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ORIGINAL ARTICLE

The development of a novel knowledge-based weaning algorithm using pulmonary parameters: a simulation study

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Abstract Weaning is important for patients and clinicians who have to determine correct weaning time so that patients do not become addicted to the ventilator. There are already some predictors developed, such as the rapid shallow breathing index (RSBI), the pressure time index (PTI), and Jabour weaning index. Many important dimensions of weaning are sometimes ignored by these predictors. This is an attempt to develop a knowledge-based weaning process via fuzzy logic that eliminates the disadvantages of the present predictors. Sixteen vital parameters listed in published literature have been used to determine the weaning decisions in the developed system. Since there are considered to be too many individual parameters in it, related parameters were grouped together to determine acid-base balance, adequate oxygenation, adequate pulmonary function, hemodynamic stability, and the psychological status of the patients. To test the performance of the developed algorithm, 20 clinical scenarios were generated using Monte Carlo simulations and the Gaussian distribution method. The developed knowledge-based algorithm and RSBI predictor were applied to the generated scenarios. Finally, a clinician evaluated each clinical scenario independently. The Student s *t* test was used to show the statistical differences between the developed weaning algorithm, RSBI, and the clinician's evaluation. According to the results obtained, there were no statistical differences between the proposed methods and the clinician evaluations.

Keywords Weaning · Fuzzy logic · Monte Carlo algorithm · Gaussian distribution method · RSBI

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1 Introduction

The weaning process is used to discontinue the use of mechanical ventilators (MVs) for patients with respiratory distress in intensive care units (ICUs). It depends on the strength of patient's respiratory systems [1]. Twenty percent of ventilated patients will fail at their first attempt at weaning [2, 3]. Thus, the patients must spend more time in ICU before they can be weaned off MVs. Prolonged MV use may cause some complications such as infection, pneumonia, and barotraumas [4–10]. However, if the clinicians cannot predict the right time to start weaning, the patients may need reintubation, and this failure may increase the percentage of morbidity and mortality [4, 11–13]. Many researchers have attempted to reduce the duration of MV use. The studies on the ventilator-weaning process have proposed reducing the weaning times via their defined protocols rather than the usual intensive care protocols [14–19].

There are three weaning predictors commonly described in published literature. These are the rapid shallow breathing index (RSBI), the pressure time index (PTI), and the Jabour weaning index (JWI) [19]. Owing to its ease of calculation, RSBI is widely used in ICUs. Over a period of 1-min spontaneous breathing by the patient, RSBI calculates the ratio of frequency to tidal volume.

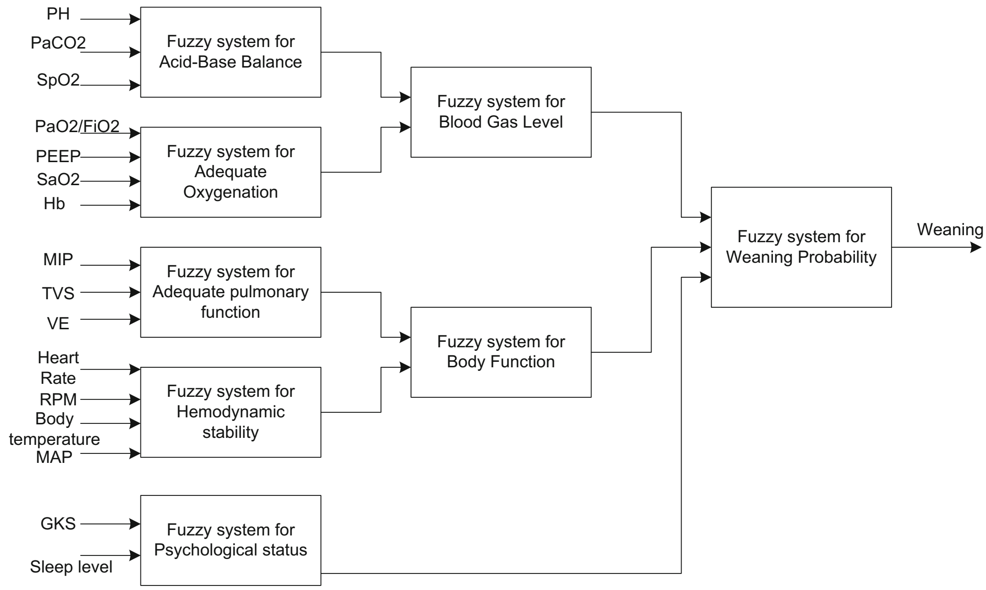


Fig. 1 The schematic outline of the developed algorithm

If this value is below the threshold of 100 (breaths per/min)/L, RSBI predicts weaning success with an accuracy of up to 97% [20]. However, prolonged MV decreases the sensitivity of RSBI, and the state of the disease influences its specificity [21]. The other predictors used in the weaning process require more detailed respiratory parameters, and so, they are not preferred by the staff of an ICU.

It is known that if physicians decide the weaning from MV, the success of weaning is only 35–60% [22]. Some researchers developed their predictor algorithms to increase weaning success above predictors described in published literature. Nemoto et al. implemented a process to wean patients' off ventilator with fuzzy logic by using parameters such as heart rate, tidal volume, breathing rate, and the percentage of oxygen saturation of arterial blood (SaO_2) [23]. They tested their developed algorithm on 13 patients with severe chronic obstructive pulmonary disease (COPD). They compared their algorithm with the decisions made by a physician. Hsu et al. developed a clinical decision support system by using a support vector machine (SVM) to predict the right weaning time [24]. In their study, frequency to tidal volume ratio, inspiratory

