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Article

ANNs in ABC Multi-driver Optimization based on Thailand Automotive Industry

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Abstract. The purpose of this research was to develop a method for Activity Based Costing (ABC) that provided accurate product production costs. ABC using Single Driver Activity Based Costing (SDABC) can result in distortion of the cost. A more accurate ABC cost calculation based on multiple cost drivers (CDs) in each activity has been devised and proven by considering the various cost drivers using the correlation coefficient or R^2. The application of Artificial Neural Networks (ANNs) to choose the CDs is Multiple Drivers Activity Based Costing (MDABC). The ANNs choose the CDs by algorithms including Multilayer Perceptron and Back-propagation. The transfer function for hidden layers is the Log-Sigmoid Function and for the output layer is the Pure Linear transfer function. The results have demonstrated that using MDABC results in more accurate cost calculations than when using SDABC.

The study found that both of the extended ABC method, SDABC and MDABC provide more accurate actual cost of production, and both are applicable to products with low turnover or those in a state of loss condition. However, MDABC is better used in situations which include a variety of production activities, while the SDABC method is best used in situations of the factory operations not being very complex. Overall, the resolution, or accuracy, of the calculated production costs is better using the MDABC method, but is more complicated in its use and operation. Computer-based ANNs overcome this problem of complexity.

Keywords: Activity Based Costing (ABC), Single Drivers Activity Based Costing (SDABC), Multiple Drivers Activity Based Costing (MDABC), Artificial Neural Networks (ANNs), Thailand Automotive Industry.

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1. Introduction

Thailand's automotive manufacturing industry has expanded significantly. Production in 2016 is predicted to be 100 million units, increasing to 106 million units in 2018. In part, this is due to government policy and support for the industry with the aim of promoting Thailand as a center for the manufacture and export of vehicle components. A significant aspect of the Government policy is to support small to medium enterprises (SMEs) in the industry. This places an emphasis on these enterprises to be competitive in all aspects of production and distribution, including price, quality and delivery reliability. In the face of almost constantly changing market demands and the imperative of ensuring customer satisfaction, competitive strategy must encompass the ability to manufacture a greater variety of products, and to be able change production lines for new products. This results in higher production costs. The manufacturing organization must adopt an agile approach to its business, which includes effective and efficient cost control as a fundamental requirement.

Due to these trends and changes in the manufacturing environment more effective production is necessary, and this has resulted in the development of Advanced Manufacturing Systems (AMS) or Flexible Manufacturing Systems (FMS). The shift from manual labour to the use of modern production technology has resulted in factories needing to find ways to both reduce costs and to calculate and allocate costs more effectively. This has introduced hitherto unknown factors related to the actual costs and consequently causing inappropriate pricing or cost and price distortions [1, 2] and a failure to clearly reflect the cost of each activity that occurs, whether in terms of direct costs or indirect costs.

Correct and accurate cost calculations of both direct and indirect costs of a product are essential to the existence of the business. Cost data will be used to determine the strategy [3–5], selling price and planned profit [6, 7], improvement of processes and control of operations [8, 9] and the decisions of the administration [10–12]. However, SMEs in the automotive parts manufacturing industry have experienced significant problems in terms of price competition. Particularly because of contemporary information and communications technology, the marketplace is more open and therefore highly competitive, where consumers can choose the most suitable product manufacturer according to price, quality and on-time delivery ability. Manufacturers with high production costs will be uncompetitive, and the business will ultimately fail. It could be said that accurate production cost information is fundamental in taking important decisions in determining the selling price of the product.

The use of conventional cost accounting methods, termed traditional cost accounting (TCA) here, has been identified as being inadequate in correctly and accurately calculating and reporting cost information. For example, Cooper and Kaplan [13], academics specializing in accounting in the United States observed this inadequacy, thus being a major cause of many businesses failing. The automotive parts manufacturing industry in Thailand has been identified as being an appropriate industry to study, identifying the problems of realistic and accurate production costing, especially due to inaccurate cost estimates when using TCA. Direct costs (materials and labour cost) are appropriately identified and reported by TCA, but this accounting method cannot show the indirect costs or overhead costs to an appropriate level of accuracy.

In industry generally there has been a transition from traditional cost accounting to a system of cost accounting referred to as Activity Based Costing (ABC). This costing method allows cost modelling encompassing all resources in all activities which can be linked to a product. A comparison between TCA and ABC found that ABC provides the best accuracy and precision in the cost calculation of the product, even though ABC is used for a single activity driver or cost driver (SCD). Use of an original cost driver in cost calculations will result in an error or distortion of cost, which will affect the decision regarding the strategy for determining the selling price [14]. ABC has been developed in order to find a way to choose the best cost drivers by considering the correlation coefficient (R^2) for determining the appropriate cost driver [15–17] but this can also be accomplished using the method of Artificial Neural Networks (ANNs) to select the appropriate cost driver by considering R^2 and Root Mean Square Error (RMSE) [18]. In addition, ANNs have been used to predict indirect cost pools for estimating the cost of the activities in the shipping industry [19], which use various parameters such as the length of the ship, width, tonnage, etc. As well, the application of a Genetic Algorithm (GA) combined with ANNs has been used to find cost drivers appropriate for calculating ABC [20, 21]. The GA can choose the optimal cost drivers from which ANNs learn the allocation of indirect costs that is non-linear, overcoming the problem of the distortion of the product cost if it was allocated in a linear manner. This is a different approach from [19–21], which used a single cost driver in the calculation of ABC which has the advantage of reducing, even removing, the complexity of selecting cost drivers. However, using a single cost driver in that manner has the disadvantage of possibly calculating an erroneous actual cost value when the single cost driver selected represents only part of the actual indirect costs incurred. An activity usually is subject to more than one cost driver and when all the appropriate cost drivers are included in the cost calculation the calculated cost is more correct and valid.

