Predicting The Development Time of Platform For Multiple-Generation Product Using Artificial Neural Network

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***Abstract*—The rapid growth of technology in the automotive industry has forced the manufacturers to continuously develop new technology and innovate. Nowadays, innovation in the automotive industry does not only refer to product innovation, but also refers to process innovation as well, namely by implementing the product platform strategy. This research aims to predict the development time of new platform for automotive product as one of the multiple-generation product line, using artificial neural network. Artificial neural network was used in this study simply because it adopts the human brain's ability to give stimuli, process it, and give output. Thus, its capability to map the pattern of input into a new pattern of output and predict possible patterns. This research was focused on the platform innovation of Toyota Kijang. The prediction from this research shows that Toyota Kijang new platform should be introduced in 32-33 quarters. This result appears to be corresponding with the ideal condition of platform innovation which is in 8-10 years. Moreover, the result shows that most of the time, company decides to introduce the next-generation platform when the older generation is still in the maturity stage of its life cycle. The research also successfully identifies the factors influencing company to introduce the next-generation platform.**

Keywords—Product platform, multiple-generation product, innovation, automotive, artificial neural network

I. Introduction

The rapid growth of technology in the automotive industry has forced the manufacturers to continuously develop new technology and innovate. The development of innovations in the automotive industry are somehow influenced by market demand and expectations, as mentioned in a previous study that there seems to be an increasing demand for sophisticated technologies and exceptional design at the luxury end of the product spectrum and basic features at an extremely low cost at the other end [1]. Therefore, innovation in the automotive industry does not simply refer to product innovation, but process innovation as well, in order to minimize the production cost and at the same time deliver best products. Hence, one of the implemented strategies in the automotive industry in order to achieve those purposes is product platform strategy.

As mentioned in [2], companies decided to implement platform strategy for different kinds of purpose, such as development of next-generation platform, additions to product families, and development of derivative and addition products. Based on the literature study conducted, until today, research on platform strategy is somehow still focused only on the implementation of platform for product families. Therefore, this study will focus on the implementation of platform strategy in multiple-generation products.

Most of the time, companies decide to develop multiple-generation products in order to prolong the life cycle of a certain product, by make it into a series of products that introduced sequentially, and also to reduce the time consumed to develop a

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new product. By implementing this strategy, companies will have a greater chance to achieve long-term success. The development of multiple-generation products also brings financial benefits to the companies.

In order to become a series of products that continuously exist throughout the years or even decades in the market, continuous improvements or innovations are critical for multiple-generation products, especially in the automotive industry. One of the common innovation found in the automotive industry is platform innovation, or the development of next-generation platform. This type of innovation is used, for example, in Toyota Kijang. Until the present day, Toyota Kijang has been well known in Indonesia for five generations and experienced four times of platform changing (body-chassis) since it was first introduced to the market in 1977 until 2014. By continuously develop new platforms for its product series, Toyota Kijang has been able to achieve brand sustainability and has constantly become the market leader for multiple purpose vehicle class in Indonesia's automotive industry until now. Therefore, this research aims to predict the development time of next-generation platforms in the automotive industry.

The rest of the paper is organized as follows. Section 2 reviews the literature on innovation, product platform strategy, multiple-generation product, product life cycle, and artificial neural network, while the next section describe the study's methodology. Section 4 presents the analysis based on the result of data processing in order to review the method's accuracy in achieving the research goals. The paper ends with conclutions and suggestions of the overall study, mainly from the results and analysis. In addition, the conclusions will also answer the problem formulation and research question in this study. While the suggestions will include input for further research.

II. Literature Reviews

A. *Research Gap and Research Position*

Based on literature review, until today, research on product platform strategy and multiple-generation product strategy are done separately. Product platform strategy was studied both qualitatively and quantitatively. De Weck conducted one of the quantitative studies about product platform strategy in 2006 by finding the optimal ratio of using platform sharing in many products [3]. Suh et al. conducted another quantitative study in 2007 [4]. The aim of the research was to develop a systematic design process in order to create a flexible platform. On the other hand, qualitative studies regarding product platform strategy has also been conducted in many researches for different kinds of purpose, such as finding the classification of platform development variants and exploring the requirements for resources, organization, and management style for a company to develop product platform strategy [2], identify the differences between product platform and product modular [5], and product platform competencies [6].