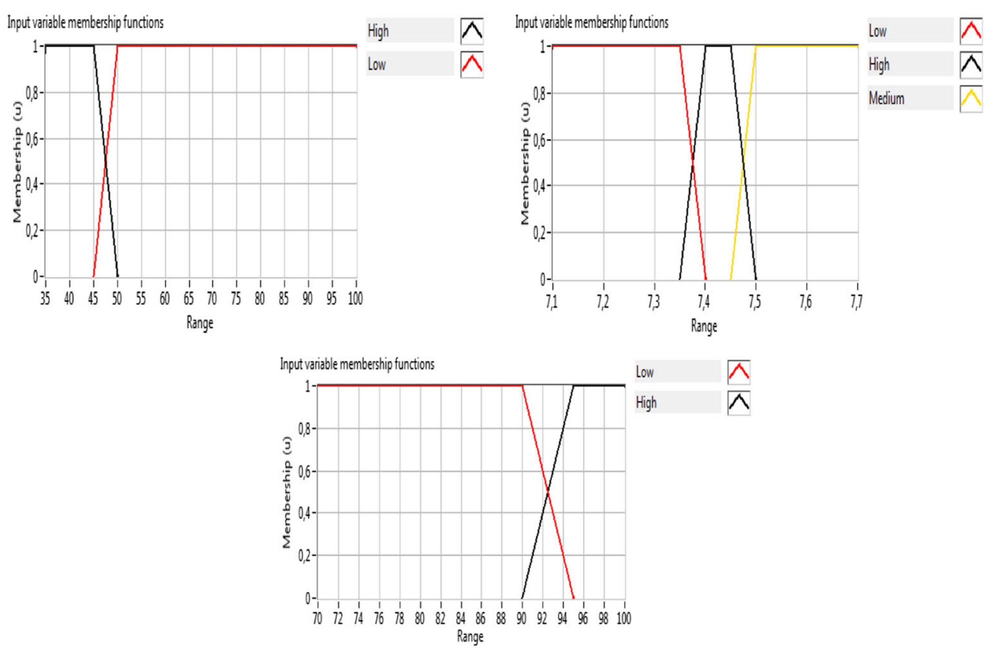


Fig. 2 The membership function for $PaCO_2$, pH, and SpO_2

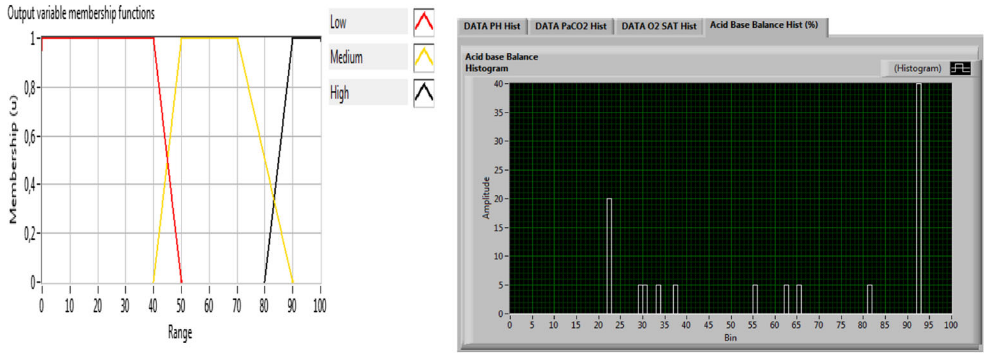


Fig. 3 The output membership function for acid–base balance, and histogram of acid–base balance

tidal volume, expiratory tidal volume, and respiration rate were used to determine the weaning time. Kilic and Kilic developed a fuzzy decision support system for weaning off mechanical ventilators; their fuzzy input variables were hemoglobin, mean arterial pressure, arterial oxygen saturation, arterial CO_2 partial pressure (PCO_2), arterial pH, fractional inspired oxygen (FiO_2), negative inspiratory pressure, and tidal volume of spontaneous ventilation. They compared its results against weaning predictors found in published literature [25].

As can be seen, the developed algorithms and protocols in literature have generally ignored some parameters such as hemodynamic stability and the psychological status of patients. It is not possible to start weaning without evaluating these parameters. The predictors used in the literature are based on mathematical formulas. However, it is known that weaning process requires human experience and knowledge instead of certain mathematical formulas. Thus, there is no weaning protocol broadly accepted by everyone. Fuzzy logic which is an expert knowledge-based system is more suitable to determine weaning process. In this paper, the goal is to develop a new knowledge-based weaning algorithm that eliminates the disadvantages of the current predictors. Twenty clinical scenarios were generated using Monte Carlo simulations and Gaussian distribution methods to test the performance of the developed algorithm. The developed knowledge-based algorithm and RSBI predictor were applied to the generated scenarios. In addition, a clinician evaluated each generated scenario independently according to the 16 parameters generated. The Student s *t* test was used to show statistical differences between these results. According to the results obtained, there is no statistical difference for a 96.1% probability between the proposed methods and the clinician's evaluation. However, there is a statistical difference at a probability of 25.2% between the proposed methods and RSBI and a statistical difference at a probability of 30.6% between the clinician's evaluation and RSBI.

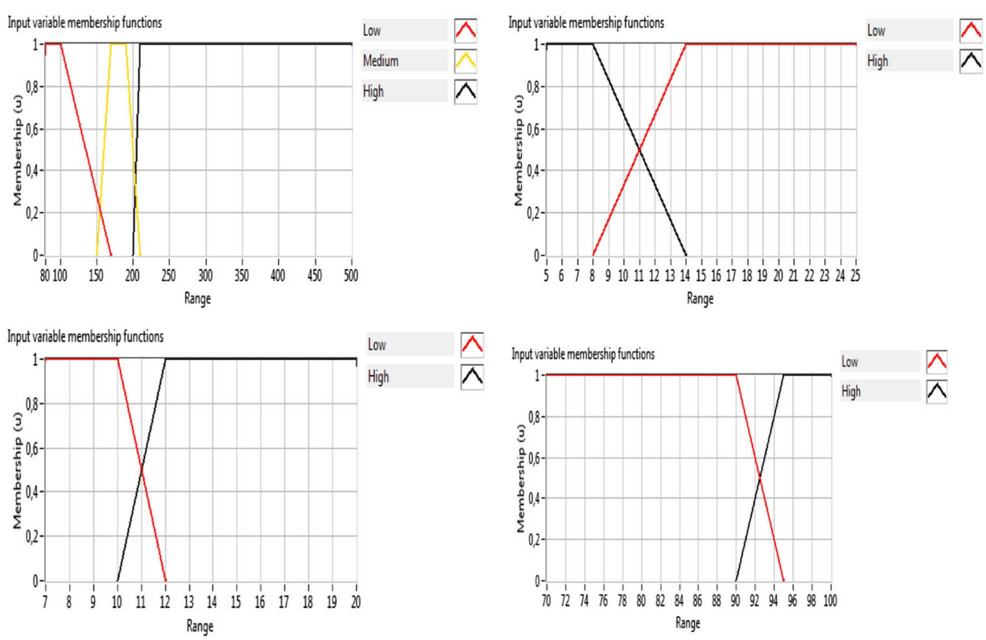


Fig. 4 The membership function for PaO2/FiO2, PEEP, SaO2, and Hb

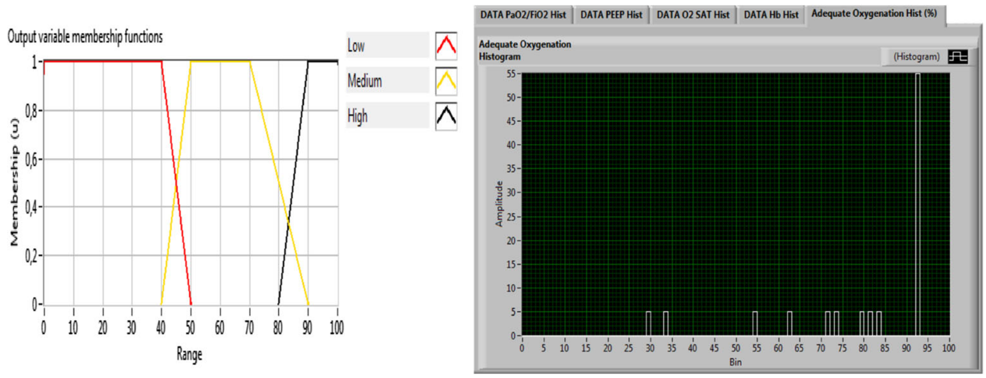


Fig. 5 The output membership function for adequate oxygenation and histogram of adequate oxygenation

