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Feasibility of ANFIS Model for Prediction of Ground Vibrations Resulting from Quarry Blasting

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Abstract

One of the most significant environmental issues of blasting operations is ground vibration which can cause damage to the surrounding residents and structures. Hence, it is a major concern to predict and subsequently control the ground vibration due to blasting. This paper presents two artificial intelligence (AI) techniques namely adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) for the prediction of ground vibration in quarry blasting site. For this purpose, blasting parameters as well as ground vibrations of 109 blasting operations were measured in ISB granite quarry, Johor, Malaysia. Moreover, an empirical equation was also proposed based on the measured data. Several AI-based models were trained and tested using the measured data to determine the optimum models. Each model involved two inputs (maximum charge per delay and distance from the blast-face) and one output (ground vibration). To control capacity performances of the predictive models, the values of root mean squared error (RMSE), value account for (VAF), and coefficient of determination (R^2) were computed for each model. It was found that the ANFIS model can provide better performance capacity in predicting ground vibration in comparison with other predictive techniques. The values of 0.973, 0.987 and 97.345 for R^2, RMSE and VAF, respectively reveal that the ANFIS model is capable to predict ground vibration with high degree of accuracy.

Keywords: Blasting, Ground vibration, ANFIS, ANN, Empirical equation.

1. Introduction

Blasting is a common technique for rock fragmentation in quarries, mining operations and some civil engineering applications such as tunneling and leveling/road construction. In quarry works, several rows of blast-holes (almost parallel to the free face of the bench) are drilled and blasted. These operations cause several impacts such as ground vibration, air-overpressure, flyrock, and back-break in the blasting environmental zone (Khandelwal and Singh 2009; Jahed Armaghani et al. 2013; Hajihassani et al. 2014a; Raina et al. 2014; Ebrahimi et al. 2015). Among them, ground vibration is recognized as an undesirable phenomenon which may lead damage to the surrounding structures (Singh and Singh 2005; Ozer et al. 2008)

When an explosive is detonated in a blast-hole, chemical reaction of the explosives produces a high pressure and temperature gas. This gas pressure crushes the rock adjacent to the blast-hole. The detonation pressure decays or dissipates quickly. A wave motion is created in the ground by the strain waves conveyed to the surrounding rocks (Duvall and Petkof 1959). Due to various breakage mechanism, like radial cracking, crushing, and reflection breakage in the free face, the strain energy carried out by these strain waves fragments the rock mass (Khandelwal et al. 2011). The strain waves are propagated as the elastic wave when the stress wave intensity reduces to the ground level. These waves are known as ground vibration. The ground vibration can be spread from the blast-hole in all direction (Dowding 1985).

High ground vibration can cause damage to the surrounding structures, groundwater conduits, and ecology of the nearby area (Khandelwal and Singh 2006; Monjezi et al. 2010). The ground vibrations are measured in terms of peak particle velocity (PPV) and frequency. As reported in several standards (New 1986; Indian Standard 1973), PPV is considered as a vibration index, which is a significant indicator to control the structural damage criteria. Several parameters such as blast design, distance from the blast-face, explosive charge weight per delay, and geological conditions are the most effective factors on ground vibration induced by blasting (Wiss and Linehan 1978; Khandelwal and Singh 2007; Iphar et al. 2008).

Various empirical predictors have been suggested for the prediction of PPV (*e.g.* Duvall and Petkof 1959; Langefors and Kihlstrom 1963; Davies et al. 1964; Ambraseys and Hendron 1968; Roy 1993). Normally, in these approaches, PPVs are obtained from two factors namely maximum charge per delay and distance from the blast-face. As a result, in many cases, these methods are not accurate enough, whereas prediction of the PPV values with high accuracy is important to estimate the blasting safety area. In addition, these empirical equations need to be updated when new blasting data is available. Aside from the empirical equations, the use of statistical methods such as multiple regression analysis in predicting PPV has received attention mainly due to their ease of use (Hudaverdi 2012). However, the implementation of the statistical prediction techniques is not reliable if new available data are different from the original ones (Khandelwal and Singh 2009; Monjezi et al. 2013).

Besides, utilizing artificial intelligence (AI) methods such as artificial neural network (ANN) in the field of earth science is recently highlighted in literatures. This may be attributed to AI capability in solving non-linear continuous functions (Dehghan et al. 2010). Isik and Ozden (2013) used ANN for predicting soil compaction parameters namely maximum dry unit weight

($_{dmax}$) and optimum water content ($_{opt}$). Ceryan et al. (2013) conducted a research to predict the uniaxial compressive strength of carbonate rocks using ANN. In another study, Verma and Singh (2013) showed capability of the ANN technique in predicting water quality parameters including biological oxygen demand (BOD) and chemical oxygen demand (COD). Moreover, Park et al. (2013) and Bi et al. (2014) applied ANN to estimate landslide susceptibility index (LSI). Dissolved organic carbon (DOC) in a river network was evaluated and predicted using ANN in the study conducted by Fu et al. (2013). An ANN toolbox was created within GIS software by Lee et al. (2014). They successfully showed capability of this toolbox for solving geotechnical problems. A hybrid ANN-based predictive model was developed to estimate pile bearing capacity in the study carried out by Momeni et al. (2014). Ocak and Seker (2013) utilized ANN technique for solving problem of surface settlement caused by tunneling. A comparative study was performed by Maiti and Tiwari (2014) to predict groundwater level using ANN and adaptive neuro-fuzzy inference system (ANFIS) models. It was found that ANN can perform better than ANFIS for prediction of groundwater level. Gordan et al. (2015) proposed a hybrid particle swarm optimization (PSO)-ANN to predict seismic stability of the homogeneous slopes. Furthermore, several researchers have been used AI techniques in the case of PPV prediction. Khandelwal and Singh (2006) utilized four empirical predictors to estimate the PPV values for 150 blasting operations and obtained results were compared to the measured data. Subsequently, an ANN model was proposed for the prediction of PPV using the same data. They found that ANN results are more accurate compared to empirical predictors. Fisne et al. (2011) used fuzzy inference system (FIS) and regression analysis to predict PPV using 33 datasets obtained from Akdaglar quarry in Turkey. In their research, charge weight and distance from blast-face were considered as model inputs. They concluded that the FIS technique can predict PPV values better than the statistical technique. Monjezi et al. (2013) predicted PPV values using ANN model and the obtained results were compared to the recorded data in Shur River Dam, Iran as well as obtained results by empirical equations. Finally, they concluded that the ANN model has higher performance capacity compared to the empirical equations. Table 1 shows some recent studies with their performances in predicting PPV induced by blasting. In this study, ANN and ANFIS models have been developed to predict PPV resulting from blasting in granite quarry. Additionally, an empirical equation was suggested for prediction of PPV values according to USBM method recommended by Duvall and Petkof (1959). Eventually, results of PPV values using empirical equation, ANN and ANFIS models, were compared and discussed.

2. Case Study and Data Monitoring

The data used in this study was collected from ISB granite quarry, Kota Tinggi, Johor, Malaysia. The quarry lies geographically in latitude 1° 44' 12" Nand longitude 103° 54' 08" E, and is located 40 km north of Johor Bahru (Fig. 1). This quarry supplies granite aggregates for many construction applications with capacity of 37000-44000 ton per month. Depend on the weather condition, 4 to 8 blasting works per month were performed in this site. All blasting operations were performed using blast-hole diameters of 89 mm and 115 mm. ANFO and dynamite were used as the main explosive material and initiation respectively. The blast-holes were stemmed using fine gravels.

During data collection, blasting parameters including hole diameter, hole depth, maximum charge per delay, burden, spacing, stemming length, powder factor and number of hole were measured. In addition, in each blasting, PPV was monitored using Vibra ZEB seismograph having transducers for PPV measurement. The nearest structure is located about 450 m to the south of the quarry. It should be mentioned that the distances between monitoring point and blast-face were set in the range of 125 m to 670 m. Hole depths used in the blasting operations were in the range of 13.5 m and 26.5 m.In total, 109 blast were recorded and PPV in each blasting operation was monitored. In this study, among all measured blasting parameters, only maximum charge per delay (MC) and distance between monitoring point and blast-face (D) were taken into consideration for the prediction of PPV values as recommended by Duvall and Petkof (1959). In addition, the mentioned parameters have been extensively-used as predictor in many PPV prediction studies (see Table 1). Figs. 2-4 show the frequency of measured values of maximum charge per delay, distance between monitoring point and blast-face and PPV, respectively.

3. Empirical Equation Development

Numerous PPV equations have been established empirically by many researchers (e.g. Ambraseys and Hendron 1968; Roy 1993). The most popular PPV equation is a typical method suggested by Duvall and Petkof (1959). In the absence of monitoring, the use of scaled distance (SD) factor is a method for prediction of PPV. A relationship between the MC and D values is formed through the SD formula as follows:

(1)

Where W is the maximum charge per delay (kg) and D represents the distance between monitoring point and blast-face (m). Afterward, PPV values can be determined using the suggested equation by Duvall and Petkof (1959) as follows:

(2)

In which *B* and *K* are site constants. By using measured data from ISB granite quarry and also necessary analysis by SPSS (18.0), an empirical formula was suggested to predict PPV values as:

(3)

Coefficient of determination, R^2, equals to 0.836 for the Eq. 3 indicates that the proposed empirical equation can predict PPV with suitable accuracy level. Logarithmic graph between monitored PPVs and scaled distance values is shown in Fig. 5.

