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The application of genetic algorithm and data analytics for total resource management at the firm level.

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ABSTRACT

Total Resource Management (TRM) in industry 3.5 relates to the evaluation and improvement of performance through the use of intelligent tools or methods in enhancing efficiency and effectiveness of operations. This paper illustrates a study of TRM in the rubberwood processing industry to prepare it towards a sustainable transition to industry 4.0. The rubberwood processing industry operates using massive production data. Such big data emerge from production using multi-processes because the various products come in different sizes and quality levels (grades). The rubberwood processing company in this study faces significant problems of inaccurate and delayed data. These problems introduce mistakes in inventory management and wage payment. The company also faces an economic issue due to confirmation which is labour-intensive. This study applied the Genetic Algorithm (GA) technique to verify accepted material or woodpiece and use data analytics to improve the efficiency of the verification system. Furthermore, a Web-Based Application (WBA) is developed for production data management. The results show a significant drop in the percentage of data inaccuracy when the GA confirmation method is applied and also a decrease in the percentage of production data discrepancy among processes. This successful sustainable transition is attributed to TRM because the achieved performance improvement enriches effectiveness in production, material, labour and service resources.

1. Introduction

In the new global economy, sustainability is a critical issue in industry and become vital global policy in the context of the new Sustainable Development Goal (Martinico-Perez, Schandl, & Tanikawa, 2018). This alternative management concept has evolved to illustrate the new challenges of business sustainability, which represents a company's efforts to go beyond focusing only on its profitability to managing its economic, social and environmental impact (Laurell, Karlsson, Lindgren, Andersson, & Svensson, 2019). Technology, being an essential component of the manufacturing system plays a vital role in the sustainable transition of industrialisation. The transition from industry 3.5 to complete realisation of industry 4.0 needs technology-based infrastructures to preserve the sustainability of the global economy.

The manufacturing systems are fast changing. The increase in the adoption of the Internet of Things (IoT), artificial intelligence, robotics and data analytics have empowered manufacturing intelligence and smart production (Chien, Tseng, Tan, Tan, & Velek, 2020). Enters now the paradigm of Industry 4.0 which is a concept that was introduced in 2011 by the German Industry–Science Research Alliance. Industry 4.0 is the vision of increasing digitisation of production or the industrial revolution based on cyber-physical systems and continuing from Industry 3.0. The 3.0 is an improved production automation using electronics and Information Technology (IT) (Buhr, 2015). Horváth and Szabó (2019) summarised the characteristics of Industry 4.0 as the application of digital technologies in manufacturing processes which is also called “smart manufacturing,” “integrated industry,” and “industrial internet.” With the advent of Industry 4.0, most developing countries may not be ready for this transition. Alternatively, “Industry 3.5” is proposed as a hybrid strategy to bridge Industry 3.0 and Industry 4.0. The innovations of Industry 4.0 must be managed since it potentially disrupts socio-economic development and also affects a firm's total resource management for sustainability (Chien et al., 2020). The latter is evident in a conceptual framework of Industry 3.5 with five features which includes digital decision, smart supply chain, smart manufacturing, total

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resource management and smart factory (Chien et al., 2017a, 2017b).

Resource is one of the basic requirements in the operations of a company. It is necessary to implement the construction of managerial methods for total resource and the corresponding evaluation of performance index (Chien et al., 2017). This idea is the perspective of Total Resource Management (TRM). From TRM, the attribute "total" scopes all partners with value-added processes of the manufacturing enterprise and involves all aspects to improve the situation. The term "management" means that performance must be planned and controlled in order to optimise the entire value-added process of companies. Consequently, the term TRM is formed which encompasses all resources, partners and design in the value-added chain of manufacturing companies (Schenk, Trojahn, & Glistau, 2011). Additionally, the term TRM can be defined as the method to enhance the effectiveness of productivity and resource utilisation through systematic management architecture (Chien et al., 2017). Also, Hsu et al. (2019) stated that the intelligent agent contributes to TRM to enhance productivity, reduce costs, and boost intelligence management. Therefore, the intelligent method is required for TRM in the industry 3.5 perspectives.

The new way of working in developing products and processes is using the IT platform. Belhadi, Zkik, Cherrafi, Yusof, and El fezazi (2019) summarised that the widespread emergence of digital technologies, advancing computing power, and expansion of the IoT have led to a new generation of networked, data analytics, information-based technologies, and predictive modeling. This new generation collectively provides unparalleled combined computing capabilities to manufacturers with better methods to extract value from an increasingly massive amount of data and gain competitive advantage. What follows is Big Data Analytics (BDA) which have received increasing attention because of its considerable impact on manufacturing processes. The enormous need of production managers for real-time, dynamic, self-adaptive, and accurate production management have brought new challenges to traditional manufacturing processes of human intensive operations. It is imperative to create manufacturing intelligence from available data to provide a precise prediction of product quality, production and processing time. This is achievable with new and effective techniques within shorter computation time for example, to control the continuous production systems, predict out-of-control processes, and identify faults and defects in an accurate and timely decision making. BDA can enhance the decision-making quality and increase organisational output by extracting and making sense of the data for different types of analytic problems namely descriptive analytics, predictive analytics and prescriptive analytics. In terms of real-time and accurate of production data, BDA contributes to the TRM. The industry should provide support through continuous resource management to handle the detailed information available for each point of the production process. Accordingly, the monitoring of real-time data enables the awareness of resource consumption and responsive production management. Consequently, flows of information or data can be considered more reliable as data acquisition becomes more sophisticated. These bring improvements to quality. Further, production management is performed through intelligent optimisation algorithms. This optimises total energy consumption on a big data processing platform (Bonilla, Silva, Terra da Silva, Franco Gonçalves, & Sacomano, 2018). Therefore, the deployment of data analytics and information-based technologies would sustain the economic, environmental, and social (or human) resources which are the firm's total resource management for sustainability. In support of this statement, Panigrahi, Bahinipati, & Jain (2019) mentioned that the monitoring and clearance of information flow through better communication are the smart firm's behaviour which encourages supply chain sustainability. Moreover, the development of an efficient application of Information Communication Technology (ICT), is a way to an effective sustainable outgrowth of SMEs in their firm and respective supply chains (Singh, Luthra, Mangla, & Uniyal, 2019).

Most companies today recognise the likely impact of Industry 4.0. This includes the rubberwood manufacturers in Thailand which are predominantly small and medium-sized enterprises (SMEs). As SMEs, they are generally less well-prepared for new technologies and expectations. The former is a digital decision suited to support situations with flexible decisions to manage operations according to the experiences of managers. However, the analysis of collected information should provide context and meaning to help users to make effective decisions. This is a crucial issue in the current manufacturing systems. A BDA method was proposed to construct a framework to discover the root causes for sub batch processing with relatively high detection accuracy and small errors (Chien et al., 2017). This paper summarises the scope of this research. The paper is structured as follows. Firstly, a review of TRM in Industry 3.5, TRM with technology base, predictive data analytics and WBA are discussed. Then, it is followed by the description of the GA methodology, application, and its experimentation in the development of WBA. Finally, the results of the GA experiment, the WBA test, and the conclusion.

