The Implementation of Hybrid Neuro Fuzzy Membership Function Analysis for Predicting Player Emotional Intelligence of Balinese Game Model

I Nyoman Putu Suwindra[1], I Ketut Gede Darma Putra[2], Made Sudarma[3], Nyoman Putra Sastra[4]

[1]Faculty of Matematics and Natural Sciences, Ganesha University of Education, Indonesia
[1*)]suwindra@undiksha.ac.id
[2.3.4]Faculty of Technology and Engineering, Udayana University, Indonesia
[2]ikgdarmaputra@unud.ac.id, [3]msudarma@unud.ac.id, [4]putra.sastra@unud.ac.id

Abstract This paper aims to examine the application of Neuro fuzzy membership function analysis to predict the emotions of children who like to play games. The game that has been developed is a type of game based on Balinese local wisdom, which innovates the Balinese culture-based legend I Rajapala. Rajapala who married an angel had a son named Durma. Rajapala and Durma are used as game characters that can be played on behalf of game players. Game-factor and emotional variable data were collected using a questionnaire integrated into the game system, as well as motivational data from points achieved and the use of time recorded in the game system. The data were analyzed by Sugeno Neuro Fuzzy system with hybrid and backpropagation methods. The results obtained are as follows: (1) Emotional Balinese game players can be predicted from game-factors and motivations of game players. This was shown from the FIS output (Eo) of the neuro fuzzy training analysis and the RMSE (Eo=36.8; RMSE=4.6610), the testing analysis was (Eo=33.0; RMSE=4.4528), and the checking analysis was (Eo=37.8; RMSE=4.7479) with a difference of less than 13% (training=2.72%; testing=3.0%, and checking=12.77%). In other words, if it is analyzed descriptively was (M=37.83; SD=5.3573), the output of neuro fuzzy is obtained more than 87.23%. (2) The emotional level of the child was categorized as a positive, the child's motivation was moderate and the response to the game was positive. These findings can be taken into consideration in choosing the type of game to be played in order to increase motivation and control children's emotions. Besides that, innovating games based on local wisdom is expected to preserve local Balinese culture.

***Key Words*— Hybrid Neuro-Fuzzy, Emotional, motivation, Balinese game**

I. Introduction[1]

THE emotional is a naturally developed human innate trait. However, that doesn't mean that emotional nature can't be controlled. Control depends largely on a person's individual externality. Objects that can be emotional can be both audio and visual. Furthermore, audio and video objects will stimulate to the brain and signals are passed to the heart so as to cause a sense of effect in the form of emotional.

The emotion areas of the brain are activated and deactivated reciprocally with areas related to cognitive functioning, and the cortex are among the brain areas shown to influence how well *to m*anage emotions [1]. The neurobiology of emotion is needed to facilitate future research on this developing construct, particularly in the areas of the development of emotional intelligence.

In today's technological era, various activities can be done through the Internet, social media, business, webinars, games, etc. Often the information being listened to, seen, played leads to uncontrollable emotions.

the number of online gaming enthusiasts all over the world each year increased 17% to 217 million people in 2007. In Indonesia, the number of game enthusiasts of the mobile version, which has increased rapidly. It causes a variety of reasons that need to be discussed in more detail [2]. Thus, it aims at making us more aware of how much benefit the mobile game gives, especially for the well-being of the game in the beloved homeland.

Neuro Fuzzy Inference System is a system which is a combination of fuzzy logic and neural network, where the values are entered first to the monitoring network through the fuzzifier modules that create ordinary numerical values. The operations in the neural network are all the same, then the output is returned to normal via the de fuzzifier module. The relationship between input and output variables can be used to predict the output variable if there is a suitable input variable.

The pleasure of playing games is almost loved by everyone, including children. Various types of traditional games in Bali, such as: *petaumpet, gangsing, tajog*, etc., are introduced heritage[3]. Uncontrolled game play tends to affect the emotions of the players. Game development needs to consider game design that can control emotional intelligence. This paper will examine the relationship between game-factor, motivation and emotional intelligence.

II. Related Work

A. Balinese Game Model

The Balinese game model that has been developed is entitled I Rajapala who is married to an angel Ken Sulasih, and has a son named I Durma. As a child, he liked to play traditional Balinese games with his friends, such as *Petaumpet, Tajog,* etc. Like children in general, before playing, I Durma told his friends about various things about norms, ethics, and manners. religion, especially Hinduism. Everything he got was from his mother. Ethics and norms are very important for children, including: Catur Guru, Tri Kaya Parisuda, Sadripu, Sadatitayi, Tri Hita Karana, etc. Like previous development studies on games based on Balinese cultural wisdom, namely: the serious game of Cupak Gerantang by Sukajaya, et al. [4], and the serious game "I Rajapala" by Suwindra, et al.[3] S. Winton [5], on traditional approaches in character education.

B. Game Factor, Motivation, and Emotional

In designing a game model requires a strategy that combines game and learning. Shi and Shih [4] explains that the macro design concept of a game consist of 11 important factors, namely: objects, mechanisms, fantasy, values, interaction, freedom, narration, sensation, challenges, sociality and mysteries. The combination of the factors can determine the quality of the game.