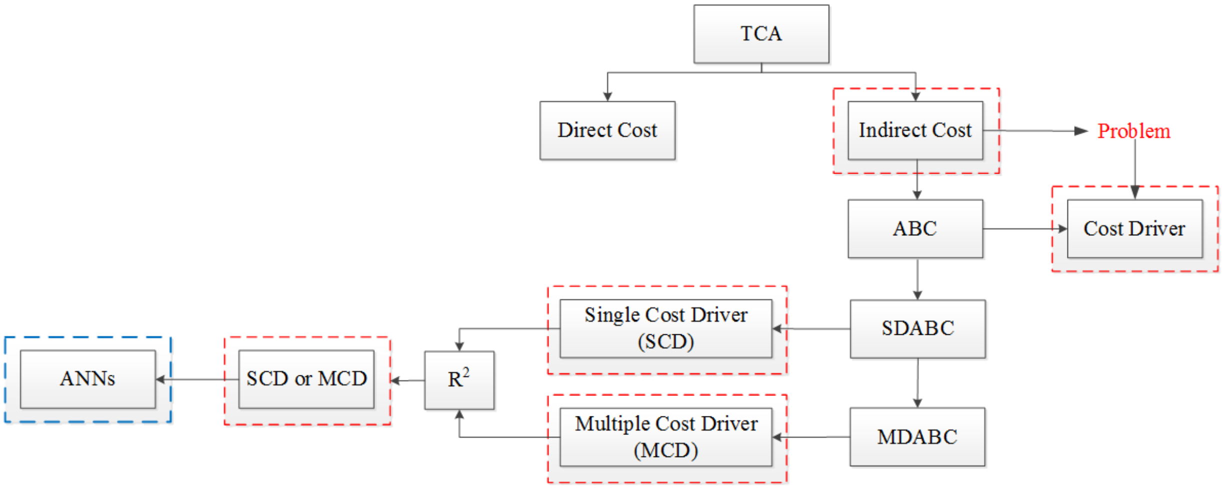

Fig. 1. Development of TCA to ABC models.

From the foregoing it can be demonstrated in Fig. 1, which the development of TCA to ABC. However, ABC has problems in the selection of appropriate cost drivers. When considering the appropriate cost drivers from R^2 in SDABC, it was found that it cannot satisfactorily reflect the total real cost; SDABC considers only a single cost driver, whereas most events have multiple cost drivers. Therefore, MDABC was used to solve such problems by considering R^2 as well as SDABC. However, the increase in the amount of data that results from the inclusion of multiple cost drivers creates a problem for both SDABC and MDABC which must continuously calculate and recalculate R^2, based on the appropriate cost drivers. The R^2 must be calculated each time in order to select the appropriate cost drivers and the problems arising from increased activity resulting from changes to production which require the consideration of more cost drivers. This problem can be solved by ANNs being used to learn which cost drivers to consider. This results in not having to continuously calculate appropriate cost drivers from R^2 and the problems arising from increased activity resulting from changes to production.

2. Activity Based Costing (ABC)

Cooper and Kaplan, academics specializing in accounting in the United States [13], observed that a major cause of many businesses falling into the unfavourable cost condition was the use of the TCA system. Due to competition in the market and changes in production management, the present conditions differ from the past, but the TCA system was based on concepts of cost that were developed as long ago as the 1880s through to 1925, at a time when there was not a great variety of products. This was due to the characteristics of production typically involving mass production using direct material and labour as the factors of production while technology did not change. The activities of the costing department included the provision of services to support the production department, and in the past, production focused on the use of machines and direct labour to attain maximum efficiency. Seeking to identify and cost the difference in the labour and production capacity by determining wastage arising from the use of machines and labour is not fully effective. So, as long as the product characteristics were constant and resources were used in predictable and constant proportions, the cost data of product calculations based on the TCA system were deemed to be appropriate. Variations in the volume of production, such as variations in raw materials, labour hours, machine hours, could exist, without significant miscalculations of production costs. However, growing complexity of production, substantial growth in the number and variety of products, huge changes in production technology has rendered TCA systems inadequate, and new costing methods became essential.

The ABC system evolved from this need for more sophisticated cost management in manufacturing enterprises. The important concept inherent in this is that activities are the drivers that raise the cost of production and ABC attempts to identify the cost drivers of each activity. In addition to being important for managers to control and reduce the cost of business the cost drivers are also a database that can be used to calculate the production cost from the activities data. The cost of a product is dependent on the extent to which the cost drivers were involved in the activities. When the calculated overhead and variable costs are integrated with the direct costs of production, this results in a more accurate and correct total cost of production for each item. Product costing in this way clearly uses the total set of activities involved in the production process of the product. Therefore, ABC systems can provide data about product costs that are more accurate than the TCA system. It is also useful to managers in making decisions about setting the product price, sourcing product components according to cost, product design and development of the production process, including the provision of various technologies related to production.

Currently, ABC is a popular cost accounting system in use to overcome the shortcomings of TCA systems. There are four key benefits to the ABC system: (1) accurate identification of product cost, especially overheads; (2) more precise information about value-added and non-value added costs by the identification of cost drivers; (3) direct allotment of costs to products or processes that consume resources; (4) identification of non-value added costs [22, 23].