On the other hand, until 2013, existing quantitative models of multiple-generation products could be roughly categorized into two types: (1) behavioral models, and (2) dynamic competition models. One of the earliest behavioral models involves the use of Bass diffusion model. Norton and Bass (1987) applied the Bass diffusion model to study the sales behavior of high-tech multiple-generation products [7]. Mahajan and Muller (1996) extended the research of Norton and Bass by proposing a new demand behavior model, which takes into account both the adoption and substitution effects of durable technological products [8].

Ofek and Sarvary (2003) looked into the dynamic competition between market leaders and followers by developing a multi-period Markov game model [9]. In 2009, Arslan et al investigated optimal product pricing policy and introduction timing for multiple-generation product scenarios under both monopoly and duopoly market competition scenarios [10]. In 2013, Lin and Kremer used dynamic state variable model to obtain an optimal introduction timing strategy [11]. In their first research, Lin and Kremer aim to predict the future sales unit of Apple Iphone and the optimal time for Apple to introduce the next-generation products. Following their first study, the second study aim to predict the optimal introduction timing strategy for Apple Ipad using data from Apple Iphone.

Considering all of the methods above, none of the models has succeeded to predict both the future sales and also the product platform life cycle by considering the sales pattern of the past product generations in each phase of life cycle. In order to achieve the purpose of this research, a suitable forecasting method is required. Therefore, the research gap of this study is to construct a model that can be used to predict the optimal timing for automotive company to make innovations and introduce next-generation platform.

B. *Innovation*

Innovation is normally done by companies to create a completely new product, which different from the previous ones, or to improve existing products. But, innovation does not only refer to product innovation, but it can also refer to process innovation as well. Product innovation is defined as the development of new products, changes in design of established products, or use of new materials or components in the manufacture of established products. On the other hand, process innovation can be defined as the implementation of a new or significantly improved production or delivery method. One example of process innovation in companies is the implementation of product platform strategy.

C. *Product Platform Strategy*

Platform is defined as a relatively large set of product components that are physically connected as a stable sub-assembly and used to develop other products [5]. Platform is commonly used in automotive and electronic industries, since this strategy allows manufacturers to gain benefits from many aspects. Basically, the main purpose of implementing product platform strategy is to gain economic benefits and reduce cost. Moreover, product platform strategy allows company to gain other benefits, e.g. increasing product variants, increasing customer's satisfaction by improving product quality, reducing lead time, good flexibility between plants, and increasing the plant's productivity by reducing the number of different elements or components used.

D. *Multiple-Generation Product*

Under a multiple-generation product strategy (MGPS), a company first launches an initial product generation to the market, then it sequentially introduces successive generations over time, each featuring the same core functionality but updated technologies, features, appearances and usability [11]. The use of such strategy enables companies to elongate the product lifespan from one single product to a line of products, and shorten the amount of time needed in developing new product. Multiple-generation product strategy is also more profitable (around 40%) than only introducing a single product generation and more profitable (around 26%) than sequentially introducing a single generation product [12]. However, in order to preserve long-term existence of the set of products, companies are required to implement the best plan and strategy, namely by continuously making improvements and innovations to the products.

E. *Product Life Cycle*

Similar to human being, products also have their own life cycle. Product life cycle is a graph that represents the sales history of a certain product in its lifetime or since the product is launched to the market until it is drawn from the market. This model suggests that the sales of a product follows a common pattern or phase, which begins from the introduction of product, growth, maturity, until the sales of product declines and the product is totally withdrawn from the market.

F. *Artificial Neural Network*

On prior researches, the use of neural network related to product life cycle can only predict sales patterns alone. There has been no research that simultaneously predict sales patterns starting from the stage of introduction to decline. Therefore, artificial neural network will be used to study and identify sales patterns based on historical data, then predict the level of sales as well as product life cycles in the future.