2 Methods

The system designed contains 16 parameters, which are easy to collect in practice, and use them to evaluate acid–base balance, adequate oxygenation, adequate pulmonary function, hemodynamic stability, and psychological status for weaning. Here, a knowledge-based weaning algorithm was designed using Fuzzy-LabVIEW software for decision making when weaning patients off MVs. To test and show effectiveness of the algorithm, clinical scenarios were generated using Monte Carlo simulations and Gaussian distribution methods for 16 vital parameters. These parameters are pH, carbon dioxide partial pressure ($PaCO_2$), oxygen saturation (SpO_2), PaO_2/FiO_2, PEEP, the oxygen saturation (SaO_2), hemoglobin (Hb), maximum inspiratory pressure (MIP), tidal volume in spontaneous breathing (TVS), respiratory minute volume (VE), heart rate, the respiratory rate per minute (RPM), body temperature, mean arterial blood pressure (MAP), glasgow coma scale (GCS), and sleep level. Fuzzy logic-based algorithms were designed to predict weaning probability, and the performance of the algorithm was tested using a Monte Carlo simulation in which random values for fuzzy inputs were taken from Gaussian distributions [26]. The Gaussian distribution equations used in this algorithm are given in eqs. 1, 2 and 3,

$$f\left(x;\mu;\sigma^2\right)=\frac{1}{\sigma\sqrt{2\pi}}*e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{1}$$

$$z=\frac{x-\mu}{\sigma} \tag{2}$$

$$x = z\sigma + \mu \tag{3}$$

where x is the new data, z is the standard normal distribution, μ is the mean value, σ^2 is the variance random value, and σ is the standard deviation. The fuzzy system development

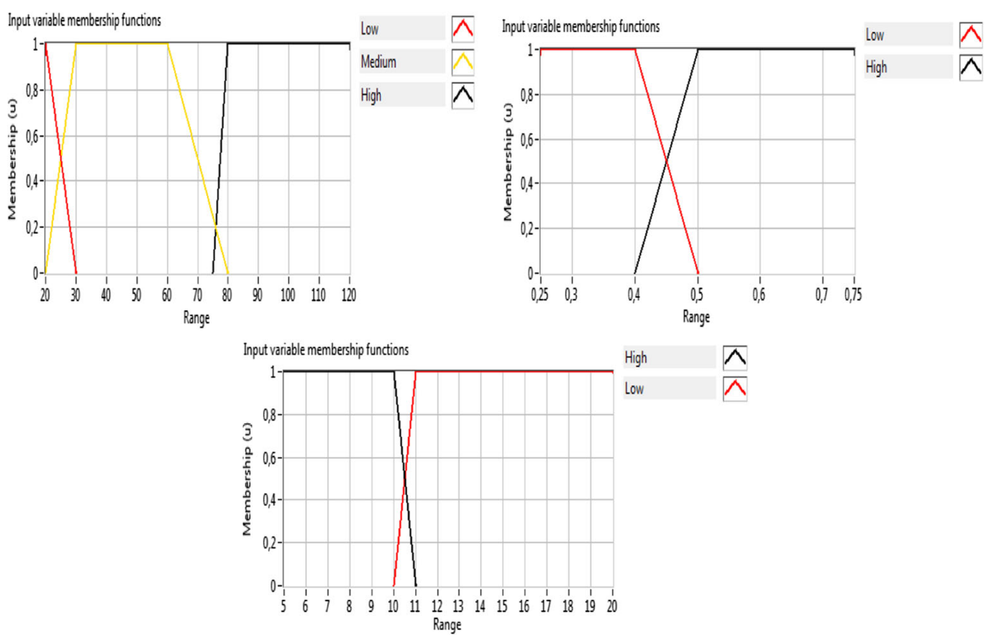


Fig. 6 The membership function for MIP, TVS, and VE

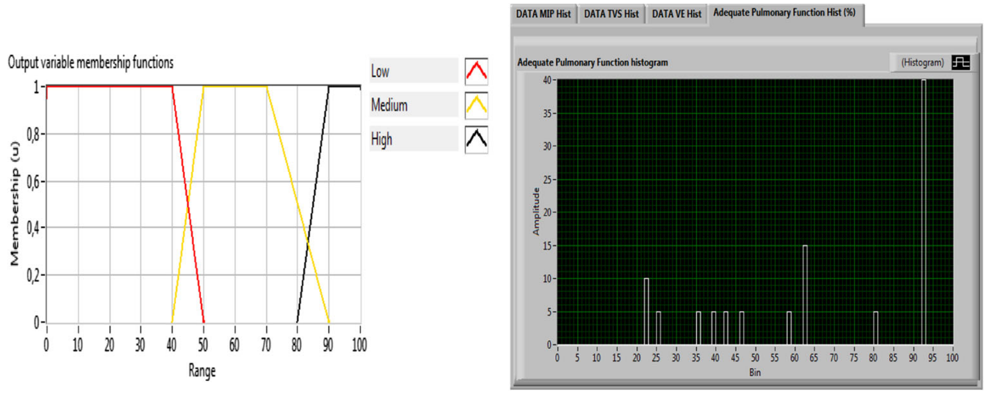


Fig. 7 The output membership function for adequate pulmonary function and histogram of adequate pulmonary function

was designed in LabVIEW software. The reason for preferring the LabVIEW program is its graphic-based structure and the ease with which a user can interface to it. The schematic outline of the developed algorithm is given in Fig. 1.

2.1 Acid–base balance

In the developed algorithm, pH, $PaCO_2$, and SpO_2 were used to determine the acid–base balance for patients. The input membership functions of $PaCO_2$, SpO_2, and pH are shown in Fig. 2. Twelve rules were created for the acid–base balance. The membership function and histogram for the acid–base balance are given in Fig. 3.