This research targets to improve the verification system efficiency of rubberwood processing companies through investment in data analytics and real-time monitoring technology. These investments will reduce inaccurate and delayed data in the production verification process. Hence, the critical question is how to incentivise the GA and WBA to improve the production confirmation system? This is in the best interest of massive production in the company. Besides, it creates a sustainable transition link from industry 3.5 to industry 4.0 in the TRM perspective. This is the focus of our paper.

2. Literature review

Small and medium companies are gradually envisaging the impact of Industry 4.0. However, based on current situation, there is still a large gap between industry 3.0 and 4.0. Hence, the purpose of Industry 3.5 especially in the TRM perspective which is technology-based. The TRM perspective is to prepare these companies for a sustainable transition to industry 4.0. The illustration of the case application of GA and WBA is our proposal for industry 3.5 in the rubberwood processing context. This section presents a literature review on TRM and its applications, predictive data analytics and the WBA.

2.1. TRM in Industry 3.5

TRM is a crucial part of Industry 3.5. The TRM perspective is significantly considered in this paper. In Industry 3.0, resources are managed separately in each area, e.g., material, production, energy and human resource. Several studies paid attention on different methods to manage different resources (Chien et al., 2017) such as the learning factory's perspective covers areas of lean management, resource efficiency management, and organization. Due to the increasing costs for resources approximating material and energy as well as the social change to an environmentally friendly atmosphere, the topic of resource efficiency has become more and more critical (Kreimeier et al., 2014). An optimization method of practical space usage and machine layout configuration are critical aspects of resource management as it directly impacts a company's profitability (Gülşen, Murray, & Smith, 2019). Moreover, broad strategies of human resource management are provided, according to human resources, which can be the most critical competitive advantage for organizations (Lo & Fu, 2016). Hence, the resource management in this industrial revolution phase focused significantly on the resources efficiency. Cohen (2010) explained the resource efficiency is a component of sustainable consumption and production and refers to the way in which resources are used to deliver value to society. Resource efficiency recognizes the need to consume fewer resources and produce less waste whilst delivering the same, or even more or improved, end services or products. Moreover, it is related to the magnitude of the resource efficiency principle such as reduce, reuse, remanufacture, recycle, redesign, by-product synergy, and waste to energy (Choi, Thangamani, & Kissock, 2019). Certainly, resource management of efficiency-based is also related to sustainability, which carries over to the sustainable transition that attributed to TRM. Continuously, the view of the integrated implementation for solving the resource problems, the basis of TRM of Industry 3.5 component, is based on the concept of "Total Quality Management" (TQM) (Laufer & Saghiv, 2018). TQM is the mutual co-operation of employees in each area of the firm and associated business processes to produce products and services which meet the needs and expectations of customers (Dale & Cooper, 1994). The integration of functional areas is subjected to provide the best product and service to the customer. Since the attribute of 'total' does not constrain only to the quality aspect of each area, TRM is formed to extend to all consumption of resources areas. According to TRM, a resource-optimized value has to be established, and some selection and valuation criteria have to be introduced, which refer to the consumption of resources over the firm (Laufer & Saghiv, 2018). The overall resource management of TQM is established based on "Enterprise Resource Planning" (ERP). ERP system acts as an efficient tool in the resource integration and profit creation for a company (Lin, Chen, & Ting, 2011). Li, Markowski, Xu, and Markowski (2008) argued that TQM is a philosophy that emphasizes on process improvement. In contrast, an ERP system is an information technology mechanism that implements enterprise-wide process management. Conceptual development and their findings suggested that ERP implementation can be successful if a TQM focus precedes it. In summary, TRM in industry 3.5 is firmly an information technology requirement in which everyone in an organization is the role player. Through Industry 4.0, resource management is expected to be in the form of self-cofiguration and self-optimization. The step of review and improvement has to be a continuous and periodic job to enhance the competitiveness of resource management (Chien et al., 2017). To allow resource management of Industry 4.0 to take place naturally, TRM in the Industry 3.5 perspective must strengthen the use of technology bases to manage holistic resources.

2.2. TRM with technology-based

The implementation of the TRM with the application steps are based on the industry atmosphere and their requirements. Firstly, the management level should establish the fundamental objectives and construct the performance indicators of the organizational resources. Then, the means objectives with tools or methods are constructed to help them reach the fundamental objectives (Chien et al., 2017). The intelligent agent contributes a tool or method to TRM to enhance productivity, reduce costs and boost intelligence. Over the past decade, most research in TRM has emphasized the use of technology such as in the agriculture industry where information technology (IT) is utilized for sophisticated engineering and it is currently available for spatial referencing. IT facilitates TRM in agriculture for the conservation and sustainable use of natural resources (Nair, 2019). Besides, the TRM approach that addresses additional factors such as soil quality, pest, residue, and nutrient management can be integrated into the demonstrations to aid water savings. The TRM will support the adoption of the best practices that most effectively address growing concerns over increasing greenhouse gas emissions (Weinheimer, Johnson, Mitchell, Johnson, & Kellison, 2013). Huang, Zheng, and Chien (2012) developed a TRM system equipped with the developed GA. This system can generate the optimal schedules for rehabilitation patients to minimize waiting time and thus enhance service quality and overall resource effectiveness of rehabilitation facilities. In addition, overall resource effectiveness is critical to enhance productivity for effective use of capital, drive various improvement directions for TRM and improve cost structure for profitability. One such study was carried out to engage the technology of data mining for enhancing the Overall Resource Effectiveness (ORE) performance in various settings (Chien, Chu, & Zhao, 2015). Through the performance evaluation, the performance indicators of the resources could be calculated to expedite the achievement of the fundamental objectives (Chien et al., 2017). Moreover, the steps of review and improvement have to be continuous and periodic jobs to enhance the competitiveness of resource management (Chien et al., 2017). Therefore, the technology-based infrastructure such as the cloud monitoring system platform, the real-time data of the production line (Chien et al., 2017), or any reasonable means are adequate systematic management architecture to deal with the issue.

2.3. Predictive data analytics

One category of data analytics is predictive analytics which aim to provide a glimpse and foresight into the future. Based on historical and current data, predictive analytics apply forecasting and statistical modeling. It gives insight into "what is likely to happen" in the future based on supervised, unsupervised and semi-supervised learning models (Gandomi & Haider, 2015). Belhadi et al. (2019) summarise the predictive data analytics from several literature reviews and multiple case studies that explain about two categories of predictive analytics techniques. The first category is statistical analytics oriented techniques which use mathematical models to induce and analyse existing data as well as infer and predict unknown information. These techniques include multinomial logit models, regression techniques, K-nearest neighbor (KNN) and Bayesian. The second category is knowledge discovery, KD-oriented techniques, which is data-driven that does not require to indicate assumptions and problems in advance. This category mainly includes machine learning techniques such as Neural Networks (NN), Multiple Backpropagation (MBP), Self-Organising Map (SOM), rough set, association rule, support vector machine (SVM), generalised sequential pattern (GSP) and GA. Knowledge Discovery in Databases (KDD) is generally defined as the broad process of discovering hidden valuable knowledge or patterns in large amounts of data. Some authors propose a new approach to instance selection that uses GA to define a set of target labels (Kim & Enke, 2017; Yukselturk, Ozekes, & Türel, 2014). For example, it is used to identify the buying and selling signals and then select instances according to three performance measures of the trading system (i.e. the winning ratio, the payoff ratio, and the profit factor) (Kim & Enke, 2017). Therefore, we applied GA of KDD in this research and a part of this GA method is detailed as follows.