Artificial Neural Network (ANN) is one of the subsidiary of Artificial Intelligence (AI) and has the same working system as human's brain. This method adopts the ability of human brain to give stimuli, process said stimuli, and give output. Therefore, neural network is capable of: a) Pattern classification, b) Mapping the pattern of input into a new pattern of output, c) Remembering patterns, d) Mapping identical patterns, e) Optimizing solutions, f) Prediction, g) Detecting outliers.

Neural network is a parallel distributed processor that has the ability to store experimential knowledge and is able to use its ability to achieve the desired goal. The characteristics of a neural network can be seen from the pattern of relationships between neurons (called architecture), the method to determine the relationship weight (called training, or algorithm) and the activation function.

The architecture of neural network consists of three essential parts, which are input layer, hidden layer, and output layer. The input layer is a layer consisting of a few neurons that receive signals from the outside and pass on to other neurons in the network. The hidden layer is a copy of neural connectors on human nervous tissue. Hidden layer also serves to increase the network's ability to solve problems. The existance of this layer may cause the training becomes more difficult or even longer. Then, the third layer or output layer serves to channel output signals resulted from the network process. The number of layers can be considered as the amount of weighted relationships between neurons.

After the neural network architecture is decided, the next step of ANN is determining the weight for each network, then continued with activation fuction. Activation function is a process for determining stimulation of the input received to be converted into the output value. In general, the method of training a neural network consists of two, which are feedforward and backpropagation. Feedforward is a method where the connection between networks goes from the input layer to the output layer with no feedback loop. On the other hand, the concept of backpropagation neural network is mapping from input pattern to output pattern by reducing the error between the actual output produced by the network and the desired output.

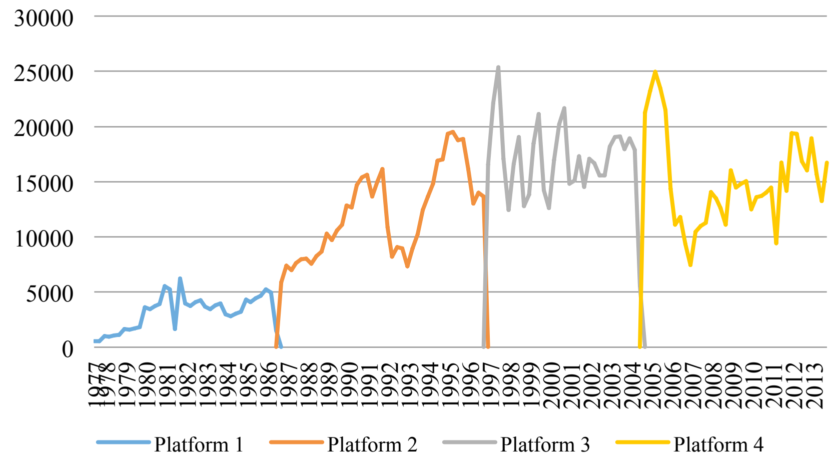

Fig. 1. Sales Chart of Toyota Kijang in Indonesia during 1977-2013

III. Research Methodology

This section explains about the data used in the study. The data used in this study was gathered from an automotive company and also through interviews.

A. *Toyota Kijang's Platform Innovation*

Toyota Kijang's platform innovation from the first generation until the present is explained below:

- Generation 1 (1977-1981) : KF10
- Generation 2 (1981-1986) : KF20
- Generation 3 (1986-1997) : KF 40 (Short) and KF50 (Long); Improvement KF42 (Short) dan KF52 (Long)
- Generasi 4 (1997-2004) : KF70 and KF80 (Gasoline) ; LF70 dan LF80 (Diesel)
- Generation 5 (2004 – now) : Ladder Frame

Based on interview, KF10 and KF20 are the same type of platform (body-chassis), therefore it can be concluded that in those five generations of Toyota Kijang, there has been four times of platform changing.

B. *Collecting Sales Data of Toyota Kijang*

The most important data to build a prediction model of platform life cycle in this study is the sales unit of Toyota Kijang during 1977-2013. Fig. 1 shows the sales data of Toyota Kijang in chart.

IV. Results and Discussion

This section explains about steps of processing the data, interpreting the results, and analyzing the results obtained in this research.