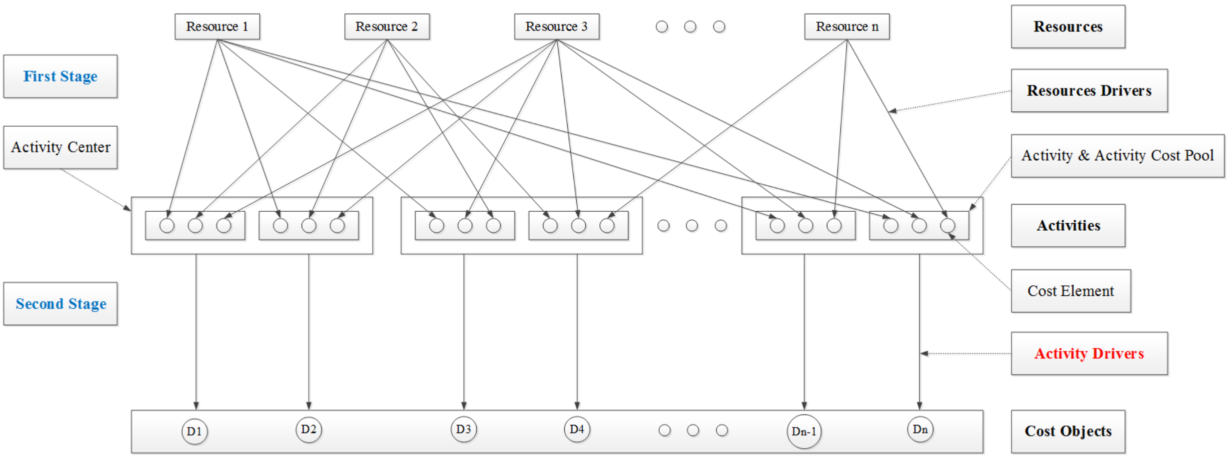

Fig. 2. Detailed cost assignment view of Single Drivers Activity Based Costing (SDABC).

Mainly, the ABC system uses a two-stage procedure of adding resource costs to cost objects [24, 25]. From Fig. 2, in the first stage, resource costs are assigned by resource drivers to activity cost pools that can be classified by activity level such as unit, batch, product and facility. Each activity level can have several activity cost pools. In the second stage, activity cost pools are assigned to cost objects by activity drivers, which are activities that incur cost [26].

Therefore, it can be concluded that ABC differs from TCA in two areas, namely: (1) ABC will determine the activity cost pool more than the cost pool; (2) Activity drivers or cost drivers are used as the basis for calculation of the product and will be structured differently from the calculations by the TCA. This is because each activity has to be analysed in terms of real cost drivers to make ABC changes. Figure 2 shows the limitations of SDABC brought about by the limited experience of the decision makers in selecting cost drivers, the knowledge of the workers involved and the complex factors related to production. This results in Activity-Based Costing systems showing distorted product costs remote from reality. Also, continually using the same cost drivers to calculate the cost results in further errors or distortion in the calculation of cost because of constant changes to production because of changing order quantities and ordered products.

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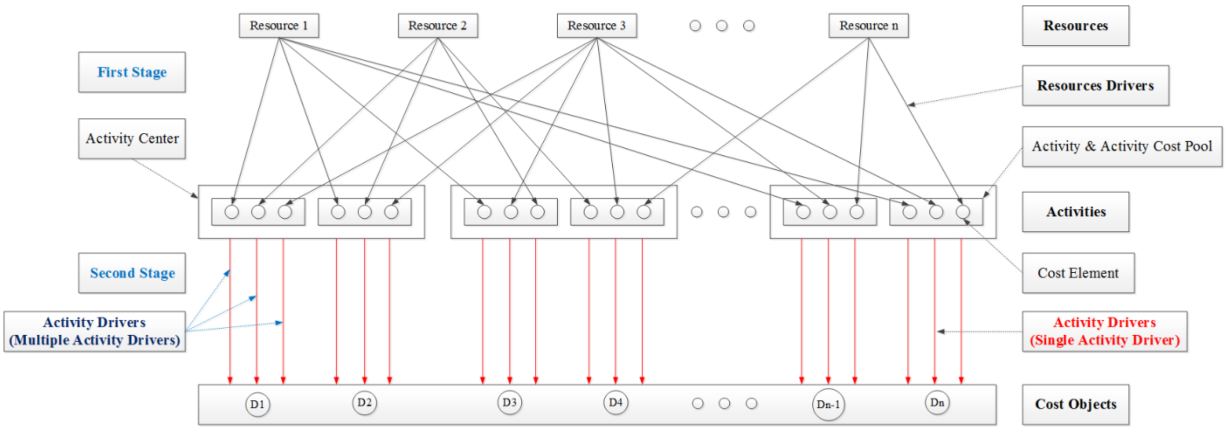

Fig. 3. Detailed cost assignment view of Multiple Drivers Activity Based Costing (MDABC).

This leads to the view that using multiple cost drivers in MDABC will reflect the real cost which enables the decision makers to better determine the many issues in production planning, such as strategies for determining the selling price and raw materials sourcing. MDABC uses multiple cost drivers based on the analysis of the actual cost drivers of each activity. Figure 3 shows how MDABC has been developed from SDABC, and illustrates the MDABC approach to production costing.

3. The Mathematical Model of ABC

The mathematical model that is used to calculate the SDABC and MDABC evolved from the ABC. This was necessary because the ABC has a problem in the selection of appropriate cost drivers. A method for cost drivers determining cost drivers by R^2 was developed [12–14], which, however, considered single cost drivers only. This was called SDABC by those researchers. Using only a single cost driver did not reflect the real cost of production all because used to cost drivers alone. In fact, in each of the activities that occurred in operating can be cost drivers more than one cost drivers. This apparent requirement to include multiple cost drivers, and to identify the most appropriate cost drivers to include, was the impetus for the current research. The SDABC model has been developed into the Multiple Driver Activity Based Costing Model (MDABC) which is used to determine R^2, similarly to SDABC but including multiple cost drivers. This results in a more correct and accurate real cost being calculated. To demonstrate the 2 types of SDABC and MDABC, both models were used to calculate R^2 to be used in selecting the appropriate cost drivers. This R^2 is then used to calculate activity cost, activity rate, cost allocation and cost per unit of product; according to Eq. (1)–(4).

$$\hat{Y}_{ijk}\,(Activity\ Cost) = \beta_{0(ijk)} + \beta_{1(ijkl)}X_{1(ijkl)} + \beta_{2(ijkl)}X_{2(ijkl)} + \ldots + \beta_{n(ijkl)}X_{n(ijkl)} \tag{1}$$

$$AR_{ijk}\,(Activity\ Rate) = \frac{\hat{Y}_{ijk}}{X_{n(ijkl)}} \tag{2}$$

$$CA_{ijk}\,(Cost\ Allocation) = AR_{ijk} \times X_{n-ture(ijkl)} \tag{3}$$

$$CP_i\,(Cost\ per\ unit\ of\ product) = \sum CA_{ijk} \tag{4}$$

The Mathematical Model of ABC meaningful following;