4. Artificial Intelligence Techniques for PPV Prediction

4.1 Artificial Neural Network (ANN)

ANNs are information processing patterns simulating the biological nervous systems which figure out the existing function from actual data. In other words, an ANN is a flexible non-linear function approximation that estimates a relationship between given input and output parameters. ANNs learn by examples in order to obtain a connection through the parameters. The earliest neuron was introduced by McCulloch and Pitts (1943), called the “Threshold Logic Unit”. Their model describes a neuron as a linear threshold, equivalent to using the unit step function; the function value is 0, if the nerve cell remains inactive, or 1, if the cell fires. Nevertheless, the first ANN was developed by Rosenblatt (1958), called the “perceptron” based on the neuron of McCulloch and Pitts (1943).

ANNs are composed of a set of parallel interconnected processing units titled nodes or neurons. There is an activation function along each neuron which transfers the activation signal between nodes. However, the ability of an ANN in data processing is mainly related to its architecture and weights (Dreyfus 2005; Engelbrecht 2007). In terms of the structure, ANNs are divided into two types; feed-forward and recurrent ANNs. In feed-forward ANNs, the neurons are usually classified into several layers. Using the connections, a signal moves throughout the input to the output layer(s). Multi-layer perceptron (MLP) is the most well-known type of feed-forward ANNs (Kosko 1994). In recurrent ANNs, the outputs of some (or all) neurons are fed back to the same neuron or into neurons in preceding layers. Therefore, the signals can move both forward and backward. Compared to other types of ANNs, feed forward MLP ANN is not complicated to implement (Bounds et al. 1998). This type of ANN has been applied successfully in various areas of engineering problems (Meulenkamp and Grima 1999; Singh et al. 2001; Tonnizam Mohamad et al. 2014).

The ability of ANNs to learn from samples and improve their performance is obtained by learning algorithm. Back-propagation (BP) algorithm is the most common training algorithm that tries to adjust the network weights during learning process by reducing the error between input and output data (Specht 1991). Fundamentally, BP learning consists of forward and backward passes in various layers of the network. The input parameters are applied to the hidden neurons and subsequently the outputs are produced. The error correction is conducted if the outputs of the network are different from the desired values. This action is conducted through the adjustment of weights and biases in which BP algorithm utilized for this purpose (Basheer and Hajmeer 2000). Eventually, the system error can be computed based on some performance criteria such as root mean square error (RMSE) (Kosko 1994; Simpson 1990).

4.2 PPV Prediction by ANN

As mentioned previously, maximum charge per delay and distance between monitoring point and blast-face were considered as model inputs for prediction of PPV values. More detail of the input and output parameters are shown in Table 2. In this study, all datasets were normalized by using following equation:

$$Xnorm = (X - Xmin) / (Xmax - Xmin) \tag{4}$$

Where X is the measured value, Xnorm is the normalized value of the measured parameter; Xmin and Xmax are the minimum and maximum values of the measured parameters in the dataset, respectively. Afterwards, all 109 datasets were divided into training and testing datasets. In this regard, 80% of the datasets were assigned for training purposes while the other 20% was used for testing of the network performance. To achieve the premier ANN performance, optimal network architecture should be determined. Hornik et al. (1989) stated that only one hidden layer in the network architecture can estimate any continuous function. Hence, in this study, one hidden layer was used. Aside from the number of hidden layer, in ANN architecture, selecting the number of nodes in the hidden layer is the most critical task (Sonmez et al. 2006). Many relations have been established to determine the number of nodes in hidden layers by some scholars as it can be seen in Table 3. According to this table, using two inputs and one output, the number of nodes which should be used in the hidden layer varies between one and six. In the next step of the analysis, the optimum number of nodes in the hidden layer must be determined. For this purpose, several networks with one hidden layer were trained and tested to predict PPV values as shown in Table 4. As tabulated in this table, each model was repeated five times by using the random distributions of datasets. In this table, results in terms of RMSE are listed for training and testing datasets, whereas RMSE values for testing datasets were set as performance criteria. Model number 6 with six hidden nodes (second iteration) indicates higher prediction performance compared to other models in predicting PPV. Therefore, this model with two inputs, one hidden layer and six nodes in the hidden layer was selected as the best ANN model. It is also worth mentioning that in construction of ANN models, the learning rate and momentum coefficient were set to be 0.1and 0.9 respectively.

4.3 Adaptive Neuro-Fuzzy Inference System

The adaptive neuro-fuzzy inference system (ANFIS) was first introduced by Jang (1993). Study by Jung et al. (1997) recommends ANFIS capability in approximating any actual continuous function. ANFIS is capable of simulating a functional mapping which approximates the prediction process of the internal system parameter. The term neuro-fuzzy is used due to the fact that in this artificial intelligence methods, the FIS concept is integrated into the ANN. Many researchers have addressed the successful application of ANFIS in solving geotechnical problems (Grima et al. 2000; Singh et al. 2012; Yesiloglu-Gultekin et al. 2013; Jahed Armaghani et al. 2014). In fact, the prime objective of ANFIS is to map a relationship between the input and output parameters. This can be done through a hybrid learning procedure for determination of the membership function (MF) distribution. A classic ANFIS network architecture comprising two input parameters x, y and a single output parameter f is presented in Fig. 6. As shown in this figure, the architecture consists of multiple layers *i.e.* 5 in the inference system, and each layer includes a number of neurons, which are defined by the neuron function.

In the previous layers, the output node is recognized as the feeding data of the present layer. After applying an operation using neuron function in the present layer, the model output forms the input signals of the next layer. To briefly illustrate the ANFIS procedure, consider a FIS model comprising, x and y as inputs and f as output. Hence, two fuzzy ‘‘if-then’’ rules can be introduced as shown in the following lines:

(rule 1)

(rule 2)

where, A_1, A_2, B_1, B_2 are defined as MFs for inputs x and y; p_1, q_1, r_1, p_2, q_2, r_2 are the output function parameters. In the following, the five-layer ANFIS comprising two fuzzy rules, x and y (inputs) and one output (f) is discussed (Jang 1993):

Layer 1: All neurons i in this layer are adaptive neurons.

$$O_{1,i} = \mu A_i(x) \tag{5}$$

$$O_{1,i} = \mu\ B_i(y) \tag{6}$$

For ri=1, 2 where x and y are set as input nodes, and A and B are the linguistic labels. Also, $\mu A_i(x)$ and $\mu\ B_i(y)$ symbolize the MFs.

Layer 2: The neurons are labeled Π and shown by a circle. The output node, then, is formed based on incoming signals.

$$O_{2,i} = \omega_i = \mu A_i(x)\ \mu\ B_i(y) \text{ with } i = 1,2 \tag{7}$$

The output node ω_i indicates the firing strength of a rule.

Layer 3: Every neuron in this layer is a fixed neuron to be identified by a circle and labeled as N. The output is obtained based on the ratio of the i^{th} rule’s firing strength over the summation of firing strength of all rules.

$$O_{3,i} = \varpi_i = \omega_i / (\omega_1 + \omega_2) \text{ with i} = 1,2 \quad (8)$$

Layer 4: In this layer, every neuron is an adaptive neuron with the neuron function like this:

$$O_{4,i} = \varpi_i f_i = \varpi_i \, (p_i x + q_i y + r_i) \quad (9)$$

Where parameters p_i,q_i, r_i are typically known as consequent parameters and ϖ_i denotes normalized firing strength.

Layer 5: In this layer the final step is taken. This step deals with generating the output amount through summation of all incoming signals:

$$O_{5,i} = \sum_i \varpi_i f_i = \sum_i \varpi_i f_i / \sum_i \varpi_i; \quad i = 1,2 \quad (10)$$

Back-propagation gradient descent forms the basic training rule of ANFIS. In this learning algorithm, the error signals from the output layer backward to the input neuron are recursively determined. Based on the architecture presented in Fig. 6 (b), the output (*f*) can be presented as a linear group of the consequent parameters. To learn the fuzzy model employing differentiable functions, ANFIS employ a hybrid-learning rule due to its ease of use. The conventional BP algorithm is mainly utilized by ANFIS to train the MF parameters. Also, the classic least-squares predictor is applied by ANFIS to train the parameter of the first-order polynomial of the Takagi–Sugeno–Kang fuzzy model as stated in a study by Jang et al. (1997).

