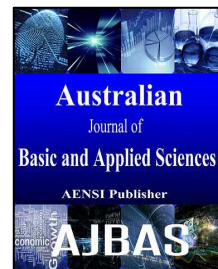




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An Artificial Neural Network Model Of Hydraulic Static Pile Driver Productivity In Silt Soil

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ABSTRACT

Rapid urban growth has caused an increase of infrastructure and building construction projects in recent years in terms of project scale and number. Many of which certainly involve the construction of deep foundation, including pile foundation. In particularly densely populated urban areas, the need for more environmentally friendly pile driving equipment, such as hydraulic static pile driver (HSPD), is therefore inevitable. The aim of this study is to study HSPD productivity in construction project using Artificial Neural Network (ANN). The objective is to produce charts model of HSPD productivity. Data were collected through site observation from four building projects in Semarang and Gresik. Some data also were got through simulation. An ANN model has been designed utilizing 252 data of point piling from the four projects and simulation, i.e. size of driven piles, piling depth, and cycle time. The results show that the productivity of HSPD for driving equilateral triangle 32 cm is 9.523 piling point/hour at 6 m of depth, 5.997 piling point/hour at 12 m of depth, 3.807 piling point/hour at 16 m of depth, and 3.350 piling point/hour at 24 m of depth. The productivity of HSPD for driving square 25 cm is 8.884 piling point/hour at 6 m of depth, 5.325 piling point/hour at 12 m of depth, 3.645 piling point/hour at 16 m of depth, and 3.157 piling point/hour at 24 m of depth. The productivity of HSPD for driving square 30 cm is 5.754 piling point/hour at 6 m of depth, 3.829 piling point/hour at 12 m of depth, 2.771 piling point/hour at 16 m of depth, and 2.597 piling point/hour at 24 m of depth. Validation of the outputs of the model shows valid result with average validity value of 98.13% and standard deviation of 1.67%. Sensitivity analysis of these outputs shows a sensitivity value of 78.54% for equilateral triangle 32 cm, 76.21% for square 25 cm, and 78.17% for square 30 cm. This research demonstrates the application of ANN for HSPD productivity assessment in silt soil and it has produced a chart of HSPD productivity. This chart is valuable for practitioners to plan and to estimate time related to the use of HSPD for a construction project.

INTRODUCTION

Rapid urban growth has caused an increase of infrastructure and building construction projects in recent years in terms of project scale and number. Many of which certainly involve the construction of deep foundation, including pile foundation. Pile foundation has been used in building constructions, bridges, and others structure since before the time. In particularly densely populated urban areas, the need for more environmentally friendly pile driving equipment, such as hydraulic static pile driver (HSPD), is therefore inevitable. HSPD uses press-in method to insert driven pile in soil (Peurifoy *et al.*, 2006). HSPD can merge grip and push or pull technique. HSPD advantages related to environmentally friendly are minimal noise, little

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vibration and pollution (Tan & Ling, 2001; White *et al.*, 2002; Deek *et al.*, 2005; Peurifoy *et al.*, 2006; and Chan, 2006).

There is important factors influence the HSPD productivity that were implied in treatment of pile in soil (Bowles, 1996), such as soil consistency, driven pile size, piling depth, and cycle time. These factors are explained and summarized in the following statements. The soil consistency differs from site to the other based on friction and soil bearing capacity. The driven pile size includes longitudinal section size and length of pile that depend on construction load and piling depth. The piling depth differs from site to the other depend on hard soil position. The piling cycle time begin from to prepare driven pile until to move HSPD to next piling point and the number of piling activities depend on piling depth and length of pile. All these factors, greatly affect the productivity of HSPD.

There is a lack of research in studying HSPD productivity. Therefore, it is necessary to use certain techniques to analyze the problem and determine the closed optimal solution. The aim of this study is to study HSPD productivity in construction project using Artificial Neural Network (ANN). The objective is to produce charts model of HSPD productivity. Current research develops sets of HSPD productivity chart in silt soil. The chart has significant effect on managing HSPD equipment. It enables practitioners to estimate production, schedule, and duration of pile construction project. In addition, it provides researchers with the methodology of designing ANN model for pile construction process use HSPD, its limitations, and future suggestion.

