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Research article

Optimizing player engagement in an immersive serious game for soil tillage base on Pareto optimal strategies



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ABSTRACT

In most cases, problems that increase player involvement in immersive serious games do so by combining fun elements with a specific purpose. Previous studies have produced models of soil porosity and plow force that use the speed of plowing, the angle of the plow's eye, and the depth of the plow as the basis for a design strategy in immersion serious games. However, these studies have not been able to show the optimal strategy of engagement of the player in the game. In the domain of serious game concept learning, strategies can be formed based on real conditions or data from experimental results. In a serious game, the aim is to increase the player's knowledge so that the player gains knowledge by coming up with strategies to play the game.

This research aims to increase the engagement of players by means of multi-objective optimization based on Pareto optima, with the objectivity of soil porosity and plow force that is affected by the speed of plow, the angle of the plow's eye, and the depth of the plow. The results of this optimization are used as a basis for the design of strategies in a serious game in the form of Hierarchy Finite State Machine (HFSM). From the results of the study, it was found that there is an optimal area for the game strategy that is also an indicator of how to successfully process the soil tillage using a moldboard plow.

1. Introduction

A serious game that has too many fun domains but lacks learning goals is just a fun game. Vice versa, if there is no fun element it will not function as a game because it will lose the immersion domain. In other words, the game will lose the immersion domain and fail to engage the player (Hämäläinen et al., 2006). A data-based approach to designing serious games tends to focus on the purpose of the game, which is mimicking a real situation and including a significant difficulty. This allows the player to learn with data-based approaches and feel as if the game is realistic and pleasurable and also is able to teach them important information. Several studies have attempted to explain how to make learning interesting in serious games. Killi uses an experimental game model that approaches the "challenge" aspect of a specific learning flow and is divided into ideation loops and the experience loop (Kiili, 2005). Another approach is to expand the theme in the game and identify

specific aspects of choice, control, collection, challenge and achievement to create motivational intrinsics in Massive Multiple Online Role-Playing Games (MMORPGs) (Dickey, 2007). Yet another approach, embodied in one of the pillars of Barab's Transformational Play theory (Barab et al., 2010), is that the actions of the players in the game must have a real impact on the game world, such as triggering changes in the landscape, changing the behavior of characters in the game, or changing the behavior of enemies and obstacles. Hartevelde, in its educational game design, describes this as 'exploration' and argues that it is an important teaching tool (Hartevelde et al., 2007). Freitas and Neumann also emphasize the use of exploration in serious games (Freitas and Neumann, 2009). This idea is supported by Squire's theory that games are 'designed experiences', where players learn by 'doing' and 'becoming' (Squire, 2006).

There are not many serious games that deal with land and agricultural processing, such as explaining the framework of the software design and

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simulation models for training agricultural driving machines. This is because the training for traditional driving depends on the actual engine, which means that training costs that are always high, inefficient and training can cause accidents (Ma et al., 2012). Realistic agricultural trainers that use historical simulations and game elements for crop cultivation and simulations in virtual reality breed, but they have not managed to balance the experience and entertainment elements (Yoo and Kim, 2014). Other research on serious games, such as research on the effect of an agricultural machinery trajectory on the land (Battiatto et al., 2013), simulate the form of a moldboard and compare it with the existing model to find the optimal form of moldboard plowing (Jeshvaghani et al., 2013). The virtual simulation of agricultural machines uses 3D interactive technology, dynamic web technology and database technology (Jianjun 2012). European projects that aim to develop serious online games for agro-ecology. There are European projects that aim to develop serious online games for agro-ecology, in which the main characteristics of the game are presented, as well as their purpose. This serious game, as well as other pedagogical resources produced during the project, is expected to provide some useful material for learning more multidisciplinary and experiential agro-ecology in European universities (Godinot, 2018). Of the various studies that have analyzed serious games in agriculture, there are even fewer that discuss immersion and especially the engagement of players in the serious game.

In a serious game concept that has a learning domain, engaging players with strategies based on real situations can improve the experience of the players so that they can achieve their goals. In previous research based on experiments using soil bin, a serious game was designed to soil tillage using a moldboard plow. The polynomial function model has been proven to be close to the actual data on the speed in plowing and the angle of the plow's eye. The depth of the plow on soil porosity is produced in the 3rd order, and the plowing force in the 4th order (Adisusilo et al., 2018a; Adisusilo et al., 2018b).