A. *Model Identification*

Based on the sales chart given above, it can be seen that only platform 1, 2, and 3 that already have a complete product life cycle, and each platform has a different kind of sales pattern. These differences will certainly cause a problem in the result of ANN, since ANN is trained to memorize the pattern of input in order to generate the pattern of output. Therefore, by doing model identification, several critical points are noted before using ANN in this study. These critical points are shown below.

- Sales pattern from platform 1 is not used in forming ANN model.
- Model formation in this study only uses sales data from 1986 until 2012.
- Sales prediction of a certain platform generation is obtained by learning the sales pattern of only one previous generation.

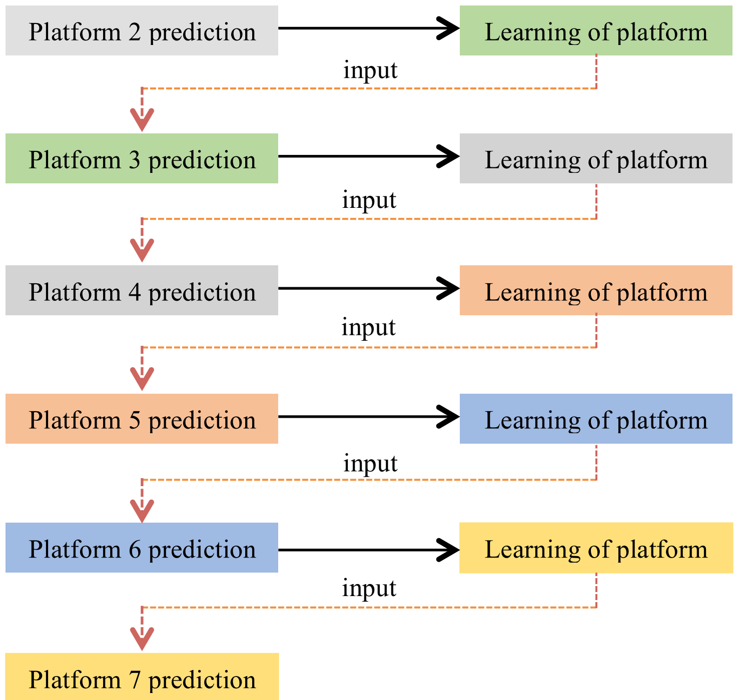

Fig. 2. Learning Process and Prediction of Platform

B. Forming ANN Architecture

Before using the data in this study for ANN training, it is necessary to normalize the input and output data into a range of 0-1 in order to simplify the training process and reduce the training time. The input data used in this study are year and quarter of platform sales, while the output data or target data are platform generation and whether the platform is an even or an odd number. The next step is weight initialization. Generally, weight initialization can be done in two methods, random method and the Nguyen-Widrom. In this research, weight initialization is done by using the Nguyen-Widrom method.

As mentioned earlier, sales prediction of a certain platform generation is obtained by learning the sales pattern of only one previous generation. Learning process can be done in two methods, feedforward and backpropagation. For the learning process of sales data from 1986 to 2012, both feedforward and backpropagation method will be used, however for the prediction of future platform generations only the feedforward method will be used.

The prediction result from ANN is released in normalized data, ranging from 0-1, and can not be straightly interpreted. Therefore, it is necessary to denormalize the output data from ANN, which is to reverse the data in range 0-1 to its normal form that can be interpreted.

C. Interpreteing the Result of ANN

The training result of ANN for platform 2-4, using sales data from 1986 quarter 4 until 2012 quarter 4, provides a very small quadratic error which is 0.01. Below is the comparison graph between actual data and ANN prediction for platform 2-4.

Based on Fig. 3, it can be concluded that the training done in this research has successfully generated life cycle predictions with quadratic error of 0.01.

The end of life cycle for platform 4 which is predicted by ANN using the learning pattern from platform 3 is shown in Fig. 4 above. As for the out sample error for the prediction of platform 4, which is obtained by calculating the Mean Average Percentage Error (MAPE), is 15.9%.

