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# An Artificial Neural Network-Based Finite State Machine for Adaptive Scenario Selection in Serious Game

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**Abstract:** Serious game is one of the pedagogical media capable of transferring knowledge to its players. This game genre requires a support system that adaptively selects the appropriate scenario for players to increase their interest and comfort. Therefore, this study proposed an adaptive scenario selection (ASS) system using a finite state machine based on an artificial neural network (ANN). The game scenario is selected by ASS based on five player preferences, including work, hobbies/interests, origin, group members, and repetition. Furthermore, the multi-layer perceptron (MLP) architecture was used in the scenario selection process for the proposed ANN method. The experimental stage was carried out using the theme of travel in several tourism destinations in Batu City, East Java, Indonesia. The experimental results show that ASS succeeded in generating adaptive game scenario choices for players based on their preference data with an accuracy of 67.25%.

**Keywords:** Serious game, Adaptive scenario, Player preference, Neural network, Finite state machine.

## 1. Introduction

Serious game is a media capable of providing knowledge on game content to players through education, analytics, visualization, simulation, and training [1]. This media combines educational content with gameplay by integrating learning objectives into the game environment. Serious game can be developed in various fields, such as tourism [2], health [3], education [4, 5], and smart grid [6]. Implementing serious games in various fields is expected to increase players' interest and engagement with the content [7].

Serious games are applications installed on computers to have fun and convey inherent knowledge [8]. The main goal of this game genre is to educate or train players through fun [9]. Serious games can visualize the content of knowledge possessed through storytelling in the form of designed scenarios [10, 11]. The study by Iqbal et al. described seven steps to designing a serious game, where one of the essential parts is the design scenario [12]. Another study states that to maximize knowledge transfer, game content needs to be visualized according to the players' needs and preferences [13]. Therefore, serious games require adaptive scenario selection capabilities to increase players' understanding of content through a scenario selection system that works according to the player's needs. Several serious game studies rarely mention the ability to choose adaptive scenarios. In this case, this ability is very important to increase the efficiency of the player's understanding of the content, because the game only runs scenarios that contain the content that the player needs.

Building serious games with adaptive scenario capabilities requires the support of qualified methods to ensure all adaptive scenario stages can work properly. This study proposes a framework that contains stages of developing adaptive scenarios based on finite state machine (FSM) as a method for designing serious game scenarios. FSM is a powerful method in designing game scenarios. Several preliminary studies have combined FSM with several other methods, for example dynamic weight TOPSIS (DWT) [14], multi-criteria recommender system (MCRS) [10], and pareto optimal [15]. However, to improve adaptive abilities in selecting serious game scenarios, in this study we propose a system called adaptive scenario selection (ASS) using the artificial neural network (ANN) method. ANN is a method in data mining that has been proven to have better capabilities than other methods. This method also results in the ability of the system to overcome classification problems even in rapidly changing and fluctuating environmental conditions [16]. The type of ANN used in this study is the multi-layer perceptron (MLP). This type of ANN has powerful capabilities for learning models, function estimation to pattern classification [17].

In the experimental phase we use the python programming language to define an exemplary MLP ANN architecture. Furthermore, the architecture is implemented in the Unity game engine using C#. In this study, the theme "tourism destinations serious game" was used to determine tourist characteristics as ANN training data. The implementation of neural network-based FSM in this study is expected to be able to make a proposed system capable of responding to the most suitable scenario choices for players based on their characteristic data. This compatibility then has the prospect of being able to increase player interest through suitability of content that is visualized as a serious game scenario.

For the research discussion to be more focused, we define several parameters that are the limitations of the research. First, the discussion is more focused on scenario design and how to implement ANN in selecting scenarios. Discussion of player responses after playing the scenario chosen by the system is our consideration in further research. Second, the output of the proposed system is limited to five scenarios with the highest suitability level of the fourteen designed scenarios. The goal is to avoid player confusion in determining the one scenario that they think is most appropriate. Furthermore, this study is divided into several sections, including the introduction, related work and contributions, system design, result, and conclusion. The introduction provides an overview of the study background, while the related work and contribution clarify the study position. The subsequent section designed the adaptive scenario systems in serious games. The results and discussion section explained and analyzed the results.

### 1.1 Related work

Several preliminary studies, specifically those related to the design and selection of game scenarios, as shown in Table 1, serve as references. In 2014, Janssens et al. investigated the tools for designing serious game scenarios using the ATTAC-L process. Furthermore, XML was used to automatically build the scenario online [8]. Luo et al. discussed the data-driven framework used to generate game scenarios [18]. In another study, Calderón et al. proposed the use of a tool called ProDecAdmin to design serious game scenarios. Game designers can design and fix various inherent deficiencies through these tools. The ProDecAdmin tool was implemented in the content software project management [19]. Some of these studies provided an overview of the ease of scenario design through the proposed tools and frameworks. The most important attribute in designing serious games is the strategies needed to make players feel comfortable and more interested in playing by selecting the exemplary scenario. Therefore, this study discusses the design capable of adapting suitable scenario choices for players.

The challenge of developing adaptive and dynamic serious game scenarios is one of the focuses of several studies. Hussain et al. examined the concept of generating scenarios based on user profiles using a series of pedagogical activities for students to achieve their learning goals. The study also identified some knowledge that can be represented by the system, including those related to concepts, learning, and serious games [20]. In another study, Laforcade and Laghouaouta discussed the design of adaptive game scenarios, but presently it was used for autism therapy learning media. They proposed the concept of scenario change using the Model-Driven Engineering framework. According to them, the scenario can change automatically based on the game description model and player profile [21, 22]. Several previous studies discussed adaptive changes in game scenarios based on player profiles. In this study, we try to provide an improvement to this concept through more detailed references based on player preferences. The goal is to increase the suitability of scenario selection for players.