HSPD Productivity Variables:

As actually, there is large number of variables that affect the estimation HSPD productivity. It is impossible to consider all of them in one research. Current study concentrates only on some of the mayor variables, such as driven pile size, piling depth, and cycle time as showed in Table 1. This study focuses in silt soil type. Driven pile sizes include equilateral triangle 32 cm, square 25 cm, and square 30 cm. Piling depths cover 6, 12, 18, and 24 m. Pile length was chosen 6 m for 6, 12, and 18 m piling depth and 8 m for 24 m piling depth. Cycle time consist of decided and undecided time. Decided time is time to prepare driven pile, welding time, and time to move HSPD to next piling point. Undecided time is pressing time, that depends on soil consistency and piling depth.

Current study only considers the above-mentioned factors according to the specified limits when estimating HSPD productivity. Three variables with 8 attributes are recognized. Collected data have been divided into three main data sets based on driven pile size, one set for each size. Within each set, data are classified into four categories according to piling depth attributes. Each category has least 30 data point to indicated cycle time.

Table 1: HSPD Productivity Variables Attribute Matrix in Silt Soil

Variables	Attributes			
Driven pile size (cm)	32x32x32		25x25	30x30
Piling depth (m)	6	12	18	24
Cycle time (hour)	Decided and undecided time			

General Concepts of ANN:

ANN is an information processing system to imitate ways of working human's brain in interrelated neural network form for problem solving with learning by means of synaptic weights as input so be got valid output. The ANN has function learning and recalling. Learning is the process of adapting the connection synaptic weights to produce the desired output corresponding to defined input. Recall is the process of accepting an input and producing an output response based on the ANN weight structure that is trained during the learning process (Zayed & Halpin, 2005a).

An ANN is composed of simple processing elements, called neural network artificial neurons, an architecture comprised of connections between the elements, and weights associated with each connection (Han *et al.*, 2011). The ANN consists of three layers, such as input layer, hidden layer, and output layer as showed in Fig. 1. The input layer is independent variables as factors or covariates that depend on data types. The hidden layer is black box that connecting between input and output layers. The output layer is result of the system. In this case, the input layer is provided to the trained ANN where the output layer is calculated after executing the ANN internal process. The predicted output of output layer is compared with the required output to establish the prediction error. This error is used to adjust the ANN connection weight to enhance its prediction accuracy.

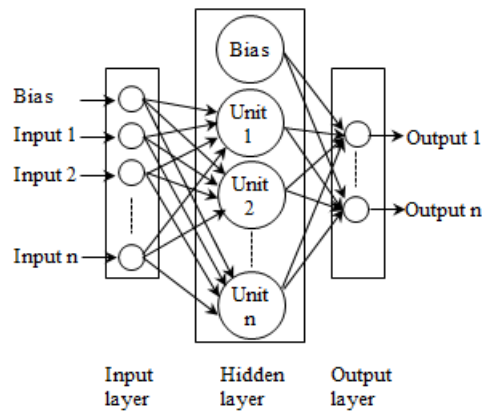


Fig. 1: Structure of ANN

An ANN program has been widely used for productivity assessment e.g. bore piles productivity (Zayed & Halpin, 2005a), productivity of concrete activities (Ezeldin & Sharara, 2006), productivity of earth moving equipment (Ok & Sinha, 2006; Han *et al.*, 2011) etc. The model showed good result. However, an ANN is never used to assess HSPD productivity.

MATERIAL AND METHODS

Data Collection:

Data were collected through site observation from four building projects in Semarang and Gresik. Each site was got minimum 30 data piling cycle time. The data were collected for driving equilateral triangle 32 cm on 9, 12, and 16 m piling depth and square 30 cm on 24 m piling depth. The data cover driven pile size, piling depth, and cycle time. Whereas soil consistency data were collected through Cone Penetration Test (CPT) data that it was got from consultants. Some data also were got through simulation to complete data. The first, simulation CPT data on several deep were based on soil consistency percentage that be got from site. The second, simulation pressing time data were based on the first simulation result, driving force concept, and trilateral congruent properties. Piling depth divides into small segment e.g. 1 m so that force change and pressing velocity can be done assumption as trilateral congruent. The simulations were done for getting data requirement for modeling.