According to Kwon and Lee [5], emotional of a person are categorized into 4 quartiles, and each of which is divided into 3 sub-quartiles, including: (1) Quartile 1 (Happy, Happy, Happy), (2) Quartile 2 (Anxiety, Angry, Annoying), (3) Quartile 3 (Drowsy, Bored, Sad), and (4) Quartile 4 (Calm, Calm, Relaxed). If a person's emotions are not controlled and managed properly, it will develop into a habit. Negative emotions such as anger, boredom, sleepiness, etc., can harm oneself and others in the environment.

C. Herodotoua, et al. al. [6], explains that emotional game players are related to personal characteristics. Emotions were also negatively related to the frequency of playing games. Lickona [7, 8] suggests that models from parents, teachers and others can develop children's character. For this reason, parents must set a good example of character for their children.

According to Agung [9], character education is expected to be a means and opportunity for students to develop various good characters such as: religious, honest, integrity, tolerance, discipline, independence, tenacity, creativity, patriotism, and friendly. Children's character will grow well if parents play a lot in introducing ethics, morals, and morality based on local culture. On the other hand, character also plays a role in controlling emotions, patience, peace and humility.

C. Hybrid Neuro Fuzzy

In general, artificial intelligence techniques based on fuzzy logic and neural networks are often applied together called Neuro-Fuzzy System (NFS). However, the term is often used to designate a particular type of system that integrates the two techniques. The characteristics of this system by the fuzzy system are fuzzy sets and fuzzy rules according to the input output pattern. There are several different implementations of the neuro-fuzzy system which is defined by each author as known Hybrid Neuro-Fuzzy technique. U. Murad, et.al [5] defines that the adaptive neuro fuzzy system can detect human emotions when there is an incoming response. In addition to the e-learning component which includes instructors, students, courses, and media, the student performance component aims to measure the success of e-learning.

According to Darina Dicheva [6], there are two objectives of game development, namely: (1) comparing the new results from the results of previous data analysis, and (2) analyzing the growth of gamification penetration in the educational process. This study explains that the mechanism of practice has gone beyond the understanding of researchers. Meanwhile, the gamification penetration process is still developing. Jae Hwab Bae [7], to streamline the game development process, the process of planning, designing, and developing a more efficient platform-based game engine. The living world presents an unscripted nonlinear process. To learn the complexities of cognitive and cultural nuances safely through cultural training that can lead to a high appreciation of the culture [8]. Andre F.S Barbosa et al [9, 10] explained that game design needs to consider game factors and the concept of real time strategy in the domain of education and learning.

Adaptive Neuro Fuzzy Inference System (ANFIS) is a model that can be used to predict cases in various fields. One such case is the neuro-fuzzy model to predict the effect of noise pollution on human work efficiency by Zaheeruddin, et.al.[11], and other cases. Ehsan Lotfi [12], the ANFIS model shows higher accuracy than conventional neural networks in oil price prediction. Raharja, at.al.[13], analysis of neuro-fuzzy membership function can predict inflation growth in Bali Province. Tiruneha, et al. [14], Neuro-Fuzzy Systems (NFS) represents the input-output relationship model of complex problems and non-linear systems in Engineering and Construction Management problems.

III. Method

This research begins with the development of games based on Balinese local wisdom. The development of the game has been carried out[3], and experiments have been carried out on children who like to play games, so that data are obtained according to the variables analyzed in this paper. The Baline game model that has developed as presented in Figure 1, and the experimental activities as presented in Figure 2,

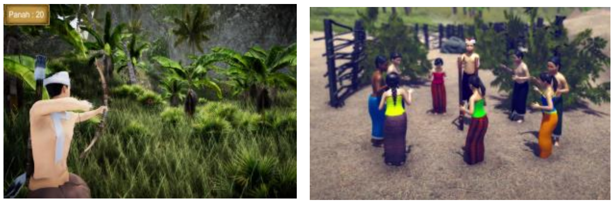


Fig. 1. The Balinese game model

Fig. 2. The experimental activities

The variables in this study consisted of children's emotional, game-factors and motivation. The data obtained by using an instrument that is integrated in the game system that has been tested for validity and reliability.

Based on output of the SPSS Pearson Correlation analysis, the correlation coefficient r of each the game-factor questionnaire item was r=0.415 to r=0.470 with p<0.01, and reliability with Cronbach's Alpha=0.684. In the same way, the emotional questionnaire, the correlation coefficient r of each the emotional questionnaire item was r=0.327 to r=0.526 with p<0.01, and reliability with Cronbach's Alpha=0.686. While the data motivation is obtained from game time and points earned recorded in the game system.

These three data variables were analyzed in relation to the neuro fuzzy system through membership function analysis. Clustering is one way to predict the stability of the output by using a neuro-fuzzy inference system [15, 16]. In this paper, the data is grouped using a 3x105 dataset, odd, and even data for training, testing, and checking analysis. Data analysis was carried out using the Sugeno Neuro Fuzzy method with the Simulink Matlab R2014b application [17]. The diagram of Sugeno Neuro Fuzzy as showed at Figure 3.