Indexes:

i	the type of product; by i = 1,2,…,I
j	the responsibility center in a department; by j = 1,2,…,J
k	the operation activity; by k = 1,2,…,K
l	the cost drivers; by l = 1,2,…,L

Parameters:

I	the total number of products
J	the number of responsibility centers j in a department producing the product i
K	the total number of activities in responsibility center j in a department producing the product i

L	the total number of cost drivers of operation activity k
β_0	the ABC constant estimated by linear regression analysis
$\beta_{0(ijk)}$	the ABC constant estimated by linear regression analysis of the responsibility center in a department of the product i, operation activity k
β_1	the variable cost drivers rate 1 estimated by linear regression analysis
β_2	the variable cost drivers rate 2 estimated by linear regression analysis
β_n	the variable cost drivers rate n estimated by linear regression analysis
$\beta_{1(ijkl)}$	the variable cost drivers rate 1 estimated by linear regression analysis of the responsibility center in a department of the rate i, operation activity k, cost driver l, highest R^2 from operation activity k
$\beta_{2(ijkl)}$	the variable cost drivers rate 2 estimated by linear regression analysis of the responsibility center in a department of the product i, operation activity k, cost driver l, highest R^2 from operation activity k
$\beta_{n(ijkl)}$	the variable cost drivers rate n estimated by linear regression analysis of the responsibility center in a department of the product i, operation activity k, cost driver l, Maximum R^2 from operation activity k
X	the cost drivers for estimated total variable cost drivers
X_1	the cost drivers 1 of total variable cost drivers
X_2	the cost drivers 2 of total variable cost drivers
X_n	the cost drivers n of total variable cost drivers
$X_{1(ijkl)}$	the cost drivers 1 of total variable cost drivers of product i, responsibility center of department j, operation activity k, cost drivers l, Maximum R^2 from operation activity k
$X_{2(ijkl)}$	the cost drivers 2 of total variable cost drivers of product i, responsibility center of department j, operation activity k, cost drivers l, Maximum R^2 from operation activity k
$X_{n(ijkl)}$	the cost drivers n of total variable cost drivers of product i, responsibility center of department j, operation activity k, cost drivers l, Maximum R^2 from operation activity k
$X_{n\text{-}true(ijkl)}$	the cost drivers n of real variable cost drivers of product i, responsibility center of department j, operation activity k, cost drivers l, Maximum R^2 from operation activity k
$\hat{Y}_{ijk}$	the estimated by linear regression analysis of the product i, responsibility center of department j, operation activity k and by using the latest data of X_n
AR	the activity rate
AR_{ijk}	the activity rate of product i, responsibility center of department j, operation activity k
CA	the cost allocation
CA_{ijk}	the cost allocation of product i, responsibility center of department j, operation activity k
CP	the cost per unit of product
CP_{ijk}	the cost per unit of product of product i, responsibility center of department j, operation activity k

By using regression analysis to determine the R^2, SDABC and MDABC can then select the most appropriate cost drivers by using the R^2. The R^2 indicates the highest correlation between the cost drivers which will be used in the calculation of SDABC and MDABC.

Table 1 illustrates this analysis. The SDABC model uses simple linear regression analysis and the MDABC model uses multiple linear regression analysis to calculate R^2. The R^2 is used in Eq. (1) for estimating the cost for SDABC or MDABC. The calculated value from Eq. (1) is then used in Eq. (2)–(4) to calculate the activity rate, cost allocation and cost per unit of product. As can be seen, SDABC suggests that CD2 is the optimal cost driver, with an R^2 of 0.77, but using the MDABC calculation indicates the combination of CD2 and CD3 to be optimal, with an R^2 of 0.88.

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Table 1. Example to consider cost drivers both SDABC and MDABC by considering R^2.

Months	Activity$_i$					
	Single Drivers Activity Based Costing(SDABC)			Multiple Drivers Activity Based Costing(MDABC)		
	CD1 (Machine hours)	CD2 (Labour hours)	CD3 (Number of times)	CD1 (Machine hours)	CD2 (Labour hours)	CD3 (Number of times)
January-2011	1173	1656	463	1173	1656	463
Febuary-2011	1266	1870	441	1266	1870	441
March-2011	1233	1781	442	1233	1781	442
⋮	⋮	⋮	⋮	⋮	⋮	⋮
November-2014	1313	1861	482	1313	1861	482
December-2014	1473	1793	457	1473	1793	457
					CD1,CD2 = 0.62	
R^2	0.38	0.77	0.51		CD1,CD3 =0.45	
					CD2,CD3 = 0.88	

4. ABC Modelling Based on an ANN

ABC calculation modelling based on an ANN was used by the researchers in order to determine the choice of cost drivers. Which cost drivers are used to calculate the ABC is determined by the maximum R^2 of the cost drivers in each activity. The use of the ANN to achieve the ABC is illustrated in Fig. 4.