A serious game is expected to consist of two main sections, that are scenario design and selection to ensure it changes automatically [14]. Arif et al. proposed the concept of scenario selection in the serious tourism game using the multi-criteria recommender system (MCRS) method. The system can select scenarios for players as potential tourists based on their ratings of tourist destination items [10]. The study also proposed controlling a serious game scenario based on item rating and player expectations using the FSM and dynamic weight topics (DWT) methods. FSM is a method in scenario design, while DWT is used in the selection process [14]. Mihajlović et al. proposed a scenario control platform for a virtual environment called the Interactive Scene Control Environment [23]. This was followed by the concept of controlling scenarios using a multi-agent system proposed by Pons et al. The system controls scenarios based on adjustments to player actions. In its implementation, scenario changes are visualized by the collective interaction

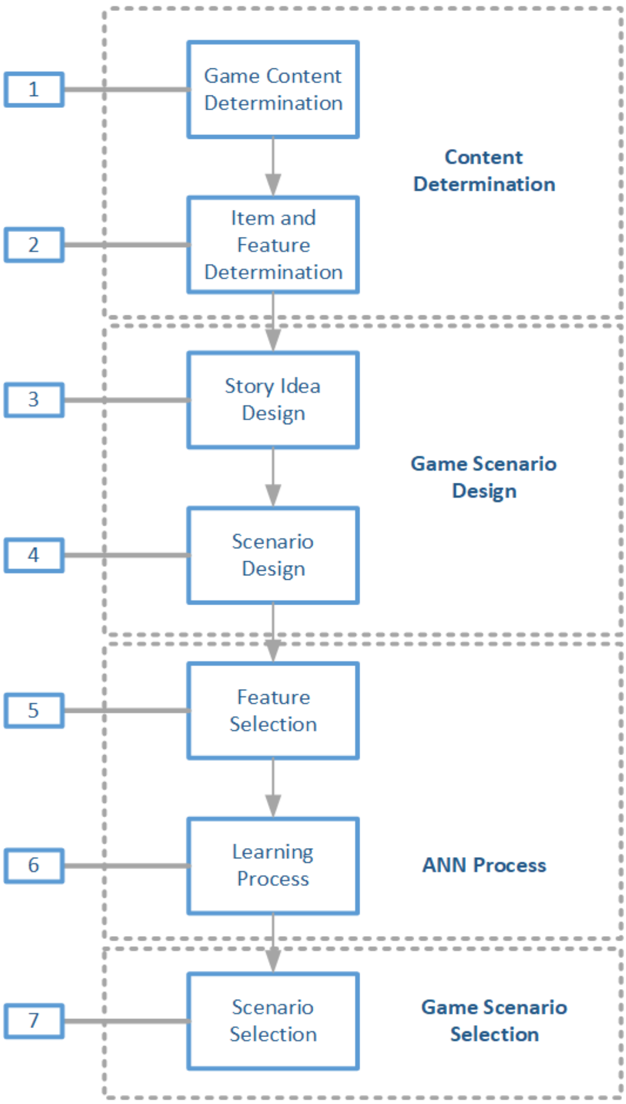


Figure. 1 Stages to develop adaptive scenario selection

between agents in the scenario adjustment process [24]. Therefore, based on these studies, a scenario control system was developed in two sections: design and selection. In this study, the scenario selection section also works to determine the most suitable scenario based on a collection of previous user preference data using the ANN method.

### 1.2 Contributions of paper

Various preliminary studies address scenarios that change adaptively with various concepts. However, this study has the motivation to improve its ability through the proposed concept of selecting adaptive scenarios based on player preferences.

This study also has several contributions, first, the ANN-based FSM was used to build an adaptive serious game scenario. These stages cover the initial process of determining the content of the strategies used to implement scenario selections in serious games. Second, it offers five features used as a reference in determining scenarios. Each criterion represents player preference data consisting of work, hobbies/interests, origin, group member, and repetition. The use of preference as a reference allows the system to be implemented in different game content. The reason is that each player has preference data, which can be used to determine scenarios even with different game content. Third, the game system offers players a model for adjusting knowledge of game content through automatic scenario determination based on their preference data.

## 2. Stages of scenario selection

This study proposed the design of adaptive scenarios in eight stages, categorized into four main stages. These include content determination, game scenario design, ANN process, and game scenario selection, as shown in Fig. 1. These stages function sequentially in adaptively determining the system.

### 2.1 Content determination

Content determination is divided into two stages: Game content determination and Item and feature determination. Game content determination is the initial stage that serves to prepare the determination of the content of the serious game. In this process, developers must consider the aims, which play a significant role from the development until the final stage. Several examples of previous studies have discussed serious games using content of health [25, 26], education [27, 28], tourism [29, 30], and business [31].