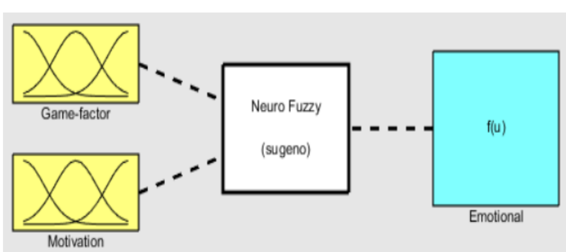


Fig. 3. Diagram of Sugino Neuro Fuzzy

The relationship between variables was determined to begins with an analysis of the membership function (mf) neuro fuzzy.

Slope analysis was determined by training datasets using membership function models in Neuro Fuzzy analysis, namely: Triangular membership function (*trimf*), trapezoidal membership function (*trapmf*), Generalized Bell membership function (*gbellmf*), Gaussian membership function (*gaussmf*), two membership functions General Bell (*gauss2mf*), Pi membership function (*pimf*). Difference sigmoidal membership function (*dsigmf*), and product sigmoidal membership function (*psigmf*). The most suitable function model is determined based on the smallest Root Mean Square Error (RMSE) from the training results and the biggest output constants of each membership function analysis. The structure of membership function analysis is shown at Figure 4.

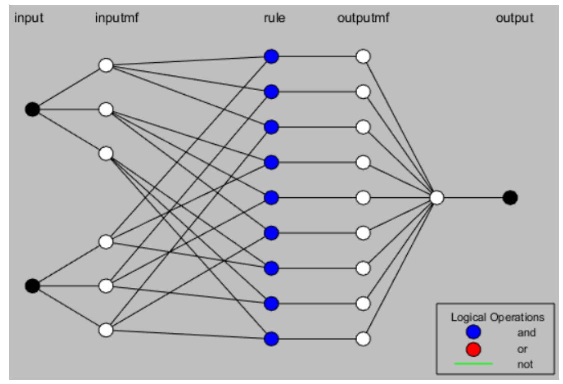


Fig. 4. Structure of Neuro Fuzzy Simulink Matlab Analysis

The neuro fuzzy membership function analysis was carried out with both hybrid and backpropagation method. Each of the Neuro fuzzy membership function analysis was performed at epochs 100-600.

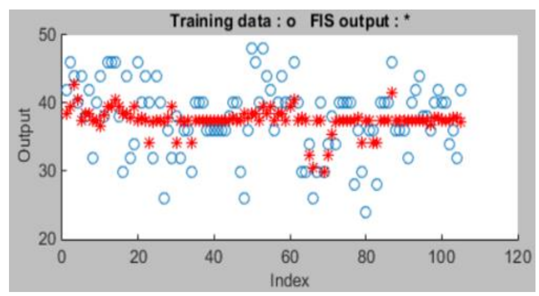


Fig. 5. Structure of Neuro Fuzzy Simulink Matlab Analysis

Figure 5 shows a graph of plotting data from the training process to produce neuro fuzzy or FIS output. The image sign is marked with a red *). The RMSE and output values training analysis were recorded for all type of membership function analysis and for each method. The FIS output value is obtained from the rule viewer display, as presented in Figure 6.

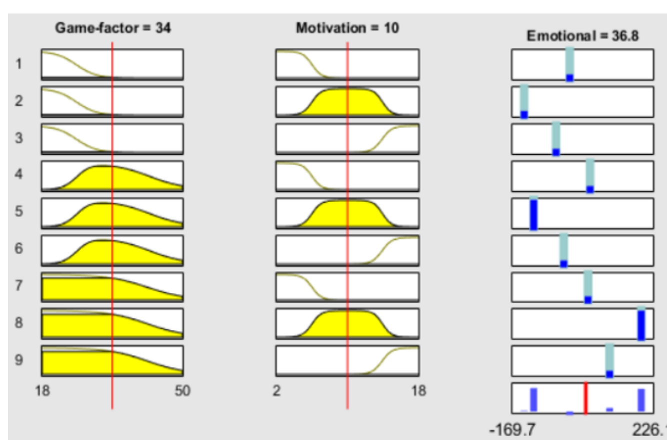


Fig. 6. The FIS output rule viewer of mf analysis

Figure 6 shown that the FIS output (Eo) for the three variables, namely: game-factor (Eo=34), motivation (Eo=10, and emotional (Eo=36.8). Whereas, the RMSE of all process analysis were recorded manually from interface page of FIS math lab application. All of the RMSE as presented at Table 2 and the output rule viewer of membership function analysis as shown at Table 3.

IV. Result and Discussion

A. Description of Variable Profile

All of the variable, game-factor, motivation, and emotional could be described descriptively as presented in Table 1.