This research aims to increase the involvement of players by using a data-based approach that is optimized based on Pareto so that in this study can design game strategies based on a scenario design using Hierarchical Finite State Machine (HFSM). The design of the scenario is based on the optimal area of the Pareto-based game, which is affected by the speed of plowing, the angle of the plow's eye, and the depth of the plow on the soil porosity as well as the plowing force. Designing game scenarios in the optimal area can increase the engagement of players based on actual data. This creates a game situation that is close to reality, allowing the players to achieve their learning objectives in serious games.

2. Background

2.1. Engagement of players in soil tillage immersive serious games (ISG)

A qualitative approach to measuring the engagement of players aims to recognize the player's behavior based on their interactions (Bouvier et al., 2014) and learning activities during gameplay (Claudia et al., 2014). The behavior of players is information that can be used to design the scenario of a game. This is done by providing feedback of the scenario, allowing the main objectives in serious games to be achieved. Determining the optimal area, to give players the basic information will direct and give choices to the players on the strategies to be used in the game, thereby increasing player engagement.

One can think of a player's engagement as being on a spectrum, with one end of the spectrum being no engagement at all, and the other end of the spectrum being total immersion (Brown and Cairns, 2004). This research focuses on optimizing the engagement of players to increase the learning objective in soil tillage Immersive Serious Games using performance feedback. It then aims to improve the partial immersion to high immersion, using a data-based approach. In the Serious Game taxonomy, we can define the classification for this engagement in the immersion domain research for soil tillage serious game, in Figure 1.

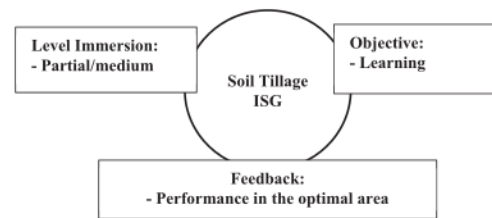


Figure 1. Classification engagement of Immersive Serious Games (ISG) for soil tillage.

Three sensory feedbacks are identified, which are the haptic, visual, and audio, and performance feedback. Performance feedback is widely employed to help players improve their performance in the game and is included in 33 (71%) games. There are certain games designed for treatment of diseases that provide performance feedback only to the doctor and not to the user. As they have evolved, serious games have been adapted to different application areas, aiming to improve or replace the traditional procedures. In health, they are used to support treatments for diseases such as epilepsy (Grewé et al., 2013), sclerosis (Peruzzi et al., 2013, 2016), autism (Cai et al., 2013), and rehabilitation of stroke patients (Seo et al., 2014).

As shown in Figure 1, the purpose of designing this serious game is to use it as a tool to educate users on how to till soil using a moldboard plow. The objective to increase player engagement through a data-based approach so players will learn better, by creating a game that performs optimally and can therefore increase the level of immersion into a medium with partial conditions, because there is no physical sensor.

2.2. Pareto optimal strategies

In general, Pareto is the optimal method. One way to find a good solution to problems with various objectives wherein a Pareto optimal game result can make at least as good and at least one player better (Nau, 2010). The rationale for the strategy in this serious game is to understand the effect of plowing speed, cutting angle of flow and the depth of tillage on soil porosity and plowing force. These parameters are the strategic choices in the game, while porosity and plowing forces are the goals and the objectives of the game. This case was taken from a real experiment using soil bin (Adisusilo et al., 2018b; Adisusilo and Hariadi, 2018), so the parameters used for the strategy were adjusted accordingly, namely;

- There are 3 initial speeds in plowing.
- There are 3 cutting angles of the plow's eye.
- There are 2 levels of depth in plowing.
- The results of porosity and minimum force must be greater or equal to the average of the results of the experiment (Adisusilo et al., 2018b).

To simplify all the possible outcomes of the strategic game the payoff matrix is used, which is a visual representation of all possible strategies and all possible outcomes (Ferguson, 2014; Nau, 2010). The speed of plowing, the cutting angle of the plow's eye and the plowing depth are a strategy whereby a is the speed with $a = \{a_1, \dots, a_i\}$, b is the cutting angle with $b = \{b_1, \dots, b_i\}$ and c is the plowing depth with strategy $c = \{c_1, \dots, c_i\}$. All of this is the strategy S of several strategies i , with $S = \{s_1, \dots, s_i\}$.

s_i will always refer to a strategy in S , with the possibility that each player will have more than one strategy. With U is the value of outcomes for porosity and plow style force with possible n outcomes, denoted by:

$$U_n = \{Sa_i, Sb_i, Sc_i\} \quad (1)$$

Table 1. The payoff/outcomes matrix model.