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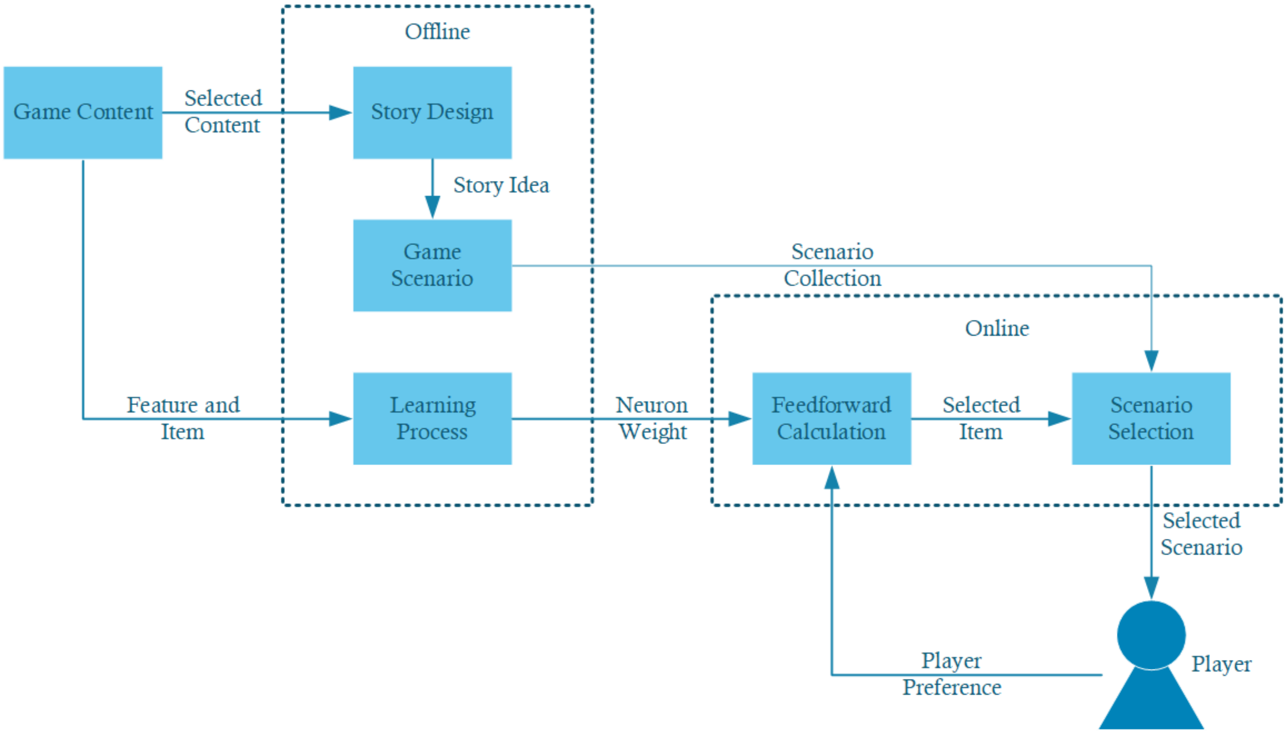


Figure. 2 Proposed adaptive scenario selection

The Item and feature determination stage involves selecting items and features based on game content used in development. Item is a representation of the game scenario selection output. Meanwhile, features are selection criteria used to reference travel scenario items. One of the criterion features that influence the selection of tourist trips is tourist preference [10].

## 2.2 Game scenario design

The next stage in ASS design is game scenario design which includes story idea design and scenario design. Story idea design is one of the important stages because it is used as a reference in the scenario design process and its follow-up processes. An interesting story will produce an exciting game scenario. There are several concepts in the design of story ideas, such as the challenge-based [32]. In 2021, Arif et al. implemented a challenge-based story idea as a reference for designing serious game scenarios regarding the selection of tourist destinations. Challenge-based story ideas create curiosity and interest for players, thereby increasing their enthusiasm for learning content through serious games [14]. Game developers can also implement the concept of story ideas in other game themes or content.

The scenario design is the next stage after the story idea design. This stage has the primary function of creating a more detailed picture related to the story description in the game, which includes the intro, rules, scenes, objects, and characters to the created virtual environment. Game developers can design game scenarios using various tools and methods such as storyboards [29 30], ATTAC-L [8], and finite state machines (FSM) [35]. These tools make it easy for developers to actualize scenario designs into computer programming. This fourth stage selects the most suitable scenarios for players.

## 2.3 ANN process

In this study, the ANN process has two sequence stages: Feature selection and Learning process. In the feature selection stage, the input to be used is determined to improve the accuracy of the classification system. Only features with a significant impact are used as input in the ANN system. Some feature selection methods commonly used are greedy, IG-ratio, Chi-square, and mRMR [36].

The next stage is the learning process, which consists of training and evaluation. At the training stage, each weight and bias on each neuron is updated continuously until the resulting output is in line with expectations. In each iteration, an evaluation is conducted to determine when to stop the forward and backpropagation in the training process. Forward propagation is a process where data from the input is transformed through each neuron in the hidden layer to the output and vice versa. The loss function measures how well the