TABLE 1
THE PROFILE OF VARIABLES

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Game Factor	105	18.00	50.00	40.2857	6.80740
Motivation	105	2.00	18.00	17.5619	2.16584
Emotional	105	24.00	48.00	37.8286	5.35734
Valid N	105				

Based on the Table 1 could be made the graph to describe the profile of these variables as presented in Figure 7.

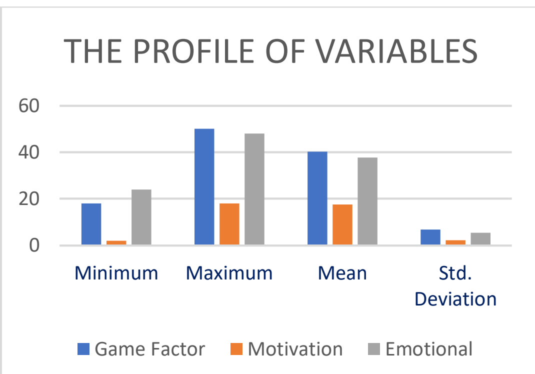


Fig. 7. The Profile of Variables

Game-Factor as an input variable is a variable that describes the game player's response to the game profile. The Game factors consist of 11 aspects represented in the serious game, including: goals, mechanisms, fantasies, values, interactions, freedom, narratives, sensations, challenges, sociality, and mystery. Based on the mean score that presented at Figure 7, game factor was more than a half of the maximum score then the game factor is classified as positive. This also corresponds to the FIS output value of variables in Figure 6.

Motivation as an input variable is a variable that describes the motivation level of the game player. The motivation aspects consist of as an encouragement to achieve the desired goals which include the need for achievement, the need for power, the need for affiliation, and the need for opportunity. Based on the mean score that presented on the graph at Figure 6, the motivation was a half of the maximum score then the motivation is classified a medium level.

Emotional as an output variable is a variable that describes the emotional level of the game player. The emotional aspects consist of 12 aspects, including: spirit, happy, happy, nervous, angry, irritated, sleepy, bored, sad, peaceful, and relentless. Based on the mean score that presented at Figure 6, emotional was more than a half of the maximum score then the game factor is classified as positive.

B. Neuro Fuzzy Analysis

(1) Training Analysis

Training analysis of all types of membership functions is intended to determine the type of membership function that best suits the characteristics of the dataset pair.

The results of the analysis obtained RMSE and FIS output of neuro fuzzy both with the hybrid method and the backpropagation method that presented in Table 2 and Table 3. Training analysis of all types of membership functions is intended to determine the type of membership function that best suits the characteristics of the dataset pair.

TABLE 2
THE RMSE VALUES OF MF TRAINING ANALYSIS

MF	Method	RMSE EPOCHS					
		100	200	300	400	500	600
trimf	BackProp	4.7518	4.6922	4.7165	4.6619	4.6613	4.6607
	Hybrid	4.7383	4.6705	4.6925	4.6619	4.6613	4.6607
trapmf	BackProp	4.7363	4.6854	4.6708	4.6621	4.6440	4.6417
	Hybrid	4.7059	4.6756	4.6681	4.6620	4.6440	4.7197
gbellmf	BackProp	4.6057	4.6703	4.6552	4.6624	4.6566	4.6546
	Hybrid	4.7219	4.6543	4.6552	4.6523	4.6516	4.6511
gaussmf	BackProp	6.9701	4.7108	4.6622	4.6616	4.6610	4.6607
	Hybrid	4.7518	4.6904	4.6622	4.6616	4.6612	4.6607
gauss2mf	BackProp	6.9347	4.6730	4.6605	4.6517	4.6516	4.5913
	Hybrid	4.8025	4.6657	4.6527	4.6517	4.6516	4.5911
pimf	BackProp	4.8342	4.6418	4.6242	4.6242	4.6242	4.6885
	Hybrid	4.6610	4.6374	4.6242	4.6242	4.6242	4.6623
dsigmf	BackProp	4.7802	4.7815	4.7836	4.6888	4.6915	4.6919
	Hybrid	4.6872	4.6874	4.6687	4.6969	4.6892	4.6610
psigmf	BackProp	4.7414	4.6964	4.7515	4.6929	4.6917	4.6908
	Hybrid	4.6136	4.6954	4.6954	4.6920	4.6907	4.6923

Training data analysis to determine the RMSE of each membership function model (*trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, and psigmf*) have been carried out with 2 inputs each with a membership number of 3 (3x3 rules number), epoch between 100-600, and both hybrid and backpropagation method. The results of the training analysis as presented as in Table 2.

Based on the Table 2, the smallest RMSE value was generated from training analysis with a double gauss membership function (*gauss2mf*) model, which was 4.5911 at epochs=600. It means that the *gauss2mf* model was considered the most suitable input for the Hybrid Neuro Fuzzy method to predict output.