The prediction for platform 5 is further obtained by using the learning pattern and weight from platform 4. Moreover, the result or prediction of platform 5 will be used as an input to predict the sales and life cycle pattern of platform 6. Similar to the previous steps, the sales and life cycle prediction for platform 7 will be obtained by using the learning pattern and weight from platform 6 as an input. ANN's sales and life cycle prediction form platform 5 – 7 is shown in Fig. 5 below.

The prediction result for platform 5 shows a sales pattern that is similar to the pattern of platfom 4. This shows that the training of ANN for platform 5 using the learning pattern and weight from platform 4 has succeed with a quadratic error of

0.01. Moreover, the prediction result for platform 6 shows a very similar sales pattern as platform 5, and also the same life cycle length as platform 5 which is 33 quarters. However, the prediction result for platform 7 is very fluctuative and does not have the similarity with the platform from previous generations. As for the length of life cycle for platform 7 is predicted to be 32 quarters, starting in 2031 quarter 1 and reaching its end of life cycle in 2038 quarter 4.

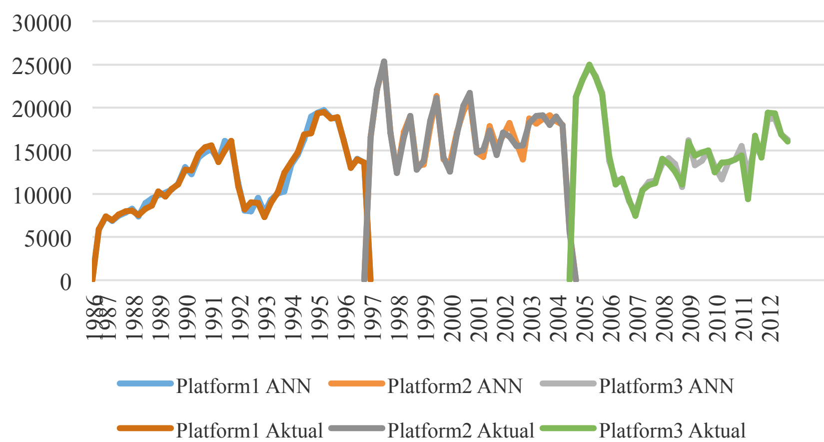

Fig. 3. Comparison Graph between Actual Data and ANN Prediction

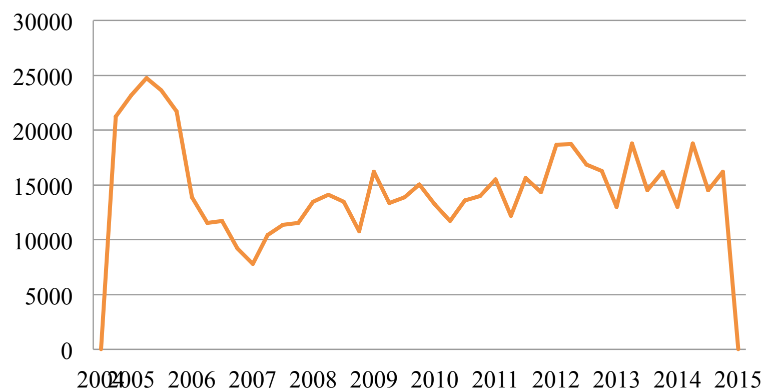

Fig. 4. ANN Prediction for Platform 4

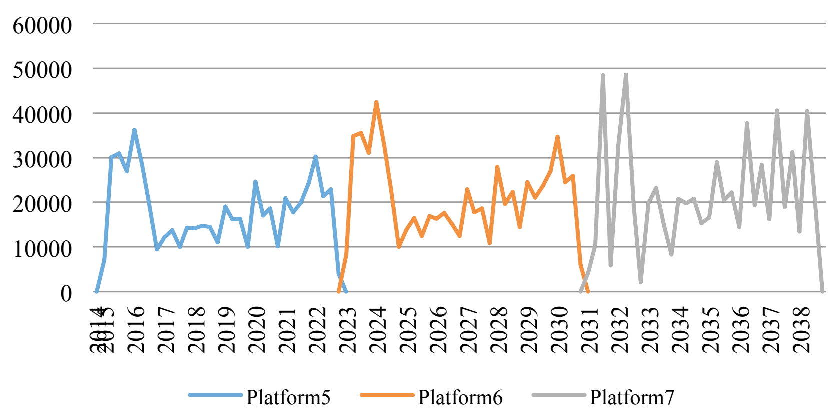

Fig. 5. ANN Prediction for Platform 5 - 7

D. Analyzing the Result of ANN

In this study, the analyze of ANN prediction result is divided into analyzing the in sample and out sample error, and analyzing the final model of ANN prediction as a whole model. The result of this research shows that when the training for ANN is conducted with target data, the prediction result has a very small quadratic error of 0.01. On the other hand, when ANN is used to predict an output without a set of target data, the out sample error or MAPE obtained in this research is 15.9%. This difference occurs since ANN will only able to predict accurately and more similar to its actual data when the target data was provided as an input, simply because ANN can do the back propagation process to reduce the error rate between actual data and prediction until it reaches the error target. In contrary, when we use ANN to predict an output without having actual data as the target, then ANN will not be able to perform the back propagation process to minimize the error.

The prediction result of ANN for the life cycle of platform 4 is somehow compatible with the ideal situation, where platform innovation is commonly done in every 8-10 years. However, this result does not match the company's plan to launch platform 5 in 2016. The difference between ANN prediction and company's plan is simply because this prediction model does not consider all factors, internal nor external, that will influence the company's decision regarding the optimal timing to launch the next-generation platform.

The sales pattern and life cycle of pattern 5 is obtained by using the learning pattern and weight from platform 4. Thus, platform 5 has a similar sales pattern with platform 4. However, the life cycle length of platform 5 is shorter than platform 4. This difference occurs since the sales value for both platforms are different and it takes a different length of time to reach the end of life cycle. Moreover, the end of life cycle prediction of platform 4 is obtained by using the pattern of platform 3 as an input; therefore it is reasonable that platform 5 has a similar life cycle length as platform 3.