The hybrid training algorithm of ANFIS uses so-called forward and backward passes. In the former, functional signals go forward till layer 4 and the consequent parameters are estimated using least-squares error criteria. Subsequently, like ANN procedure, to update the premise parameters, the obtained errors are backwardly propagated. This process is repeated using gradient descendent method until reaching a desirable output. The final output can be illustrated in the following manner:

(11)

where p_1, q_1, r_1, p_2, q_2, *and* r_2 are consequent parameters. The prime advantage of implementing an ANFIS model is efficient determination of the consequent and optimal premise parameters during training procedure.

4.4 PPV Prediction by ANFIS

This paper provides an insight into the application of ANFIS for predicting PPV. Similar to ANN part, the required datasets for modelling were randomly divided into two subsets: 80% of the dataset was set for training the model and the rest was considered for testing purposes. In this study, the numbers of fuzzy rules were determined using a trial-error method. Numerous models with different fuzzy rule combinations (e.g. 2, 3 and so on) were used for this reason. Eventually, it was concluded that the ANFIS structure with 5MFs for each input performs best when the results of RMSE were compared. In overall, the conducted parametric study suggested that the best prediction performance of the model is expected when ANFIS model is trained with 25 fuzzy roles (5 5). The type of MF utilized for each input is the Gaussian MF. Gaussian MFs are the most well-known MF in the literatures of fuzzy system, as they provide both simplicity and flexibility (Tutmez et al. 2007). In the next step of the modeling, ANFIS models were built to predict PPV values. Prediction performances of these models are shown in Table 5. This table indicates that PPV values were repeated 5 times using different training and testing datasets randomly. According to the presented results in this table, model number 4 outperforms other models. Hence, the aforementioned model *i.e.* model number 4 was chosen for prediction of PPV. RMSE values equal to 0.983 and 1.017 for training and testing datasets show the high performance capacity of the ANFIS model in predicting PPV. In model number 4, the MFs of the inputs were adjusted after 29,700 epochs using the hybrid optimization method. This optimization method includes BP for the parameters associated with the input MFs and also estimation of least-squares for the parameters associated with the output MFs.

Figs.7 and 8 display the assigned input MFs after training step. The linguistic variables assigned for ‘‘maximum charge weight per delay’’ and ‘‘distance’’ are very low (VL), low (L), medium (M), high (H), very high (VH), and very close (VC), close (C), normal (N), far (F), very far (VF), respectively. Additionally, the type of output membership function was set to be linear. It should be mentioned that all ANN and ANFIS predictive models were constructed using MATLAB (version 7.14.0.739). SPSS package (18.0) was used to determine RMSE values as well as statistical calculations. The suggested ANFIS structure is shown in Fig. 9.

5. Results and Discussion

In this study, an attempt has been made to examine the ability of ANN and ANFIS models for prediction of PPV values induced by quarry blasting. For this purpose, a database comprising of 109 blasting operations was prepared. Several ANN and ANFIS models were built using two inputs namely maximum charge per delay and the distance from the blast-face. Additionally, using the same datasets based on suggested method by Duvall and Petkof (1959), an empirical equation was proposed. Fig. 10 shows the PPV values predicted by empirical equation against monitored PPVs. R^2 value equal to 0.836 reveals that this equation is able to predict PPV with suitable accuracy. Fig. 11 displays the predicted PPVs by employing conventional ANN technique plotted against the measured PPV values for training and testing datasets. The R^2 values of 0.955 and 0.902 for training and testing datasets show that the ANN approach can predict PPV with high accuracy level. Moreover, in the prediction of PPV using the ANFIS technique, R^2 values of 0.974 and 0.969 for training and testing datasets suggest the superiority of this technique in predicting PPV compared to proposed empirical equation and ANN technique (see Fig. 12).

In order to demonstrate the capability of developed models, the widely-used PPV empirical equations were applied. Table 6 shows these PPV predictor equations as well as their site constants for granite. Using the presented equations in Table 6 and collected parameters from the site, PPV values were predicted. Figs 13 to 17 illustrate measured PPVs against predicted PPVs by Langefors – Kihlstrom, general predictor, Indian standard, Ghosh - Daemen predictor, and CMRI equations, respectively. The results show lower performance capacities of the empirical models in comparison to proposed models in this study.

To check the capacity performance of the predictive models as well as empirical PPV predictors, vales of RMSE and value account for (VAF) were obtained as follows:

$$\mathrm{RMSE} = \sqrt{\_\sum \qquad},\tag{12}$$

$$VAF = [1 - \underline{\qquad} \qquad ,\tag{13}$$

Where y and y' are the obtained and predicted values, respectively and N is the total number of data. When the RMSE value is zero and VAF value is 100, the model`s performance is perfect. Table 7 shows the performance indices achieved by all mentioned models in this study. As it can be seen in this table, the ANFIS model can provide higher performance capacity in predicting PPV induced by blasting compared to other predictive techniques. The values of 0.973, 0.987 and 97.345 for R^2, RMSE and VAF respectively reveal that the ANFIS model is capable to predict PPV with high degree of accuracy. It is important to note that proposed model based on USBM in this study can predict PPV values better than empirical PPV predictors. This can be seen clearly based on obtained RMSE values. RMSE value of 2.469 for proposed model based on USBM shows superiority of this model in predicting PPV, while these values were obtained as 10.473, 6.391, 7.821, 6.233 and 4.078 for Langefors – Kihlstrom, general predictor, Indian standard, Ghosh - Daemen predictor, and CMRI models, respectively. The presented results show that all proposed models are able to estimate PPV induced by quarry blasting. Nevertheless, the ANFIS model may be used when PPV values with higher degree of accuracy is required. Cautious step needs to be taken when the range of future data is beyond the range of the data used in this study.

6. Conclusions

In this study, several models have been proposed to predict ground vibration induced by quarry blasting. The model dataset include blasting parameters and PPV values of 109 blasting works in ISB granite quarry, Johor, Malaysia. The maximum charge per delay and distance from blast-face were considered as model inputs for prediction of PPVs. Several ANN and ANFIS models were trained and tested using the mentioned inputs-output configuration and finally two models were chosen as best models of ANN and ANFIS. Apart from that, using the same input parameters, a model based on USBM was proposed for prediction of PPV values. To show the ability of the proposed models, some empirical predictors were also applied to predict PPVs. Finally, the results indicated that the ANFIS predictive model is able to predict PPVs with higher accuracy compared to other models. It is worth noting that in practice all proposed methods have the applicability of PPV prediction. However, depending on the condition, they should be used accordingly.

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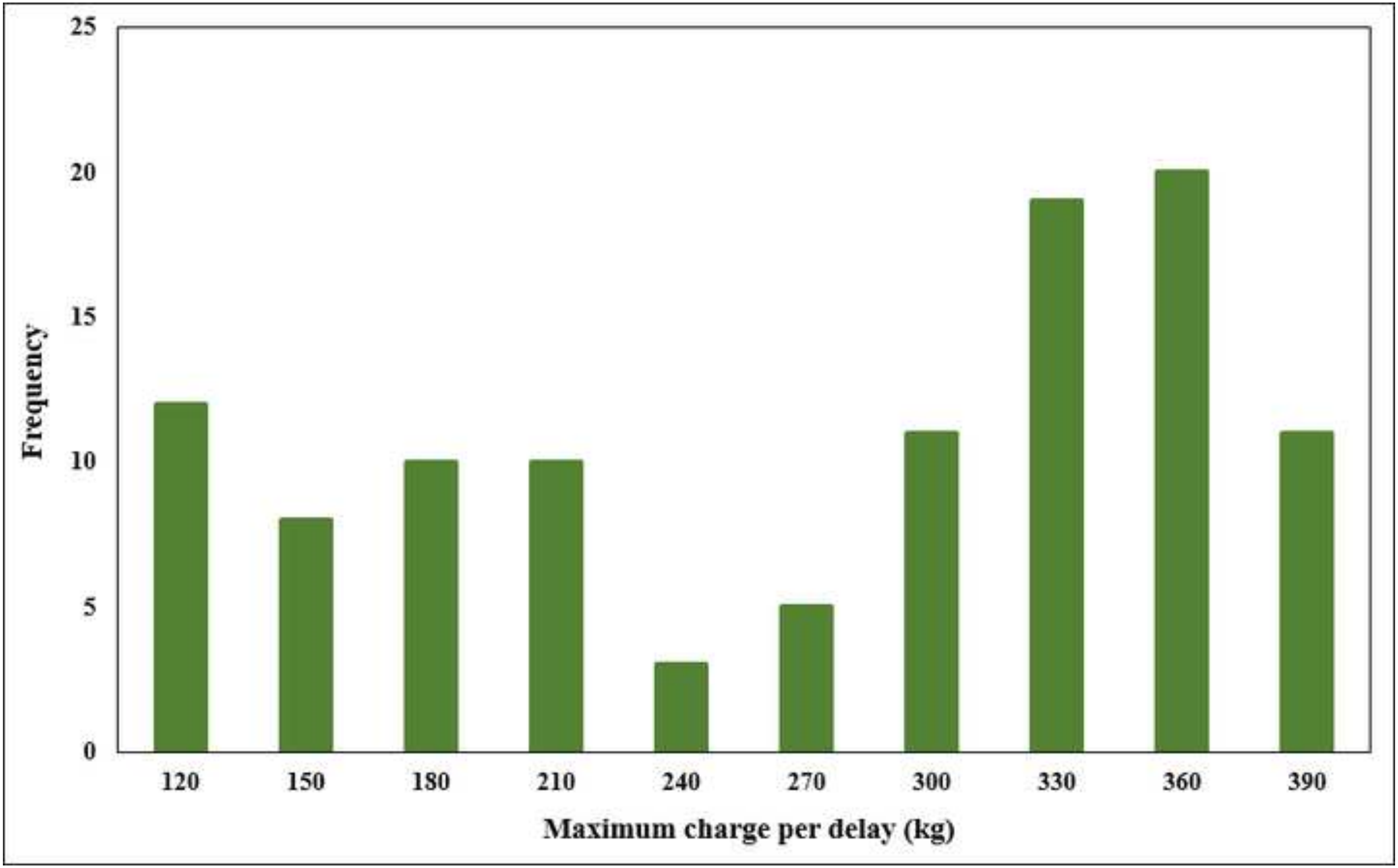