Learning or training analysis was conducted on the eight types of membership function models with epochs: (100, 200, 300, 400, 500, 600), and with both backpropagation and hybrid methods, 48 pairs of RMSE values were obtained. From the 48 pairs of RMSE values, 6 pairs or 12.5% of the RMSE values with the backpropagation method are smaller than the RMSE values with the hybrid method. The equal RMSE values were 13 pairs or 27.08%, and 29 pairs or

60.42% of the RMSE values with the hybrid method are smaller than the RMSE values with backpropagation. This means that the error rate of training analysis with the hybrid is smaller than the error rate with the backpropagation method. In other word the hybrid method is better than the backpropagation method.

Based on RMSE values at Table 2, each method could be made graph which describes the distribution of RMSE values and could determine the smallest values of the RMSE and the bigger FIS output value of training analysis as presented at Figure 8, and Figure 9.

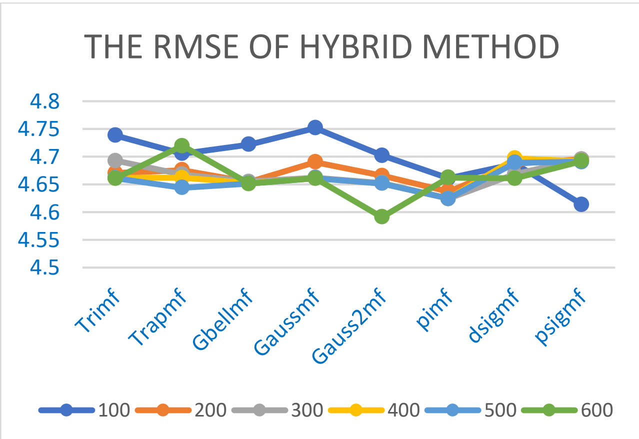


Fig. 8. Graph of the RMSE values with Hybrid method

Figure 8 shows a graph of the RMSE result of membership function analysis using the hybrid method. It can be seen in the picture that the lowest RMSE value is in the membership function on *gauss2mf* type with epoch=600 where RMSE=4.5911. This is in accordance with the figures in Table 2. Likewise, Figure 8 of the RMSE graph obtained by the backpropagation method. It appears that the lowest RMSE value in the membership function is also in the *gauss2mf* type with epoch=600 where RMSE=4.5913.

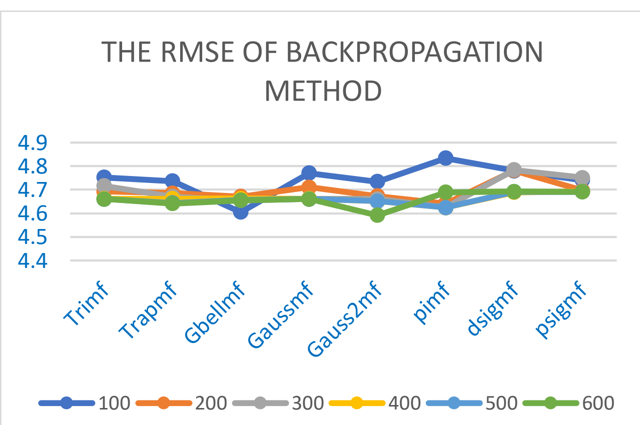


Fig. 9. Graph of the RMSE values with Backpropagation method

However, from the smallest RMSE values in Figure 8 and Figure 9, the FIS output obtained from the *gauss2mf* type is smaller than the FIS output value in the *dsigmf* type also at epoch=600 with the value of both the hybrid and backpropagation method, Eo=36.8 according to Table 3, Figure 10, and Figure 11. This is in accordance with the distribution of FIS values for the output of membership function neuro fuzzy analysis in Table 3 of Eo=36.8 with RMSE=4.6610 for the hybrid method, and RMSE=4.6919 for the method.

TABLE 3
THE FIS OUTPUT VALUES (EO) OF MF TRAINING ANALYSIS

MF	Method	FIS OUTPUT EPOCHS					
		100	200	300	400	500	600
trimf	BackProp	26.8	27.3	28.3	30.0	30.1	30.2
	Hybrid	26.8	29.6	33.3	30.0	30.1	30.3
trapmf	BackProp	26.8	32.8	31.3	31.6	31.9	29.40
	Hybrid	33.4	31.6	31.4	31.6	31.9	32.1
gbellmf	BackProp	36.3	35.3	35.2	35.2	35.2	35.2
	Hybrid	33.0	35.2	35.2	35.2	35.2	35.2
gaussmf	BackProp	31.7	29.2	29.8	29.9	30	30.2
	Hybrid	26.8	30.3	29.8	29.9	30.1	30.2
gauss2mf	BackProp	33.5	33.4	34	34.3	34.3	30.7
	Hybrid	33.3	33.6	34.2	34.3	34.3	30.7
pimf	BackProp	35.2	26	26	26.0	26.0	26.0
	Hybrid	35.1	26	26	26.0	26	26
dsigmf	BackProp	36.9	36.9	36.9	36.9	36.8	36.8
	Hybrid	35.9	35.9	35.8	35.9	35.7	36.8
psigmf	BackProp	36.3	35.2	36.2	35.0	34.9	34.8
	Hybrid	32.50	36.40	36.20	36.30	36.30	36.20

