based automated system	ICU patients	Mamdani FIS with MAP and HUO as inputs and IFR as output	A controlled method for fluid resuscitation	Very simplified design with moderate number of MFs

TABLE 1: Some relevant literatures on automatic resuscitation

FL, Fuzzy Logic; DSS, Decision Support Systems; TBSA, Total Body Surface Area; ICU, Intensive Care Unit; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; PID, Proportional-Integral-Derivative; MAP, Mean Arterial Pressure; HUO, Hourly Urine Output; MFs, Membership Functions

Design of the FIS framework

The proposed FIS model to determine IFR for burn patient uses the %TBSA and HUO as the crisp input vectors and the IFR as the crisp output vector of the system. The theoretical model is illustrated in Figure

1, where %TBSA, HUO, and IFR are indicated by the symbols A, B, and Y, respectively. The two input sets are fuzzified through the fuzzification process generating fuzzy sets as the fuzzy inputs of the FIS model. In the fuzzification step, three distinct MFs, like triangular, trapezoidal, and Gaussian, are employed distinctively. An appropriate set of designed rules are incorporated in the fuzzy knowledge-base, which also works with the fuzzy inference engine (FIE) or FIS. The aggregator is a part of FIE, which accumulates the individual outputs of each fuzzy rules. The output fuzzy variable is also designed based on three corresponding MFs, triangular, trapezoidal, and Gaussian, separately. Finally, the aggregated fuzzy output set is processed through the defuzzification process in the defuzzifier unit, which produces crisp vector as the reasoning of IFR. The subsequent subsections present detailed descriptions supported by the required mathematical and logical formulations.

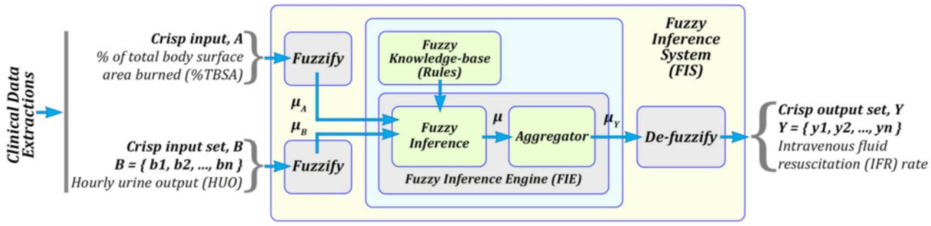

FIGURE 1: Proposed framework of clinical decision support systems for fuzzy fluid resuscitation model

Design of universe of discourse (UoD)

%TBSA as Input UoD

An important aspect of burn treatment is managing patients during the first 24 hours, as this period significantly impacts the severity of the disease and the likelihood of mortality [15]. To provide care in such cases, the primary task is to estimate %TBSA to acquire an approximate estimation of burn size for calculating a patient's fluid resuscitation requirements. Research statistics show that a patient's quality of life diminishes with the higher percentage of TBSA affected [12]. Hence, estimating the percentage area of total body surface is vital for the initial treatment of a burn patient, as it provides vital information for immediate clinical supervision and the need for essential fluid resuscitation [38,39]. The %TBSA can be estimated using various clinical methods, including the Lund and Browder Chart, palmar surface assessment, and Rule-of-Nines, with the Rule-of-Nines [40], as presented in Figure 2, being the most widely used.

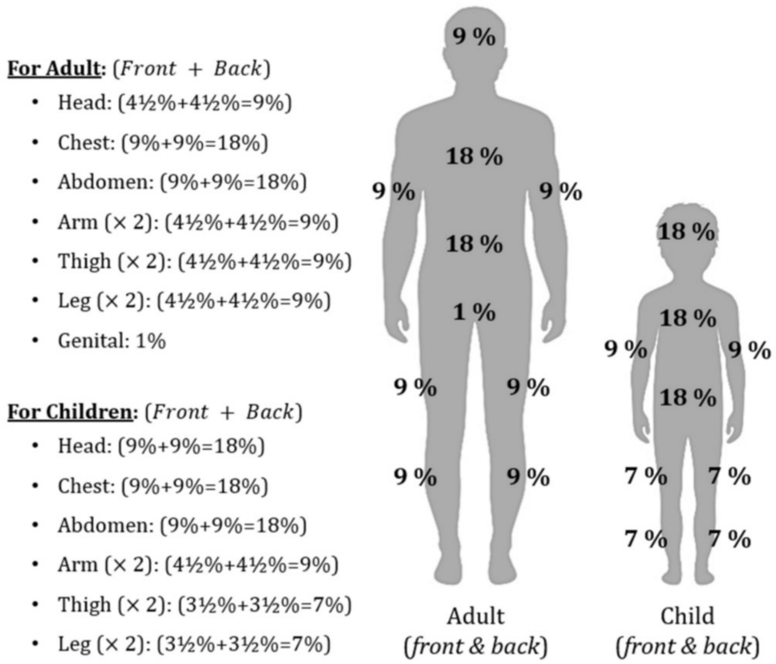

FIGURE 2: Rule-of-nine for calculating %TBSA

Adapted from [40]

%TBSA, Percentage of Total Body Surface Area

Patients with burns affecting less than 20% of their TBSA may not require formal IV fluid resuscitation, as the inflammatory response associated with such burns usually does not result in significant capillary leakage. Burns affecting more than 20% require continuous IV fluid resuscitation, and the severity increases with the increased %TBSA [26-29]. In this study, the %TBSA is considered an input fuzzy variable of the proposed system. The universe of discourse of the fuzzy variable (U_{TBSA}) is designed with four boundary conditions, low (minor-moderate burns), medium (major burns), high (severe burns), and very-high (most-severe burns), within the range of 0.00% to 100.00%. The boundary conditions are presented in Equation (1).

$$U_{TBSA} = \begin{cases} 00.0\% \rightarrow 20.00\% & Low \\ 20.0\% \rightarrow 30.0\% & Medium \\ 30.0\% \rightarrow 55.0\% & High \\ 55.0\% \rightarrow 100.0\% & Very-high \end{cases} \quad (1)$$

HUO as Input UoD

HUO is routinely monitored in critically ill patients, as it is crucial for predicting the severity of illness and reducing mortality rates [41]. Monitoring HUO with great care enables clinicians to make vital decisions that can save the lives of many critically burned patients. Accurate measurement of HUO is essential for the proper adjustment of fluid resuscitation rates in burn patients [42]. On average, HUO is about 30-50 ml/h in adult burn patients [26,43]. During the resuscitation process, HUO may increase or decrease. To determine a patient's HUO, a clinician must be aware of both the quantity of urine produced and the duration over which it was produced [40]. The formula for calculating a patient's HUO is provided in Equation (2).

$$HUO = \frac{\text{Urine output volume (ml)}}{\text{Total hours needed to produce the volume}} \quad (2)$$

In this study, the HUO is considered the second fuzzy input variable through which the crisp values of HUO are converted into fuzzy set. In the proposed design, three categories of HUO level (fuzzy values: low, medium, and high) are chosen that determine the range of the universe of discourse (ranging from 0.00 ml to 80.00 ml) for the input variable. Equation (3) presents the boundary conditions of the designed fuzzy values of the input variable U_{HUO}.

$$U_{HOU} = \begin{cases} 00.00ml \rightarrow 30.00ml & LowHUM \\ 30.00ml \rightarrow 50.00ml & NormalHUO \\ 50.00ml \rightarrow 80.00ml & HighHUO \end{cases} \quad (3)$$

IFR as Output UoD

To determine the output fuzzy sets of the IFR, the burn resuscitation protocol is considered, taking into account the %TBSA and HUO goals, as suggested by the Parkland formula and McGovern Medical School, University of Texas, USA (4 ml*%TBSA*Weight (kg)). This formula calculates the total fluid infusion required over 24 hours for any adult patient [25,26,28,32]. However, the crisp output values generated by the designed FIS model estimate the amount of IFR per kg weight of the body; thus, the total body weight of a patient must be multiplied with the crisp output values of the proposed system. For example, if the FIS model estimates IFR as 90 ml/kg, the final estimated IFR value for a patient with 50 kg of body weight becomes (90*50) = 4,500 ml in 24 hours.