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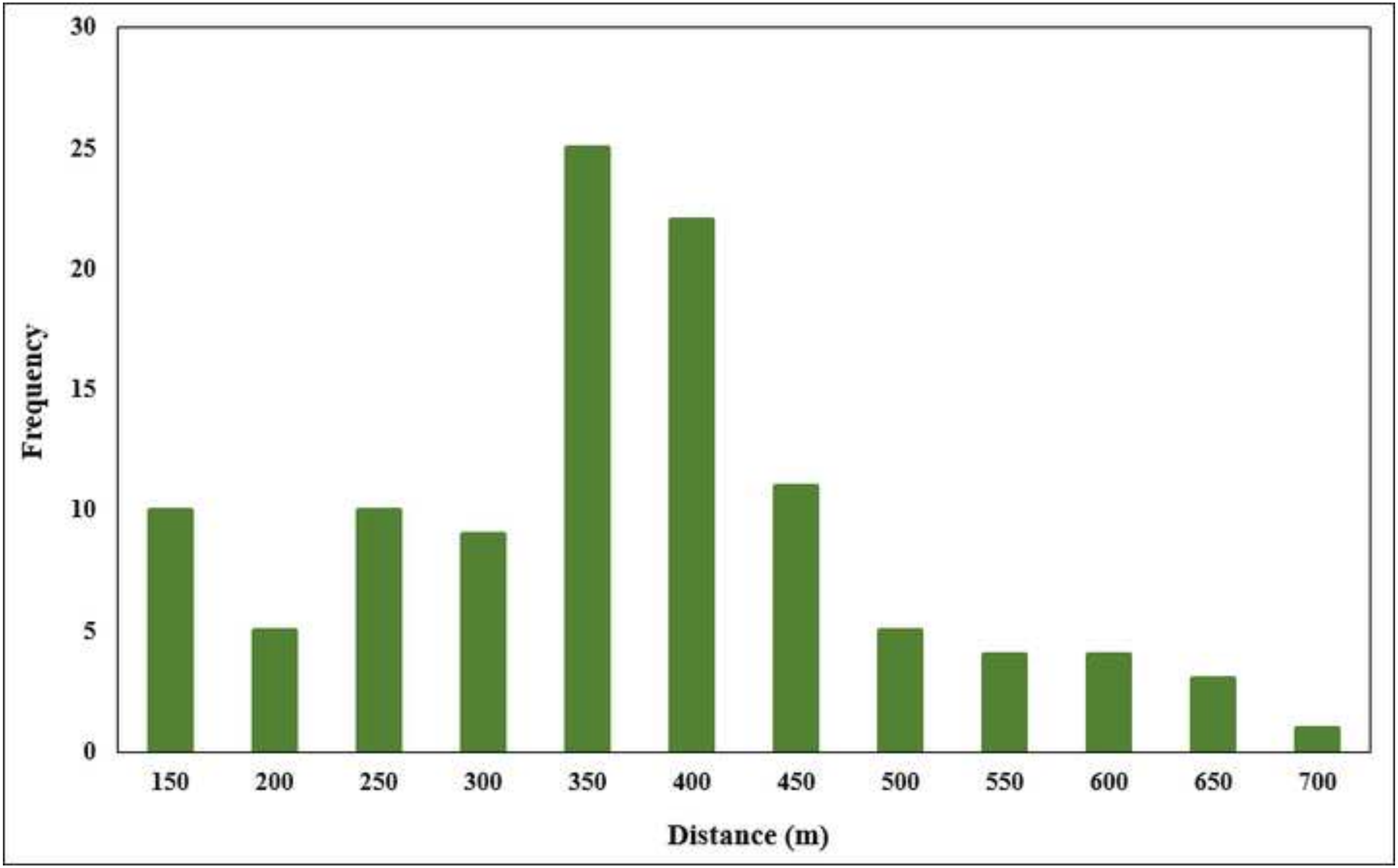

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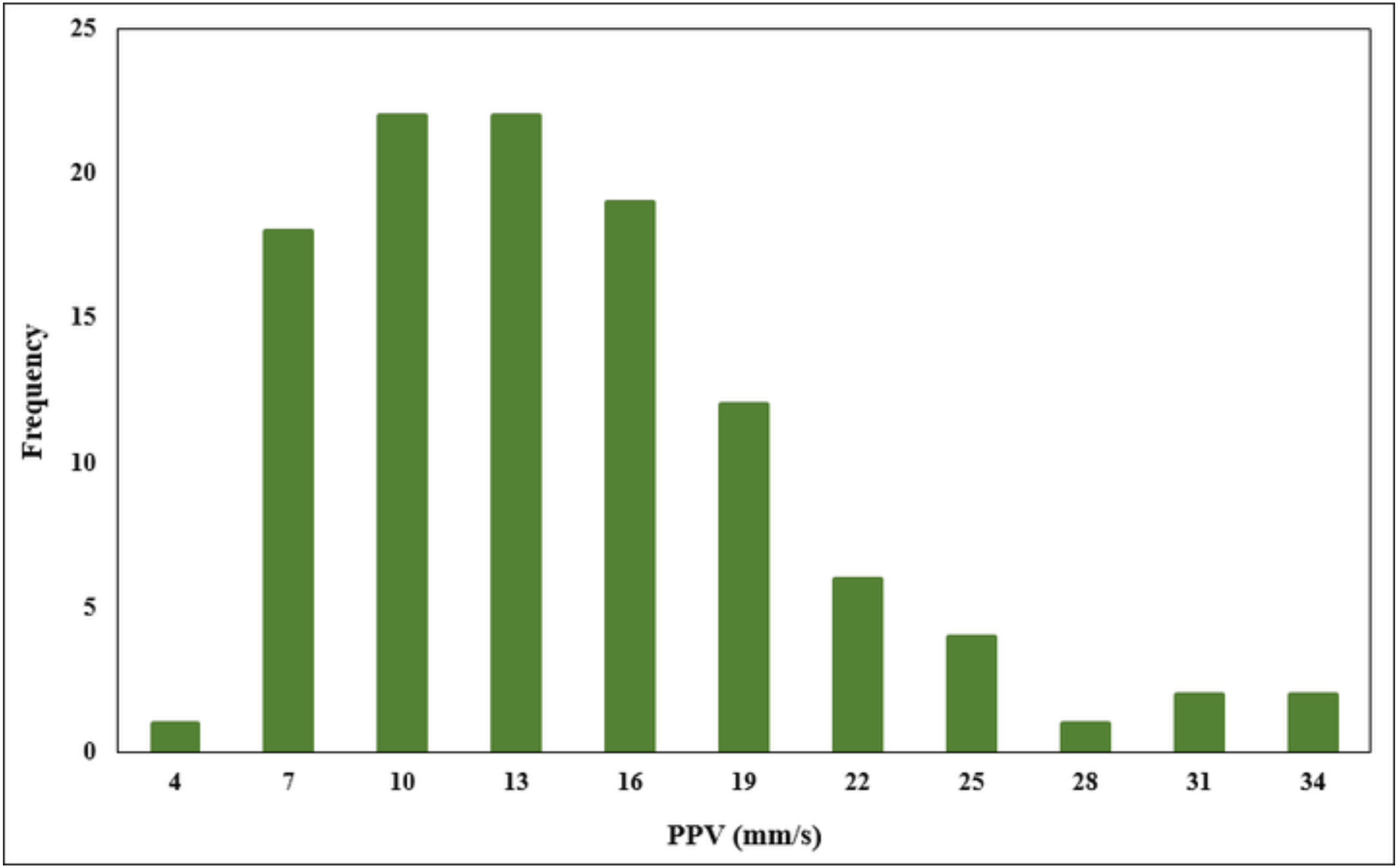