2.4. The WBA

The web is now used for deploying applications that do more than merely deliver information, the purpose for which it was initially devised. The WBA is applications using the web as the application infrastructure to perform its functions. They have significant complexity in logic processing as opposed to just data-intensive content and rely on web browsers and web protocols (mainly HTTP). These provide the user interface in the form of web pages, delivered and connected to the rest of the application (Zhao, Kearney, & Gioiosa, 2002). The usage of WBA as one of the marketing tools in various firms provides extensive benefits such as better management information between employers and employees which lower transaction costs (Punnuluk et al., 2010). In this instance, the WBA was applied to the production data management for the propose of rapid production development (Lan, Ding, Hong, Huang, & Lu, 2004), effective performance monitoring (Khan et al., 2012) or any decision managerial supported. With the application of the WBA to information management, database performance would have a significant impact on the performance of the web application. Database performance is indicative of the response time of the database management system for retrieving/storing records. It also represents how efficiently the database handles multiple read/write requests to different database tables (Adnan, Singleton, & Longley, 2010). Therefore, the database should be well designed.

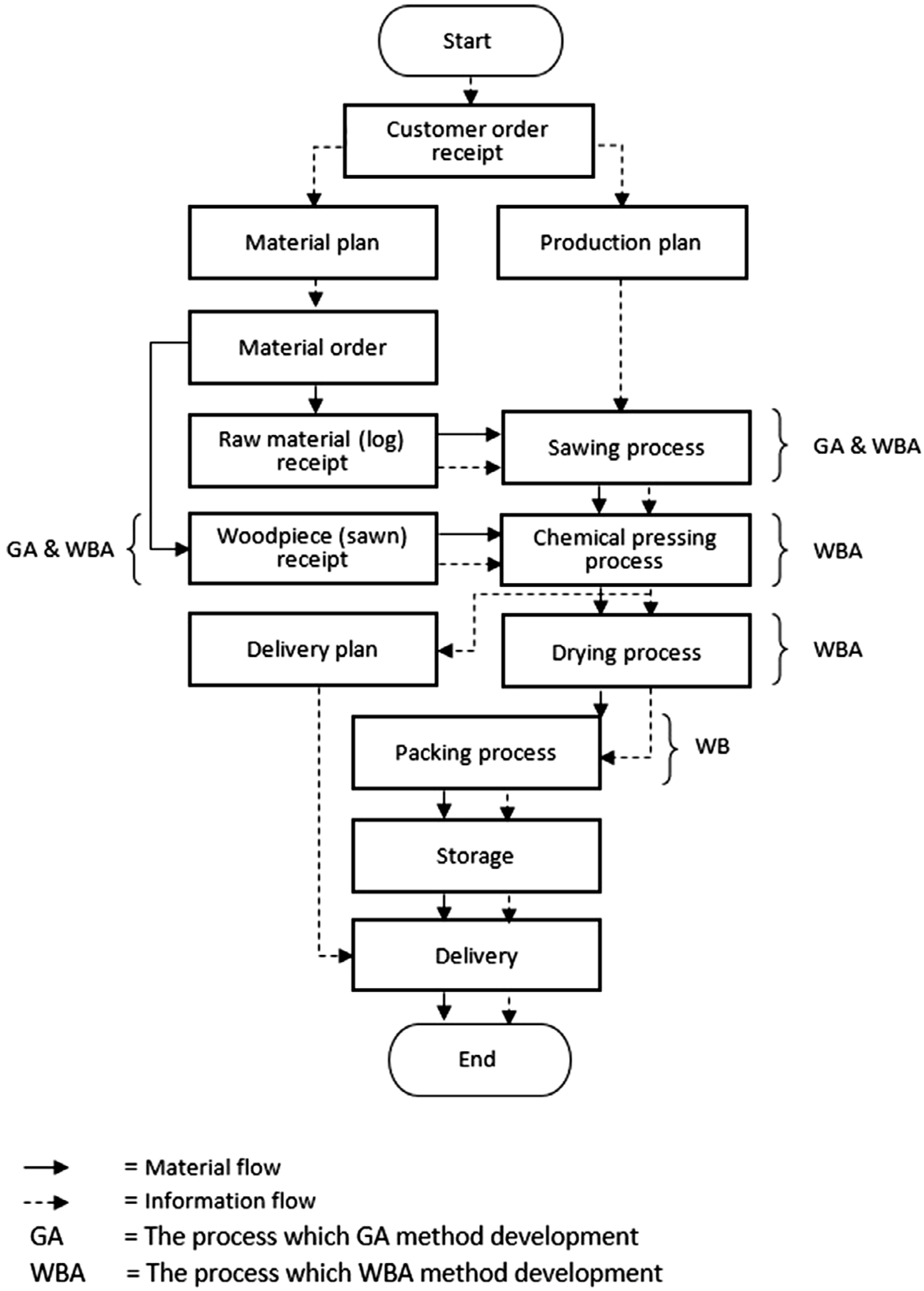

Fig. 1. The rubberwood processing company process and scope of methods application

3. Methodology

This section explains the GA method, the application of the method and the development of WBA. These are shown in Figure 1.

Figure 1 shows the material flow of the rubberwood processing company. The suppliers deliver two types of raw materials as a woodpiece (piece) and log (tonne) where the latter is sawn in-house. After that, all woodpiece will enter the chemical compression process followed by drying in the oven. The dried wood will be packed and stored for delivery to customers according to the delivery plan. This is supported by the material and production plans based on customers' orders. The pieces of sawn or purchased woodpieces are controlled by manual counting. The in-house sawn quantity is used to calculate production yield and wage payment. This quantity data is recorded on paper and forwarded to the next process. Recorded data is verified or confirmed again at the chemical compression process in order to meet the delivery plan. The packing process which follows the drying process verifies the inventory which is used to evaluate the drying process condition/quality. The condition is defined by the defect ratio such as bending piece from overheating. The development of the GA counting method will be used to confirm the input data of the woodpiece at the sawing and receiving process instead of counting manually. The development of WBA will be used in all processes to replace paperwork.

3.1. GA method

The GA method starts with chromosome encoding and decoding. The length of a chromosome (string) is R (where R is the number of

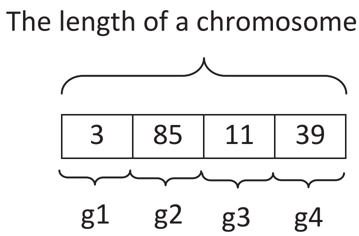

Fig. 2. Chromosome encoding

items to verify), the string representation would be [1, 2, 3, …, R]. R denotes the size of the predictive set represented by the string on value encoding, and the subsequent elements g1, g2, ..., gR subset of genes or the quantity of each item to verify. The example of the verifying chromosome is shown in Figure 2.