2.2 Adequate oxygenation

The four parameters of PaO_2/FiO_2, PEEP, SaO_2, and Hb were used to determine the oxygenation levels of patients. The input membership functions for PaO_2/FiO_2 rate, PEEP, SaO_2, and Hb are illustrated in Fig. 4, and Fig. 5 shows the output for adequate oxygenation and a system histogram.

2.3 Adequate pulmonary function

MIP, TVS, and VE parameters were chosen as fuzzy inputs for adequate pulmonary function. The membership functions for input are shown in Fig. 6, and the output membership function and system histogram are given in Fig. 7.

2.4 Hemodynamic stability

Heart rate, RPM, body temperature, and MAP were used to determine hemodynamic stability in the developed system. The membership functions of these four parameters are illustrated in Fig. 8, and membership function of hemodynamic stability and system histogram is shown in Fig. 9.

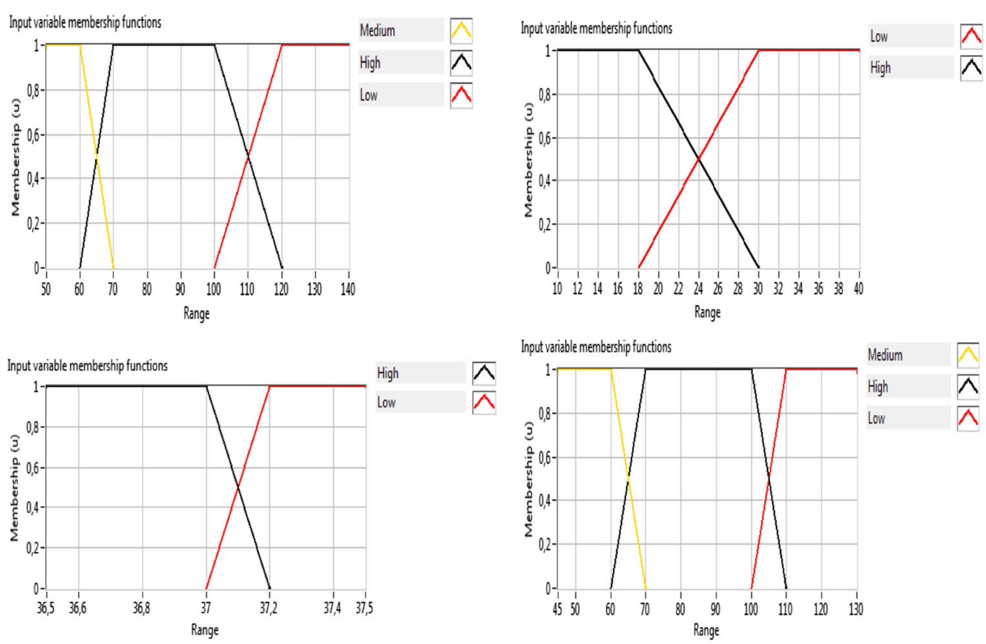


Fig. 8 The membership function for heart rate, RPM, body temperature, and MAP

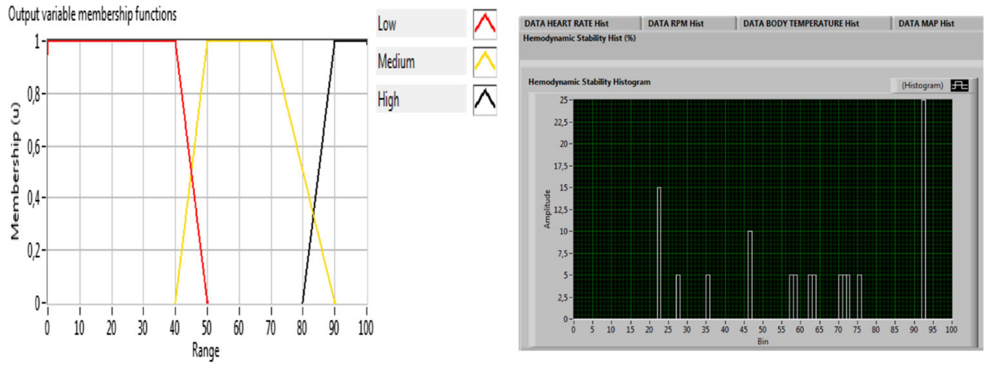


Fig. 9 The output membership function for hemodynamic stability and histogram of hemodynamic stability

2.5 Psychological status of patient

The GCS and sleep level for the patient were chosen to determine the patient's psychological status. The input membership functions for GCS and sleep level of the patient and the output membership function and system histogram are shown in Fig. 10.

2.6 Blood gas level and body function

Acid–base balance and adequate oxygenation were chosen to determine blood gas level percentage of the patient, and adequate pulmonary function and hemodynamic stability were used to evaluate body function percentage. Figure 11 shows the output membership function for blood gas levels and the output membership for body function.

The developed algorithm description involves many block diagrams and front panels. Some of these front panels and block diagrams are shown in Figs. 12, 13, 14, and 15.

Sixteen parameters are used to estimate the percentage probability for weaning of patients. Some of these parameters have been grouped together in the developed system; otherwise, the fuzzy system would have nearly 300,000 rules. Such unmanageable rule tables could not possibly be generated by an expert clinician. In the developed system, the numbers of total rules generated are 135. Grouping some related parameters together decreases the huge rule tables for the system. The final rule table for the weaning probability for a patient is given in Table 1. In the system, all the rules are created by an expert clinician.

3 Results

Twenty clinical scenarios were randomly generated using Monte Carlo simulations and Gaussian distribution methods to test the weaning probability. Each clinical