Data Processing:

Decided time (time to prepare driven pile, welding time, and time to move HSPD to next piling point) from observation was collected and be chosen randomly, furthermore be added by undecided time (pressing time) for getting the cycle time. The cycle time was classified based on driven pile size and piling depth (L). The cycle time was used to calculate actual production (AP). The driven pile size included section and length size of driven pile. Each section size of driven pile used 6 m (for 6 m, 12 m, and 18 m piling depth) and 8 m (for 24 m piling depth) driven pile length so that there is three kind of the number of driven pile each point piling (BTP) that is 1 BTP, 2 BTP, and 3 BTP.

There is 360 data of point piling for three driven pile size section and four piling depth that be got by observation and simulation. The collected data sets are split randomly into two data subsets: 70% for modeling that is 252 data and 30% for validation that is 108 data. The AP values each section size of driven pile were classified based on L and BTP. The AP values in modeling data subsets were done normality test for knowing data distribution whereas L and BTP no need normality test because they are not as collected data but as certain values for data classifying.

Artificial Neural Network Modeling:

The conceptual framework of ANN application to the pile driving process is derived into three phase as showed in Fig. 2. The first phase includes the modeling phase: AP data, L data, and BTP data are fed into the ANN input, train the ANN, and finally, conclude the ANN output. The output is estimation of actual productivity. The ANN in this study is described as Multilayer Perceptron (MLP) procedure where use feedforward architecture structure with one hidden layer. The MLP procedure produces a predictive model dependent variables based on the values of the predictor variables (independent variables). The feedforward architecture structure shows connections in the network flow forward from the input layer to the output layer without any feedback loops. The modeling uses 70% collected data are split randomly into three samples: 71.4% for training, 19% for testing, and 9.5% for holdout. In the second phase, the ANN outputs are compared with the validation data subsets (30%) to check the ANN validity. If these results do not match the validation data, then

the ANN should be improved to produce close result to the validation data. The third phase includes sensitivity analysis that checks the effect of changing ANN model inputs on outputs. The outputs of sensitivity model are compared with the output of ANN model to get sensitivity percentage and the both productivity chart pattern are compared. The model limitation was got from this modeling.

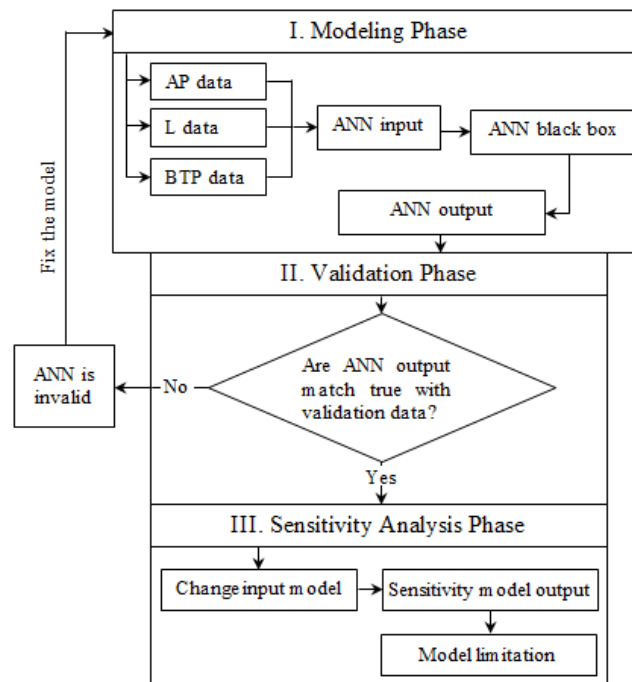


Fig. 2: ANN Conceptual Framework for Pile Driving Process

Artificial Neural Network Validation:

Validation model was done by comparing the estimation actual productivity with the actual productivity to check the validity percent. The validity factor (*VF*) and the average validity percent (*AVP*) term are used to represent the validity of the develop models. The *VFs* are found expression in fitness percent, if the calculated result more than 100% so this values were subtracted by 200% for getting the values less than 100%. Furthermore be calculated the number of *VFs* that more than a certain limitation divided with the number of data so be got fitness percent. The *AVP* shows average validity percent of model. For example, on *VF* > 90% of the model output has 80% fitness with data collected, and *AVP* = 90%, it means that the model is valid to represent the data with 90% valid. The *VF* and *AVP* are determined using the following Equation (1) and Equation (2) that be modified from Zayed & Halpin (2005a & 2005b), respectively:

$$VF = \frac{AP_{EM}}{AP} \cdot 100\% \quad (1)$$

$$AVP = \left(\sum_{i=1}^n VF \right) / n \quad (2)$$

where *VF* is validity factor, *AVP* is average validity percent, AP_{EM} is actual productivity of model estimation outcome, *AP* is actual productivity that be got from 30% data subsets, *i* is number of data, and *n* is maximum number of data.