The chromosome will be used in the decoding process to evaluate using the fitness function

$$Min(Z) = |W_a - \sum (n_i \times \bar{x}_i)| \tag{1}$$

where W_a= the actual weight of all items from a weight balancing process when receiving. And, $\sum (n_i \times \bar{x}_i)$ = is the part of an estimated weight of all items from the data set, where n_i is the quantity of item 1 to i, and $\bar{x}_i$ is the average weight of item 1 to i.

We have formed the initial population by creating R random strings, where the population size R is a value from 1 to 259. This is because 259 is the approximate value when transferring from the decimal number to binary number system in the next process according to the maximum quantity of each item placed in a handle unit. The number of an initial population affects the opportunity of finding optimal or near optimal solutions on complicated and vast spaces in a possible solution and also the solution time. To accommodate them, we proceeded with the parameter tests and found that 1,000 chromosomes for the initial population are approximated. Then, the process of chromosome selection continues. We use the Roulette Wheel (Djellali & Adda, 2017; Hmida, Hamida, Borgia, & Rukozb, 2018; Ooi & Tan, 2003; Sharma & Saroj, 2015; Yukselturk et al., 2014) method for this step. The next process is cross over which applies the one-point intracluster crossover (De Paula Filho et al., 2011) method with a probability of crossover, $P_c \leq 0.7$. In this step, the value encoding of the decimal number system is going to change to binary number system as in Figure 3. This transformation is for a more efficient crossover process due to the requirements for more positions of crossover. The example of cross over method is shown in Figure 4. Two offspring binary chromosomes were produced through the exchange of genes or clusters between the two parents. This probabilistic process was repeated until all parent chromosomes have been considered.

After the chromosomes were crossover, they mutate. The mutation operations were also applied at probability; $P_c \leq 0.1$ on each of the offspring chromosomes produced from the crossover. The method randomised two points through chromosome (from 8 × R points). The example of the mutation event is shown in Figure 5.

The chromosome at the end of the mutation process goes into the fitness evaluation. Then, repeat into the selection, crossover, and mutation process until the operation is completed according to the number of parameters of the number of duty generations. The generation number is another important parameter in determining the best answer. Because, if the generation is set too little, the solution may not be the best answer. Alternatively, if we set too much, it may result in wasted hours of work if the best answer could be found in the earlier generation. So, the generation parameter was tested and found 100 cycles are approximated. The chromosome with the best overall fitness in a particular run may not necessarily always correspond to the 'best' answer in the final or last generation. Moreover, it is common to compare all the 'best' from each generation with one another to determine the ultimate chromosome with the highest overall fitness (Ooi & Tan, 2003).

3.2. Application of the GA method

We apply GA primarily to verify the quantity of raw materials in the receiving process of the rubberwood industry in addition to obtaining the best answer from the specified fitness function. However, we need to get the correct answer or an answer that is similar to the number of items according to the item size that we receive. There is only one correct answer and this is challenging. Therefore, the application of genetic methods to verify the number of raw materials needed to determine other factors subject to a guideline for obtaining the answer that is close to the single correct answer which should be acceptable as well. Then we study the error rate when manual counting using the Taguchi method (Mitra, Jawarkar, Soni, & Kiranchand, 2016) during the experiment. The error rate experiment determines the control factors which are the factors related to the error of human counting: (a) the size of the wood according to the thickness, (b) the number of items per handling unit and, (c) the total quantity of the wood pieces per handling unit. The levels of factors are shown in Table 1.

From Table 1 regarding the factors and the levels above, it can be used to define the orthogonal array, which gives the results of L_4 (2^3) arrangement. The orthogonal array is shown in Table 2.

In this experiment, the disturbing factors which are defined as counting speed is the counting time of more than three minutes per handling unit (N_1) and less than three minutes (N_2) and considering the average counting rate of about three minutes per handling unit. The results of thirty experiments are shown in Table 3.

The results of the experiment in Table 3 is explained as follows. This experiment considers the SNR (Signal-to-Noise Ratio) from -10log$_{10}$(MSD), where MSD (Mean Square Deviation) is the average of N_1^2 and N_2^2. The lowest SNR was found at -6.13 from experiment 3. We can conclude that for the thickness of 0.50-0.875 inches and arranged 1-2 items per handling unit with a total quantity of more than 370 pieces, the counting yielded the highest percentage error. In addition, the range of 4.56 percent was found in the sum values and depended on the thickness of wood; and 1.57 percent depend on the quantity of wood per pallet. A factor of the number of items per handling unit yielded a minimum difference of 1.08 percent. Therefore, the factor that has the highest tolerance was the size of the wood by thickness. Therefore, we will use the acceptable error value with the wood size of 5.00% (round up 4.56%) for all wood sizes. Then apply this value in the data parameter set of the modified GA.

Next, we applied the method of fitness functions with a penalty Banerjee & Abu-Mahfouz, 2018; Fathalla, Ek´art, & Gherghel, 2018), which is a feature of bringing the constant into the function objective ((1) in order to increase the fitness value significantly. This made it improbable as the choice in selecting chromosome for the next generation. The punitive objective function applied was

$$Min(Z) = \begin{cases} |W_a - \sum (n_i \times \overline{x_i})| & when \;\; (s_i - e) \leq n_i \leq (s_i + e) \\ |W_a - \sum (n_i \times \overline{x_i})| + K & otherwise \end{cases} \tag{2}$$

where s_i is the quantity of item 1 to i on a handle unit that suppliers inform, e,is the acceptable error quantity (5.00% of s_i), and K is the high

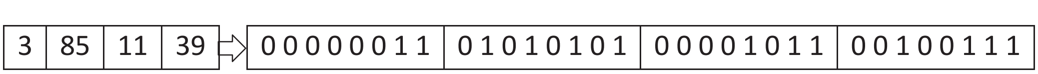

Fig. 3. Chromosome encoding transferring

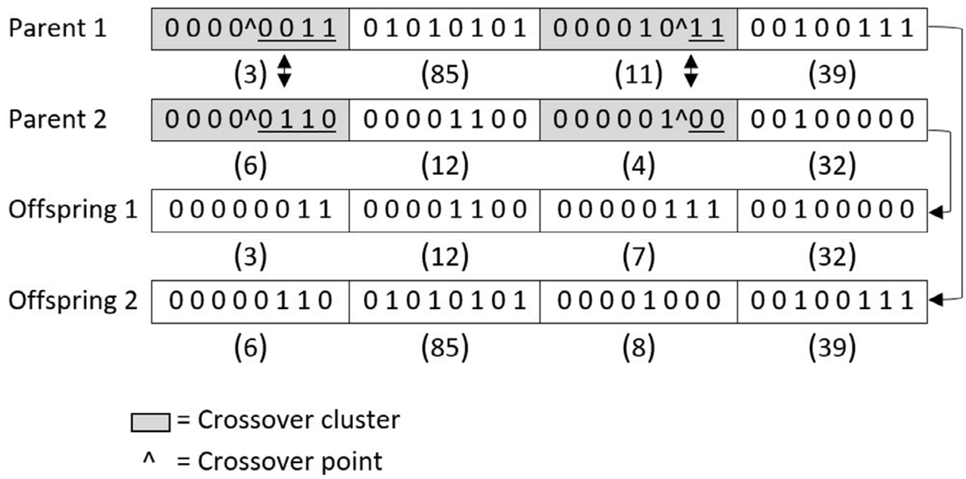

Fig. 4. The one-point intracluster crossover

constant value.