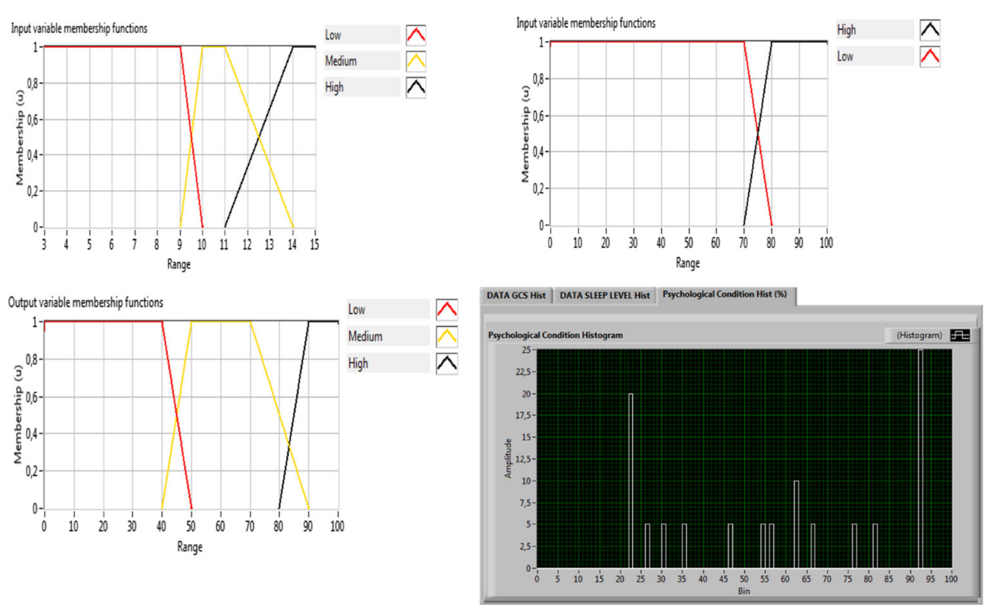


Fig. 10 The membership function for GCS and sleep level of patient and the output membership function for for psychological status of patient. **b** Histogram of psychological status of patient

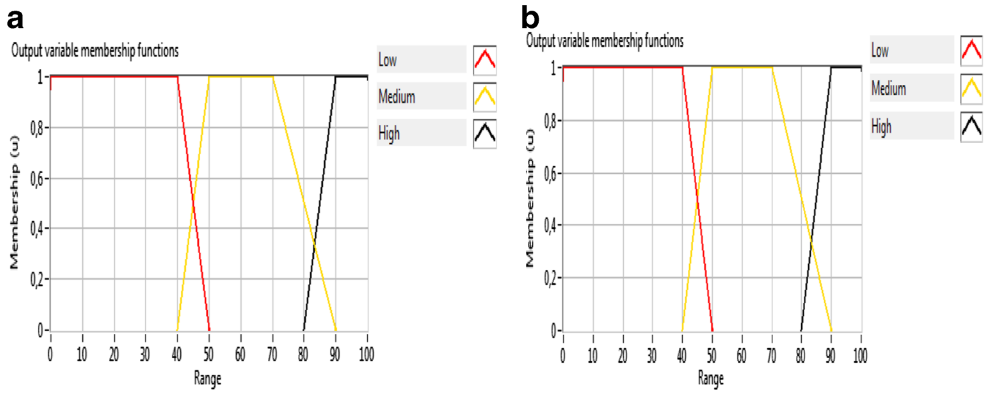
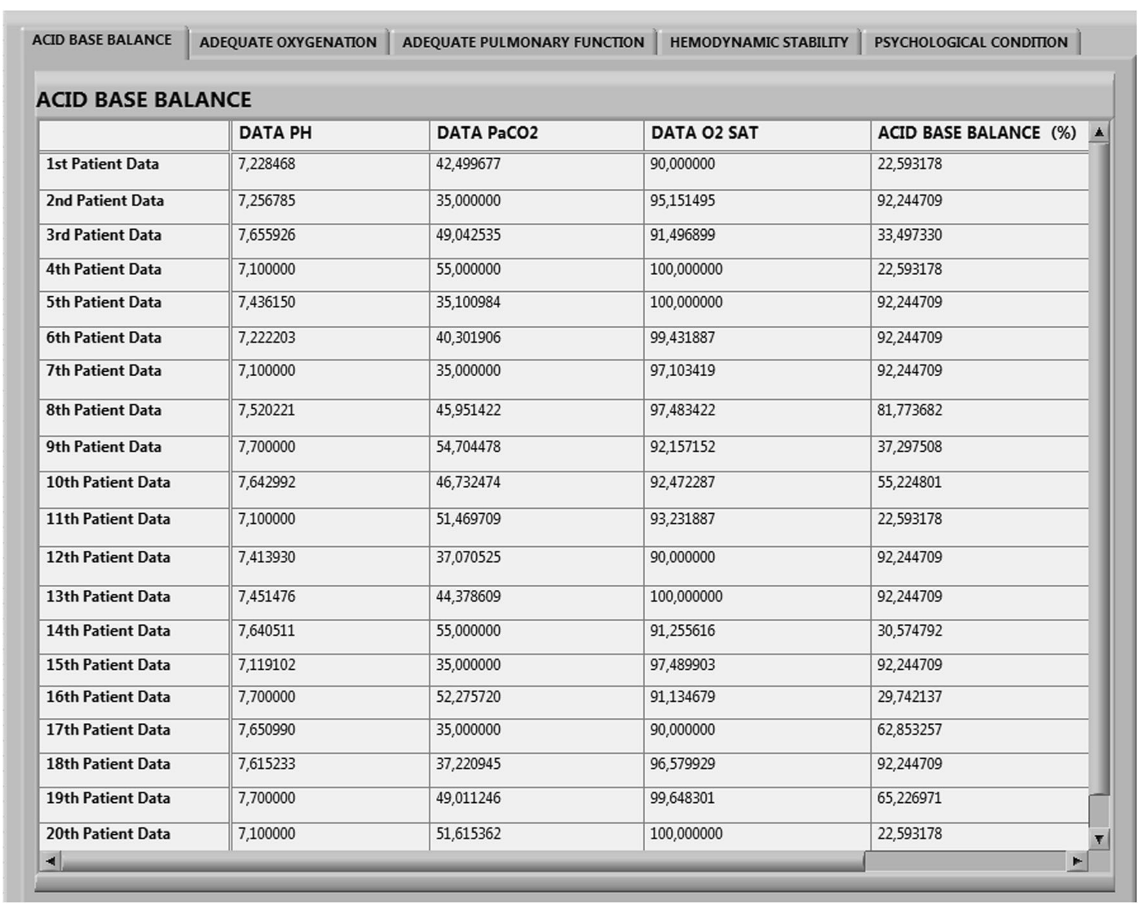


Fig. 11 **a** The output membership function for blood gas level. **b** The output membership function for body function

scenario represented a patient in the system. Sixteen vital parameters for each scenario were used to make a decision about weaning in the developed predictor. The weaning probabilities obtained, RSBI results, and the percentages obtained from the clinician's evaluations for each scenario are given in Table 2.