		Plowing depth (c_i)			Plowing depth (c_i)		
		Cutting angle			Cutting angle		
		b_1	b_2	b_i	b_1	b_2	b_i
Speed of plowing	a_1	$U_{a1,b1,c1}$	$U_{a1,b2,c1}$	$U_{a1,b_i,c1}$	$U_{a1,b1,c2}$	$U_{a1,b2,c2}$	$U_{a1,b_i,c2}$
	a_2	$U_{a2,b1,c1}$	$U_{a2,b2,c1}$	$U_{a2,b_i,c1}$	$U_{a2,b1,c2}$	$U_{a2,b2,c2}$	$U_{a2,b_i,c2}$
	a_i	$U_{ai,b1,c1}$	$U_{ai,b2,c1}$	$U_{ai,b_i,c1}$	$U_{ai,b1,c2}$	$U_{ai,b2,c2}$	$U_{ai,b_i,c2}$

to make it easier to use the payoff/outcomes matrix model, as shown in Table 1.

In general, for Pareto optimal the value of $U_n \geq U_{n+1}$, should be a value that makes every player at least as good as the average and at least one player better as the average, for all strategies denote:

$$\forall (S_{a1}, S_{b1}, S_{c1}), \dots, (S_{ai-1}, S_{bi-1}, S_{ci-1}), (S_{ai+1}, S_{bi+1}, S_{ci+1}), \dots, (S_{an}, S_{bn}, S_{cn}),$$

Where U_n is the optimal value, OP_p is the porosity and OP_f is the plowing force.

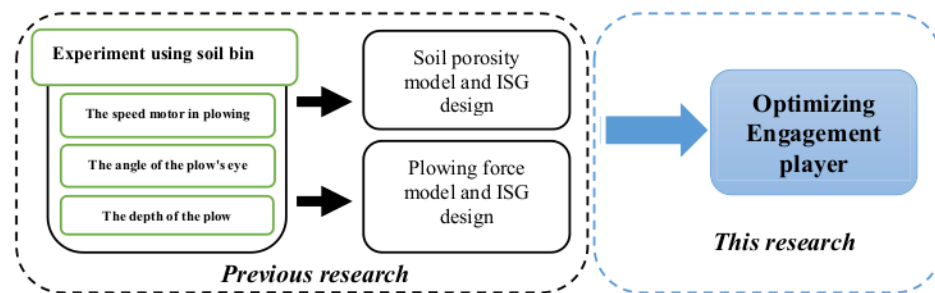
$$U_n = OP_p \text{ or } OP_f \begin{cases} U_n(\dots, S_i, \dots) \geq U_n(\dots, S'_i, \dots) \\ \text{and} \\ U_n(\dots, S_i, \dots) > U_n(\dots, S'_i, \dots) \end{cases} \quad (2)$$

$$OP_p \geq \sum_{i=1}^n \frac{p_i}{i} \quad (3)$$

$$OP_f \geq \sum_{i=1}^n \frac{f_i}{i} \quad (4)$$

3. Methods

This research will inform a part of the design of a serious game on soil tillage with a moldboard plow. The serious game design is based on actual data taken in experiments that use a soil bin tool, and the parameters taken are the effect of the speed of plowing, the angle of the plow's eye, and the depth of the plow on the soil porosity and the plowing force (Adisusilo et al., 2018a; Adisusilo et al., 2018b). The sustainability of the research is shown in detail in Figure 2.

**Figure 2.** Methods of the design of a serious game on soil tillage with a moldboard plow.**Figure 3.** Methods of the optimizing engagement player in the immersive serious game for soil tillage base on pareto optimal strategies.

Based on previous research, the speed of the motor engine is set to 3 parts, depending on the gear. One gear has a speed of 6.808 cm/s, two gears have a speed of 10.169 cm/s and a three gear has a speed of 19.917 cm/s and is expressed by variable a . The angles of the plow's eye in three types of plows that have different vertical cutting angles are 60° , 65° and 70° , and are expressed by variable b . Moreover, there are two depths of the plow, at 3.5 cm and 7 cm. The depth of the plow based on the soil's surface on the box against the plow is expressed in variable c . From preliminary research, a model of soil porosity and plowing forces for designing immersive serious games has been produced. In this research, the polynomial model is based on the understanding that the suitability of the data will make the serious game more immersive, but that if we put too much emphasis on real circumstances the game will lost its entertaining element (Adisusilo et al., 2018a; Adisusilo et al., 2018b). Therefore, the player strategies that can be used to increase the engagement of players are also difficult to achieve.