We have designed and developed the application (1) using Java language on the eclipse program to develop data analysis application and (2) using Microsoft Excel 2010 for data sets collection. This modified GA method replaced human counting. It could be used to improve the efficiency of the system to verify the number of raw materials received. The counting application is generated under the conditions of low development cost, feasibility in use, and short development time. We set the goal of the system to get the best answer or the smallest error value according to the fitness function. It would be the answer with a tolerable error or an answer set which is lower than human counting from the results in the experiment. The results of the application tests are presented in the next section.

3.3. Development of WBA

In order to develop WBA, initially we studied the information flow and the architecture of WBA to create the database structure. The information flow and WBA system architecture are shown in Figure 6 while the database structure is shown in Figure 7.

In Figure 6, this platform was developed to collect quantitative data of woodpiece as confirmed by the GA method at the sawing and receiving process. Also, this data is shared with the administration staff at chemical pressing, drying, and packing process. An application is designed for the smartphone for data input. The uploaded data constitute records. All information are stored in the SQL database and analysed to generate reports.

In Figure 7, we designed the database structure and relationship of data tables according to the transferring data among the primary process. The tables in the relational database store data related to the sawn date, type (in-house or purchased), and product description in sawing

Table 1
The level of experiment factors

The control factors	Level High	Low
(a) the size of the wood (inch)	1.0-3.0	0.50-0.875
(b) the number of items per handling unit (item)	1-2	3-4
(c) the total quantity of the wood pieces per handling unit (piece)	≤370	>370

Table 2
The orthogonal array of L_4 (2^3)

The experiment	Level of factor (a)	Level of factor (b)	Level of factor (c)
1	Low	Low	Low
2	Low	High	High
3	High	Low	High
4	High	High	Low

and receiving process that links to the chemical compressing process. In the chemical compressing process, the lot number is generated then link to the drying and packing process respectively. The tools used for WBA development are (1) Dreamweaver CS6 for creating web pages using jQuery Mobile Framework, (2) Apache Web Server for computer simulation as a server simulation, (3) PHP Script Language for processing PHP commands, (4) MySQL Database for creating databases and storing data, and (5) phpMyAdmin for managing MySQL databases.

4. Results and Discussion

This section will first discuss the application development followed

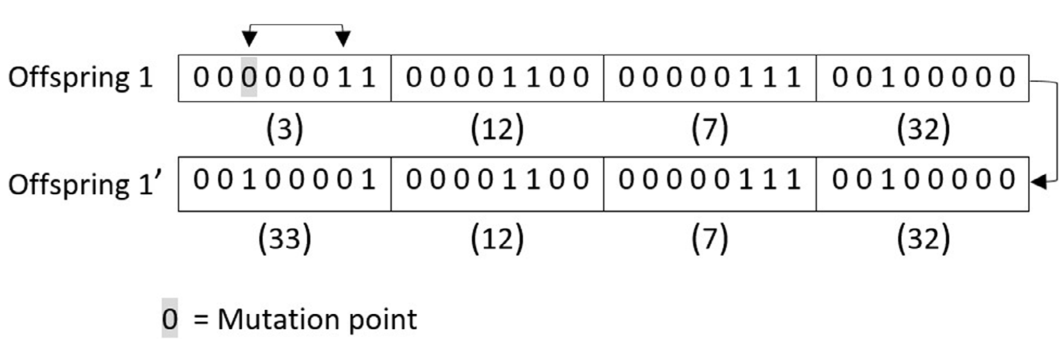

Fig. 5. The mutation process

Table 3
The experiment results of manual counting

The experiment	The control factors (a) Size (inch)	(b) No. of item (item)	(c) Total quantity (piece)	N_1 Percentage of error (%)	N_2	Total percentage of error (%)	MSD	SNR
1	1.0-3.0	1-2	≤370	0.33	0.73	1.06	0.32	4.94
2	1.0-3.0	3-4	>370	0.41	0.79	1.20	0.40	4.02
3	0.50-0.875	1-2	>370	1.77	2.25	4.02	4.10	-6.13
4	0.50-0.875	3-4	≤370	0.60	2.20	2.80	2.60	-4.15
Tl. %Low	2.26	5.08	2.92					
Tl. %High	6.82	4.00	4.49					
%Diff.	4.56*	1.08	1.57					

by the experimental results and the development of WBA and its test results.

4.1. GA Application Development and Experimental Result

We developed data analysis applications in order to evaluate the number of wood pieces named "Wood piece Prediction" shown in Figure 8. The application organisation consists of three parts. First is the user interface window or part for calculation. In this part, the user input the required data which are thickness, width, length, total weight, and the volume of each item. The total weight is from the balance of wood pieces varying in width in one handling unit. The volume of the items is identified by the seller shown in the delivery note. After completing all input data, the application will predict the answer set according to the GA process and display in the results area or prediction data blocks. The second part, which is the part of the data set used to improve the wood piece database is shown in Figure 9. Thirdly, is the adjustment of various parameters of the GA approach in Figure 10. The last two parts link the user interface window and the admin user.

We tested our developed application to verify the quantity of materials received following the GA above. We also determined the experiment that corresponded to the experiment of manual counting according to the Taguchi method. Therefore, we required an experiment with the four conditions shown in Tables 4–7 with thirty experiments in each condition. Besides, each condition had different inputs of data error rate between 0% and 5.00%. Since the approximate parameters set up with 1,000 initial populations and 100 generations, the application solution time was about two minutes per round. The experimental results are shown in Figures 11–14 and Table 8.

The results from all four experiments show that the maximum error rate that the application provided is lower than the acceptable error value at 5.00%. It also could reduce the error rate of the input data and revealed the error from the solution was lower than the entered error rate of 2.50-5.00%. It also revealed the analysis from the experimental handle unit with the minor weight (experiments 1, 3, and 5) resulted in the fitness values that were stable than the massive weight of the unit handle (Experiment 2). However, when the input data entered had much more error, the fitness value showed a high value (around K value). This means the answer was unidentified. There was a significant drop in the percentage of data inaccuracy when the GA confirmation method was applied. In other words, accuracy of the data improved. The results of data analysis show that using GA is one of the successful methods of sustainable transition in this case study. It supports economic and social sustainability because it reduced material inventory that caused the errors. Also, reduced the counting operators through the better efficiency in material and human resources management.