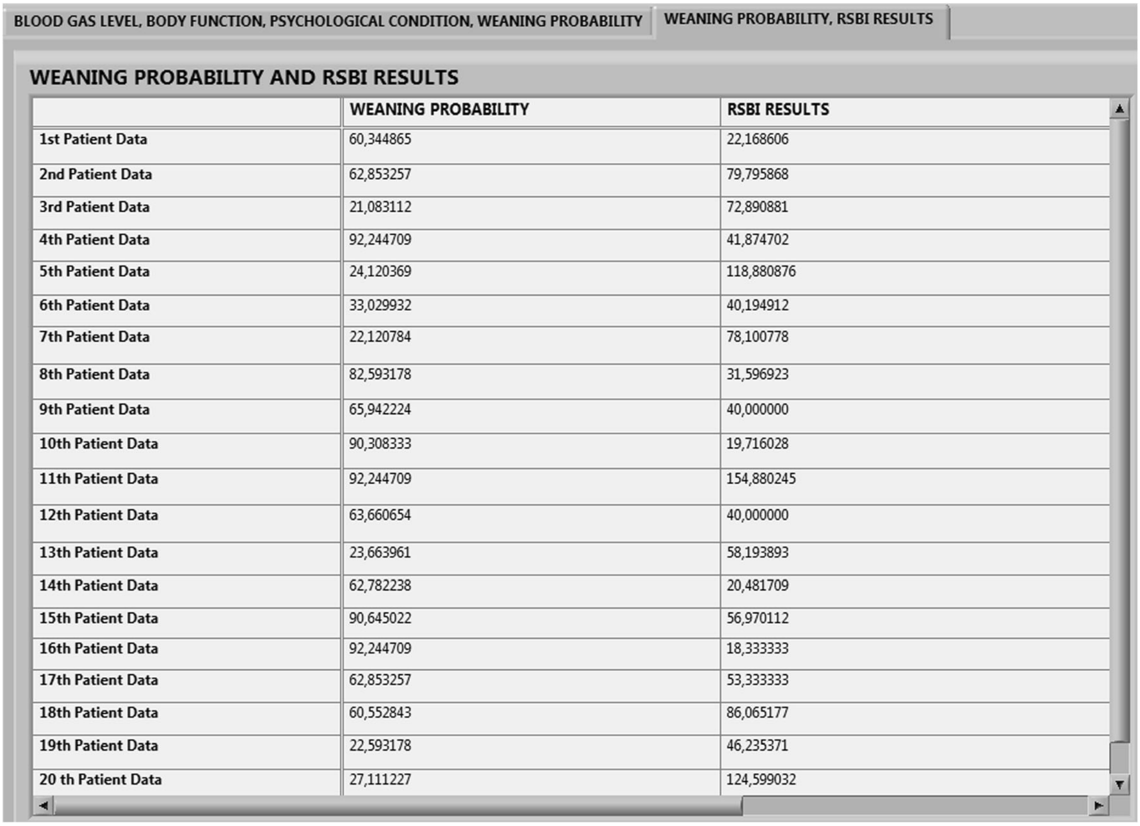
Figure 16 shows box and whisker plots for the developed algorithm, RSBI, and the clinician's evaluation. In this figure, it can be shown that the developed algorithm performs better than the RSBI predictor's results in terms of the median value and the upper and lower ends of the boxes. In addition, the developed algorithm produces results that are very close to the clinician's evaluation according to the generated scenario.

The results show that the developed algorithm gave a different decision than RSBI for the 3rd, 6th, 7th, 11th,



	DATA PH	DATA PaCO2	DATA O2 SAT	ACID BASE BALANCE (%)
1st Patient Data	7,228468	42,499677	90,000000	22,593178
2nd Patient Data	7,256785	35,000000	95,151495	92,244709
3rd Patient Data	7,655926	49,042535	91,496899	33,497330
4th Patient Data	7,100000	55,000000	100,000000	22,593178
5th Patient Data	7,436150	35,100984	100,000000	92,244709
6th Patient Data	7,222203	40,301906	99,431887	92,244709
7th Patient Data	7,100000	35,000000	97,103419	92,244709
8th Patient Data	7,520221	45,951422	97,483422	81,773682
9th Patient Data	7,700000	54,704478	92,157152	37,297508
10th Patient Data	7,642992	46,732474	92,472287	55,224801
11th Patient Data	7,100000	51,469709	93,231887	22,593178
12th Patient Data	7,413930	37,070525	90,000000	92,244709
13th Patient Data	7,451476	44,378609	100,000000	92,244709
14th Patient Data	7,640511	55,000000	91,255616	30,574792
15th Patient Data	7,119102	35,000000	97,489903	92,244709
16th Patient Data	7,700000	52,275720	91,134679	29,742137
17th Patient Data	7,650990	35,000000	90,000000	62,853257
18th Patient Data	7,615233	37,220945	96,579929	92,244709
19th Patient Data	7,700000	49,011246	99,648301	65,226971
20th Patient Data	7,100000	51,615362	100,000000	22,593178

Fig. 12 The developed front panel for acid–base balance



	WEANING PROBABILITY	RSBI RESULTS
1st Patient Data	60,344865	22,168606
2nd Patient Data	62,853257	79,795868
3rd Patient Data	21,083112	72,890881
4th Patient Data	92,244709	41,874702
5th Patient Data	24,120369	118,880876
6th Patient Data	33,029932	40,194912
7th Patient Data	22,120784	78,100778
8th Patient Data	82,593178	31,596923
9th Patient Data	65,942224	40,000000
10th Patient Data	90,308333	19,716028
11th Patient Data	92,244709	154,880245
12th Patient Data	63,660654	40,000000
13th Patient Data	23,663961	58,193893
14th Patient Data	62,782238	20,481709
15th Patient Data	90,645022	56,970112
16th Patient Data	92,244709	18,333333
17th Patient Data	62,853257	53,333333
18th Patient Data	60,552843	86,065177
19th Patient Data	22,593178	46,235371
20 th Patient Data	27,111227	124,599032