Results generated from previous experiments using the soil bin have been displayed in a matrix to show all the possible outcomes of the game's strategy. The resulting matrix creates a Pareto-based design space, which then determines the criteria of the resulting strategy. Based on this criteria, design for the engagement of players is in the form of game scenarios, which then take the form of flow strategies and game scenarios, shown in Figure 3.

It is said that the game is serious if there is a learning side in it that does not ignore the entertainment side (Connolly et al., 2012; Squire, 2006) (Hämäläinen et al., 2006). To develop this research, this study optimizes the multi-objective optimization function based on Pareto optimal, so that there is an area that is dynamic as a form of gameplay design in the serious game. The area is an optimal area as a strategic choice of the player in the game and raises the side of the experience so that the involvement in the area is expected to increase the immersive side of the serious game for tillage using the moldboard plow.

4. Results and discussion

4.1. The outcomes matrix for soil tillage ISG

The Pareto optimal strategy method based on experimental results has been implemented in the outcomes matrix, as shown in Table 2.

The average result of the value of soil porosity is 46.8 and of the plowing forces is 145.94. The shaded values in the matrix outcomes of Table 2 are the values that fulfill the optimal pareto condition. The value for the optimal pareto condition in this case is where the porous or

Table 2. The outcomes matrix for porosity and plowing forces.

Plowing forces Soil porosity		Plowing depth ($c_1=3,5$)			Plowing depth ($c_2=7$)		
		The angle of the plow's eye			The angle of the plow's eye		
		$b_1=60$	$b_2=65$	$b_3=70$	$b_1=60$	$b_2=65$	$b_3=70$
Speed of plowing	$a_1=6,8$	105.87 44	68.78 38	18.04 45	221.88 40	105.24 42.9	93.08 49
	$a_2=10,2$	118.46 42.9	70.66 44	39.01 46.9	314.04 49.9	187.01 48	112.74 48
	$a_3=19,9$	173.76 50	101 50	48.98 50	316.64 55	306.30 47	225.36 52

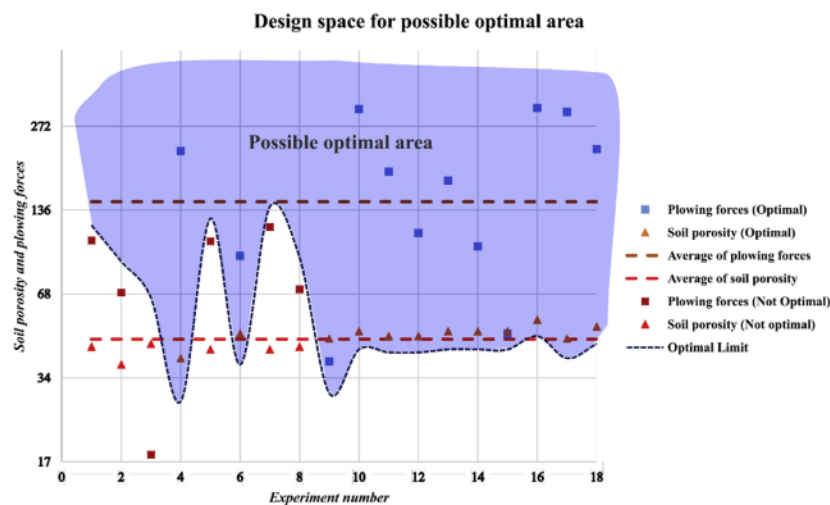


Figure 4. Design space for possible optimal area for porosity and plowing force.

plowing forces are greater or equal to the average. Therefore, the porosity is greater or equal to 46.8, or the plowing forces are greater or equal to 145.94.

4.2. Design space for possible optimal area

The first step to solving a multi-objective problem is to gain an understanding of the feasible region. In this case, there were two constraints: soil porosity and plowing forces. The design of the space is based on the objective model of the plowing force and soil porosity as found in previous research (Adisusilo et al., 2018b).