4.2. Development of WBA and Test Result

We completed the development of WBA for all working processes. The different user interface depended on the database structure and required that some of the portions which were automatically created such as the date and lot number. The example of WBA is shown in Figure 15. We also tested our developed WBA in the evaluation of its application efficiency. We tested by recording the 205 lots of woodpiece sawn in-house and those received from suppliers then direct to the compressing and drying process that were produced within one day. This whole lot of woodpiece was incubating in the drying process that

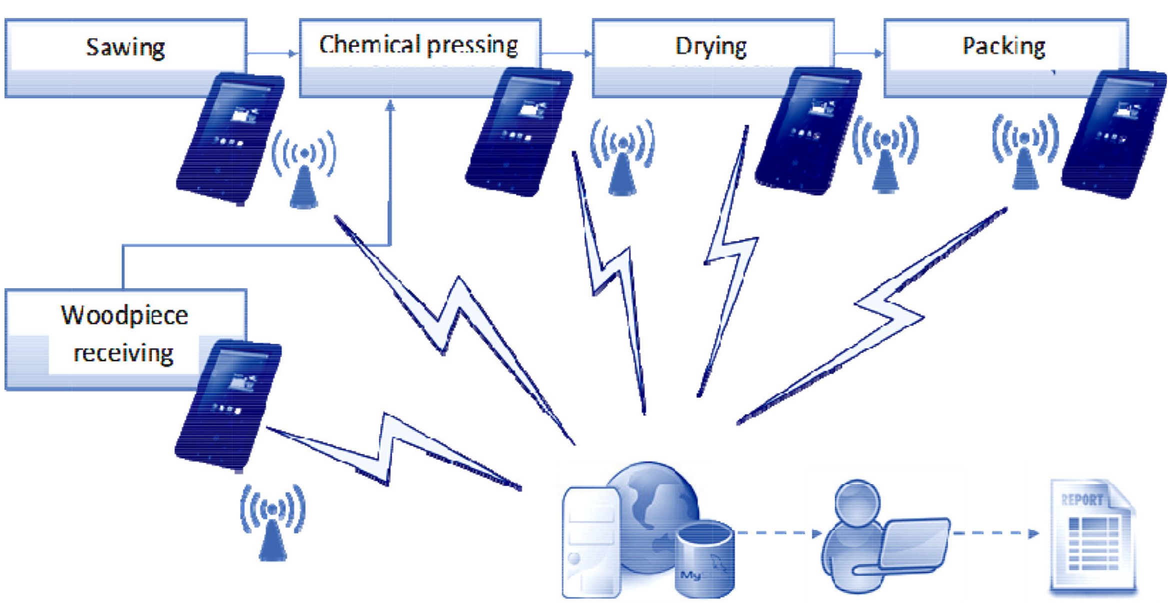

Fig. 6. The information flow and WBA system architecture

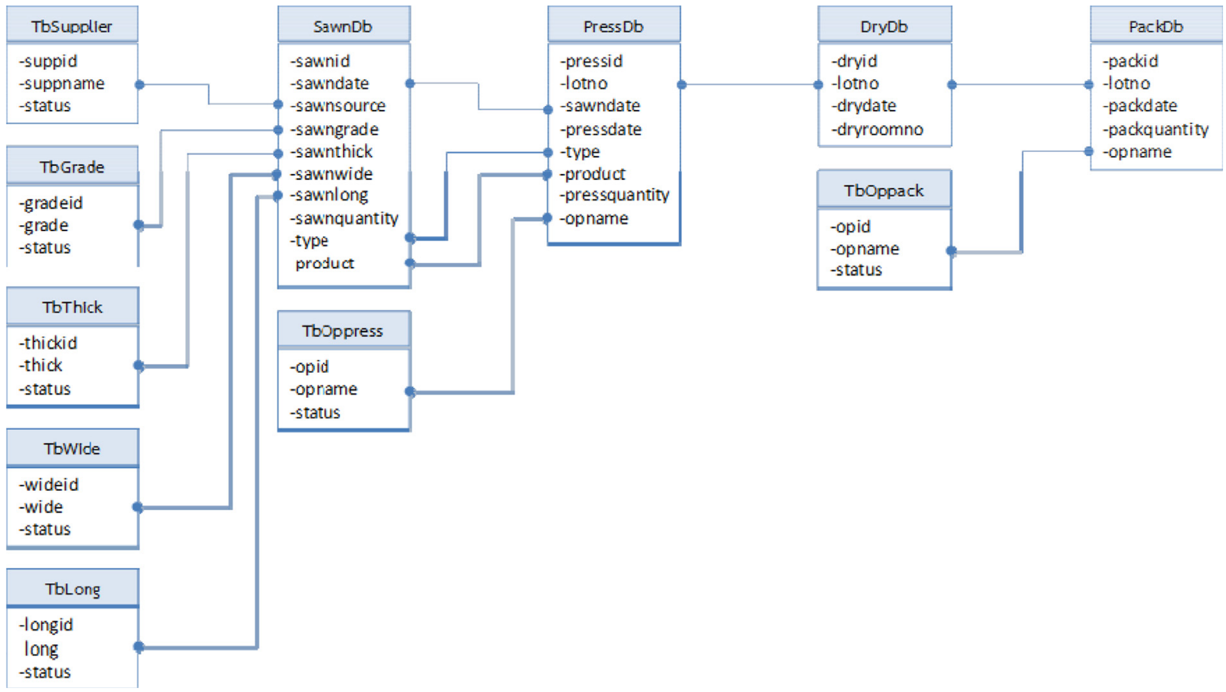

Fig. 7. The database structure

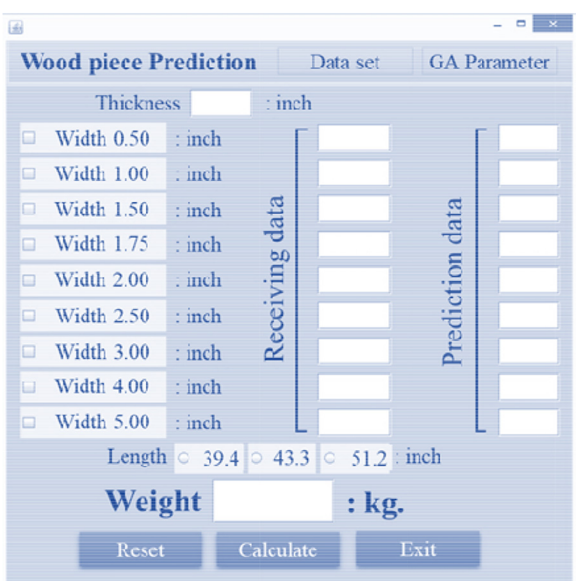

Fig. 8. The application user interface

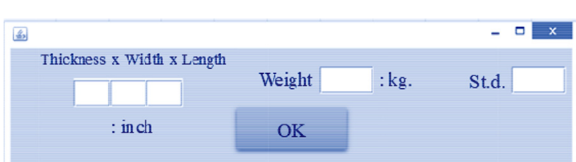

Fig. 9. The data set update window

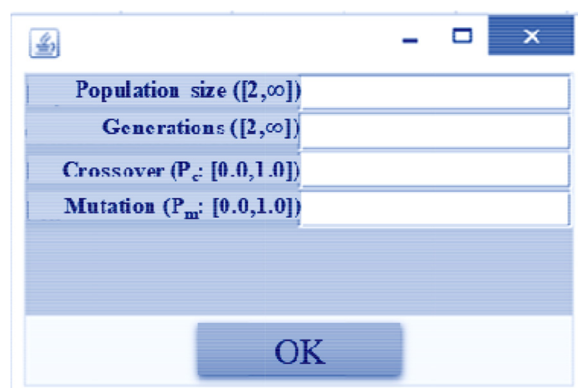

Fig. 10. The GA parameter adjustment window

Table 4
The experiment 1

Size (thickness × width × length; inch)	Actual quantity
2.0 × 2.0 × 43.3	65
2.0 × 3.0 × 43.3	98
Total	163
Actual weight (kg.)	795

Table 5
The experiment 2

Size (thickness × width × length; inch)	Actual quantity
2.0 × 2.0 × 43.3	105
2.0 × 3.0 × 43.3	113
2.0 × 4.0 × 43.3	96
2.0 × 5.0 × 43.3	65
Total	379
Actual weight (kg.)	2,296

could take seven to fourteen days. Following that, we completed recording the data of the packaging process and completed it within seven days. This refers to all 205 test lots from the oven. We present the testing results of Summation of Error (SE) according to (3) and a summary of the results is shown in Table 9.