Depending on the four stages of %TBSA and three stages of HUO, the fluid fusion rate or IFR as fuzzy output variable in milliliter per kilogram (ml/kg) is designed with six levels as Trivial, Low, Medium, High, Very-high, and Extreme. The span of the fuzzy output universe of discourse (UIFR) is designed as 0.00–400.00 ml/kg, as illustrated in Equation (4).

$$U_{IFR} = \begin{cases} \leqslant 80.00ml/kg & TrivialIFR \\ 80.00 \rightarrow 120.00ml/kg & LowIFR \\ 120.00 \rightarrow 200.00ml/kg & MediumIFR \\ 200.00 \rightarrow 320.00ml/kg & HighIFR \\ 320.00 \rightarrow 400.00ml/kg & VeryhighIFR \\ \geqslant 400.00ml/kg & Extreme \end{cases} \quad (4)$$

Design of the input-output MFs

MFs are the building blocks of fuzzy logic system [19,44,45]. For this study, three types of MFs are experimented: Triangular, Trapezoidal, and Gaussian. The Triangular MF (μ_i), the most common MF, can be denoted with three variables as a lower bound a_i, an upper bound c_i, and a ceiling bound b_i, so that a_i<b_i<c_i. Trapezoidal MF (μ_p) can be represented by using four parameters: a lower limit a_p, an upper limit d_p, a lower ceiling b_p, and an upper ceiling c_p, where a_p<b_p<c_p<d_p. Gaussian MF (μ_g) can be specified by two parameters: mean value as c_g and standard deviation value as σ_g. The Z-MF (μ_z) and S-MF (μ_s) take two parameters each, where a_z and b_z are lower extreme point (at ceiling) and upper extreme point (at base) of the *Z* curve, and a_s and b_s are lower extreme point (at base) and upper extreme point (at ceiling) of the *S* curve, respectively. All these MFs can be expressed by using fuzzy set operation formulas, as shown in Equation (5). Example MFs are illustrated in Figure 3.

$$\left.\begin{array}{lcl} \mu_i(x) & = & \vee(\wedge((x-a_i)/(b_i-a_i),(c_i-x)/(c_i-b_i)),0) \\ \mu_p(x) & = & \vee(\wedge((x-a_p)/(b_p-a_p),1,(d_p-x)/(d_p-c_p)),0) \\ \mu_g(x) & = & exp(-1/2((x-c)/\sigma)^2) \\ \mu_Z(x) & = & \begin{cases} 1 & if x \leq a_z \\ 1-2((x-a_z)/(b_z-a_z))^2 & if a_z < x \leq (a_z+b_z)/2 \\ 2((x-b_z)/(b_z-a_z))^2 & if(a_z+b_z)/2 < x \leq b_z \\ 0 & if b_z < x \end{cases} \\ \mu_S(x) & = & \begin{cases} 0 & if x \leq a_s \\ 2((x-a_s)/(b_s-a_s))^2 & if a_s < x \leq (a_s+b_s)/2 \\ 1-2((x-b_s)/(b_s-a_s))^2 & if(a_s+b_s)/2 < x \leq b_s \\ 1 & if b_s < x \end{cases} \end{array}\right\} \quad (5)$$

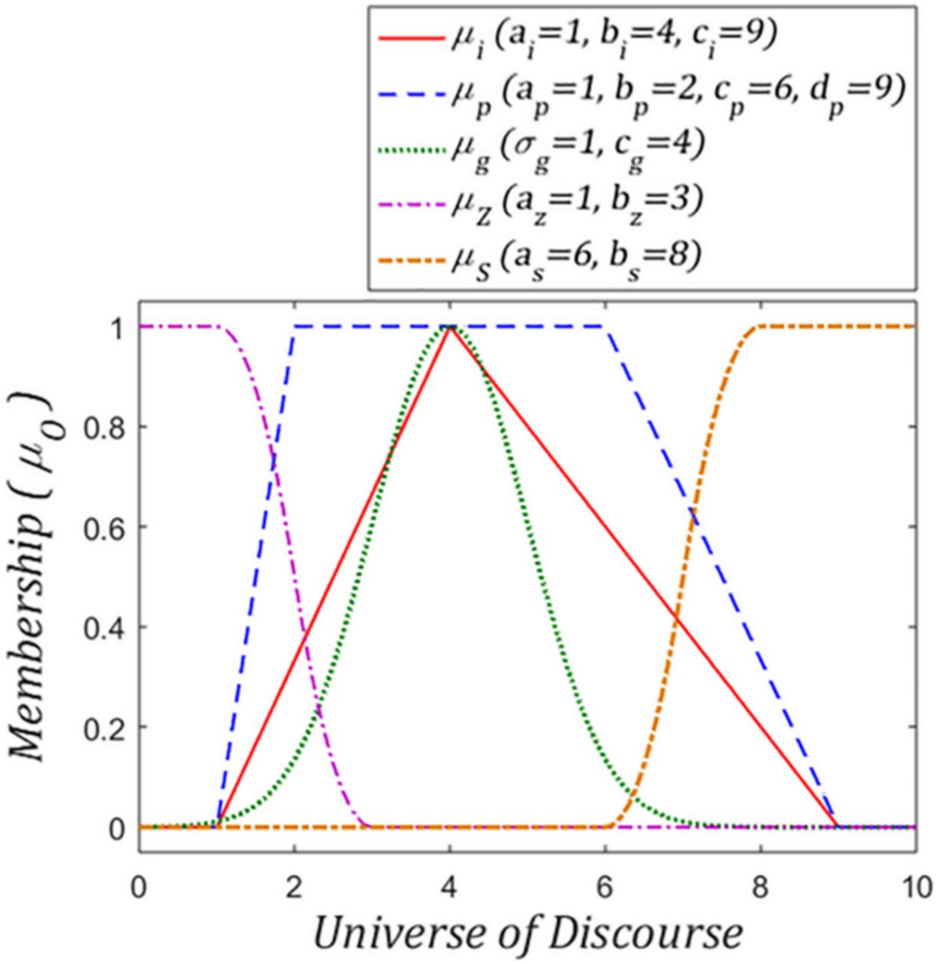

FIGURE 3: Examples of various membership functions (MFs); triangular (μ_i), trapezoidal (μ_p), Gaussian (μ_g), Z-MF (μ_z), and S-MF (μ_s)

The first fuzzy input variable %TBSA contains four fuzzy values (linguistic values) in terms of MFs. Similarly, the other two fuzzy variables, HUO as second input and IFR as output, contain three and six MFs, respectively. In designing the MFs, certain overlapping is considered for two consecutive fuzzy values. In the first FIS model, the terminal (first and last) MFs of each of the fuzzy variables are considered as trapezoidal MFs. while the intermediate MFs are designed based on triangular MFs. The second and third FIS models are designed by considering trapezoidal and Gaussian MFs, respectively. The terminal MFs of the input output fuzzy variables of third FIS model are designed by using Z-MF and S-MF. Pictorial forms of the three FIS models with input-output MFs are demonstrated in Figures *4*, *5*, and 6. Equations (6), (7), and (8) illustrate the fuzzy sets of the designed input-output fuzzy variables based on the basic types of MFs.