The design of the space is based on the objective model of the plowing force and soil porosity (Adisusilo and Hariadi, 2018; Audi Susilo et al., 2018), and also based on an outcome matrix designed to create an optimal game strategy. Then, if $P = f(p)$ is the soil porosity model that is affected by the function of soil porosity $f(p)$, and $F = p(f)$ is the plowing force model that is affected by function porosity $p(f)$.

Therefore, the relationship between the soil porosity and plowing force with a Pareto optimal strategy from the outcomes matrix is:

$$P = f(p) \Rightarrow OP_p \geq \sum_{i=1}^i \frac{p_i}{i} \text{ for soil porosity} \quad (5)$$

$$F = p(f) \Rightarrow OP_f \geq \sum_{i=1}^i \frac{f_i}{i} \text{ for plowing forces} \quad (6)$$

The graph of the design space of the soil porosity and plowing forces is:

In the graph in Figure 4, if the results of the soil porosity are below the average yield but the plowing force exceeds the average, then the design space still enters the optimal area. Vice versa, if the plowing force is below average but the porosity is above average, then the design space enters the optimal area, to determine the optimal game strategy.

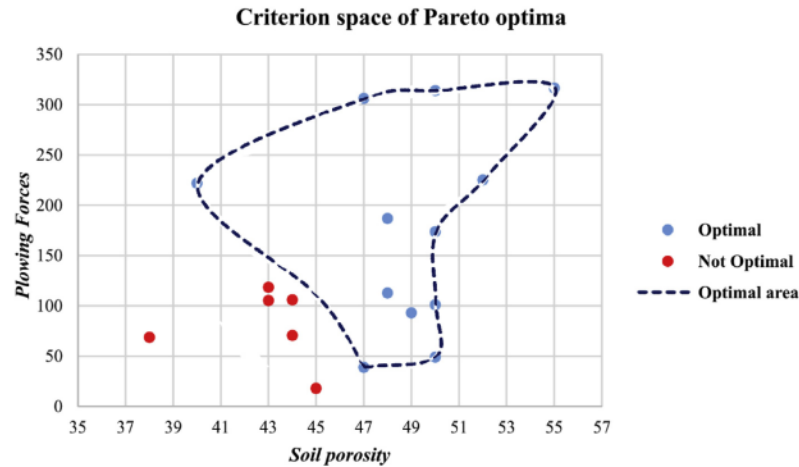


Figure 5. Criterion space to optimum value in Serious Game base pareto optima.

4.3. Criterion space of optimum value

The criterion space chart for the outcomes matrix, in Figure 4, for optimal strategies based on soil porosity and plowing forces.

The graph in Figure 5 shows the area of the optimal strategy space for soil tillage based on soil porosity and plowing forces. This area is a value that will be used as a reference for information given to players, so that players can determine the game strategy with a reference to real situations, which will increase the engagement of the players.

4.4. Engagement of players in optimal space

The design of the serious game refers to the concept of the optimal scenario, which is based on the experiment and the optimal Pareto concept in the game. This allows more than one optimal value to emerge so that many strategies are available as choices for the players. For every choice the player has that is carried out, there is a return value that influences how the next strategy is selected during the playing of the game. The idea behind engaging in an optimal strategy is to create more challenges, and since there are many strategic choices that can be made, this

creates a more immersive experience for the player. This experience arises intrinsically from the game process, or unconsciously due to immersive achievement. It also arises because of the playfulness of the game, which at the same time has an informative side. The concept of engagement of the player in the serious game for tilling that has been discussed in this research is shown in Figure 6.

Every time the game begins, the player uses a new strategy by comparing the output that has been implemented. This is different at the beginning of the strategy game, which is based on the initial knowledge of the user. Each output is compared to the optimal value in the criterion space that has been stored in the output. If not in the optimal data, then a choice of strategies is randomly chosen, and if the output is in the optimal data then a greater or equal value is selected, denoted by:

$$S \geq S' \text{ or } md(U_n) \quad (7)$$

From the space criterion chart we can implement a plot design for the serious game using HFSM (Herarchical Finite State Machine), so that it looks more like the strategic selection process in the game and how players are involved when playing.