As (3) the SE was formulated as

Table 6
The experiment 3

Size (thickness × width × length; inch)	Actual quantity
0.5 × 1.5 × 43.3	178
0.5 × 2.0 × 43.3	212
Total	390
Actual weight (kg.)	518

Table 7
The experiment 4

Size (thickness × width × length; inch)	Actual quantity
0.5 × 1.5 × 43.3	106
0.5 × 2.0 × 43.3	135
0.5 × 2.5 × 43.3	52
0.5 × 3.0 × 43.3	63
Total	356
Actual weight (kg.)	542

$$\mathrm{SE} = \frac{\sum_{i=1}^{n}(a_i + b_i + c_i + d_i + e_i + f_i)}{\sum_{i=1}^{n}(Sm_i + Sb_i + PSm_i + PSb_i + DSm_i + DSb_i)} \times 100 \tag{3}$$

When

a_i is the absolute difference quantity from in-house sawing process (Sm_i) compared to chemical pressing process (only in-house woodpiece) (PSm_i) for product item i,
b_i is the absolute difference quantity from purchased woodpiece (Sb_i) compared to the chemical pressing process (only purchased woodpiece) (PSb_i) for product item i,
c_i is the absolute difference quantity from the chemical pressing process (only in-house woodpiece) (PSm_i) compared to drying then direct to packing process (only in-house woodpiece) (DSm_i) for product item i,
d_i is the absolute difference quantity from the chemical pressing process (only purchased woodpiece) (PSb_i) compared to drying then direct to packing process (only purchased woodpiece) (DSb_i) for product item i,
e_i is the absolute difference quantity from drying then direct to packing process (only in-house woodpiece) (DSm_i) compared to in-house sawing process (Sm_i) for product item i, and
f_i is the absolute difference quantity from drying then direct to packing process (only purchased woodpiece) (DSb_i) compared to buying woodpiece (Sb_i) for product item i.

Moreover, n is the total product item produce in a rubberwood processing company, which $n \in R$.

From Table 9,

$$\mathrm{SE}=\frac{(320+49+58+12+356+23)}{(12,554+4,029+12,469+4,105+12,513+4,065)} \times 100$$
$$= 1.64\%.$$

In summary, the test on the 205 lots of woodpiece using the WBA found the SE percentage was 1.64, a decrease from previous 4.81. The previous value of SE was the average summary of order using paperwork recoding. There is a noteworthy decrease in the percentage of production data discrepancy among each process using WBA. The procedure related to the sustainable transition that is successfully implemented in this organisation. The results support economic, environmental, and social sustainability because the inventory which was caused by the error in production volume could be reduced. Besides, verification time and paper usage were also reduced through better efficiency in production, service, and human resources management.

5. Conclusion and recommendation

From the results, the GA application tool designed to handle large amounts of data could verify the accuracy of the input data. In other words, the new GA application tool could verify the data of woodpiece sawn or received from vendors in the Rubberwood processing industry. We would conclude that the system could verify results effectively because it provided an accurate answer better than verification by human counting or traditional method. It could also help to deal with the error of delivery data caused by suppliers too. The application will allow the industry to reduce the labour-intensive receiving and sawing process and working time. However, the above development of the counting application of GA will be limited when the input data is imprecise such that the system could not find the best answer. Therefore, the industry still needs a precise manual system.

Besides, the GA system also has limitations in other control factors such as the length of the wood pieces which are poorly controlled by some manufacturers. This factor will affect the accuracy of the data set especially the average weight. In addition, the moisture factors could also affect the average weight. These limitations could be researched in the future to improve the effectiveness of the verification system. The use of image processing systems to assess the total number of wood pieces might be significant also. The image processing system will support the verification system with a more accurate total quantity.

The development of WBA to manage production data is an efficient method attributed to the change from paperwork to digital forms. However, the development of WBA discovered the limited knowledge and competence of participating employees. This limitation hinders understanding of information systems and consequently technology