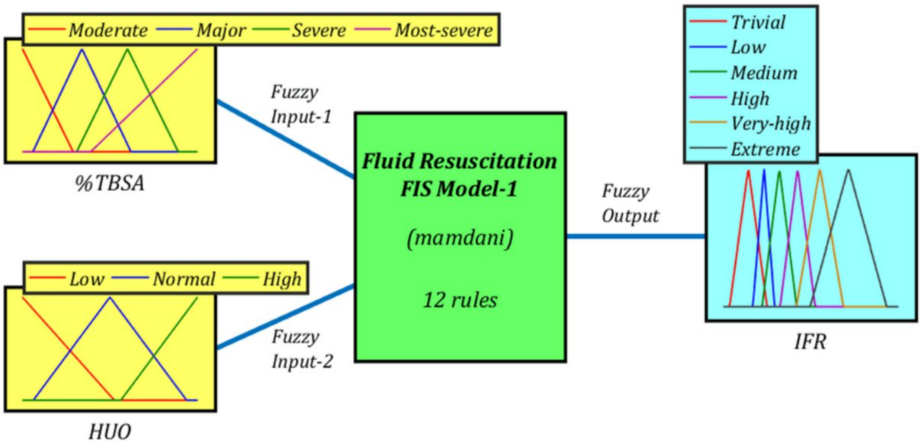

FIGURE 4: FIS model 1 (2 inputs, 1 output, 12 rules) with triangular membership functions

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

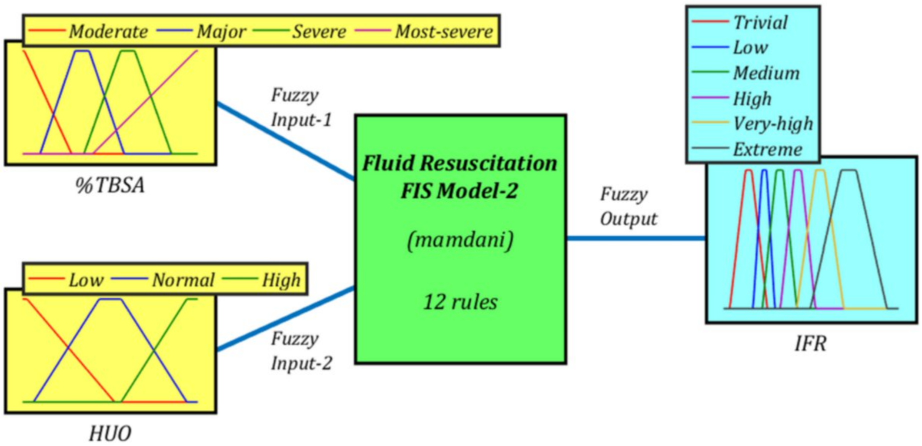

FIGURE 5: FIS model 2 (2 inputs, 1 output, 12 rules) with trapezoidal membership functions

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

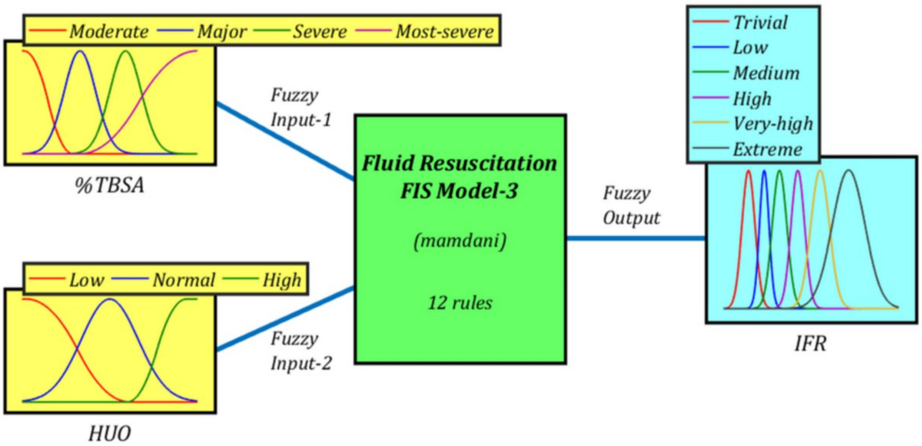

FIGURE 6: FIS model 3 (2 inputs, 1 output, 12 rules) with Gaussian membership functions

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

$$\left.\begin{array}{l} \%TBSA_{Tri} = \left\{\begin{array}{ccc} Moderate & = & \{(0,0),(0,1),(29,0)\} \\ Major & = & \{(6,0),(34,1),(62,0)\} \\ Severe & = & \{(31,0),(60,1),(89,0)\} \\ Most-severe & = & \{(39,0),(100,1),(100,0)\} \end{array}\right. \\ HUO_{Tri} = \left\{\begin{array}{ccc} Low & = & \{(0,0),(0,1),(42,0)\} \\ Normal & = & \{(5,0),(40,1),(75,0)\} \\ High & = & \{(45,0),(80,1),(80,0)\} \end{array}\right. \\ IFR_{Tri} = \left\{\begin{array}{ccc} Trivial & = & \{(-75,1),(0,1),(75,0)\} \\ Low & = & \{(18,0),(63,1),(105,0)\} \\ Medium & = & \{(55,0),(124,1),(193,0)\} \\ High & = & \{(127,0),(197,1),(267,0)\} \\ Very-high & = & \{(192,0),(286,1),(380,0)\} \\ Extreme & = & \{(247,0),(400,1),(553,0)\} \end{array}\right. \end{array}\right\} \quad (6)$$

$$\left.\begin{array}{l} \%TBSA_{Trap} = \left\{\begin{array}{ccc} Moderate & = & \{(-1,0),(-1,1),(1,1),(28,0)\} \\ Major & = & \{(10,0),(30,1),(38,1),(58,0)\} \\ Severe & = & \{(35,0),(56,1),(64,1),(85,0)\} \\ Most-severe & = & \{(40,0),(99,1),(101,1),(101,0)\} \end{array}\right. \\ HUO_{Trap} = \left\{\begin{array}{ccc} Low & = & \{(-2,0),(-2,1),(2,1),(42,0)\} \\ Normal & = & \{(5,0),(35,1),(45,1),(75,0)\} \\ High & = & \{(45,0),(75,1),(85,1),(85,0)\} \end{array}\right. \\ IFR_{Trap} = \left\{\begin{array}{ccc} Trivial & = & \{(-75,0),(-12,1),(12,1),(75,0)\} \\ Low & = & \{(18,0),(54,1),(72,1),(105,0)\} \\ Medium & = & \{(55,0),(111,1),(137,1),(193,0)\} \\ High & = & \{(127,0),(184,1),(210,1),(267,0)\} \\ Very-high & = & \{(192,0),(269,1),(303,1),(380,0)\} \\ Extreme & = & \{(247,0),(370,1),(430,1),(553,0)\} \end{array}\right. \end{array}\right\} \quad (7)$$

$$\left.\begin{array}{lll} \%TBSA_{Gaus} & = & \left\{\begin{array}{lll} Moderate & = & \{\sigma=01, c=29\} \\ Major & = & \{\sigma=09, c=33\} \\ Severe & = & \{\sigma=09, c=59\} \\ Most-severe & = & \{\sigma=33, c=100\} \end{array}\right. \\ HUO_{Gaus} & = & \left\{\begin{array}{lll} Low & = & \{\sigma=02, c=49\} \\ Normal & = & \{\sigma=13, c=40\} \\ High & = & \{\sigma=48, c=75\} \end{array}\right. \\ IFR_{Gaus} & = & \left\{\begin{array}{lll} Trivial & = & \{\sigma=26, c=0\} \\ Low & = & \{\sigma=19, c=63\} \\ Medium & = & \{\sigma=29, c=124\} \\ High & = & \{\sigma=27, c=197\} \\ Very-high & = & \{\sigma=37, c=286\} \\ Extreme & = & \{\sigma=65, c=400\} \end{array}\right. \end{array}\right\} \tag{8}$$

Formulation of fuzzy knowledge-base

In the proposed FIS model, %TBSA burned and HUO are considered as fuzzy inputs, where IFR is the fuzzy output variable of the system. In this design, there are four fuzzy values (MFs) for %TBSA, three fuzzy values (MFs) for HUO, and six fuzzy values (MFs) for IFR. The two fuzzy inputs need to be mapped with the output variable, which produces 12 'if-and-than' conditions as fuzzy knowledge-base also known as fuzzy rules. Table 2 illustrates the mapping table among the input-output fuzzy variables. According to the mapping table, for each combination of fuzzy input values of %TBSA and HUO, an individual behavioral pattern for the rate of fluid as fuzzy output is determined. For instance, if the fuzzy values of %TBSA and HUO are moderate and high, respectively, it indicates that the urine output rate is unexpectedly elevated despite a smaller burned area. In such cases, the need for an increased fluid rate for resuscitation becomes negligible. Similarly, if the fuzzy values of %TBSA are most-severe and HUO is low (urine output rate is low with largely affected burn), the requirement of fluid infusion rate must be very-high. Based on the input-output matrix (Table 2), 12 rules are designed for the proposed FIS model, which are listed in Table 3. The overall system and its design parameters are presented in Table 4.