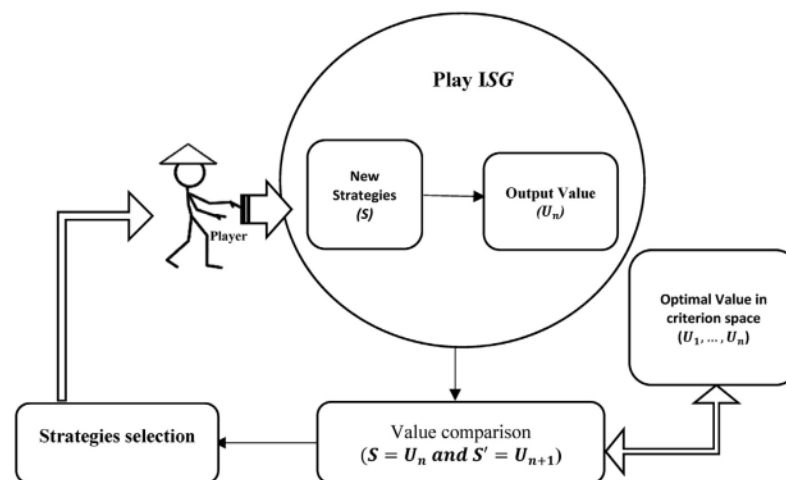


Figure 6. Design of the engagement of the player. Flow diagram to show selection strategies in Immersive Serious Game base on Pareto optima.

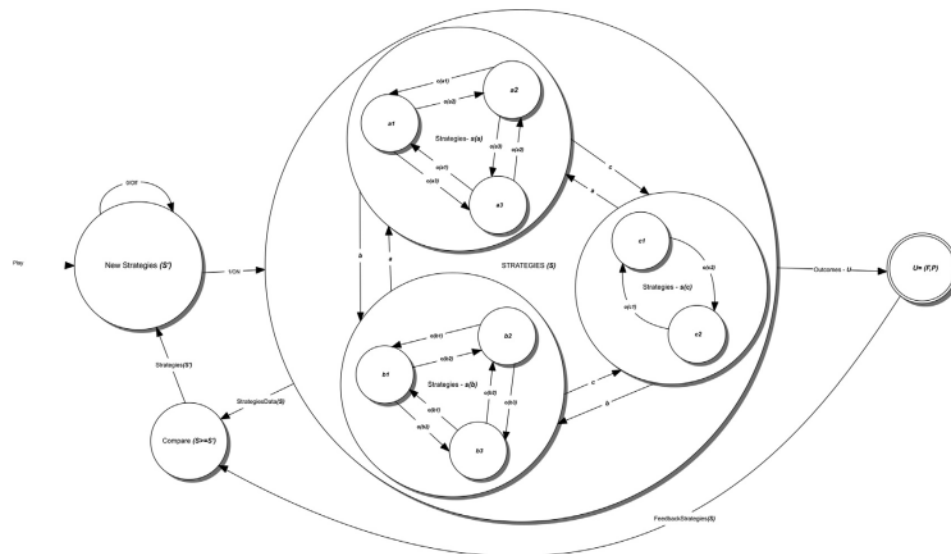


Figure 7. HFSM Serious Game for tillage base on pareto optima.

The design of serious games using HFSM is shown Figure 7 and is based on the engagement of the player, wherein HFSM starts with a new state strategy (S'). The new strategy is run as a strategy (S) in the state of hierarchy, based on state hierarchy of speed of plowings $s(a)$ with state ($a1, a2, a3$), state cutting angle $s(b)$ with state ($b1, b2, b3$) and state plowing depth $s(c)$ with state ($c1, c2$), output from hierarchy state strategy (S) is an outcome (U) value as in the outcomes matrix Table 2, which is the porosity value and plowing force $U = (F, P)$. The U value which is the result of the S strategy is included in the comparator state, to compare the value of U with the condition that the strategy to be implemented must be better or equal to the strategy contained in the data, because the new strategy to be implemented is an optimal strategy based on Pareto optima.

5. Conclusions

The choice of strategy has two effects. These are: creating more involvement, engagement and immersion for the player and bringing in a more fun side, because the game does not have a static playing strategy. Of the 18 outcomes matrixes produced, 12 outcomes were in the optimal Pareto area and 6 were not. These 12 outcomes have soil porosity and plowing force values, where one of these values is greater or equal to the average value of the experiment. The players are engaged by performing the strategy implemented in the serious game, which is shown from the outcomes, namely at the state $U = (P, F)$ of the HFSM serious game design. The result is a performance that has value, which is based on information from criterion space and is used to inform the game through feedback.

6. Declarations

Author contribution statement

A. K. Adisusilo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

M. Hariadi, E. M. Yuniarno: Conceived and designed the experiments; Analyzed and interpreted the data.

B. Purwantana: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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