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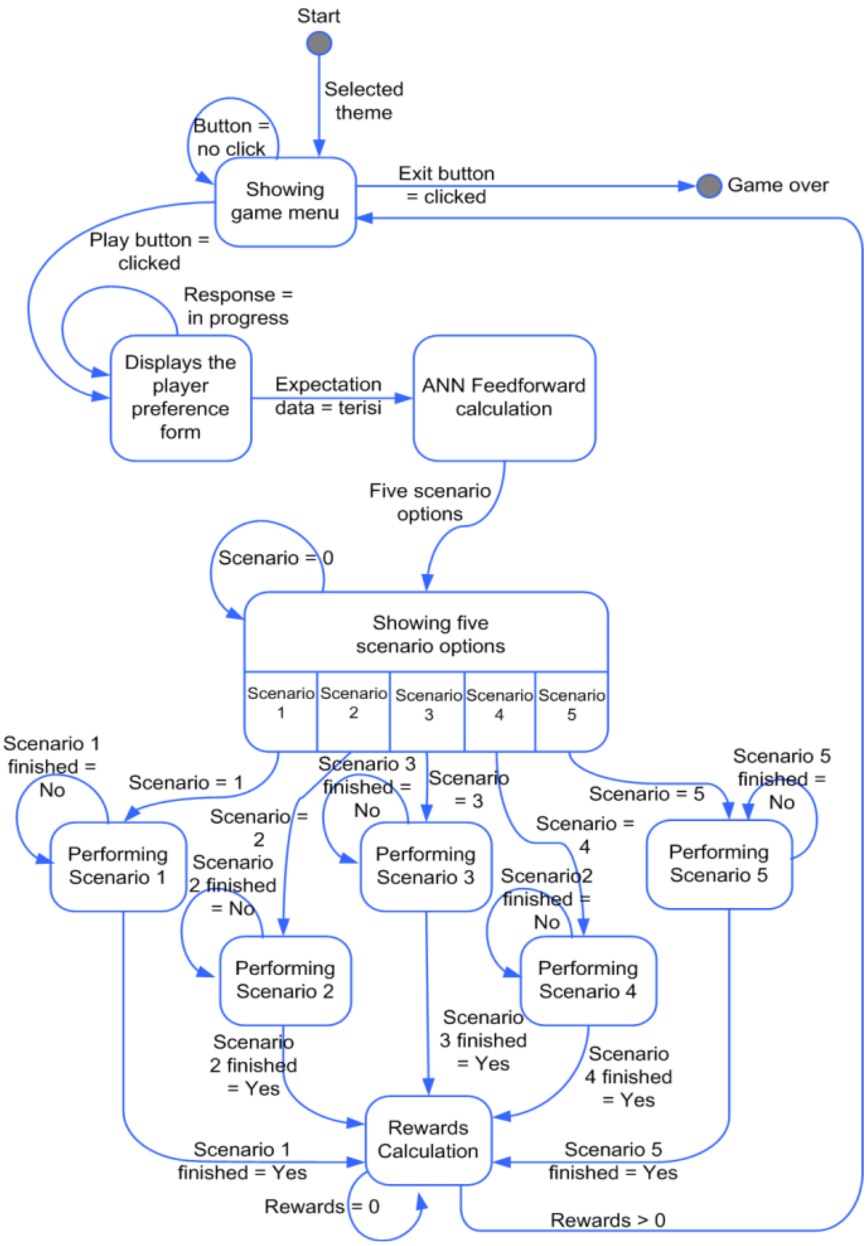


Figure. 3 Scenario design in FSM

neural network predicts the target and determines an error. Backpropagation is a process that aims to readjust each weight and bias based on the error obtained during the forward pass. These two processes will be repeated until the weight and bias values are obtained, providing the smallest possible error value in the output layer. The single-layer perceptron (SLP) and multi-layer perceptron (MLP) architectures in the training process can be used to determine the results.

### 2.4 Game selection

The final stage in building the ASS in this study is the selection of scenarios. This stage implements the architectural results and calculates the weights and biases of each layer of the neural network into the game mechanism. The system performs computations to get the most suitable scenario for the player. In the end the system displays several items with the highest scores as scenario choices.

## 3. Artificial neural network-based finite state machine

This study proposed an adaptive scenario selection design with several mutually supporting parts, as shown in Fig. 2. The proposed system consists of several offline and online working parts. Offline conditions are processes carried out prior to the gaming session, which become a reference when the game is in progress. The processes carried out offline are story design, scenario, and the learning process. While the online conditions include feedforward calculations and implementation of scenario selection.

### 3.1 Determining game content and story idea

In this study, we set the selection of tourist destinations as the theme used in the experiment. The theme is interesting, where the game system must have the ability to choose tourist destination scenarios according to the player's preferences as potential tourists. A story of ideas is designed and used from the determined content theme to translate serious game scenarios. There are several question criteria in challenge-based story ideas, including those based on questions of what, when, where, how, and why [14]. The "what criteria" was selected as a reference for story ideas in this study. These criteria describe the challenges for players to carry out travel scenarios according to what tourist spots are interesting to visit. Therefore, each scenario designed and selected describes the journey of each tourist destination. The aim is for players to be challenged while exploring any exciting tourist spots.

### 3.2 Scenario design using finite state machine

In this study, the scenario design stage was conducted using FSM, which translated the description of the story idea into state activities of the travel scenario. This made it easier to write the game engine program code. Fig. 3 shows the scenario design of a serious travel game using FSM. The first state displays the menu, while the second comprises players' preference form. After the preference data is filled in, the system runs the state ANN Feedforward calculation using feedforward calculations according to the ANN architecture. This process is carried out by selecting the five highest-ranking scenarios from the 14 travel items. Furthermore, it displays five scenario options for players to play. They travel virtually in every scenario of selected tourist destinations comprising spots similar to actual conditions. Furthermore, the system calculates players' rewards at each visited tourist spot.