HUO (ml/h)	%TBSA (%)			
	Moderate (<20)	Major (20-30)	Severe (30-55)	Most-Severe (> 55)
Low (<30)	Trivial	High	Very-high	Extreme
Normal (30-50)	Trivial	Medium	High	Very-high
High (>50)	Trivial	Low	Medium	High

TABLE 2: Fuzzy input-output mapping table (input-output matrix)

TBSA, Total Body Surface Area; HUO, Hourly Urine Output

No.		%TBSA is		HUO is		IFR is
1	IF	Moderate	AND	Low	THEN	Trivial
2				Normal		
3				High		
4		Major		Low		High
5				Normal		Medium
6				High		Low
7		Severe		Low		Very-high
8				Normal		High
9				High		Medium
10		Most-Severe		Low		Extreme
11				Normal		Very-high
12				High		High

TABLE 3: Design of fuzzy knowledge-base (Rules)

TBSA, Total Body Surface Area; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

System parameters	Descriptions
Target patient	Adult male patients
Fuzzy model type	Mamdani Type-1 FIS
Input 1	%TBSA with four MFs
Input 2	HUO with three MFs
Output	IFR with six MFs
Rules	12 rules
AND operation	Fuzzy min($\mu_A(x)$) operation
Aggregation method	Disjunctive method, max($\mu_A(x)$)
Types of MFs	Triangular, Trapezoidal, and Gaussian (for three separate designs for comparative analysis)
Defuzzification	CoA, BoA, MoM, LoM, and SoM
Formula (without fresh frozen plasma)	Simple Parkland (Baxter) formula: 4 ml/kg/%TBSA with ±20% for HUO if <30 ml/h & >50 ml/h

TABLE 4: Proposed system at a glance

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; TBSA, Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output; MFs, Membership Functions

Fuzzy inference engine

Mamdani FIS architecture is applied to design the inference system. The FIE adjusts the fuzzy variables to fit into the adopted universe of discourse, finds the degree of fitness of inputs with respect to the knowledge-base (rules), generates the fuzzy outputs depending on the associated rules, and finally derives aggregated fuzzy output set from the individual outputs of each associated rule. The fuzzy implication adopts ‘min’ operation, and the aggregation process of the proposed FIE follows the disjunctive (max) method. The ‘And’ and ‘Or’ terms are reflecting the ‘min’ and ‘max’ operations, respectively. The output fuzzy set (aggregated output) is processed through five defuzzification methods to predict the IFR level in terms of scalar outputs.

Defuzzification strategies

Defuzzification is the method of converting fuzzy values into precise, measurable outcomes represented as crisp values. Several defuzzification techniques are utilized in this study, such as the Centroid of Area (CoA), Bisector of Area (BoA), Largest of Maximum (LoM), Smallest of Maximum (SoM), and Mean of Maximum (MoM). For a continuous system, the defuzzification methods can be expressed mathematically, as shown in Equation (9), where Y^* is the crisp output (or output vector), min and max are the limits of the discourse, and U_{IFR}, $\mu(Y)$ is the fuzzy value of Y on the U_{IFR}.

$$\left.\begin{array}{lcc} Y^*_{CoA} & = & (\int_{min}^{max} \mu(Y).YdY)/(\int_{min}^{max} \mu(Y)dY) \\ Y^*_{BoA} & = & Y_{BoA} \ni \int_{min}^{BoA} \mu(Y)dY = \int_{BoA}^{max} \mu(Y)dY \\ Y^*_{MoM} & = & (\int_{\alpha}^{\beta} YdY)/((\beta-\alpha)+1) \ni \begin{cases} \alpha & = & min\{y|y \in max(\mu(Y))\} \\ \beta & = & max\{y|y \in max(\mu(Y))\} \end{cases} \\ Y^*_{LoM} & = & \beta \in \beta = max\{y|y \ni max(\mu(Y))\} \\ Y^*_{SoM} & = & \alpha \in \alpha = min\{y|y \ni max(\mu(Y))\} \end{array}\right\} \quad (9)$$

Results And Discussion

The design and simulation of the fuzzy fluid resuscitation model were conducted using MATLAB simulation software. By applying three MFs with five defuzzification methods, the model outputs are compared with conventional estimation methods. Figure 7 presents the behavior pattern of the traditional Parkland formula alone: Figure 7(a) shows a 3D graph of the predicted IFR for %TBSA (0–100%) and HUO (0–80 ml/h), while Figure 7(b) displays the estimated IFR for five discrete %TBSA values (20%, 30%, 50%, 70%, and 80%) within the HUO range from 0 ml/h to 80 ml/h.

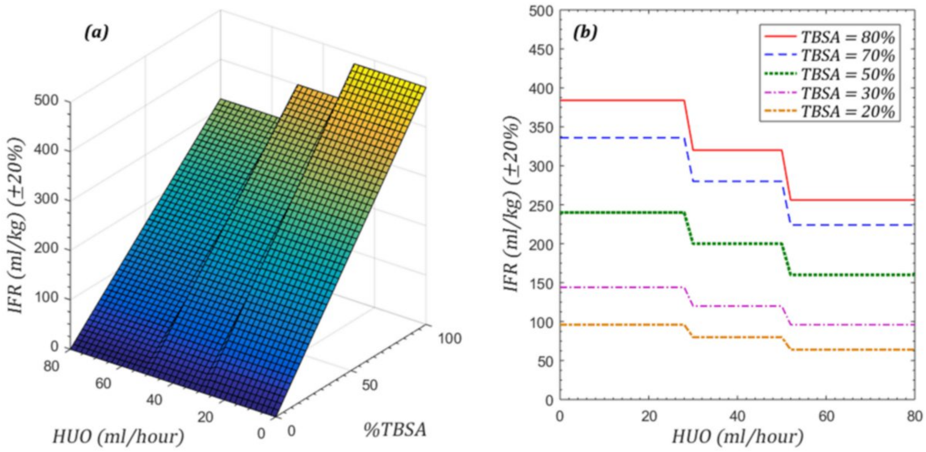

FIGURE 7: Traditional calculation process using the Parkland formula: (a) 3D graph of IFR calculation for various inputs of %TBSA and HUO, and (b) changes in IFR based on HUO variations for five stages of %TBSA

%TBSA, Percentage of Total Body Surface Area; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

According to the results shown in Figure 7, there are some abrupt shifts (a decrease or increase of ≈20%) at the transition states of HUO at 30 ml/h and 50 ml/h. For lower %TBSA, the change in IFR is less compared to higher %TBSA. For example, if the %TBSA is 20%, the IFR is determined as 80 ml/kg for normal HUO (30-50 ml/h), which changes to 96 ml/kg for HUO < 30 ml/h and 64 ml/kg for HUO > 50 ml/h. On the other hand, if the %TBSA is 80%, the calculated IFR shifts from 320 ml/kg to 384 ml/kg or 256 ml/kg (±64 ml/kg). Maintaining a constant IFR for a certain period can cause fluid overload or underload during the course of resuscitation. Additionally, a quick correction of IFR (±20%) is not suitable for maintaining fluid uniformity in the patient's body. Therefore, the adjustment (increase or decrease) of IFR should follow a gradual pattern of change.