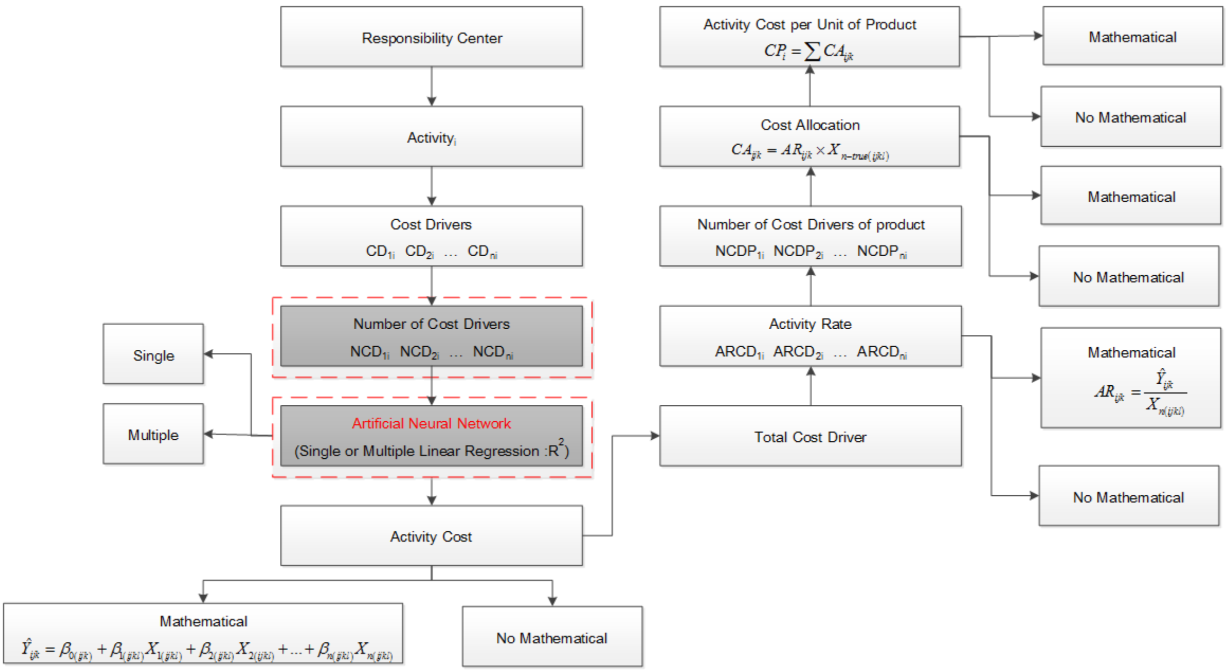

Fig. 4. The ANNs choose the cost drivers by applying calculation methods.

In Fig. 4, we can see that, to calculate the ABC, each responsibility centre in each department must be defined and the activities in each department must be determined. The activities in each department will have various cost drivers which may be related. The strength of these relationships will be calculated by single or multiple linear regression functions, which calculates the R^2, which is then used in the selection of the appropriate cost drivers. The R^2 must be calculated each time in order to select the appropriate cost drivers and the problems arising from increased activity resulting from changes to production which require the consideration of more cost drivers. This however is based on historical data, which is essentially static. The primary need is to be able to calculate essentially in real-time. However, this requires using new information on a continuous basis and continually recalculating R^2 and the problems arising from increased activity resulting from changes to production. To overcome this problem of timeliness, or, more to the point lack of timeliness, the research team developed and applied an ANN to the problem.

The ANNs choose the cost drivers by applying calculation methods and algorithms in the Weka (Version 6.3) software. These include the Multilayer Perceptron method, Back-propagation algorithm method. The transfer function for hidden layers is the Log-Sigmoid Function and for the output layer is the Pure Linear Transfer Function.

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The ANN was designed with the total cost drivers being input into the input layer then transferred by the transfer function into the hidden layer where the weights are adjusted. The output layer displays the data showing the best mix of the cost drivers for the activity. The ANN model uses Back-propagation Multilayer using the Multilayer Perceptron model, with training by using the Back-propagation algorithm. The transfer function from the hidden layers is the Log-Sigmoid Function and the output layer is the Pure Linear Transfer Function. This process is shown in Fig. 5.

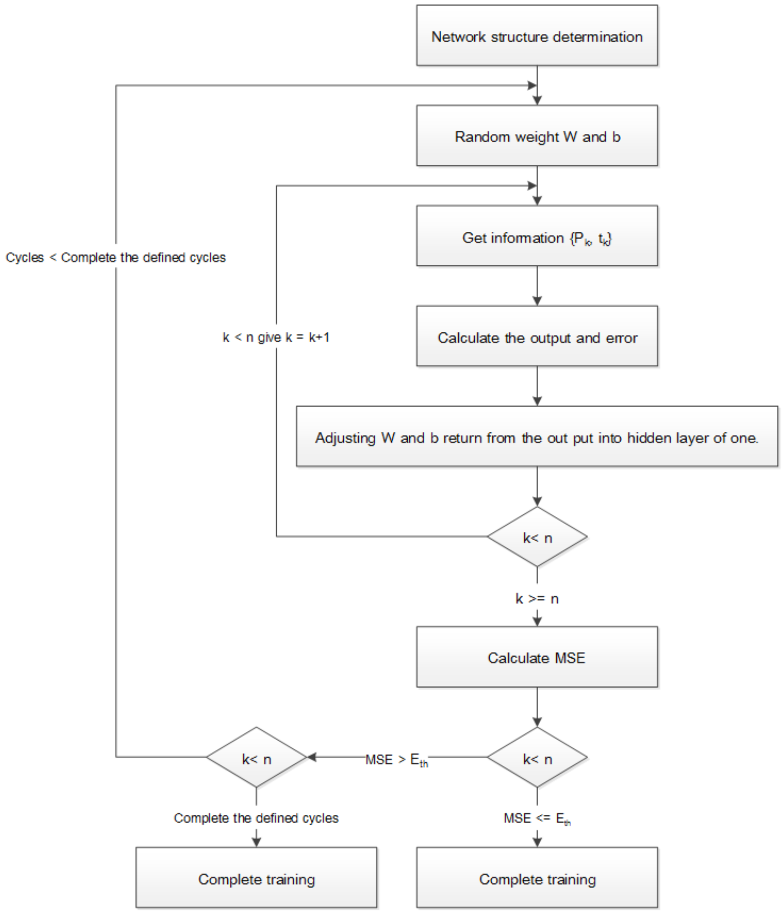

Fig. 5. Learning process of the ANNs.

Figure 5 shows the learning process of the ANN, which starts from the structure determination of the network by selecting the learning rates (small value to near zero) to determine the minimum acceptable error and the maximum learning iterations. The sampling weight (W) and bias (b) for the training data is set into the network and the output value for each hidden layer and the error is calculated. After adjusting the weights and bias returned from the output layer into the first hidden layer, the slope of the error is calculated, the weights are adjusted and the bias of the output layer, and then the weights and bias of layer one are calculated. If $k = 1 < k = n$ given $k = k + 1 = 2$, continue recalculating the received data sets by training the network until $k \geq n$ in all steps, then calculate the mean square error (MSE). If the MSE is higher than the minimum acceptable error (Eth) reiterate the process of data sets training of the network until MSE ≤ Eth, or complete processing to the learning maximum cycle limit, thus completing the training and the process of Back-propagation algorithm, as shown in Fig. 6.