### 3.3 Data preparation

The data preparation process is an important stage in system design. In this study, we used Batu City tourist destination data as content data used in the experiment. Cities located in the East Java Province of Indonesia were chosen because they have diverse tourist characteristics, cultural heritage, and man-made and natural landscapes, as shown in Table 1. While, Table 2 is example of lists of tourist preference features and tourist destination selection items [37]. There are ten notations *X1* through *X10*, representing traveler preference features, and fourteen notations *Y1* through *Y14*, denoting selected items for travel scenarios, were used in each tourism destination. Furthermore, the dataset was prepared by distributing questionnaires to 227 respondents to tourists. The distribution consists of 80% training data and 20% testing data.

The next important process in designing an ASS system is feature selection and data normalization. There are several methods that are often used in the feature selection process, but in this study, we chose to use the Chi-square method. The reason is because of its better performance, especially to be implemented in a multiclass architecture. Meanwhile, for data normalization, the min-max process was used. This technique can linearly transform the output from one range of values to another [38]. The scale used in the transformation

Table 1. Item example

| **Item** | |
|---|---|
| **Notation** | **Tourism Destination** |
| $\boldsymbol{Y1}$ | Jatim Park 1 |
| $\boldsymbol{Y2}$ | Jatim Park 2 |
| $\boldsymbol{Y3}$ | Jatim Park 3 |
| $\boldsymbol{Y4}$ | Museum Angkut |
| $\boldsymbol{Y5}$ | Selecta |
| $\boldsymbol{Y6}$ | BNS |
| $\boldsymbol{Y7}$ | Eco Green Park |
| $\boldsymbol{Y8}$ | Alun – alun Kota Batu |
| $\boldsymbol{Y9}$ | Kusuma Agro |
| $\boldsymbol{Y10}$ | Cangar |
| $\boldsymbol{Y11}$ | Coban Talun |
| $\boldsymbol{Y12}$ | Pemandian Songgoriti |
| $\boldsymbol{Y13}$ | Coban Rais |
| $\boldsymbol{Y14}$ | Predator Fun Park |

Table 2. Preference feature example

| **Feature** | | |
|---|---|---|
| **Notation** | **Preference** | **Chi-Square Result** |
| $\boldsymbol{X1}$ | Gender | 3.5 |
| $\boldsymbol{X2}$ | Age | 5.5 |
| $\boldsymbol{X3}$ | Work | **19** |
| $\boldsymbol{X4}$ | Hobbies/Interests | **12** |
| $\boldsymbol{X5}$ | Motivation | 5.5 |
| $\boldsymbol{X6}$ | Marital status | 5 |
| $\boldsymbol{X7}$ | Origin | **6.5** |
| $\boldsymbol{X8}$ | Group Member | **16** |
| $\boldsymbol{X9}$ | Education | 5.5 |
| $\boldsymbol{X10}$ | Repetition | **7** |

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Table 3. Weight and bias value for hidden layer 1 to hidden layer 2

| | | Neuron of hidden layer 2 (*k*) | | | | |
|---|---|---|---|---|---|---|
| | | **Neuron 1** | **Neuron 2** | **Neuron 3** | **Neuron 4** | **Neuron 5** |
| **Neuron of hidden layer 1 (*j*)** | **Neuron 1** | $V_{1.1}$ | $V_{1.2}$ | $V_{1.3}$ | $V_{1.4}$ | $V_{1.5}$ |
| | | 0,5304773 | -0,57577044 | 0,04045011 | 0,24046099 | -0,48769492 |
| | **Neuron 2** | $V_{2.1}$ | $V_{2.2}$ | $V_{2.3}$ | $V_{2.4}$ | $V_{2.5}$ |
| | | 0,56448185 | -0,5510965 | 0,58683383 | 0,58683383 | 0,5441814 |
| | **Neuron 3** | $V_{3.1}$ | $V_{3.2}$ | $V_{3.3}$ | $V_{3.4}$ | $V_{3.5}$ |
| | | -0,23397495 | 0,04813131 | 0,07361175 | 0,3900345 | -0,47334445 |
| | **Neuron 4** | $V_{4.1}$ | $V_{4.2}$ | $V_{4.3}$ | $V_{4.4}$ | $V_{4.5}$ |
| | | -0,44781095 | 0,5718088 | 0,15218572 | 0,60868657 | 0,47986734 |
| | **Neuron 5** | $V_{5.1}$ | $V_{5.2}$ | $V_{5.3}$ | $V_{5.4}$ | $V_{5.5}$ |
| | | 0,02614102 | -0,19816184 | -0,15770291 | -0,5555946 | 0,40536523 |
| | **Neuron 6** | $V_{6.1}$ | $V_{6.2}$ | $V_{6.3}$ | $V_{6.4}$ | $V_{6.5}$ |
| | | 0,6180892 | -0,6306269 | -0,22825265 | -0,4242948 | -0,2918585 |
| | **Neuron 7** | $V_{7.1}$ | $V_{7.2}$ | $V_{7.3}$ | $V_{7.4}$ | $V_{7.5}$ |
| | | -0,3422928 | -0,53030276 | 0,26136044 | 0,19401918 | -0,17973594 |
| | **Bias** | $V_{o1}$ | $V_{o2}$ | $V_{o3}$ | $V_{o4}$ | $V_{o5}$ |
| | | 0,01457165 | -0,01429752 | -0,06413733 | -0,07254104 | 0,0085065 |