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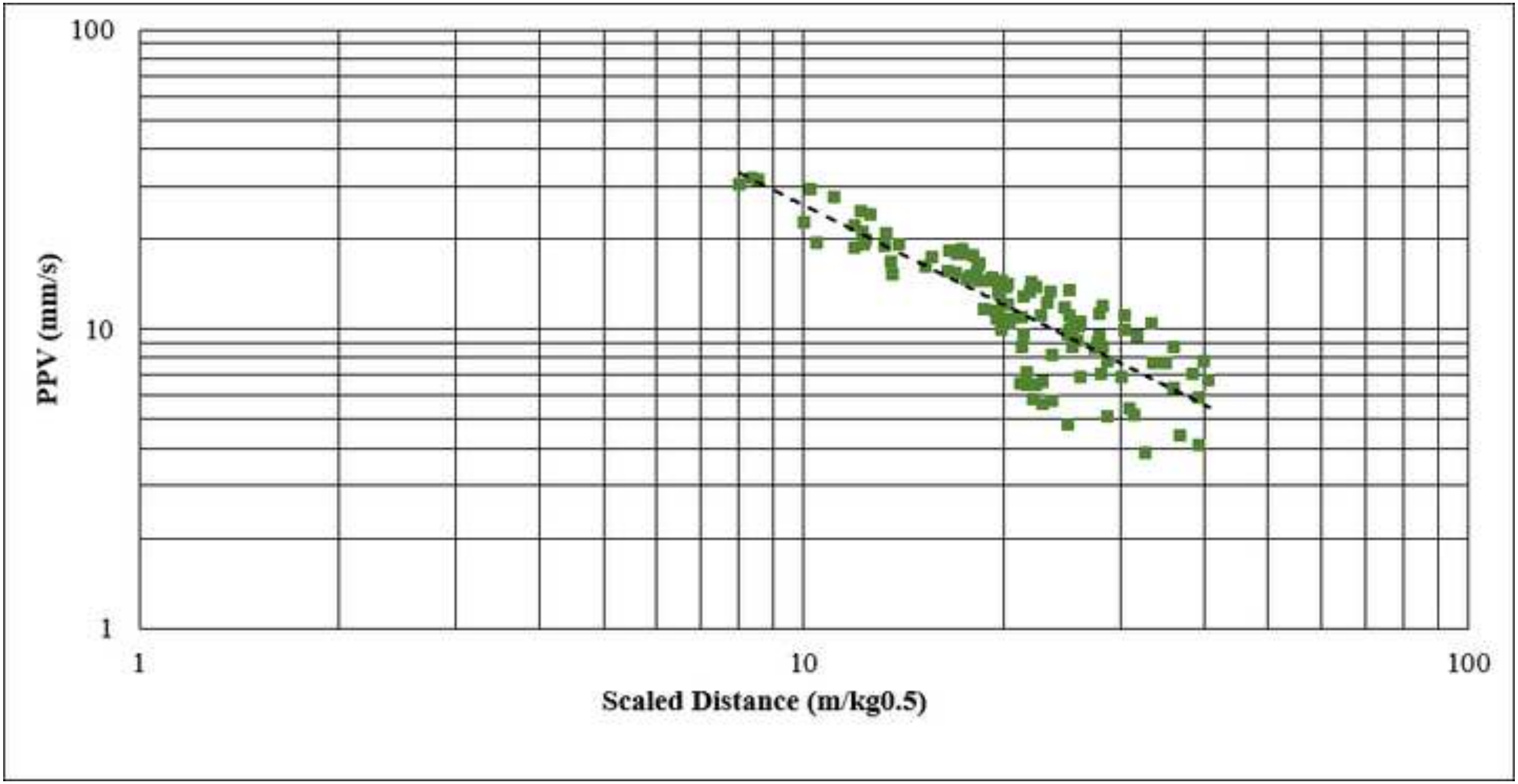

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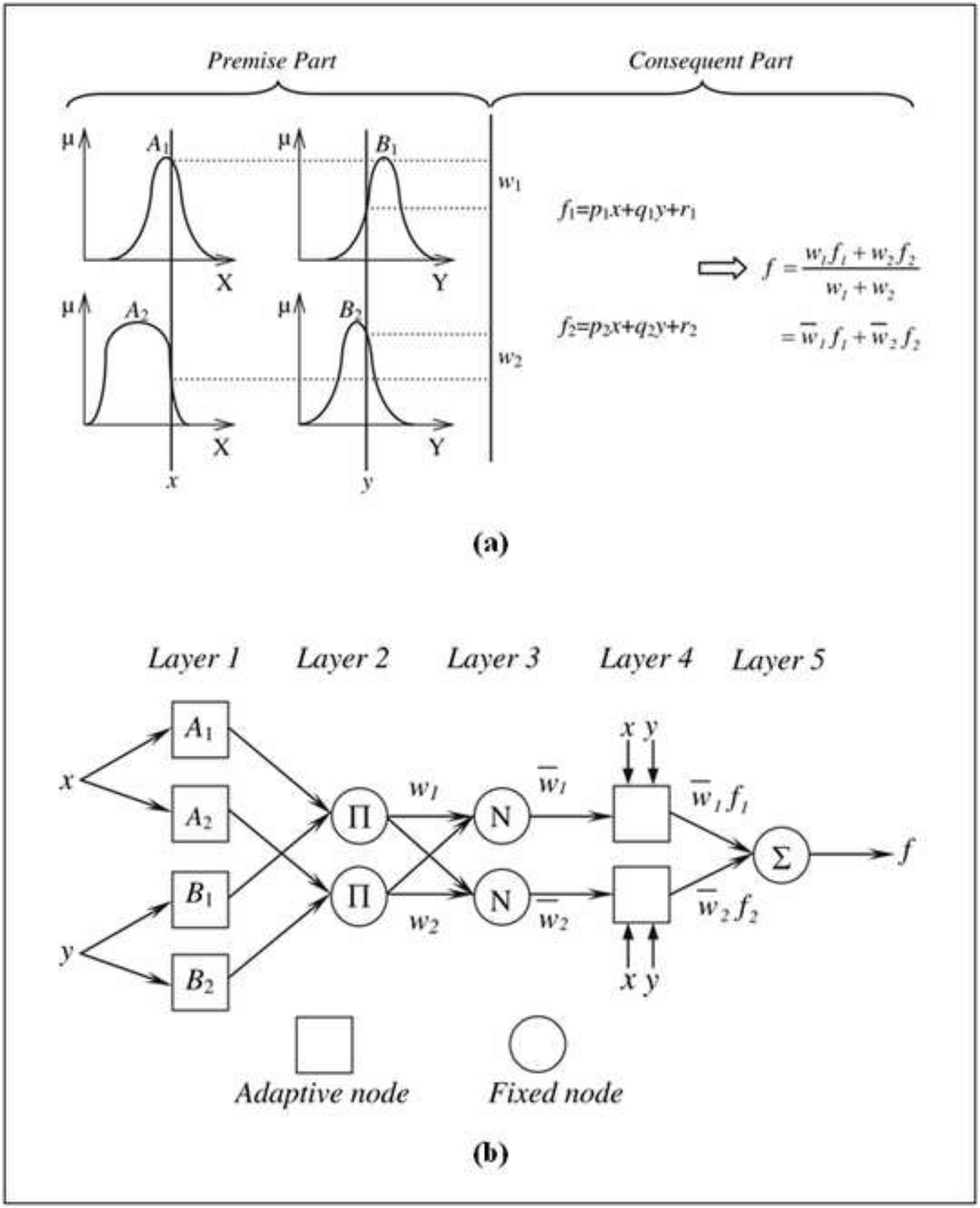