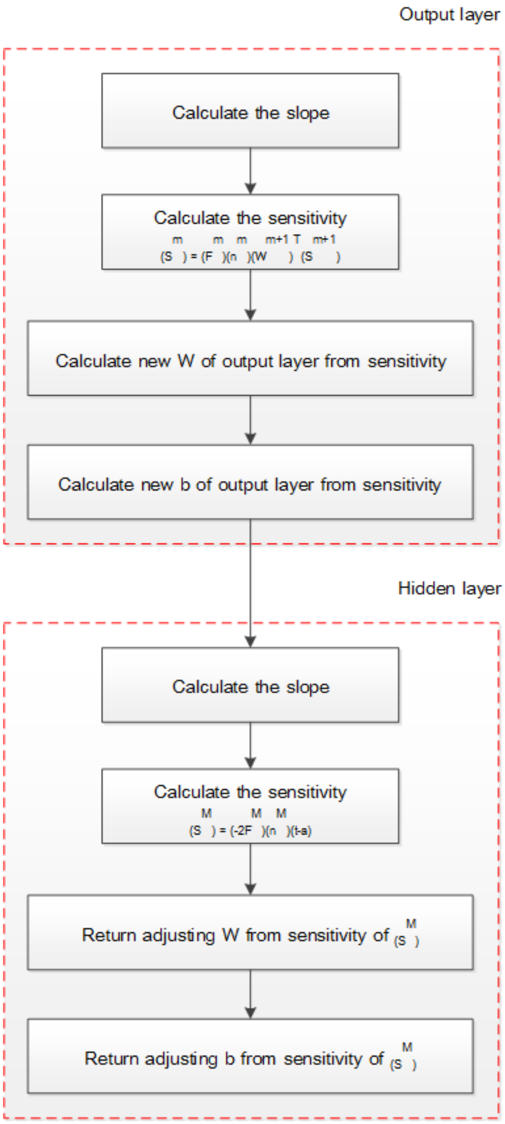

Fig. 6. The process of Back-propagation algorithm.

There are three types of learning process for ANNs; Supervised Learning, Unsupervised Learning and Reinforcement Learning. In this experiment, the experimental process used Supervised Learning. For the creation of the ANN, the researchers selected an ANN model of Back-propagation Multilayer by using the Multilayer Perceptron, training by using the Back-propagation algorithm and the transfer function for the hidden layers was the Log-Sigmoid Function. The output layer is the Pure Linear Transfer Function. This requires three layers in the calculation, consisting of an input layer, hidden layer (which has multiple layers in it) and output layer, as shown in Fig. 7. The input layer determines the number of nodes in the learning process by taking the number of cost drivers (attribute) of the data set used to test each product, while the output layer defines the node number by the number of cost drivers from each activity (class). The data used for training and testing the ANN of the 4 types of products including A, B, C and D. The prediction data then predicts the classification and data used for training and testing the ANN and has been conducted to test the performance of the model by 3 folds.

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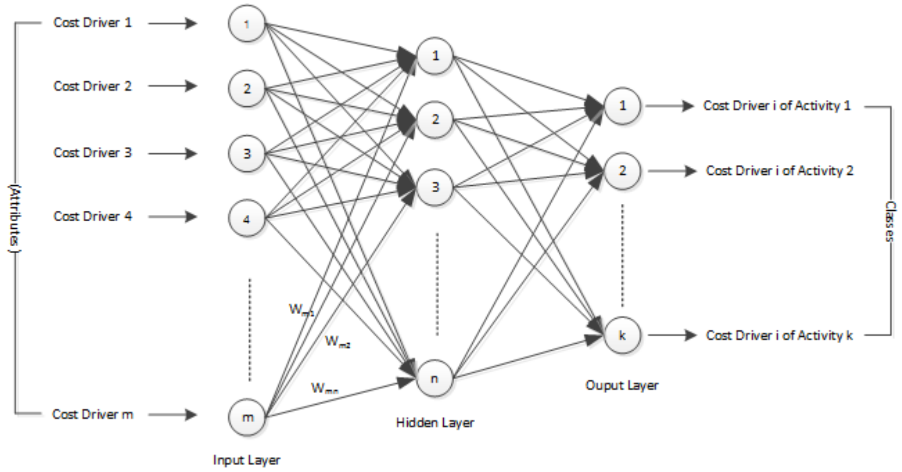

Fig. 7. The ANNs structure have 3 layers.

5. Result and Discussion

Calculating SDABC and MDABC by selected cost drivers from R^2 uses the maximum relationship for considering the cost drivers used to calculate the ABC. SDABC and MDABC are used to calculate both simple and multiple linear regressions. Using regression analysis to determine the R^2 can thus be a model to estimate the ABC. SDABC and MDABC are based on ANNs, so the researchers used an ANN which has the greater ability to resolve the complexity problem, and are able to learn the classification of the chosen cost drivers from learning the relationship between the input and output values of the historical data. So, the application of an ANN is effective and efficient for the various aspects of the costing process; (1) for learning the classifications for choosing the cost drivers, which are used in the replacement calculation R^2, (2) reducing the recalculations necessary when the cost drivers are known, and (3) overcoming the problem of the increased activity arising from changes to production, and the need to consider the various cost drivers. The ABC of 4 products is shown in Tables 2 & 3, from December 2014. This is the most current data available at the time of the research project. The comparisons of the cost per unit of the four products shown in Tables 4–7, cover the 12 months of that year.

Table 2. ABC in December 2014 for the 4 products.