Sensitivity Analysis:

The sensitivity analysis checks consistency and stability model outcome. This test was done with changing model input that is the number of driven pile each point piling (*BTP*). The changing *BTP* influences pressing time. All pressing time data for sensitivity test were simulated adjusting length driven pile change whereas the other driving activities time are same with modeling data. The new cycle time was used to calculate the productivity. The new data were used to input ANN modeling for getting new model as applied model (*PT*). The applied model was compared with the initial model to know its deviation and pattern.

If the models show the same pattern, its mean that the model is consistent and stable. The deviation can be calculated to determine a model confidence degree that is found expression in sensitivity percent. Relationship

both sensitivity and confidence degree is like relationship both reliability and confidence degree that is found expression in Bayes Theorem. The sensitivity degree can be calculated by Equation (3) that be modified from Bayes Theorem (Reksoatmodjo, 2009).

$$R = (1 - C)^{\frac{1}{n+1}} \cdot 100\% \tag{3}$$

where R is model sensitivity degree, C is confidence degree, and n is maximum number of data.

RESULTS AND DISCUSSION

Data Processing:

The CPT data were used to determine soil composition with Robertson *et al.* (1983) chart service so that was got silt soil composition that is 6%-13% clay soil, 50%-81% silt soil, and 11%-42% sand soil. This chart needs q_c (cone bearing) and f_R (friction ratio) from CPT to get it. This silt soil composition was used as based a CPT data simulation on the location was not observed so that was got CPT data for four kind of piling depth as showed in Fig. 3. The chart is showed the same pattern, it mean that the CPT data simulation can represent soil condition in this study. In Fig (3), q_c in 6 m and 24 m piling depth are observation result whereas q_c in 12 m and 18 m piling depth are simulation result.

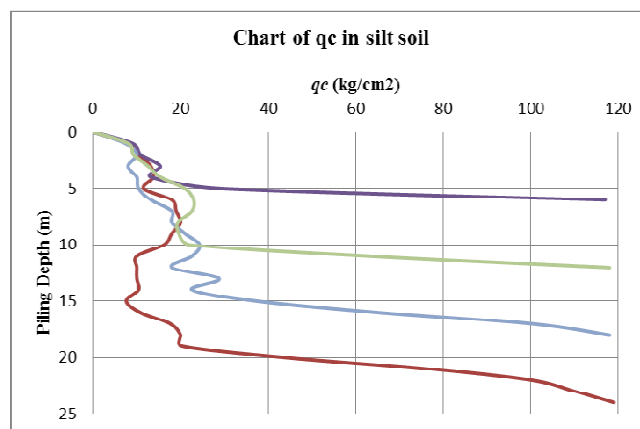


Fig. 3: Chart of q_c in This Study

A driving has four main activities: to prepare driven pile, welding, pressing, moving to next piling point. Time for preparing, welding, and moving are decided time whereas time for pressing is undecided time where is influenced by piling depth and driven pile size. The pressing time can be simulated based on CPT data in Fig. 3, Fig. 4, Equation (4), and Equation (5).