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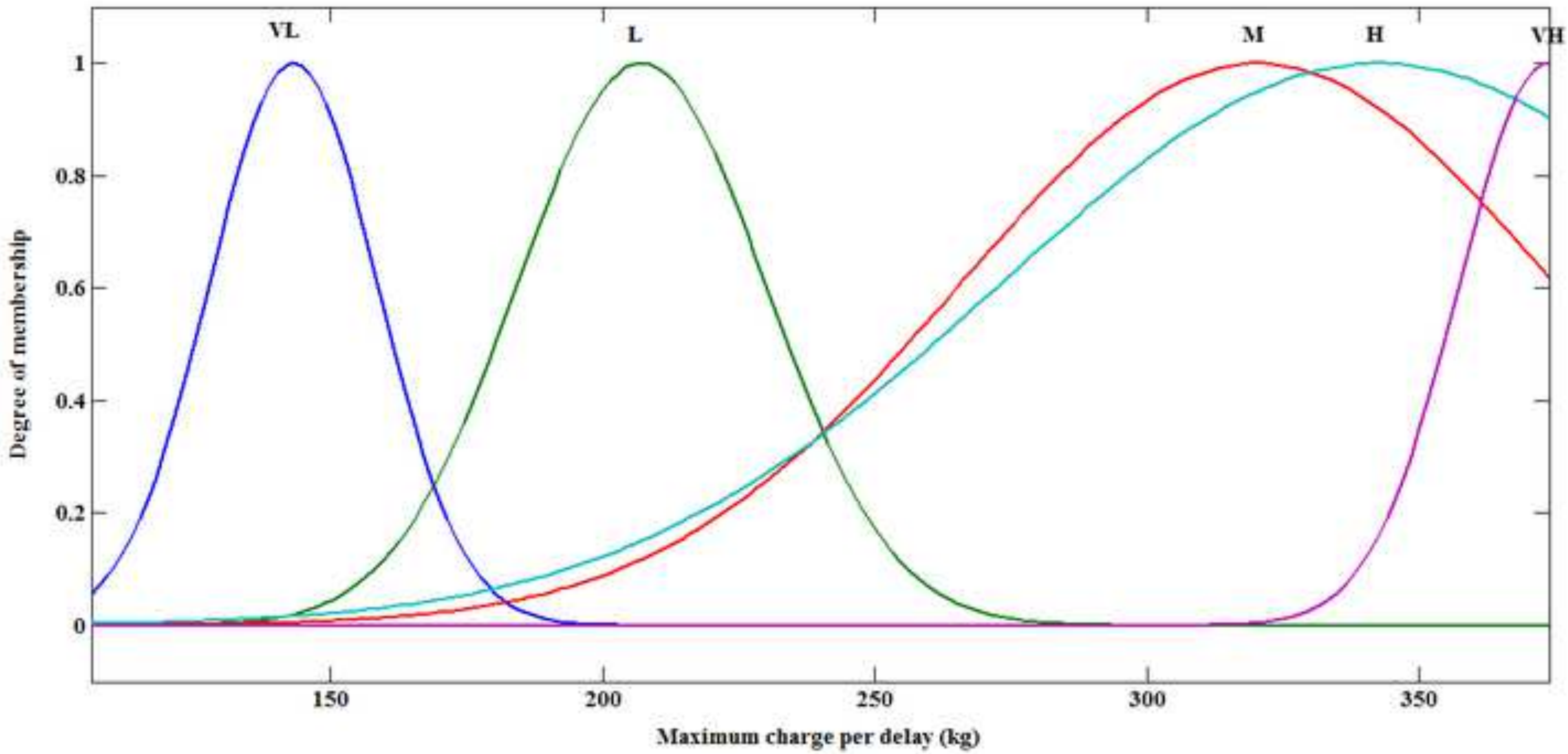

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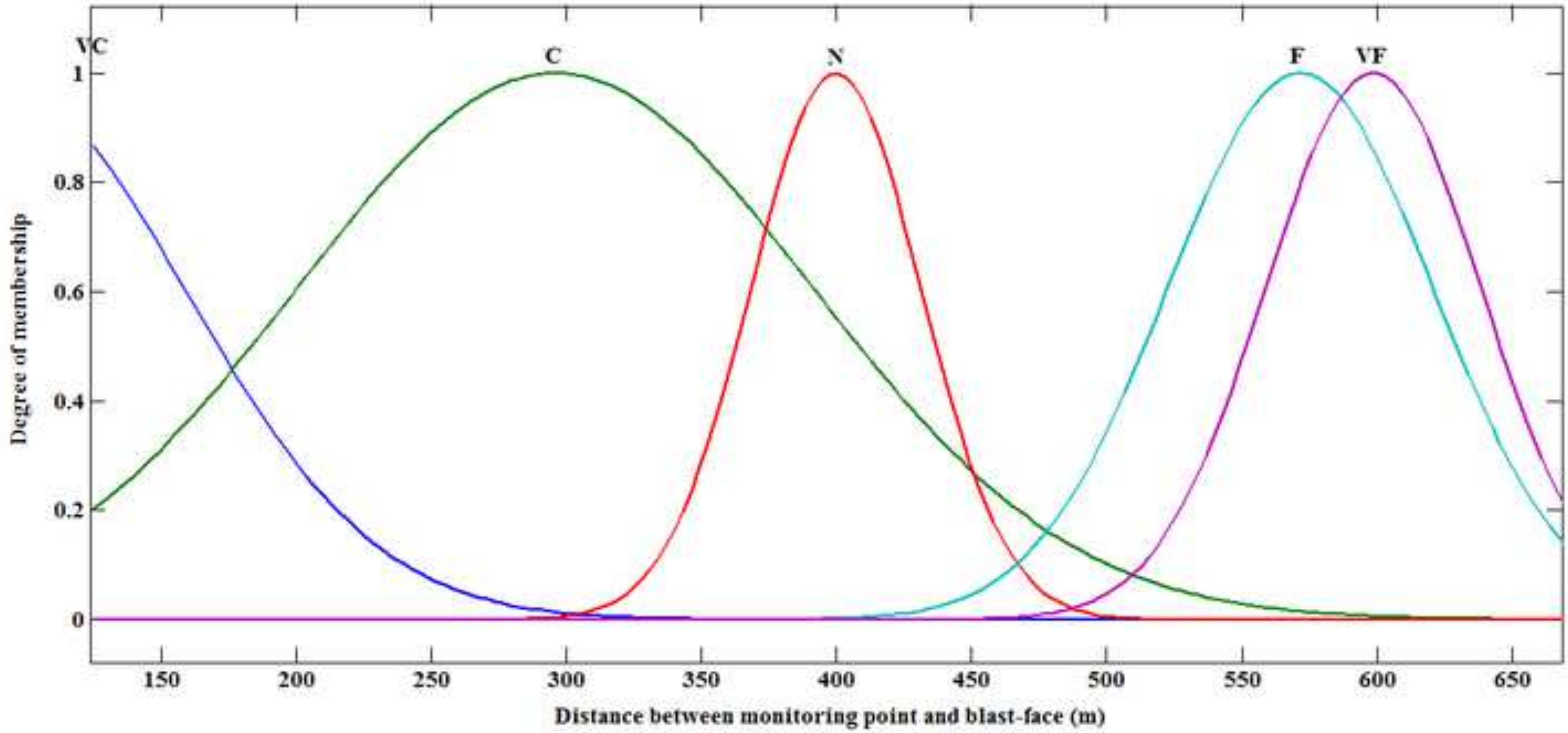

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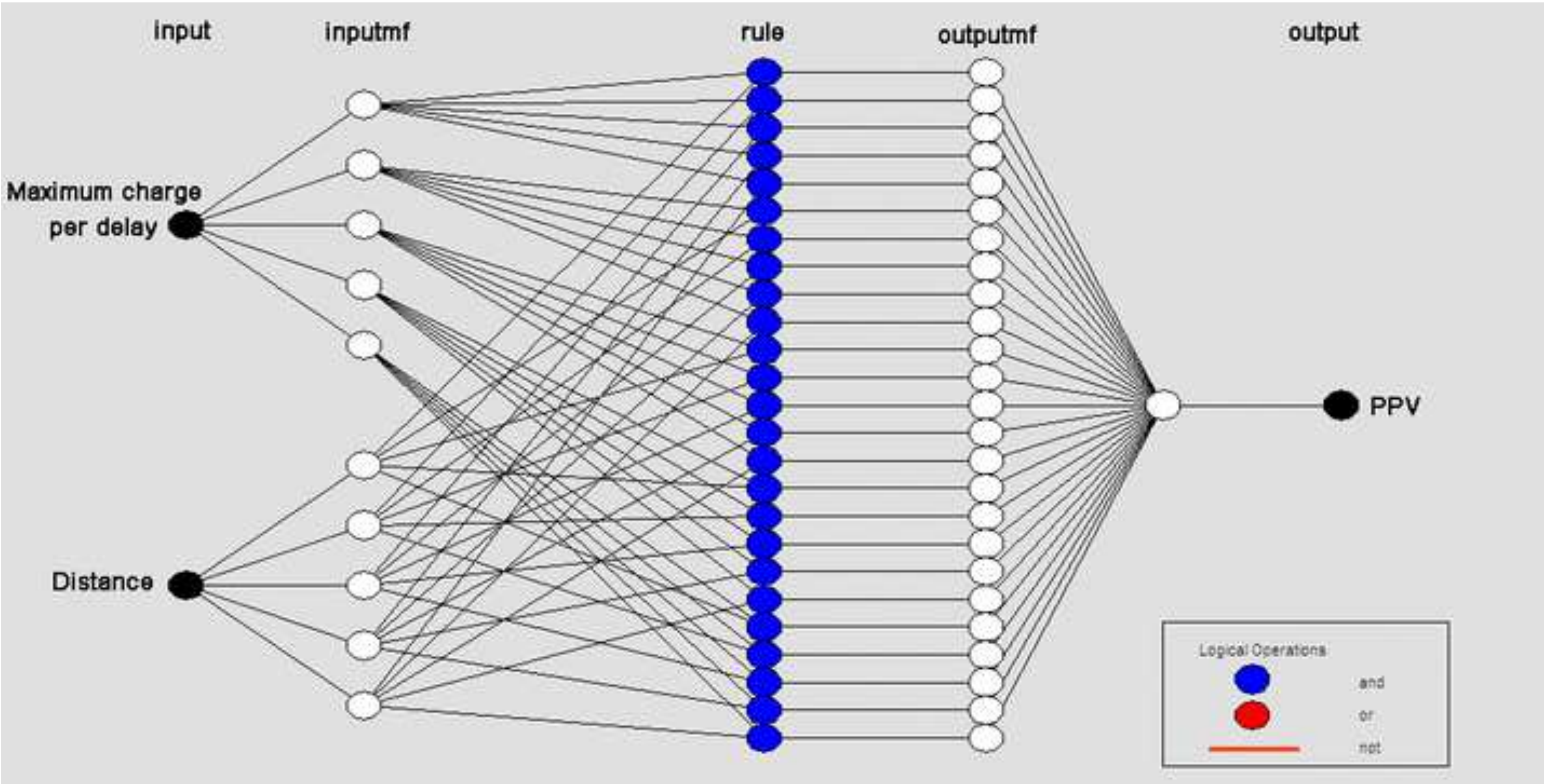