Products	ABC (Baht)	ABC Equation (Baht)	ANN in ABC (Baht)	Hidden nodes	Correct (%)	Class
A (SDABC)	1.723	1.872	1.438	8	78.8972	18
A (MDABC)	2.145	2.284	2.636	6	80.3140	32
B (SDABC)	1.658	1.503	1.812	8	73.9130	15
B (MDABC)	1.882	1.516	2.137	10	79.9517	30
C (SDABC)	4.525	4.886	4.659	6	91.8519	18
C (MDABC)	4.347	4.707	4.874	8	99.8148	29
D (SDABC)	1.223	1.185	1.367	6	84.3137	19
D (MDABC)	1.354	1.592	1.404	10	93.7908	31

Tables 2 & 3, show the ABC and cost per unit in December 2014 for the 4 products considered. For each product, costs were calculated using the three methods; traditional ABC, ABC applying the mathematical model shown as Eq. (1), (2), (3), & (4) above, and applying the ANN to the cost calculations. This was done applying both the SDABC approach (single cost driver) and the MDABC approach (multiple cost drivers). The training and testing of the ANN was done by conducting tests of the performance of the model by 3 folds with the 31 attributes with a learning rate equal to 0.1, maximum learning epoch equal to 100,000 and has hidden layers, correct cost driver selection as a percentage and the number of classes. The number of hidden nodes that occur for each product are the hidden node of the neural network that provide the most accurate percentage for learning which cost drivers to choose. Class refers to the type of cost driver associated with each product. In this example, Product A (SDABC) has a 8 hidden nodes, which are calculated to be the most accurate; 78.90% derived from the actual eighteen cost drivers for the product. Similarly, in the MDABC processing, Product A has 6 hidden nodes, which are calculated to be the most accurate; 80.31% derived from the actual thirty two cost drivers for the product. These calculations are done for each product, and the values of these variables vary according to each product and to the method of calculation. The results of the production ABC are thus adjusted as shown in Tables 3 and 4.

Table 3. Cost per unit December 2014 for the 4 products.

Products	Cost per Unit(Baht)		
	Direct cost + Indirect cost (ABC)	**Direct cost + Indirect cost (ABC Equation)**	**Direct cost + Indirect cost (ANN in ABC)**
A (SDABC)	47.066	47.215	47.215
A (MDABC)	47.488	47.627	47.627
B (SDABC)	17.752	17.597	17.597
B (MDABC)	17.976	17.610	17.610
C (SDABC)	5.895	5.744	5.744
C (MDABC)	6.246	6.074	6.074
D (SDABC)	4.061	4.203	4.203
D (MDABC)	4.192	4.430	4.430

Table 3 shows the production costs for December 2014. In the calculations the cost per unit are obtained from the direct costs (material costs and labour costs) combined with the indirect costs that can be directly allocated to each products (machine cost, cost of the equipment used in the production, etc.) and indirect costs that are considered to be 'factory overhead' which cannot be directly allocated to any specific product or activity (tap water charge, electricity charge, etc.). Table 3 shows these costs calculated by each of ABC, SDABC and MDABC. Tables 4–7 show the cost values and comparisons of the production costs of the four sample products, for each month of the whole of the year 2014, calculated by these three methods and compared against the production costs as calculated by the factory using TCA. The TCA calculations done by the factory did not correctly reflect the indirect or overhead costs, which were clearly overstated in every case. By using MDABC the real costs of production are calculated by including the indirect and overhead costs included in the selected cost drivers. Therefore, result in an understatement of profit per unit, resulting in perhaps inappropriate on-going management decisions.

Table 4. Comparison of monthly cost per units of Product A during 2014.

Month	**Cost per unit (Baht)** : (**Direct cost + Indirect cost**)						
	SDABC	**SDABC Equation**	**MDABC**	**MDABC Equation**	**ANNs in SDABC**	**ANNs in MDABC**	**TCA (Factory)**
January	46.364	46.511	46.784	46.817	46.086	47.266	57.633
February	46.825	47.123	47.365	47.453	46.544	47.853	57.633
March	44.587	44.328	44.885	44.717	44.319	45.347	57.633
April	45.204	45.648	45.721	46.146	44.933	46.192	57.633
May	44.673	44.284	45.233	45.145	44.405	45.699	57.633
June	43.786	43.424	44.178	44.237	43.523	44.633	57.633
July	46.401	46.547	46.648	46.823	46.123	47.128	57.633
August	46.785	47.123	47.272	47.343	46.504	47.759	57.633
September	47.236	47.887	48.034	47.905	46.953	48.529	57.633
October	45.498	45.252	45.652	45.749	45.225	46.122	57.633
November	46.315	46.151	46.631	46.556	46.037	47.111	57.633
December	47.066	47.215	47.488	47.627	46.784	47.977	57.633

Tables 4–7 show the production cost calculations for product A, B, C and D for each month of 2014. Table 4 shows the cost sequence over the time period, and the inter-month comparisons. It can be seen that for Product A the lowest costs occurred in June and the highest in September. The production volume was the lowest and highest in these months as well, obviously being directly related; volume to cost incurred. The TCA calculations assumed fixed production volume, whereas the other calculations, especially the MDABC calculations, encompass other factors which contributed to production costs in a

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variable production volume environment, such as the cost of materials, labour input and cost as well as appropriate indirect costs and overhead cost apportionments. The research outcomes demonstrated that the production cost values from the MDABC more correctly reflected the true production costs per unit of production. So, it has been demonstrated that by including multiple cost drivers and choosing the most appropriate cost drivers, results in greater accuracy in calculating production costs.

These outcomes shown in Table 4 demonstrate first that there are three main methods of TCA, SDABC and MDABC which can be used in calculating per unit production costs. However, in all cases the TCA calculated the production costs to be some 25%-30% higher; the highest. This is due to the failure of TCA to allocate the indirect costs appropriately, or at all. The TCA calculations were based on a fixed volume formula, and only considered direct labour hours and direct machine hours. It is apparent that TCA was a manual activity, whereas the new alternatives of SDABC and MDABC are effective applications of information technology in modern production. The SDABC method models the use of all resources in all the activities that use resources, and can be linked to each product and is able to display all cost, direct or indirect as appropriate. When both methods are compared, SDABC method demonstrably provides the greater accuracy and precision in calculating the value of the product cost. However, this approach still manifests the problem of using only activity driver or cost driver. The choice of this particular cost driver depends on the experience of the staff primarily. This was confirmed in interviews with these staff members. However, it is clear that each activity has more than one cost driver, and the selection of a single cost driver, as is done in the SDABC method, results in a distortion of reality. The MDABC method was demonstrated to calculate the most accurate total cost per product, due to using multiple cost drivers, and selecting the most appropriate cost drivers from amongst the various available cost drivers. The calculations by the MDABC method sometimes showed a high production cost than the SDABC method and sometimes a lower cost. So it can be concluded that MDABC can better reflect the true total production cost than the SDABC method.