Fig. 13 The developed final front panel of the system

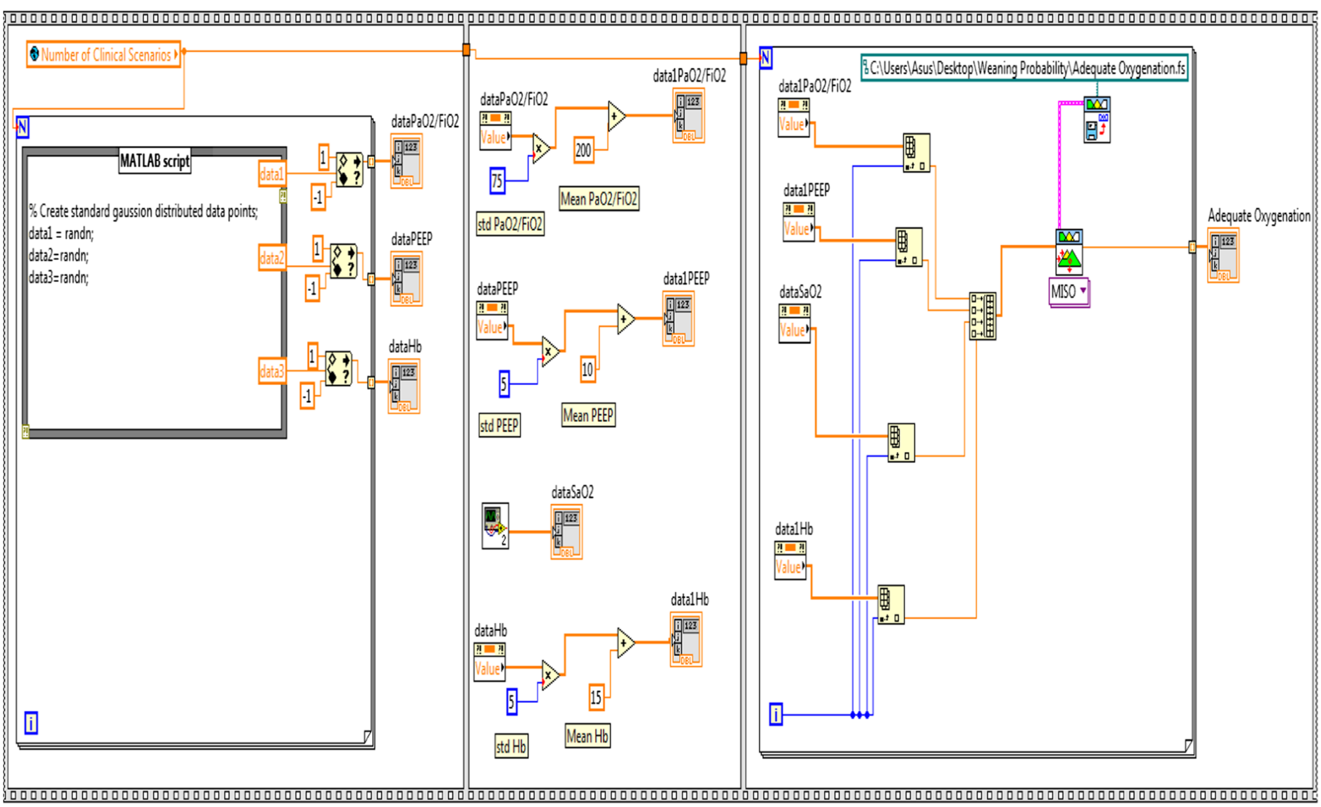


Fig. 14 The developed fuzzy systems for adequate oxygenation

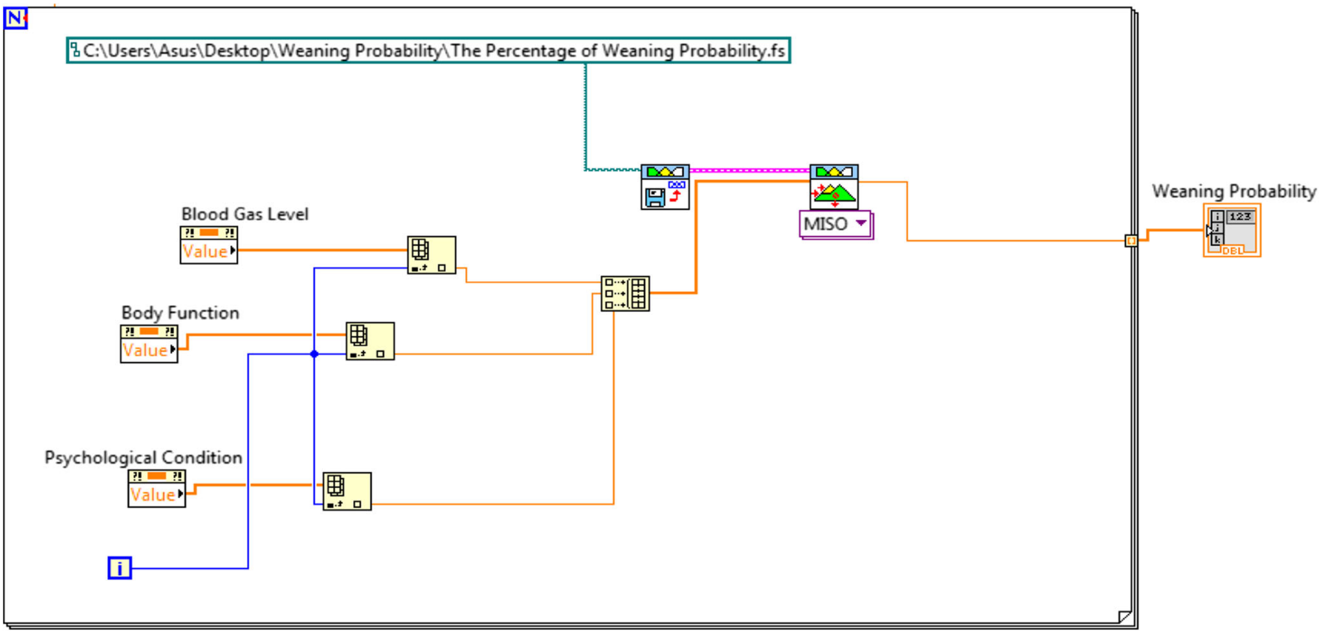


Fig. 15 The developed fuzzy systems for weaning probability

Table 1 The final rule table for weaning probability of patient

Blood gas level	Body function	Psychological condition	Weaning probability
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Low
Low	Medium	Low	Low
Low	Medium	Medium	Medium
Low	Medium	High	Medium
Low	High	Low	Low
Low	High	Medium	Medium
Low	High	High	High
Medium	Low	Low	Low
Medium	Low	Medium	Medium
Medium	Low	High	Medium
Medium	Medium	Low	Medium
Medium	Medium	Medium	Medium
Medium	Medium	High	High
Medium	High	Low	Medium
Medium	High	Medium	High
Medium	High	High	High
High	Low	Low	Medium
High	Low	Medium	Medium
High	Low	High	High
High	Medium	Low	Medium
High	Medium	Medium	High
High	Medium	High	High
High	High	Low	High
High	High	Medium	High
High	High	High	High

Table 2 The obtained results from the developed algorithm and clinician's evaluation