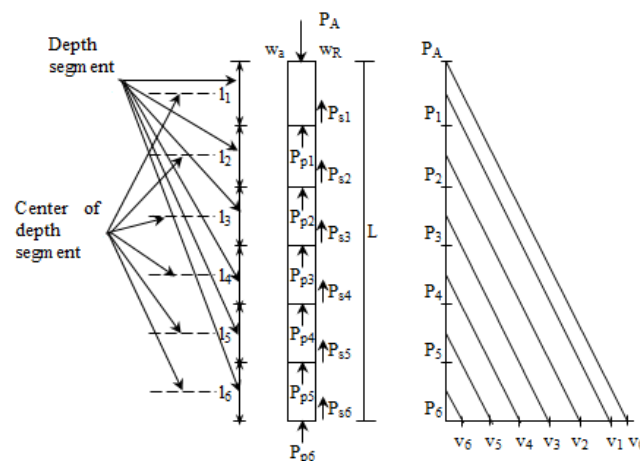


Fig. 4: Chart of q_c in This Study

$$v_i = v_0 \frac{P_i}{P_A} \tag{4}$$

$$t_i = \frac{l_i}{v_i} \tag{5}$$

where v_i is driving velocity until i depth, v_0 is equipment pressing velocity unloaded, P_i is remainder of pressing force on i depth, P_A is equipment pressing force, t_i is pressing time until i depth, and l_i is i depth.

The piling depth has to be divided into equal small depth segment (l). The pressing time at the beginning of the depth segment is different from at the end of the depth segment. To consider this concept, the small depth segment (l) has to so small so that the pressing time difference between the upper and lower in each segment is small. It is assumed that the pressing time does not change inside each depth segment, which is the center (average) point. Hence, the pressing time at the center of each segment represents the pressing time through the entire segment (Zayed & Halpin 2005b). The pressing time one segment can be calculated using Equation (5) and the pressing time all segments are summation the pressing time each segment. The pressing time chart as showed in Fig. 5.

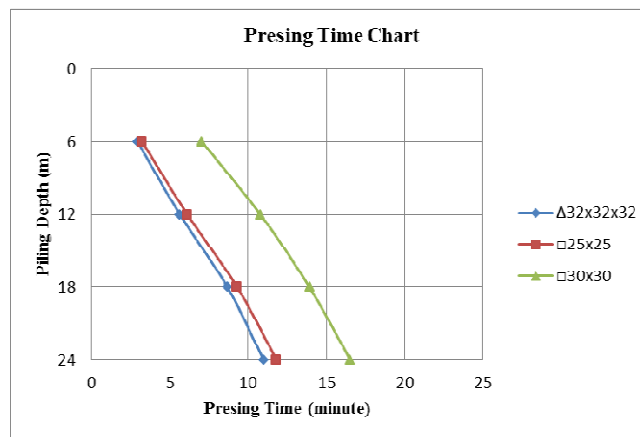


Fig. 5: The Pressing Time Chart

The pressing time at driven pile size $\Delta 32 \times 32 \times 32$ cm at 6 m piling depth and $\square 30 \times 30$ cm at 24 m are observation result whereas the other points are simulation result. The chart in Fig. 5 showed that the pressing time shaping straight line almost, it means that the pressing time appropriate with q_c pattern in Fig. 3. The value of q_c in Fig. 3 showed almost same value and the equipment pressing force that stable caused pressing time change that almost same too so that the pressing time showed comparable change inter-piling depth.

The decided time and the pressing time are added up for getting the cycle time. The productivity can be calculated from this cycle time. Composite both observed and simulation data have been this study data.

ANN Modeling:

Input and output variables selection greatly affects the ANN architecture. The input variables are piling depth (L) and number of driven pile each point piling (BTP). The output variable is actual productivity (AP). Each variable is represented by one artificial neuron in the network’s input layer. Hence, to build the ANN architecture, there should be two neurons in the input layer and one neuron in the output layer.

Several trials have been done to select the best architecture that gives the best output. Changing input order and architecture design has been done for that aim. The selection was made based on the least sum of squares error. Figure 6 show the network diagram. This study used one hidden layer with three units, activation function used hyperbolic tangent in hidden layer and identity in output layer, rescaling method for input and output used standardize.