The above concerns can be addressed effectively by adopting the proposed FIS architecture. The results of the proposed fuzzy fluid resuscitation models are presented in this study and analyzed from various perspectives to select the best possible design. Figure 8 demonstrates the outputs of the first model (FIS model 1), which is designed using Triangular MFs for five different defuzzification strategies: CoA, BoA, MoM, LoM, and SoM. From the results, it is observed that the CoA and BoA defuzzification methods (Figures 8(a) and (b)) show smooth transitions across various levels of HUO. In contrast, the other three methods (MoM, LoM, and SoM, as presented in Figures 8(c), (d), and (e)) exhibit abrupt changes in the IFR level, reflecting sudden jumps in adjustment, and thus may not be ideal. The other two models (FIS Model-2 and Model-3), which are based on Trapezoidal and Gaussian MFs, show similar behavior for the five different defuzzification methods, as illustrated in Figures 9 and 10.

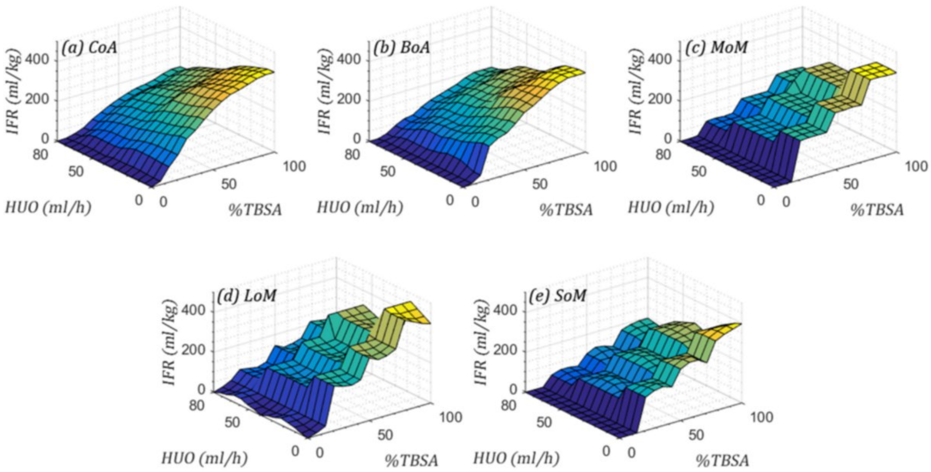

FIGURE 8: Surface plot of five different outputs for five defuzzification strategies applied to the Triangular MF-based FIS Model 1: (a) CoA, (b) BoA, (c) MoM, (d) LoM, and (e) SoM methods

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; %TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

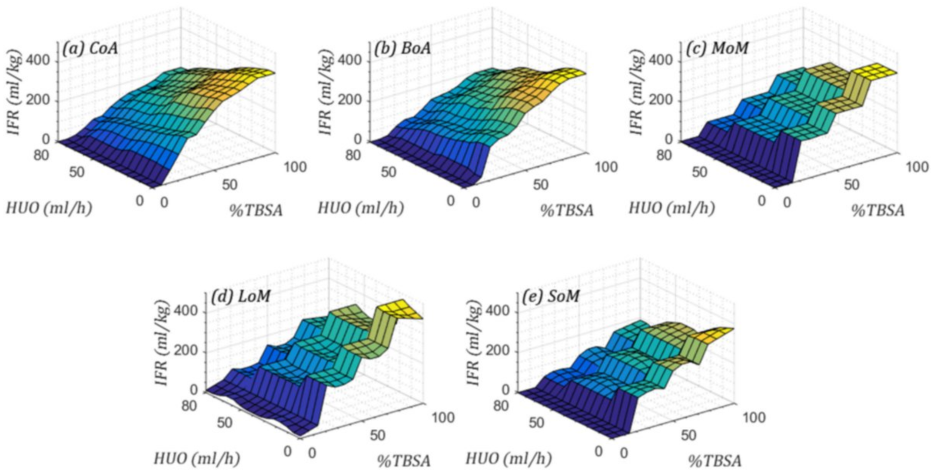

FIGURE 9: Surface plot of five crisp outputs of five defuzzification processes applied for the FIS model 2 with Trapezoidal MFs: (a) CoA, (b) BoA, (c) MoM, (d) LoM, and (e) SoM methods

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; %TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

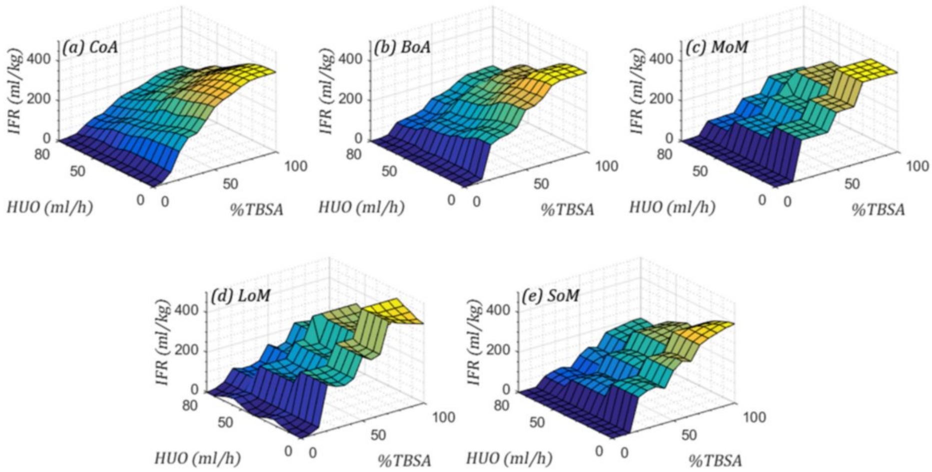

FIGURE 10: Surface plot of five crisp outputs of five defuzzification approaches applied on the Gaussian MF-based FIS model 3: (a) CoA, (b) BoA, (c) MoM, (d) LoM, and (e) SoM methods

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; %TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

The transitions of IFR using the CoA method (Figures 8(a), 9(a), and 10(a)) exhibit comparatively smoother gradient behavior than those observed with the BoA method (Figures 8(b), 9(b), and 10(b)), indicating more consistent IFR transitions during resuscitation. Moreover, the BoA strategy does not show steady behavior for lower %TBSA values, as shown in the graphs, and its calculation process is slightly more complex compared to CoA. Therefore, the CoA defuzzification technique appears to offer better clinical interpretability, making it a more suitable choice among the four methods evaluated.

Other observations regarding the upper and lower bound conditions of IFR, %TBSA vs. IFR under different HUO conditions, and HUO vs. IFR across varying %TBSA values are presented in Figure 11 for FIS model 1, Figure 12 for FIS model 2, and Figure 13 for FIS model 3, all based on the CoA defuzzification method. According to the upper-lower bound graphs, model 1 and model 2 appear unresponsive at lower %TBSA levels, for %TBSA < 5 and %TBSA < 10, respectively. In contrast, IFR results from model 3 (Figure 13(a)) demonstrate responsiveness across the entire %TBSA range from 0 to 100. Therefore, the Gaussian MFs-based model (FIS Model-3) using the CoA method could be reliable compared to the other models presented in this study.

The individual %TBSA vs. IFR graphs in Figures 11(b), 12(b), and 13(b) present comparative results between the traditional method and the proposed fuzzy-based models. The results show that IFR estimates using the Parkland method are much higher (≈500 ml/kg or more). Furthermore, the fuzzy-based models maintain IFR values below a certain level (≈400 ml/kg), indicating a saturation level. This behavior suggests a saturation level for IFR which can be achieved if fuzzy based intelligent decision support system is modeled.