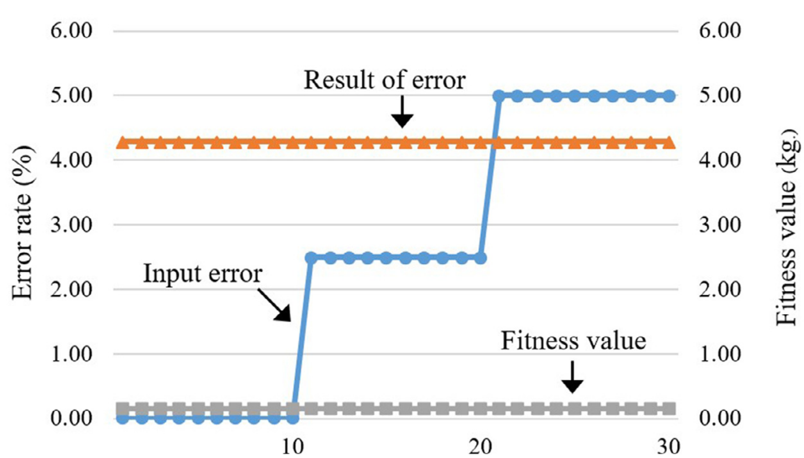

Fig. 11. Results of experiment 1

Fig. 12. Results of experiment 2

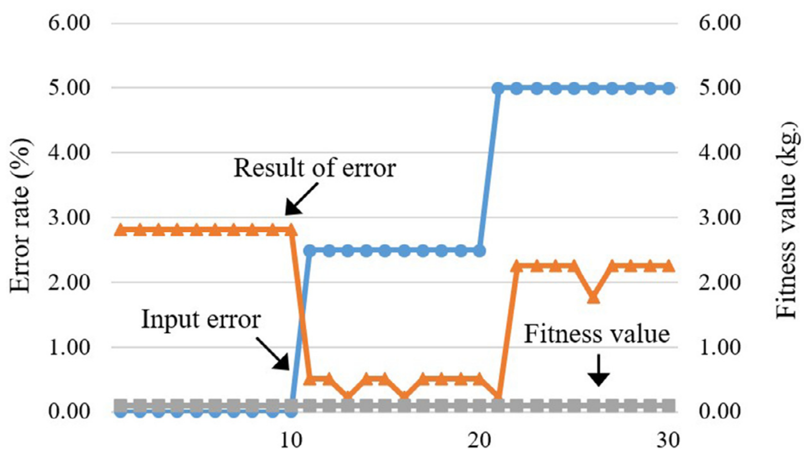

Fig. 13. Results of experiment 3

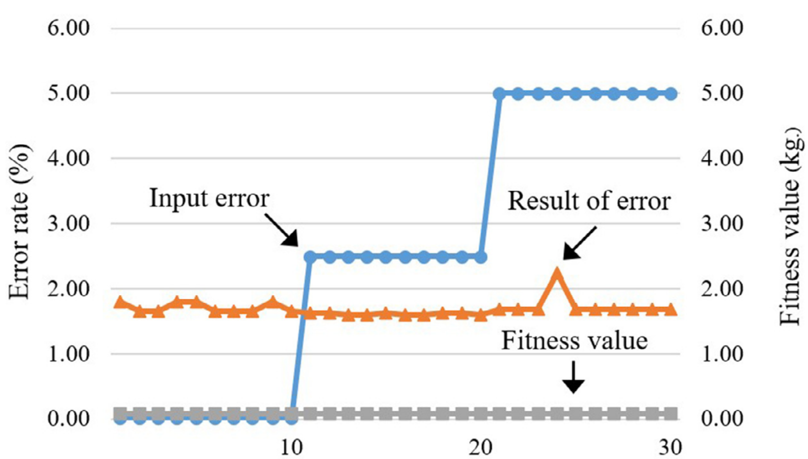

Fig. 14. Results of experiment 4

access. Therefore, further clarifying guidelines in managing the production data and increasing the length of training time could help overcome these limitations.

Accordingly, TRM in industry 3.5 relates to the evaluation and improvement of performance index through the effective usage of resources such as production, material, human, and service. In summary, data analytics and information-based technologies improve the economics because of fewer errors, better work efficiency, and paperless procedures which sustains the environment. In social terms, the workforce is less labour intensive and more skillful at information technology. In summary, sustainability is achieved through all portions of firm's total resource management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 8
Experiment result of counting application

The experi-ment	The control factors (a) Size (inch)	(b) No. of item (item)	(c) Total quantity (piece)	Counting application result Maximum error rate (%) (1) at input error 0%	(2) at input error 2.50%	(3) at input error 5.00%	All maximum error rate (%)
1	1.0-3.0	1-2	≤370	4.29	4.29	4.29	4.29
2	1.0-3.0	3-4	>370	2.11	2.85	4.49	4.49
3	0.50-0.875	1-2	>370	2.82	0.51	2.26	2.82
4	0.50-0.875	3-4	≤370	1.80	1.63	2.25	2.25

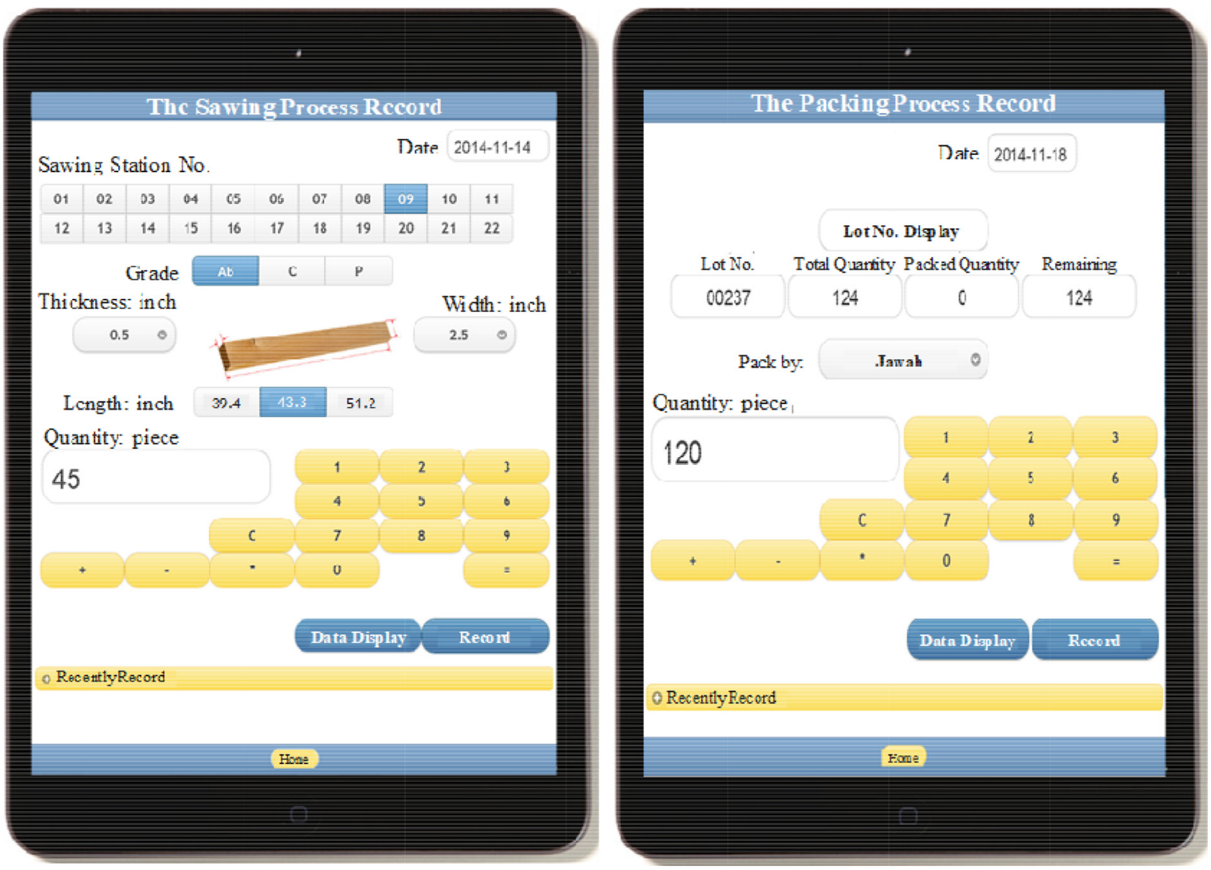

Fig. 15. The examples of WBA developed

Table 9
The result of WBA Testing

Production process	Testing Quantity (piece)	Difference Quantity (piece)
Sawing	$\sum_i Sm_i = 12{,}554$	$a_i = \sum_i \lvert Sm_i - PSm_i \rvert = 320$
Woodpiece receiving	$\sum_i Sb_i = 4{,}029$	$b_i = \sum_i \lvert Sb_i - PSb_i \rvert = 49$
Chemical pressing	$\sum_i PSm_i = 12{,}469$	$c_i = \sum_i \lvert PSm_i - DSm_i \rvert = 58$
	$\sum_i PSb_i = 4{,}105$	$d_i = \sum_i \lvert PSb_i - DSb_i \rvert = 12$
Drying and Packing	$\sum_i DSm_i = 12{,}513$	$e_i = \sum_i \lvert DSm_i - Sm_i \rvert = 356$
	$\sum_i DSb_i = 4{,}065$	$f_i = \sum_i \lvert DSb_i - Sb_i \rvert = 23$

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