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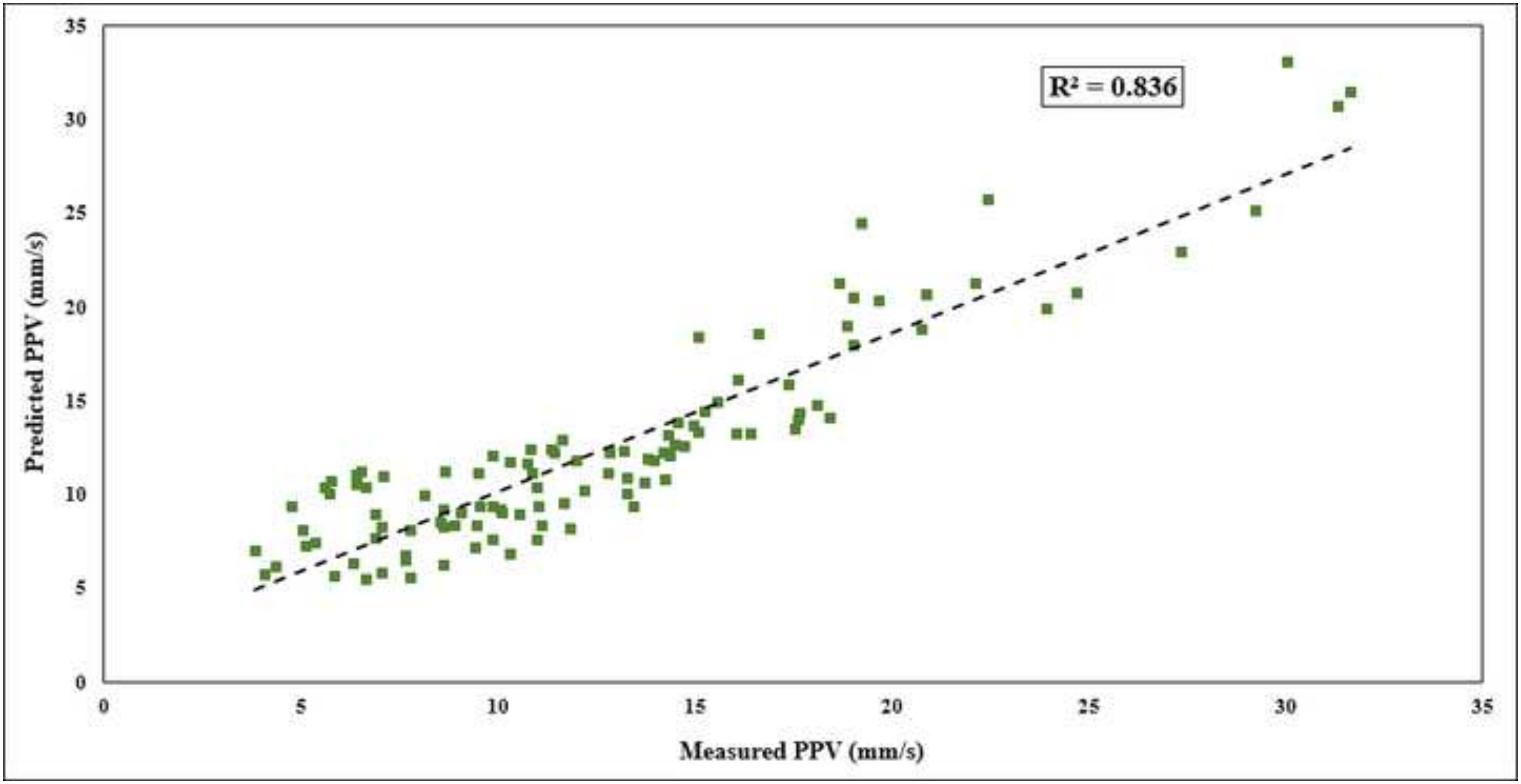

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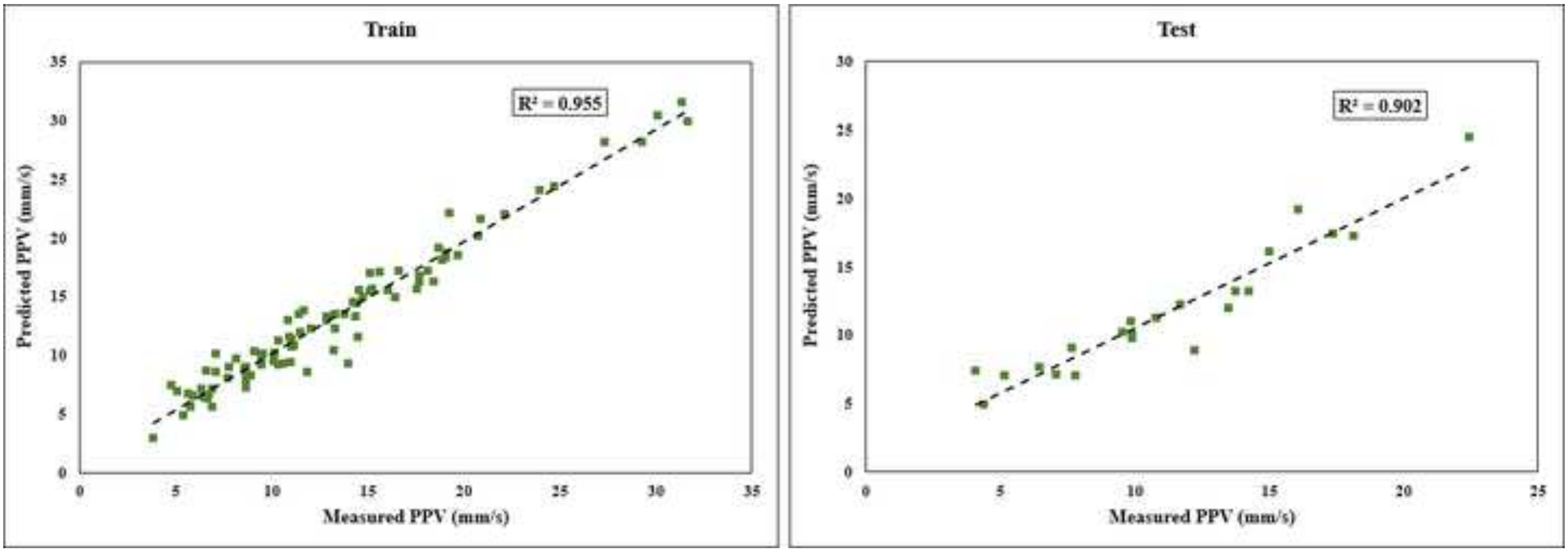

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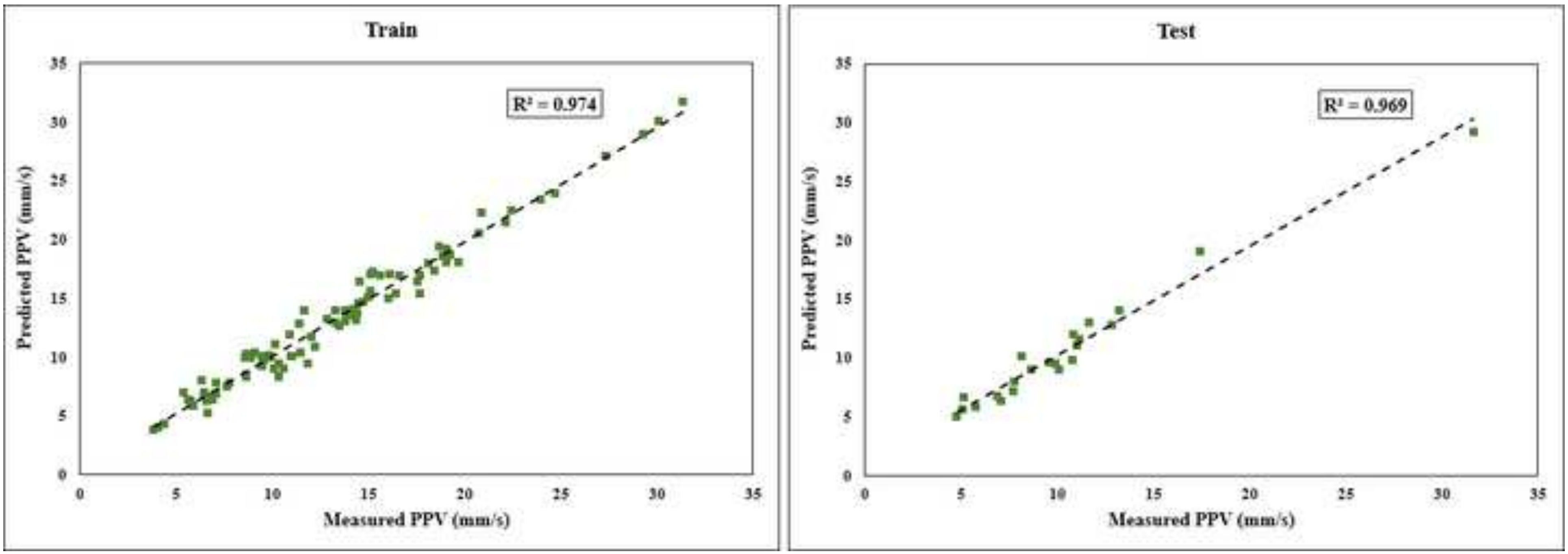