The results presented in the HUO vs. IFR graphs in Figures 11(c), 12(c), and 13(c) also compare the IFR transitions determined by the traditional method and the fuzzy models. These results suggest that the constant IFR levels and their abrupt shifts can be overcome by adopting the proposed FIS model with Gaussian MFs and CoA. The overall comparative results are illustrated in the %TBSA vs. IFR graphs for various HUO (Figure 14(a)) and the HUO vs. IFR graphs for different %TBSA (Figure 14(b)). These graphs demonstrate that the results of FIS model 1 and model 2 are almost identical, with some deviations observed in model 3 under specific conditions.

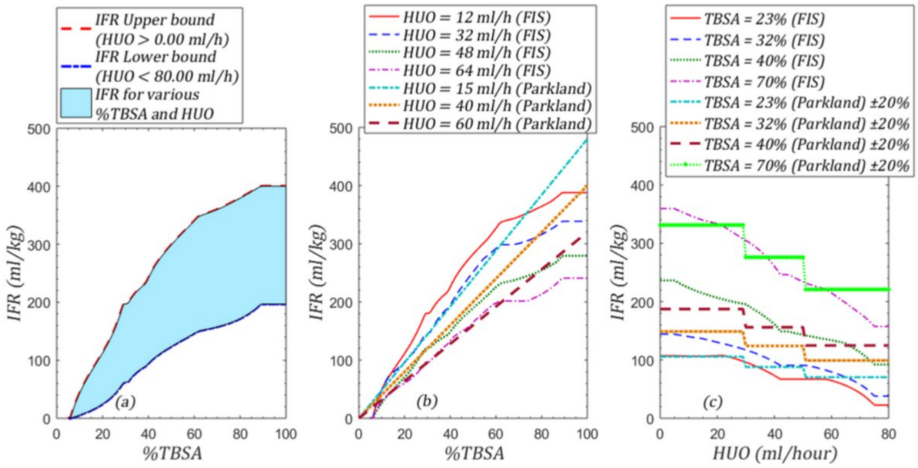

FIGURE 11: Behavioral graph of FIS model 1 with Triangular MFs and CoA method. (a) Upper and lower bounds of IFR, (b) %TBSA vs. IFR for various HUOs, and (c) HUO vs. IFR for various %TBSA

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

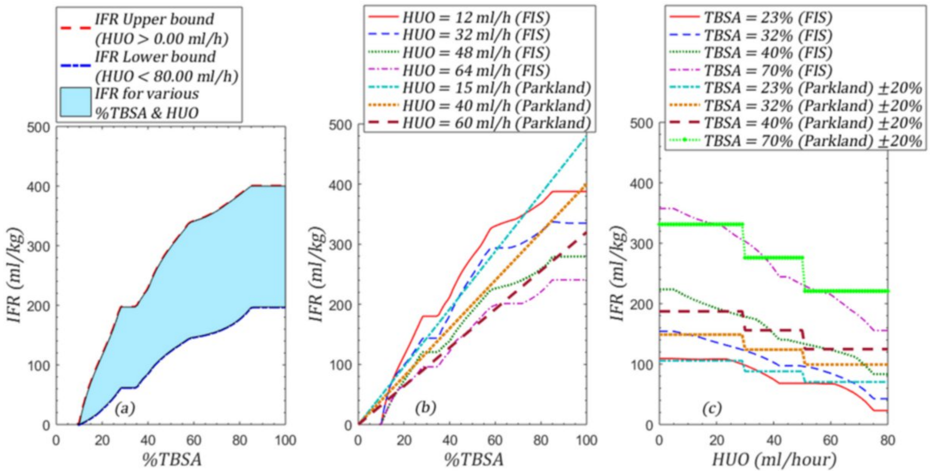

FIGURE 12: Behavioral graph of FIS model 2 with Trapezoidal MFs and CoA. (a) Upper and lower bounds of IFR, (b) %TBSA vs. IFR for various HUOs, and (c) HUO vs. IFR for various %TBSA

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

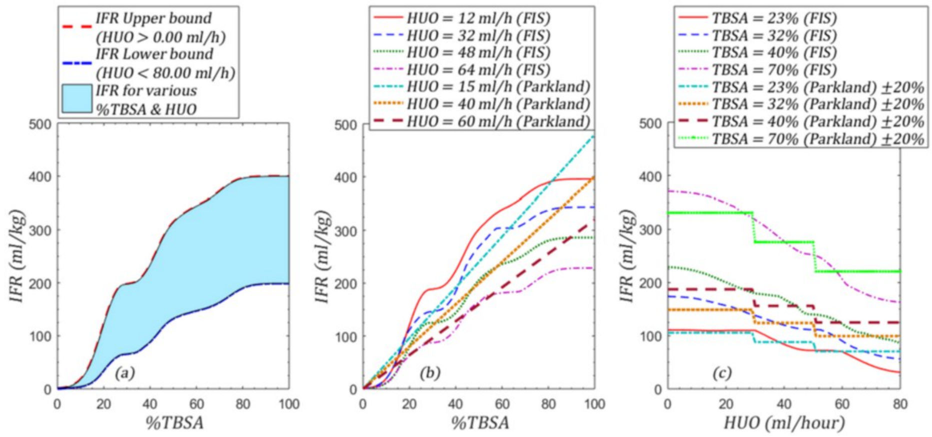

FIGURE 13: Behavioral graph of FIS model 3 with Gaussian MF and CoA method. (a) Upper and lower bounds of IFR, (b) %TBSA vs. IFR for various HUOs, and (c) HUO vs. IFR for various %TBSA

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

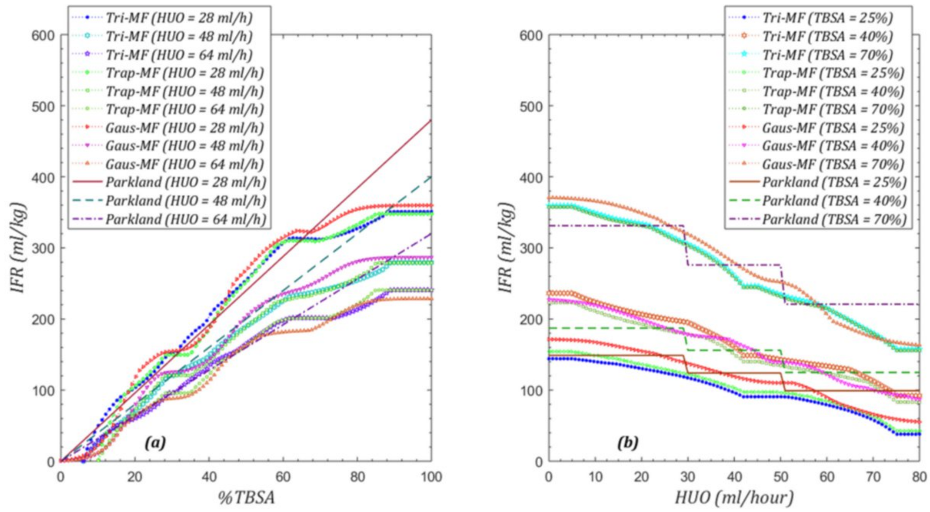

FIGURE 14: Behavioral graph comparison of CoA method among Triangular, Trapezoidal, and Gaussian MFs with traditional Parkland method

CoA, Centre of Area; TBSA, Total Body Surface Area; FIS, Fuzzy Inference System; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output; MFs, Membership Functions

The fuzzy output (results to which defuzzification methods are applied) of FIS Model-3 (Gaussian MFs) for six different test cases is shown in Figures *15*(a)-(f). The graphs also display the six different outputs (IFR) for five defuzzification methods, along with the traditional method, applied to each graph (fuzzy output areas). For each test case, the estimated IFR values for the traditional method and CoA defuzzification method are almost identical (distances are ≈0.4 to ≈2.4, with an average of 1.05). A comparison between the traditional and BoA methods reveals distances ranging from ≈2 to ≈26 (with an average distance of ≈10.73). The outputs of the other three methods, MoM, LoM, and SoM, show much higher deviations from the IFR values estimated using the traditional method. These results again confirm the reliability of the CoA method for the defuzzification process, as recommended in this study. Comparative results of the five defuzzification methods are presented in Table *5*.