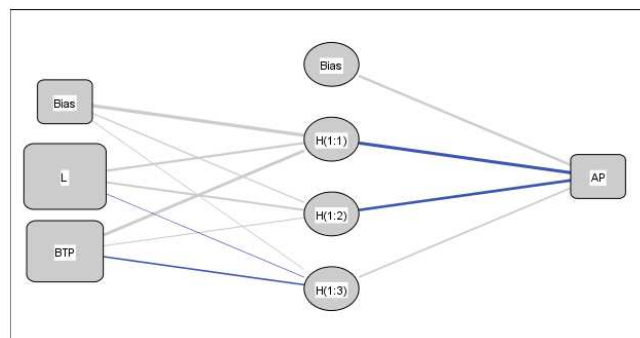


Fig. 6: Network Diagram

The ANN modeling was done for three kind size of driven pile that is $\Delta 32 \times 32 \times 32$ cm, $\square 25 \times 25$ cm, and $\square 30 \times 30$ cm. ANN output is actual productivity of model estimation (AP_{EM}) as showed in Fig. 7 and Table 2 as summary. Decreasing productivity is along with piling depth change, the deeper the smaller. Difference of driven pile section size influences productivity value, the wider the smaller.

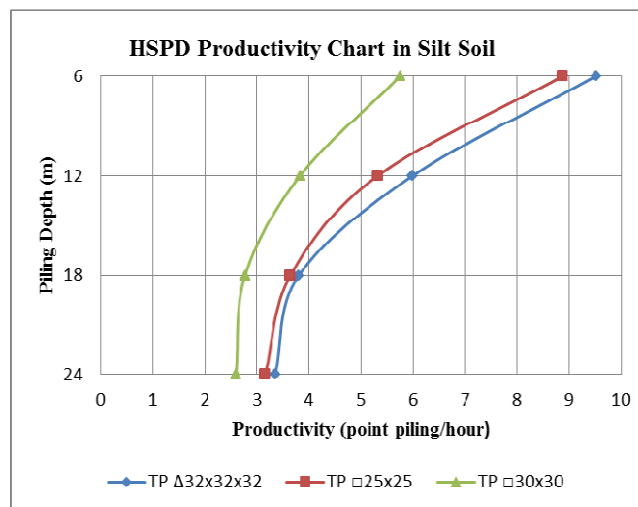


Fig. 7: The Productivity Chart of HSPD

Table 2: The AP_{EM} (piling point/hour) in Silt Soil

BTP (stick)	L (m)	Driven pile section size		
		$\Delta 32 \times 32 \times 32$	$\square 25 \times 25$	$\square 30 \times 30$
1	6	9.523	8.884	5.754
2	12	5.997	5.325	3.829
3	18	3.807	3.645	2.771
3	24	3.350	3.157	2.597

Model Validation:

Validation is so important because a model cannot be used in practice unless it is valid. The outputs of model in Table 2 have to be validated by validation subset data so that it can be used for productivity estimating. There is 108 data to validate that outputs, 9 validation data each output. The validation factor (VF) can be got by Equation (1). If the model provides close numbers to the validation data, it is valid and can be used to represent this process in the real practice. Into the bargain, are calculated too average validity percent (AVP) using Equation (2), standard deviation (SD) of VF, and data fitness percent on 95% and 90% validity.

The average of VF each piling depth, AVP, and SD as validation result as showed in Table 3. Before the VF was done average, prior the fitness percent was calculated. On $VF > 95\%$ of the model output has 96.30% fitness data and on $VF > 90\%$ of the model output has 100% fitness data, it means that the model is valid to HSPD productivity estimating. The AVP showed a high value and small SD, it means that the model is a good model.

Table 3: The Validity Result of AP_{EM} in Silt Soil

BTP (stick)	L (m)	Driven pile section size (cm)	Average of VF (%)
1	6	$\Delta 32 \times 32 \times 32$	99.14
2	12		98.99
3	18		97.92
3	24		99.63
1	6	$\square 25 \times 25$	95.75
2	12		97.79
3	18		99.10
3	24		99.27
1	6	$\square 30 \times 30$	99.06
2	12		97.34
3	18		96.23
3	24		97.30
AVP			98.13
SD			1.67

Model Sensitivity:

The model has been built using composing BTP: 1, 2, 3, 3 in order appropriate piling depth respectively. The composing BTP changes to 1, 3, 4, 4 as model input, it is caused productivity change. The new data was

used for modeling so that produce a new productivity that known as applied model (PT). Both PT and AP_{EM} points were compared for getting deviation so that got sensitivity degree using Equation (3). The calculation has done so that got $R = 78.54\%$ for driven pile $\Delta 32 \times 32 \times 32$ cm, $R = 76.21\%$ for driven pile $\square 25 \times 25$ cm, and $R = 78.17\%$ for driven pile $\square 30 \times 30$ cm. The pattern of PT and AP_{EM} charts as showed in Fig. 8. The pattern and R values showed good condition, it means that the model is consistence and stable.