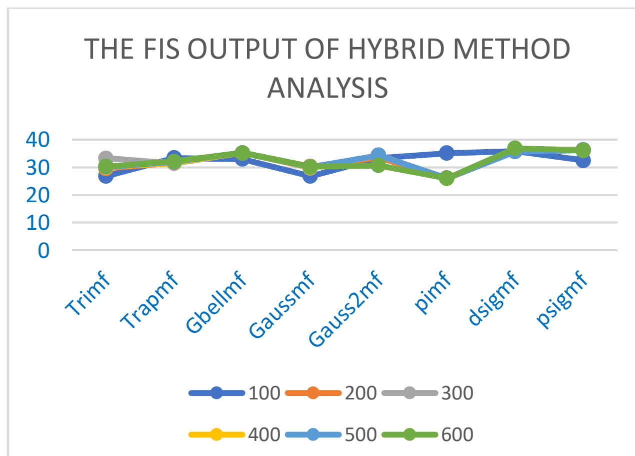


Fig. 10. Graph of the FIS output values with Hybrid method

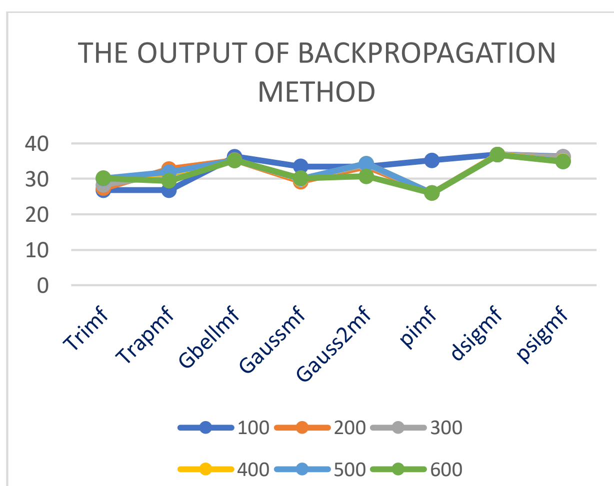


Fig. 11. Graph of the FIS output values with Backpropagation method

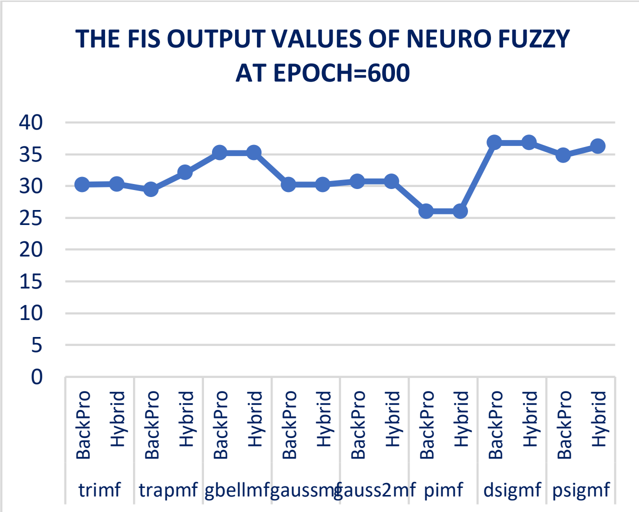
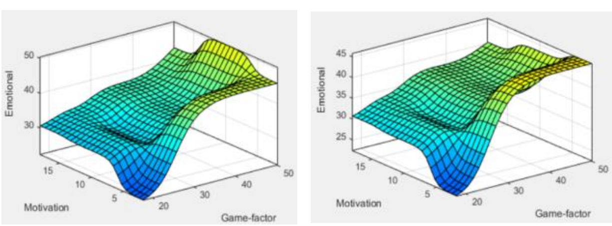


Fig. 12. Graph of the FIS output values

Figure 12 shows that the FIS output value of the membership function analysis at epoch=600 for all types of membership functions: *trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf dsigmf*, and *psigmf* both analyzed using the hybrid and the backpropagation method. It can be seen in the graph that a high and stable FIS output value is generated from the membership function type *dsigmf* with both hybrid and backpropagation methods Eo=36.8. So the *dsigmf* type of membership function is considered the most suitable for predicting the output by the input variables.

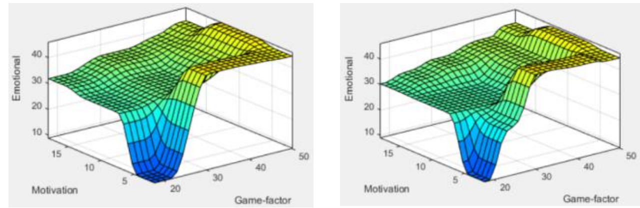


(a) (b)

Fig. 13. Graph display *dsigmf* pattern Training analysis with method (a) hybrid, (b) backpropagation

Based on Figure 13, it can be explained that the display patterns three dimension (3D) of the relationship between game-factor, motivation, and emotional of the membership function models appear to be almost the same or similar between the hybrid and backpropagation method.