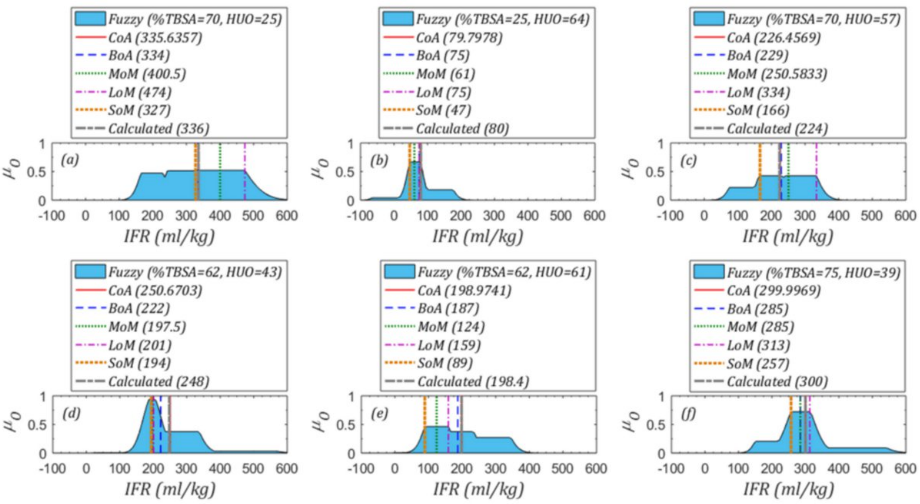

FIGURE 15: Aggregated fuzzy output graph (Gaussian MF-based design) and resultant values of various defuzzification methods for six different test cases: (a) inputs TBSA = 70% & HUO = 25 (high-low), (b) inputs TBSA = 25% & HUO = 64 (low-high), (c) inputs TBSA = 70% & HUO = 57 (high-high), (d) inputs TBSA = 62% & HUO = 43 (medium-medium), (e) inputs TBSA = 62% & HUO = 61 (medium-high), and (f) inputs TBSA = 75% & HUO = 39 (high-medium)

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; TBSA, Total Body Surface Area; IFR, Intravenous Fluid Rate; HUO, Hourly Urine Output

%TBSA & HUO	CoA	BoA	MoM	LoM	SoM	Theoritical
20% & 45	81	96	124	159	89	80
25% & 50	114	124	124	145	103	100
30% & 40	133	124	124	131	117	120
35% & 40	141	131	124	124	124	140
40% & 45	155	131	124	145	103	160
45% & 50	171	159	124	159	89	180
50% & 65	162	138	124	252	96	160
55% & 64	177	152	124	145	103	176
60% & 62	192	173	124	152	96	192
65% & 42	259	243	198	215	189	260
75% & 40	296	285	285	313	257	300

TABLE 5: Observations of the five defuzzification methods for Gaussian MF-based FIS model 3

CoA, Centre of Area; BoA, Bisector of Area; MoM, Mean of Maximum; LoM, Largest of Maximum; SoM, Smallest of Maximum; %TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; HUO, Hourly Urine Output

The overall behavioral pattern can also be observed in the time vs. IFR graph. To simulate this behavior, MATLAB Simulink is used to design the model, as presented in Figure *16*. The simulation model consists of two process blocks: one for the Parkland formulation and the other for the proposed FIS model. The inputs to the simulation model are %TBSA and HUO. HUO follows a sinusoidal pattern with an amplitude of 40, a frequency of π/5, and a phase of −π/2 (one cycle, low-peak to low-peak), with a peak-to-peak value of 80.

To prevent negative values, a constant value of 40 is added. The other input signal, %TBSA, is varied discretely (e.g., 35, 45, and 75), as shown in Figure 17. The HUO sinusoidal design reflects the variations in urine output of a patient over a 10-hour period.

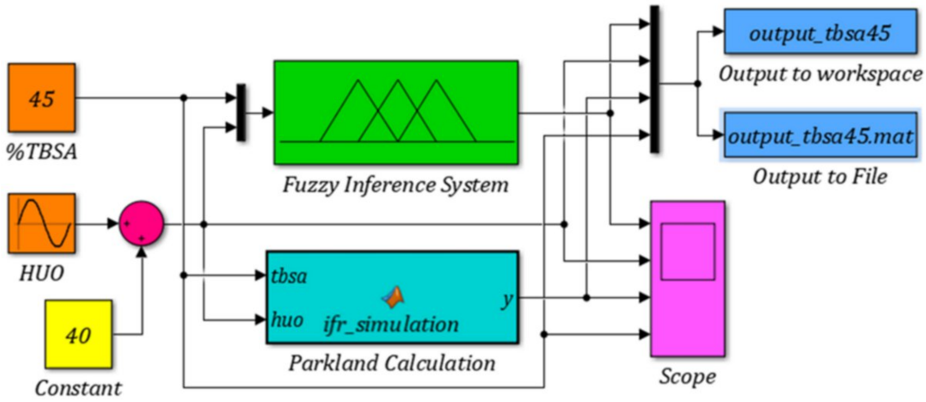

FIGURE 16: Simulation block diagram of %TBSA IFR estimation for various HUO change with time

%TBSA, Percentage of Total Body Surface Area; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

Although the HUO input in the simulation model may not represent a real-world scenario, as it is highly unpredictable for an actual patient, the chosen pattern helps observe the system's responses. For the three cases, the traditional Parkland formula shows IFR prediction characteristics that are steady for most of the time, with sharp deviations occurring at the transition states of HUO (at 30 ml/h and 50 ml/h). These IFR behaviors may lead to fluid overload or underload. In contrast, the FIS model response demonstrates a gradual adjustment of IFR in response to changes in HUO over time.