Table 4. Weight and bias value for hidden layer 2 to hidden layer 3

| | | Neuron of hidden layer 3 (*m*) | | |
|---|---|---|---|---|
| | | **Neuron 1** | **Neuron 2** | **Neuron 3** |
| **Neuron of hidden layer 2 (*k*)** | **Neuron 1** | $C_{1.1}$ | $C_{1.2}$ | $C_{1.3}$ |
| | | -0,5198651 | -0,5196005 | -0,4054136 |
| | **Neuron 2** | $C_{2.1}$ | $C_{2.2}$ | $C_{2.3}$ |
| | | 0,65274894 | 0,9054215 | 0,21533541 |
| | **Neuron 3** | $C_{3.1}$ | $C_{3.2}$ | $C_{3.3}$ |
| | | -0,71790564 | -0,09685819 | -0,24999532 |
| | **Neuron 4** | $C_{4.1}$ | $C_{4.2}$ | $C_{4.3}$ |
| | | 0,14337844 | 0,33757776 | 0,3664421 |
| | **Neuron 5** | $C_{5.1}$ | $C_{5.2}$ | $C_{5.3}$ |
| | | -0,10200363 | -0,00610876 | -0,5657872 |
| | **Bias** | $C_{o1}$ | $C_{o2}$ | $C_{o3}$ |
| | | 0,20466062 | 0,01022854 | -0,21786755 |

process is located between 0 to 1 or -1 to 1. Eq. (1) is used for calculating the min-max normalization value of $X'$. $X$ is the actual value, $X_{min}$ is the minimum actual data value, and $X_{max}$ represents the maximum actual data value.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Table 2 also shows the ranking results through the feature selection process using the Chi-Square method. The five highest notation preferences chosen are $X3$, $X4$, $X7$, $X8$, and $X10$, with a total score of 61. These preferences are the most considerable influence on item selection.

### 3.4 ANN for adaptive scenario selection

In developing an adaptive scenario selection system, this research needs to be supported by the use of appropriate methods. We propose an ANN that uses a multi-label classification technique because the data that is classified has more than one class. While at the design stage we use a multi-layer perceptron (MLP) architecture with a backpropagation learning algorithm. Furthermore, the best accuracy results are determined through several trials using python programming, and 5-7-5-

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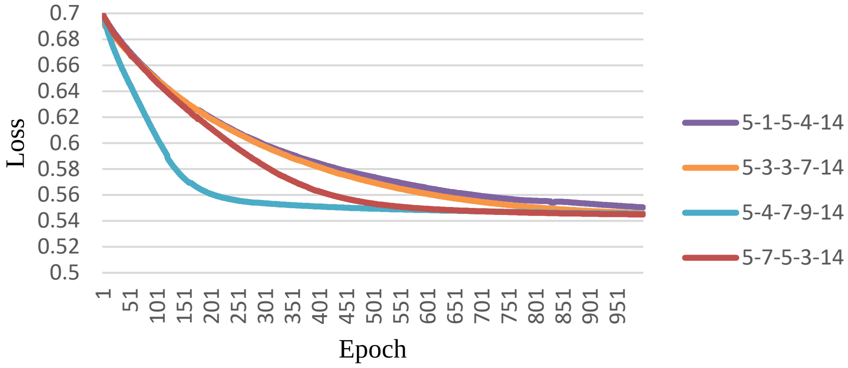
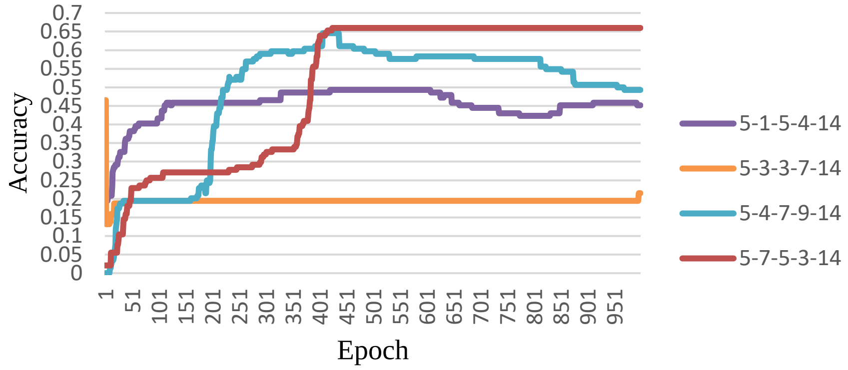



(a)




(b)

Figure. 4 Accuracy and loss comparison of MLP architecture (a) Loss value and (b) Accuracy value

3-14 is produced as the layer combination with the best accuracy. Fig. 4 shows a comparison of the loss values and accuracy of several examples of MLP architecture experiments.

Furthermore, the ASS system was used to determine the choice of a scenario using a feedforward calculation that refers to the selected layer architecture. Eq. (2) to (9) show the feedforward calculation using the updated weight and bias values with the ReLU activation function in each hidden layer and the sigmoid activation function in the output. Eq. (2) calculates the output value in the first hidden layer, while Eq. (3) shows the ReLU activation function applied.

$$Z_{in_j} = \sum_{i=1}^{5} x_i \, w_{ij} + w_{oj} \tag{2}$$

$$Z_j = f\left(Z_{in_j}\right) = f\left(0\,, Z_{in_j}\right) \tag{3}$$

Eq. (4) shows the calculation used to determine the output in the second layer. Eq. (5) determines the result after the ReLU activation process. Table 3 shows the distribution of the updated weight and bias values for hidden layers 1 to 2.