The sales pattern for platform 6 is very similar to platform 5 and both platform has the same length of life cycle, which is 33 quarters. However, a great amount of error accumulation occurs in the prediction of platform 7. In result, the sales pattern for this platform generation no longer have a similarity with its previous generations. However, despite the sales pattern differences, the length of life cycle for platform 7 is somehow still similar to its previous generations, which is 32 quarters. The sales pattern differences that occur among the platforms are very reasonable since no one is able to predict what will happen exactly in the future, especially since platform innovation is done in 8-10 years. In 8-10 years, there will be a lot of change, e.g. the economic conditions, amount of competitors, customer's buying power, and other factors influencing the optimal time of introducing the next-generation platform.

V. CONCLUSION

The result of this research successfully predicted the life cycle of the three upcoming generations of Toyota Kijang's platform using artificial neural network (ANN). Optimal prediction is obtained until platform 6. However, if the prediction is continued forward, the accumulation of error in the program will be greater and the result will no longer be optimal. Therefore, it can be concluded that ANN is not capable of predicting the platform life cycle for a very long period of times.

The result also successfully answered the research questions in this study. First, platform innovation for multiple purpose vehicle (MPV) is oftenly done in 8-10 years, which is in accordance with the result of this study. Second, the decision to develop next-generation platform is oftenly considered by companies while the older-generation is still in its maturity stage of the life cycle, not when it has reached the decline phase. The result shows that this paradigm is also happening in Toyota. Third, platform innovation is influenced by many factors, both internal and external factors. The main factor that influence company to introduce next-generation platform is the market needs and demand. Other factors are company's sales target for the current product generation, economic condition in Indonesia, competitors, sales of products from other segment but under the same company or brand, and also the occurence of natural disaster.

For future research, the neural network can be combined with fuzzy logic and the result can be compared to this research's. Moreover, future research can be done by using other forecasting or optimization techniques, such as dynamic state variable model. The complexity of model can be increased by considering several factors that affects the sales pattern, such as the economic state in Indonesia, and the amount of competitors. In addition, future research can also be conducted for other type of multiple-generation products, namely electronic products.

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BIOGRAPHY

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