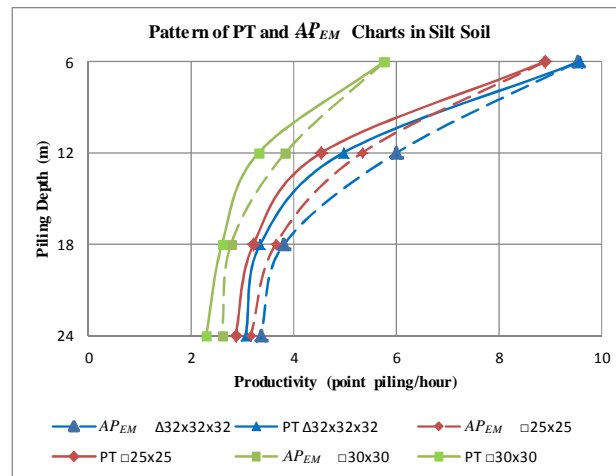


Fig. 8: The Pattern of PT and AP_{EM} in Silt Soil

Model Limitation:

This model has advantages that are the program easy to apply, the accuracy result is fast got, the chart is easy used, these chart change is consistent. Into the bargain, this model refer to data only and not pay attention process to get data so that has limitations that are easy occur prediction mistake if the data are got by ones who no understand about needed data characteristic, needed carefulness in program design, and needed suitable input and output variables.

Conclusion:

The ANN model is used to assess HSPD productivity in silt soil that has composition: 6%-13% clay soil, 50%-81% silt soil, and 11%-42% sand soil. The ANN input and output variables have been selected. Two inputs and one output used data of observation and simulation. The data divided into three groups: driven pile section size $\Delta 32 \times 32 \times 32$ cm, $\square 25 \times 25$ cm, and $\square 30 \times 30$ cm. Each group has four sub groups: piling depth 6 m, 12 m, 18 m, and 24 m. Each sub group has 30 data, 70% for modeling and 30% for validating.

The ANN architecture has three layers: input layer, hidden layer, and output layer. One hidden layer with three unit neurons was selected in this study. Selecting the best number of hidden layer neurons has been done by several trials. The designed ANN has been trained using the training data set and resulted in reasonable output.

The ANN output is known as actual productivity of model estimation (AP_{EM}) that is: on driven pile section size $\Delta 32 \times 32 \times 32$ cm, respectively is 9.523, 5.997, 3.807, 3.350 point piling/hour at 6, 12, 18, 24 m piling depth; on driven pile section size $\square 25 \times 25$ cm, respectively is 8.884, 5.325, 3.645, 3.157 point piling/hour at 6, 12, 18, 24 m piling depth, on driven pile section size $\square 30 \times 30$ cm, respectively is 5.754, 3.829, 2.771, 2.597 point piling/hour at 6, 12, 18, 24 m piling depth. That collecting AP_{EM} shaped the productivity chart of HSPD as ANN outcome.

The ANN outputs have been validated by comparing with validation collected data. The VF and AVP concepts have been designed to check the fitness degree of the designed ANN. On $VF > 95\%$ of the model output has 96.30% fitness data and on $VF > 90\%$ of the model output has 100% fitness data, it means that the model is valid to HSPD productivity estimating. The value of $AVP = 98.13\%$ and $SD = 1.67\%$, which are fairly good and acceptable. Sensitivity analysis has been done by changed input model so that was resulted an applied model (PT). Comparing both PT and AP_{EM} points resulted sensitivity degree (R) respectively is 78.54%, 76.21%, 78.17% for driven pile $\Delta 32 \times 32 \times 32$ cm, $\square 25 \times 25$ cm, and $\square 30 \times 30$ cm. The pattern of PT and AP_{EM} charts as showed the same pattern, it means that the model is consistence and stable.

The productivity chart of HSPD is valuable for practitioners to plan and to estimate time related to the use of HSPD for a construction project. In addition, this study provides the researchers with the methodology of applying ANN to the driving process using the other size of HSPD and driven pile at different piling depth although this approach has limitation.

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