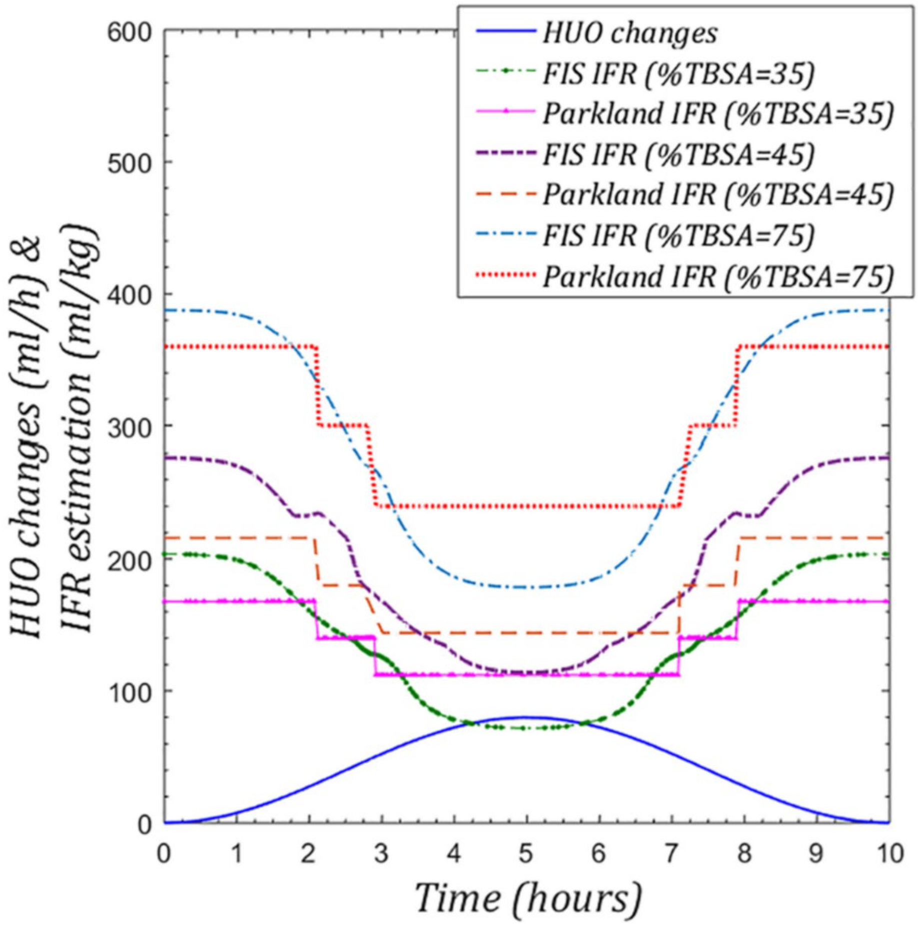

FIGURE 17: Time vs IFR graph for continuous variation of HUO

%TBSA, Percentage of Total Body Surface Area; FIS, Fuzzy Inference System; HUO, Hourly Urine Output; IFR, Intravenous Fluid Rate

Comparative analysis

A similar study was conducted earlier, where the output UoD (IFR) was designed using the distributions of five MFs [15]. However, five MFs are insufficient to produce precise results. The study did not compare the output with the SoM defuzzification method. Moreover, the proposed design does not solve the issue of the sudden shift in IFR levels, as observed in the presented results. While the study attempted to show outputs similar to those calculated using the Parkland formula, this is only possible under a few optimal conditions. Another observation is that the design features very shallow overlaps between or among the MFs for specific UoDs of inputs or outputs. These shallow overlaps result in weaker correlations (fuzzy relation and composition operations) with lower membership strengths in the output. For this comparative analysis, the proposed design was reproduced using Gaussian MFs and the CoA defuzzification method, resulting in some inconsistencies in the presented outputs.

On the other hand, the proposed design in this research uses six MFs in the output UoD. Additionally, the MF for each input and output UoD has sufficient overlaps, resulting in strong fuzzy relations among the various MFs of the input UoDs and producing comparatively higher membership strengths in the output. Furthermore, the proposed design maintains a reliable rate of IFR, overcoming the problems of fluid overload or underload in the patient's body caused by the sudden shifts in IFR determined by manual calculations. It is important to note that the fuzzy output is obviously producing different results (suggestions) than the manual calculations, except in a few specific cases. These differences are clearly visible in the simulated graphs shown in Figure *17*. Some comparative results for various test cases are presented in Table *6*.

The table does not present any error calculations because it is irrelevant to describe the distances among the produced results. Furthermore, the predicted outputs are based on the behavior patterns of the inputs, not on data or datasets produced manually. The results predicted by the compared model [15] show abrupt changes in values compared with the results produced by the proposed model of this research. This clearly shows that the outputs of the compared model need further processing to meet the requirements. In contrast, the proposed model does not require any further processing of its outputs. More interestingly, the proposed system maintains a consistent and gradual increase or decrease in IFR, as observed in the behavior of the two test cases (15 and 16) shown in Table 6. With the change in the higher boundary condition of HUO (HUO = [50 ml/h ↔ 51 ml/h]), the manual calculation shows that IFR varies by 52 ml/h, shifting from 260 ml/h to 208 ml/h and vice versa, while the proposed model produces a minor change in its outputs (242 ml/h to 241 ml/h and vice versa), ensuring gradual adjustment in the IV fluid resuscitation rate. Although this behavior is observed in the results of the compared model, the resuscitation rate is much higher (371 ml/h) compared to the proposed model.

Test cases	%TBSA	HUO (ml/h)	Proposed model (Gaussian MF; CoA; without FFP) (ml/h)	Compared model [15] (Gaussian MF; CoA; without FFP) (ml/h)	Manual calculation (without FFP) (ml/h)
1	56%	35	283	264	(4×%TBSA)=224
2	25%	15	167	116	(4×%TBSA)+20%=120
3	75%	59	225	284	(4×%TBSA)-20%=240
4	20%	15	117	65.6	(4×%TBSA)+20%=96
5	35%	30	156	334	(4×%TBSA)=140
6	30%	75	69.5	54.1	(4×%TBSA)-20%=96
7	50%	25	273	395	(4×%TBSA)+20%=240
8	60%	20	327	377	(4×%TBSA)+20%=288
9	70%	60	206	259	(4×%TBSA)-20%=224
10	85%	30	349	384	(4×%TBSA)=340
11	35%	41	140	221	(4×%TBSA)=140
12	45%	45.6	180	223	(4×%TBSA)=180
13	75%	22.5	360	401	(4×%TBSA)+20%=360
14	55%	50	222	233	(4×%TBSA)=220
15	65%	50	242	371	(4×%TBSA)=260
16	65%	51	241	371	(4×%TBSA)-20%=208

TABLE 6: Comparative results for various test cases

%TBSA, Percentage of Total Body Surface Area; HUO, Hourly Urine Output; CoA, Centre of Area; FFP, Fresh Frozen Plasma; MF, Membership Functions

Conclusions

In most cases, prediction of IFR is highly dependent on the rate of urine output and the %TBSA of individual burn patient. Traditional procedure sometimes becomes extremely difficult to perform while supporting a very critical and crisis situation. Besides, the traditional calculation may not produce the most appropriate guesses of IFR for a particular condition. Moreover, in this technological digital era, most of the traditional and manual procedures are introduced to modern AI-enabled autonomous systems. This study introduces a fuzzy system-based intelligent model of IFR prediction for burn resuscitation process where two major factors, %TBSA and HUO, are considered. Such automated measures, pending clinical validation, could be beneficial in rapidly and accurately estimating the required IFR, as well as in its automatic application and adjustment for burn patients. In this study, simulations of the proposed system have been conducted based on three different models of MFs and five different methods of defuzzification strategies, and a comparative analysis has been carried out. Based on the observations and analysis of the results, the CoA defuzzification method and Gaussian MFs for input and output fuzzy variables have been recommended. The output behavior of the proposed model has also been analyzed through simulation, with adaptive behavior in estimating IFR being shown instead of any steady-state condition or sudden shift in IFR levels. The study has also been benchmarked with similar research showing significant improvements in design as well as decision making.

A number of applied-research opportunities have been opened up by the proposed model, such as a software application for assisting quick and accurate prediction of IFR, decision support system, a fully automated medical setup (automated fluid resuscitation system) to monitor, maintain, and adjust IFR for a burn patient, and more. However, in this study, only two fuzzy variables are considered, but the model can be enriched with additional fuzzy input variables, such as heart rate, cardiac output, and body weight. Simultaneously, the design of the output variables could be enhanced to support the first 8 hours and last 16 hours IFR model. The current research has primarily focused on conditions of adult male patients; therefore, by including conditions for female and child patients in modeling such an FIS-based intelligent resuscitation model, the system would be made more sophisticated.

Additional Information

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All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** The study received supports from the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Research Project under grant number RGP2/441/46. **Financial relationships:** Author 8: Quadri Noorulhasan Naveed, Department of Computer Science, College of Computer Science, King Khalid University, Abha, K.S.A. Author 9: Ali M. Aseere, Department of Computer Science, College of Computer Science, King Khalid University, Abha, K.S.A. Author 10: Shafat khan, Department of Computer Science, College of Computer Science, King Khalid University, Abha, K.S.A. declare(s) a grant from King Khalid University, Abha, K.S.A. The study received supports from the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Research Project under grant number RGP2/441/46. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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