Patient data (P.D.)	The percentage of developed weaning probability (%)	RSBI results	The percentage of clinician probability (%)
1st P.D.	60,344865	22,168606	65
2nd P.D.	62,853257	79,795868	60
3rd P.D.	21,083112	72,890881	30
4th P.D.	92,244709	41,874702	95
5th P.D.	24,120369	118,880876	25
6th P.D.	33,029932	40,194912	30
7th P.D.	22,120784	78,100778	25
8th P.D.	82,593178	31,596923	85
9th P.D.	65,942224	40,000000	65
10th P.D.	90,308333	19,716028	95
11th P.D.	92,244709	154,880245	95
12th P.D.	63,660654	40,000000	70
13th P.D.	23,663961	58,193893	30
14th P.D.	62,782238	20,481709	65
15th P.D.	90,645022	56,970112	90
16th P.D.	92,244709	18,333333	95
17th P.D.	62,853257	53,333333	55
18th P.D.	60,552843	86,065177	60
19th P.D.	22,593178	46,235371	30
20th P.D.	27,111227	124,599032	25

13th, and 19th scenarios. In these scenarios, when the algorithm developed and clinician decided to start weaning process, it was not possible to wean the patient from MV according to the RSBI results. The developed algorithm's results and the clinician's evaluation were the same for those scenarios. The Student's t test for $p < 0.05$ was applied to the percentage of weaning probability obtained, the RSBI result, and the percentage from clinician's evaluation. The Student's t test was used to determine statistical difference because it assesses whether the means of the three groups are statistically different from each other. This test is appropriate whenever a person wants to compare the

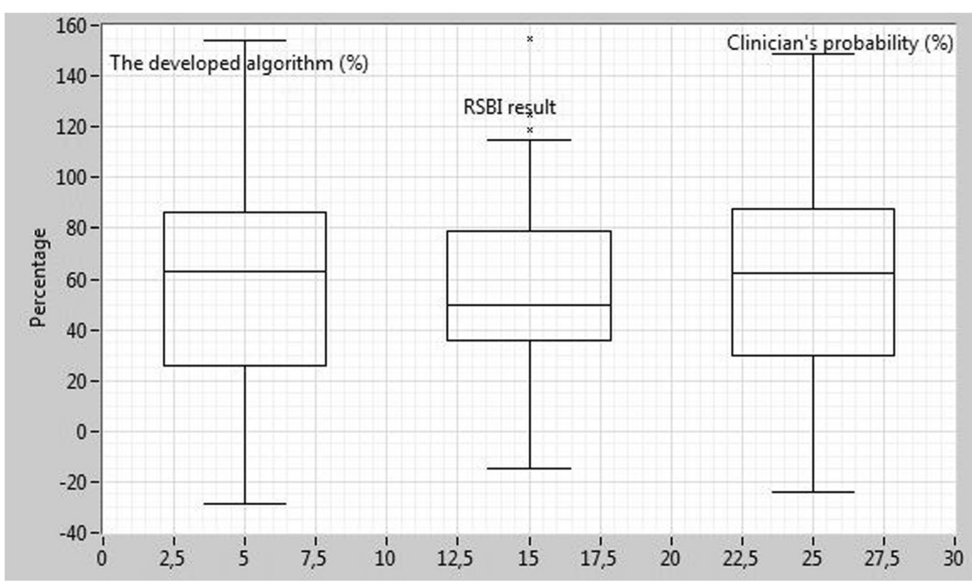


Fig. 16 *Box-and-whisker plots* of the developed algorithm, RSBI, and clinician's evaluation

means of two or more groups [27–29]. Equations 4, 5, and 6 were used to calculate the statistical difference.

$$\overline{X} = \frac{\sum x}{n} \tag{4}$$

$$s^2 = \frac{\sum \left(x - \bar{x}\right)^2}{n-1} \tag{5}$$

$$t = \frac{\left(\overline{x_1} - \overline{x_2}\right)}{\sqrt{\frac{s_1^2}{n_1 - 1} + \frac{s_2^2}{n_2 - 1}}} \tag{6}$$

where $\bar{x}$ is the arithmetic mean, S^2 is the variance, t is the test formula, x is the investigated group, and n is the number of data points in the group. According to the results from the t test, there is no statistical difference for 96.1% probability between the percentage of developed algorithm results and evaluations by the clinician. In addition, there are statistical differences at 25.2 and 30.6% between the percentages of the developed algorithm results and the RSBI results and between the RSBI results and the percentages from the clinician's evaluation, respectively.

4 Discussion

In ICUs, clinicians try to promptly withdraw ventilator support when patients no longer need this support. This decreases complications, costs, and prolonged mechanical ventilation. Thus, many studies about weaning prediction algorithms and protocols have been carried out. Currently, there are many weaning protocols such as RSBI, PTI, and JWI. RSBI is a widely used protocol for weaning patients off MVs. Since these algorithms and protocols have generally ignored some parameters such as hemodynamic stability and the psychological status of patients, there is no weaning protocol broadly accepted by everyone. In this study, all the individual parameters used in literature were taken into account to estimate the weaning probability percentage for patients. Sixteen vital parameters were used to determine the weaning decision in the fuzzy systems. Since there were so many parameters used in this study, related parameters were grouped together to decrease the numbers of rule tables in the fuzzy system. Three parameters, pH, carbon dioxide partial pressure ($PaCO_2$), and oxygen saturation (SpO_2), were used to determine acid–base balance percentage. Four other parameters were used to determine the percentage for adequate oxygenation. These parameters were PaO_2/FiO_2 rate, the oxygen saturation (SaO_2), the hemoglobin (Hb), and the positive end-expiratory pressure (PEEP). The three parameters, maximum inspiratory pressure (MIP), tidal volume in spontaneous breathing (TVS), and respiratory minute volume (VE), were used to determine the percentage required for adequate pulmonary function. In addition, heart rate, the respiratory rate per minute (RPM), the body temperature, and MAP were used to determine the percentage of hemodynamic stability. The Glasgow Coma Scale (GCS) and sleep level were used to evaluate a percentage for the psychological status of the patients. After this calculation, the acid–base balance and oxygenation determined the blood gas level. Adequate pulmonary function and hemodynamic stability were used to determine the level of body function. Then, the blood gas level, the level of body function, and psychological status of patients were used to determine the percentage probability to commence weaning. The all algorithms were implemented in LabVIEW software. In this study, the generated clinical scenarios were firstly applied to the developed algorithm and RSBI, and then, a clinician determined the weaning probability percentage for patients according to each scenario. According to the results obtained, the developed algorithm and the clinician's evaluation gave nearly identical results, but RSBI failed to accurately estimate the weaning probability. The results show valuable proof of concept for the role of fuzzy logic in the management of the weaning process.

5 Conclusion

The weaning process is an important issue for patients and clinicians. If clinicians do not start the weaning process at the right time, it may result in prolonged mechanical ventilation, and it may cause some complications including infection, pneumonia, and barotraumas. Thus, the knowledge-based weaning process can determine the right time to start weaning, and it can be said that the developed algorithm may create a future research-driven protocol for weaning patients off the ventilators.

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