Tables 5 to 7 shows the same data as Table 4, but each for a different product; Product B, C and D. In each case, the costs calculated by the TCA method were significantly different to the values produced by the SDABC and MDABC methods. The TCA values were usually higher, but in a small number of cases a little lower. One conclusion to be drawn therefore is that it is not product dependant nor volume dependant, but in all cases it is the selection of appropriate, or multiple, cost drivers that is the differentiating factor.

When considering all of the 4 products included in the comparative analysis, this was seen to be the case for each product; MDABC calculates production costs more accurately.

Table 5. Comparison of monthly cost per units of Product B during 2014.

Month	Cost per unit (Baht) : (Direct cost + Indirect cost)						
	SDABC	**SDABC Equation**	**MDABC**	**MDABC Equation**	**ANNs in SDABC**	**ANNs in MDABC**	**TCA (Factory)**
January	16.823	17.269	17.447	17.528	16.971	17.695	22.622
February	17.326	17.551	17.850	17.684	17.478	18.103	22.622
March	17.529	17.474	17.752	17.687	17.683	18.004	22.622
April	17.431	17.546	17.755	17.889	17.584	18.007	22.622
May	17.634	17.909	18.258	17.992	17.789	18.517	22.622
June	16.936	17.282	17.460	17.195	17.085	17.708	22.622
July	17.639	17.384	17.863	17.997	17.794	18.117	22.622
August	17.542	17.787	17.965	18.170	17.696	18.220	22.622
September	17.144	16.889	17.468	17.302	17.295	17.716	22.622
October	17.547	17.692	17.971	17.705	17.701	18.226	22.622
November	17.349	17.194	17.573	17.707	17.502	17.823	22.622
December	17.752	17.597	17.976	17.610	17.908	18.231	22.622

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Table 6. Comparison of monthly cost per units of Product C during 2014.

Month	SDABC	SDABC Equation	MDABC	MDABC Equation	ANNs in SDABC	ANNs in MDABC	TCA (Factory)
	Cost per unit (Baht) : (Direct cost + Indirect cost)						
January	4.828	5.025	5.317	5.468	4.938	5.307	5.835
February	4.762	4.663	4.992	5.180	4.870	4.983	5.835
March	5.366	5.491	5.798	5.689	5.488	5.787	5.835
April	5.651	5.411	5.807	6.035	5.779	5.796	5.835
May	5.918	6.130	6.354	6.440	6.052	6.342	5.835
June	5.275	5.156	5.554	5.417	5.395	5.543	5.835
July	4.985	4.830	5.247	5.426	5.098	5.237	5.835
August	5.254	5.398	5.515	5.478	5.373	5.505	5.835
September	5.626	5.476	5.892	6.064	5.754	5.881	5.835
October	5.718	5.580	5.954	5.821	5.848	5.943	5.835
November	5.415	5.592	5.718	5.631	5.538	5.707	5.835
December	5.895	5.744	6.246	6.074	6.029	6.234	5.835

Table 7. Comparison of monthly cost per units of Product D during 2014.

Month	SDABC	SDABC Equation	MDABC	MDABC Equation	ANNs in SDABC	ANNs in MDABC	TCA (Factory)
	Cost per unit (Baht) : (Direct cost + Indirect cost)						
January	4.353	4.217	4.556	4.797	4.508	4.715	4.610
February	4.576	4.362	4.751	4.656	4.738	4.808	4.610
March	3.809	3.973	4.262	4.443	3.944	4.313	4.610
April	4.033	4.123	4.392	4.267	4.176	4.444	4.610
May	4.221	4.061	4.450	4.326	4.371	4.503	4.610
June	4.672	4.414	4.803	4.942	4.838	4.860	4.610
July	3.969	4.182	4.417	4.322	4.110	4.470	4.610
August	4.158	4.280	4.489	4.627	4.306	4.542	4.610
September	4.535	4.376	4.789	4.632	4.696	4.846	4.610
October	4.347	4.492	4.631	4.784	4.501	4.686	4.610
November	4.237	4.187	4.467	4.594	4.387	4.520	4.610
December	4.061	4.203	4.192	4.430	4.205	4.242	4.610

6. Conclusion

The research found that the automotive parts industry of Thailand has usually calculated production costs using the TCA method, apparently because of the flexibility of the calculation in low production volume environments. The ability to do these calculations manually was an important factor in their continuing use. However, the availability of information technology, providing the ability to do large volume calculations at high speed has introduced a new dimension, which can overcome the short comings of the traditional approach in these low production volume situations.

In this new technology environment, SDABC and MDABC methods have been demonstrated to be entirely feasible, and have been shown to achieve more accurate values for total production costs. Some enterprises have developed the SDABC method to achieve greater accuracy of product cost by including indirect variable and fixed overhead cost allocation in the total cost calculation.

The major short coming identified in the SDABC method is the selection of only one, single, cost driver. To overcome this short coming, the MDABC method has been developed to include multiple cost drivers, thus achieving greater accuracy. Implementing MDABC as an Artificial Neural Network (ANN) application has enabled the selection of the best cost drivers to be included in the multiple cost driver list, especially with frequently changing production schedules.

Overall, this research has achieved the objective of developing a production costing system that results in more accurate and correct production costs figures, thereby supporting executive decision-making more successfully, and demonstrating to producers the advantages of this approach. The only barrier to wide scale implementation is being able to convince production organizations of the effectiveness of this approach.

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