$$T_{in_k} = \sum_{j=1}^{7} z_j \, v_{jk} + v_{ok} \tag{4}$$

$$T_k = f\left(t_{in_k}\right) = f\left(0\,, t_{in_k}\right) \tag{5}$$

Eq. (6) calculated the output value in the third hidden layer, while Eq. (7) was used to determine the output value after applying the ReLU activation function. Table 4 shows the distribution of the updated weight and bias values for hidden layers 2 and 3.

$$S_{in_m} = \sum_{k=1}^{5} t_k \, c_{km} + c_{om} \tag{6}$$

$$S_m = f\left(s_{in_m}\right) = f\left(0\,, s_{in_m}\right) \tag{7}$$

The final feedforward calculation stage in this study is shown in Eqs. (8) and (9). Each notation used in Eq. (2) to (9) is explained in Table 5.

$$Y_{in_p} = \sum_{m=1}^{3} s_m \, b_{mp} + b_{op} \tag{8}$$

$$Y_p = f\left(y_{in_p}\right) = \frac{1}{1+e^{-y_{in_p}}} \tag{9}$$

Each stage of the feed forward calculation is outlined in the C# program on the Unity game

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Table 5. Notation list

| Notation | Description |
|---|---|
| $Z_{in_j}$ | Input neuron signal from input layer ($i$) to hidden layer 1 ($j$). |
| $x_i$ | Input data at the input layer. |
| $w_{ij}$ | Weight value from input layer ($i$) to hidden layer 1 ($j$). |
| $w_{oj}$ | Bias value in hidden layer 1 ($j$). |
| $Z_j$ | Output neuron after activation in hidden layer 1 ($j$). |
| $T_{in_k}$ | Neuron input signal from hidden layer 1 ($j$) to hidden layer 2 ($k$) |
| $v_{jk}$ | Weight value from hidden layer 1 ($j$) to hidden layer 2 ($k$). |
| $v_{ok}$ | Bias value in hidden layer 2 ($k$). |
| $T_k$ | Output neurons after activation in hidden layer 2 ($k$). |
| $S_{in_m}$ | Input neurons from hidden layer 2 ($k$) to 3 ($m$) |
| $c_{km}$ | Weight value from hidden layer 2 ($m$). |
| $c_{om}$ | Value bias in hidden layer 3 ($m$). |
| $S_m$ | Output of neurons after ReLU activation in hidden layer 3 ($m$). |
| $Y_{in_p}$ | Input value of neurons from hidden layer 3 ($m$) to the output layer ($p$). |
| $b_{mp}$ | Weight value from the hidden layer 3 ($m$) to the output layer ($p$). |
| $b_{op}$ | Bias value at the output layer ($p$). |
| $Y_p$ | Notation for neuron output after activation in ($p$). |

engine. Through these calculation stages, the game system computes the player's preference input to determine the choice of scenarios from several that have been previously designed.

## 4. Result and discussion

This section discussed the visualization of the menu and virtual environment, the process of implementing the ASS system in serious games, and the results of measuring its performance. In the experimental stage, a serious game was built as the parent of ASS according to the theme of story ideas and travel scenarios in Batu City as a popular tourism destination in Indonesia.

### 4.1 Result of adaptive scenario selection

To increase player interest, a game needs to be supported by an attractive user interface design and virtual environment. This study used Unity 3D as a game engine to build a user interface, virtual environment, and visualization of scenario selection in serious games.

In the experimental stage, feedforward calculations are written in the programming language used in the Unity game engine. The input data for the calculation process are five preference players, and the output is five travel scenario options. Fig. 5a shows the display form for filling out the five-player preference data that ASS uses to reference in selected scenarios. At the same time, Fig. 5b is a visualization of the scenario options generated by the ASS system. Approximately five scenarios with the highest ranking were selected from a total of 14 travel scenarios which are the experimental themes in this study. Fig. 6a, and 6b visualize the virtual environment of Alun-Alun and Jatim Park 1.

Subsequently, the confusion matrix was used to determine the performance of the scenario selection results by ASS. It also compares the results of the scenario selection from ASS with the actual choices desired by players. The variables calculated by the matrix include accuracy (*A*), precision (*P*), recall (*R*), and F1 score (*F*). To obtain each of these variables, the number of possibilities, including true positive (*TP*), true negative (*TN*), false positive (*FP*), and false negative (*FN*) were determined. *TP* is the number of conditions when the system choice scenario is the same as the actual player's choice. *TN* is the number of conditions where the system and players do not select the scenario item. *FP* is defined as the number of conditions when the system does not select the item that players want. Meanwhile, *FN* is the number of conditions in which the system provides a choice of scenarios without players' consent. Eqs. (10-13) show the formulas for obtaining the *P*, *R*, *A*, and *F* values, respectively.

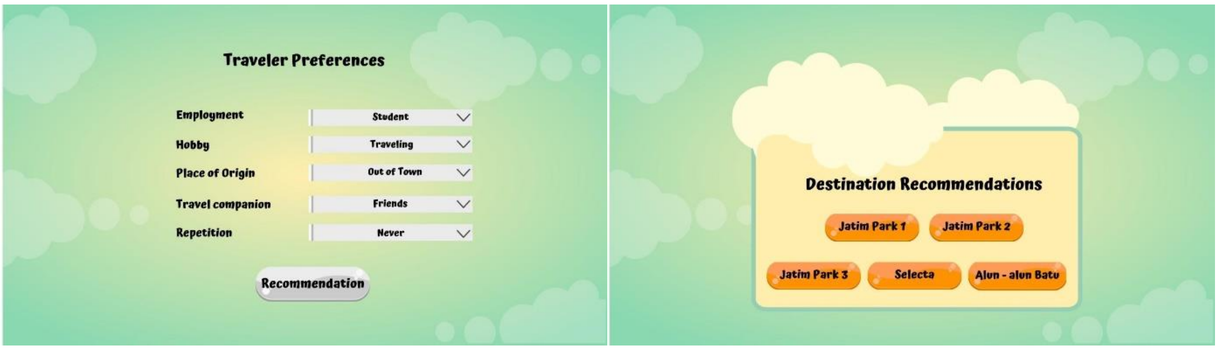
In the testing process, 46 players were used to compare the scenario choices from the ASS system. The result showed that P, R, A, and F have values of 53.58%, 61.73%, 67.23%, and 57.36%. This value is obtained based on a travel scenario theme in Batu City tourism destinations. The difference in the characteristics of the theme and the data used in the experiment can certainly affect the results of the confusion matrix variable obtained.