In terms of the RMSE values, the RMSE=4.6610 with the hybrid method is smaller than the RMSE=4,6919 with the backpropagation method. This is clearly observed as shown in Table 2. Based on the analysis of training data that has been done it can be concluded that with the Hybrid Neuro Fuzzy Inference System there is a relationship between game factor, motivation, and emotional. In other words, the emotional intelligence of a game player can be predicted from game-factor and motivation with a mean of 36.8 and a RMSE of 4.6610.



(a) (b)

Fig. 14. Graph display *pigmf* pattern Training analysis with method (a) hybrid, (b) backpropagation

Figure 14 shows that the FIS output pattern of *pimf*, Eo=26.0 is smaller than the FIS output pattern of *dsigmf*, Eo=36.8 on the same epoch=600 in according to Table 3, and Figure 12. The pattern of *pimf* are similar to the letter "V" (pi) as the name implies pi membership function (*pimf*).

(2) Testing Analysis

Testing data analysis was carried out using the same method, namely Sugeno Neuro Fuzzy (hybrid and backpropagation) with the difference sigmoidal membership function (*dsigmf*) as input to epoch=600. Figure 15 shows display of the FIS output graph display testing analysis.

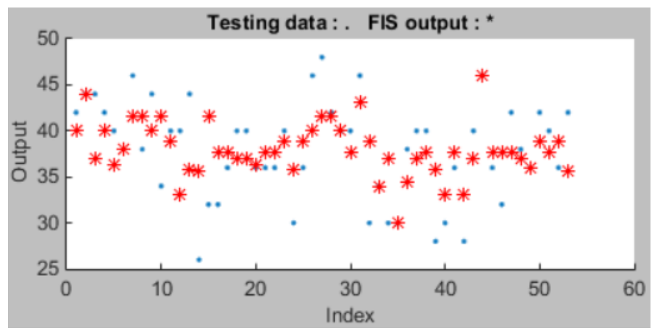
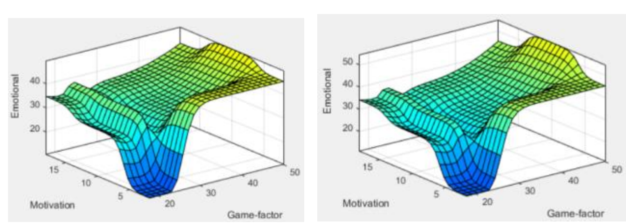


Fig. 15. Graph display FIS output Testing data

The results of the analysis are as follows. For the testing data analysis, the RMSE values and the FIS output (RMSE=4.4528; Eo=33.0) with the hybrid method are smaller than the RMSE and FIS output values with backpropagation method (RMSE=4.7479; Eo=37.8). The graph display of the relationship between game-factor, motivation, and emotional for both analysis are shown in Figure 16.



(a) (b)

Fig. 16. Graph display *pigmf* pattern Testing analysis with method (a) hybrid, (b) backpropagation

(3) Checking Analysis

checking analysis is also carried out in the same way as testing analysis. Figure 16 shows display of the FIS output graph display testing analysis.

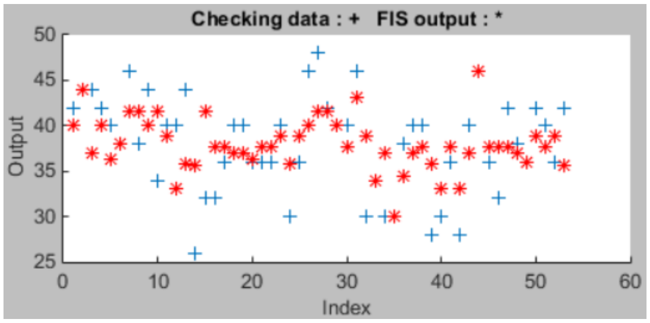
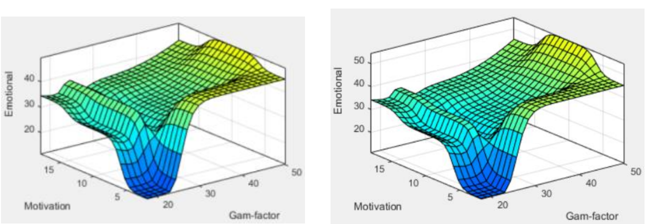


Fig. 17. Graph display FIS output Checking data

The checking analysis shows that the value of RMSE=4.4536 with the hybrid method is a smaller than the value of RMSE=4.4544 with the backpropagation method. Figure 17 shows display of the FIS output graph display checking analysis.

Otherwise the FIS output value, Eo=33.0 with the hybrid method is bigger than the FIS output value, Eo=30.8 with the backpropagation method.

This means that the checking data, the Hybrid Neuro Fuzzy is interpreted according to training data analysis. The graph display of the relationship between game-factor, motivation, and emotional for the checking analysis are shown in Figure 18.



(a) (b)

Fig. 18. Graph display *pigmf* pattern Checking analysis with method (a) hybrid, (b) backpropagation

(4) The Effectiveness of Hybrid Neuro Fuzzy Analysis

The data analysis results of the Neuro-Fuzzy with a difference sigmoidal membership function (*dsigmf*) as mf input at epoch=600. The summary of analysis is presented in Table 4.