### 4.2 Comparison study of serious game scenario

One of the main motivations for this research is to produce a scenario selection system that is adaptive for serious games. The experimental results prove that the proposed scenario selection system has worked adaptively in selecting scenarios for players. To analyze its advantages and disadvantages, we try to compare it with several other studies that discuss the design and selection of scenarios for serious games, as shown in Table 6.

Table 6. Comparison study of serious game scenario

| Reference | Content | Scenario Selection | Scenario Design | Input Data | Adaptive |
|---|---|---|---|---|---|
| [18] | Education | Not mentioned | ATTAC-L and XML | Not mentioned | No |
| [19] | Software project management | Not mentioned | ProDecAdmin | Not mentioned | No |
| [21] | Autism therapy | Model-driven engineering | Not mentioned | Game description model and player profile | Yes |
| [20] | Education | Not mentioned | Pedagogical scenario | User profile | No |
| [10] | Tourism | MCRS | FSM | Item rating | No |
| Ours | Tourism | ANN | FSM | Player preference | Yes |




(a) (b)

Figure. 5 Display of player preferences form and scenario selection results (a) Player preferences form (b) Scenario selection result

(a) (b)

Figure. 6 Some examples of virtual environments in serious game experiments (a) Alun-alun Batu (b) Jatim Park 1

Several previous studies have proposed management scenarios for serious games with various themes including education [18, 20], software project management [19], autism therapy [21], and tourism [10]. From some of these studies, Reference [10] uses the same tourism case study as this research. In addition, the reference also uses the same scenario design method, namely FSM. The difference is the scenario selection method, where the reference uses MCRS which is based on rating player. Even though they have the same theme and scenario design method, this research proposal has a significant advantage, namely the ability of adaptive scenarios based on changes in player preferences.

Table 6 also shows that reference [21] has scenario adaptive capability. However, the difference is the reference to scenario changes based on the game description model and player profile. When compared with several previous studies, only this proposal uses player preference as a trigger for changing the serious game scenario. Preference is a variable that is always attached to the player. The use of preference as a reference for the adaptive scenario system is expected to increase the suitability of the results of the choice of scenarios carried out by the serious game.

## 5. Conclusions

In conclusion, this study discussed the ASS system for serious games using ANN-based FSM. It also proposed the use of seven stages in designing ASS to be able to adaptively select the appropriate scenario for players based on their input data preferences. The Chi-Square method was used to determine five of the ten preference variables, including work, hobbies/interests, origin, group member, and repetition variables. Furthermore, a combination of MLP architecture 5-7-5-3-14 was selected as the ANN architecture and used as a reference for calculating feedforward in implementing scenario selection.

The experimental stage was carried out using the theme of a travel scenario in Batu City. Therefore, data from 14 tourist destinations in the city were selected as the scenario choice items and 227 preference data from previous tourists. The ASS system works by adaptively selecting travel scenarios according to the five preference variables entered by players. The test results on 46 players showed that the system has precision, recall, accuracy, and F1 score values of 53.58%, 61.73%, 67.23%, and 57.36%.

Further studies are planned to be carried out using the ASS system with different machine learning methods to determine the system with the highest accuracy. The system is also expected to be implemented in different themes such as education, health, and others, so that it can be seen how the results of system characteristics for other scenario themes. We hope that the proposed ASS system can also be implemented in multi agent objects, for example to set the dynamic behavior of Non-Playable Characters. If the concept can work, of course it can improve game scenarios to be more interesting and interactive.

## Conflicts of interest

The authors declare no conflict of interest.

## Author contributions

Conceptualization, Y.M. Arif; methodology, Y.M. Arif, H. Nuhayati, and F. Nugroho; software, Y.M. Arif, A.F. Karami, and F. Nugroho; validation, Y.M. Arif, and F. Kurniawan; formal analysis, Y.M. Arif, H. Nurhayati, F. Nugroho and F. Kurniawan; investigation, Y.M. Arif; resources, Y.M. Arif, H. Nurhayati, and A.F. Karami; data curation, Y.M. Arif; writing—original draft preparation, Y.M. Arif, H.A. Rasyid, Q. Aini, N.M. Diah, and M.B. Garcia; writing—review and editing, Y.M. Arif, H.A. Rasyid, Q. Aini, N.M. Diah, and M.B. Garcia; visualization, Y.M. Arif, and H. Nurhayati; supervision, H.A. Rasyid, Q. Aini, N.M. Diah, and M.B. Garcia; project administration, Y.M. Arif, H. Nurhayati, and A.F. Karami; funding acquisition, Y.M. Arif, H. Nurhayati and F. Kurniawan.

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