TABLE 4
SUMMARY ANALYSIS

Analysis	Mean± SD Statistic	FIS (Eo ± RMSE) Epoch=600 Hybrid	Backpropagation	Δμ(%)	
Descriptive	37.8± 5.36				
Training		36.8 ± 4.66	37.8 ± 4.69	2.72	2.72
Testing		33.0 ± 4.46	37.8 ± 4.75	3.0	0.01
Checking		33.0 ± 4.45	30.8 ± 4.45	12.8	18.6

Based on Table 4, it can be explained as follows. Judged based on the all RMSE value of the analysis: training (4.66<4.69 or (4.6610<4.6919) in Table 2, testing (4.46<4.75), and checking (4.45≤4.45) show that the Hybrid method is better than the Backpropagation method. When viewed from the FIS output value of emotional variables from the three Hybrid Neuro-Fuzzy analyzes, the numbers show some varieties, namely: training (36.8), testing (33.0), and checking (33.0). While the percentage difference to the mean statistically, training (2.72%), testing (3.0%), and checking (12.8%). So the hybrid neuro fuzzy membership function analysis can predict the emotional intelligence of game players more than 87% or 87.2%.

B. Discussion

The smallest RMSE value was generated from training analysis with a difference sigmoidal membership function (*dsigmf*) model, which was 4.6610 at epochs= 600. It means that the difference sigmoidal membership function (*dsigmf*) model was considered the most suitable input for the Hybrid Neuro Fuzzy method to predict FIS output. It was suitable to the prediction of slope stability using adaptive neuro fuzzy inference system based on clustering methods [15].

In the analysis, the result found the relationship between game-factor, motivation, and emotional of children as the game player analyzed by using the Neuro-Fuzzy with hybrid method. This is indicated by the FIS output values of hybrid neuro-fuzzy analysis carried out. It was obtained that: training analysis (36.8±4.66), testing analysis (33.0±4.46), and checking analysis (33.0±4.45) with the percentage difference to the mean statistically, training (2.72%), testing (3.0%), and checking (12.8%). In other words, emotional can be predicted from game-factor motivation players. These results indicate compliance with that expressed the neuro-fuzzy model for predicting in many cases, namely by: Zaheeruddin, at.al. [11], Ehsan Lotfi [12], Raharja, at.al.[13], and Tiruneha, et.al.[14].

Based on the analysis result, it can be interpreted that the emotional can be predicted from the game-factor and motivation player. It can be explained from the analysis of the mean difference between the descriptive statistical method and the neuro fuzzy method with both hybrid and backpropagation method (2.72%). This is supported by Shi and Shih [4] about the macro design concept of a game, Kwon and Lee [18] about the category of person's emotions, and Lickona [19, 20] about the development of the children character. This means that games based on local Balinese wisdom can mediate to control the emotional, and to develop of the children's character. in the field of education, as expressed by Sukajaya, et.al.[21], and Suwindra, et al.[3].

Based on the Table 1, the children who were involved in playing the game respond positively to the game based on game-factors with a mean of (40.3±6.81) out of 50 max scores, and motivation category with a mean of (17.6±2.17) out of 24 max scores. This will impact on the success of the learning process, as expressed by S. Winton [22], traditional approaches to emotional, and character education, Andre F.S Barbosa et al [9, 10] serious game design needs to consider game factors and real time strategy concept, Darina Dicheva study [6] the goal of game development, and Jae Hwab Bae [7], for the efficiency of game development process.

These findings can be taken into consideration in choosing the type of game to be played in order to increase motivation and control children's emotions. Besides that, innovating games based on local wisdom is expected to preserve local Balinese culture. The benefit for the player, in playing games avoiding types of games that have bad effects for bad emotions. Examples of challenge games, war games can cause bad effects. Likewise, in playing games should be able to control the emotions.

The implication of further research is that the Hybrid Neuro Fuzzy method, in the further research can be carried out about the Decision Support System based on Hybrid Neuro Fuzzy that integrated in the game.

V. Conclusion

The conclusions of this study are as follows:

(1) Emotional Balinese game players can be predicted from game-factors and motivations of game players. This was shown from the output of the hybrid neuro fuzzy training analysis and RMSE (Eo=36.8; RMSE=4.6610), the testing analysis was (Eo=33.0; RMSE=4.4528), and the checking analysis was (Eo=37.8; RMSE=4.7479) with a difference of less than 12.77% (training=2.72%; testing=3.0%, and checking=12.77%). In other words, if it is analyzed descriptively was (M=37.83; SD=5.3573), the output of neuro fuzzy is obtained more than 87.23%.

(2) The emotional level of the child was categorized as a positive, the child's motivation was moderate and the response to the game was positive.

(3) These findings can be taken into consideration in choosing the type of game to be played in order to increase motivation and control children's emotions. Besides that, innovating games based on local wisdom is expected to preserve local Balinese culture.

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