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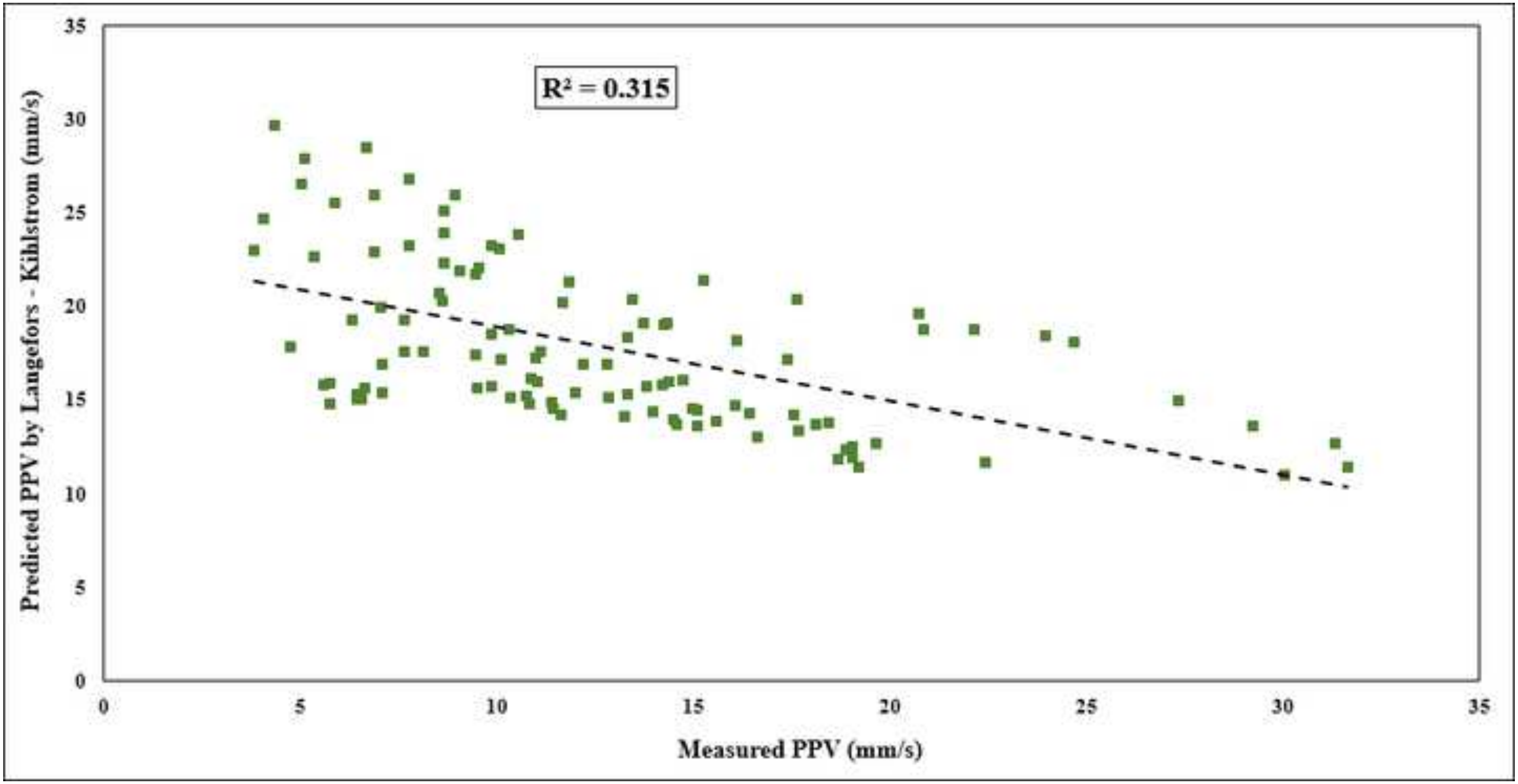

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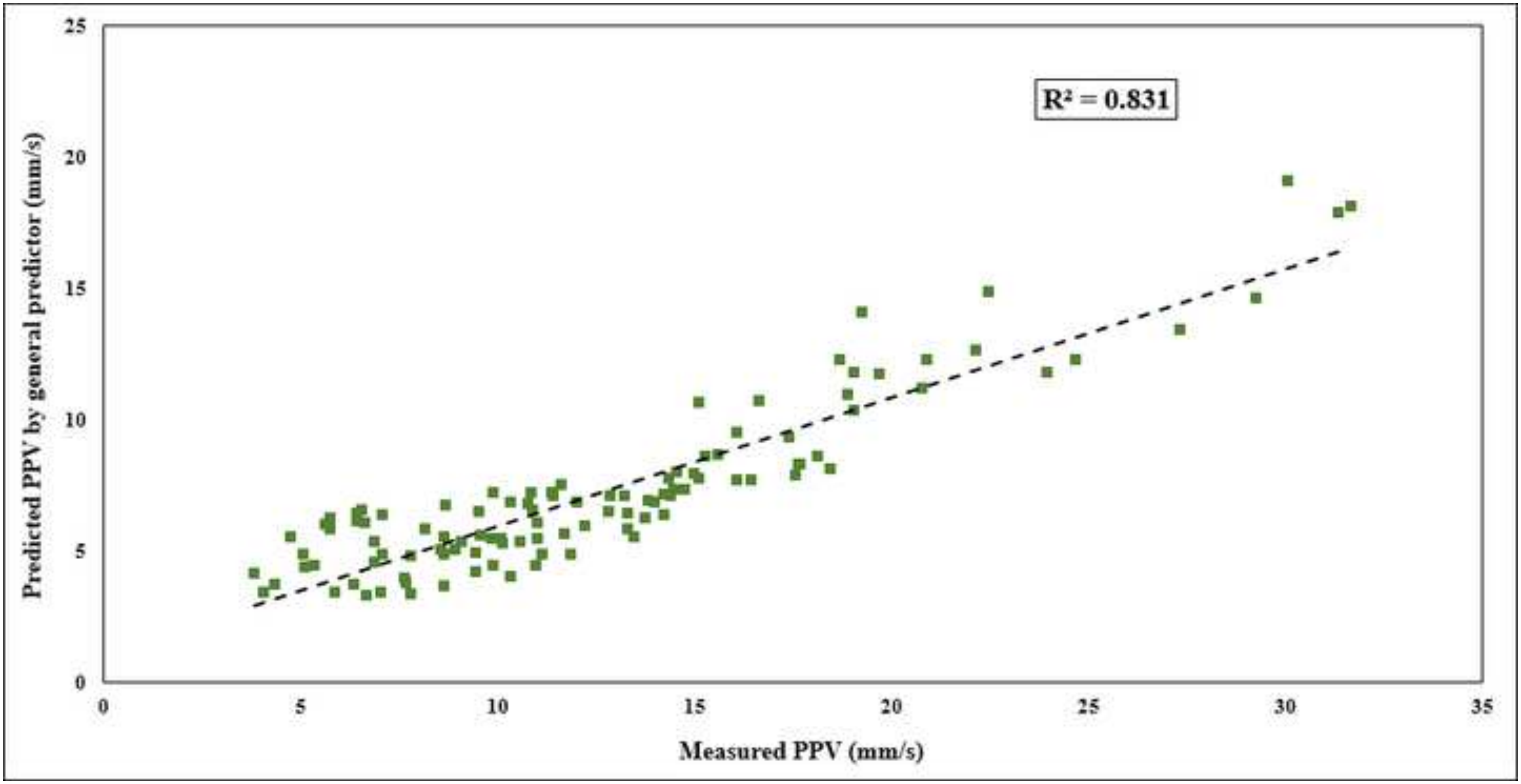

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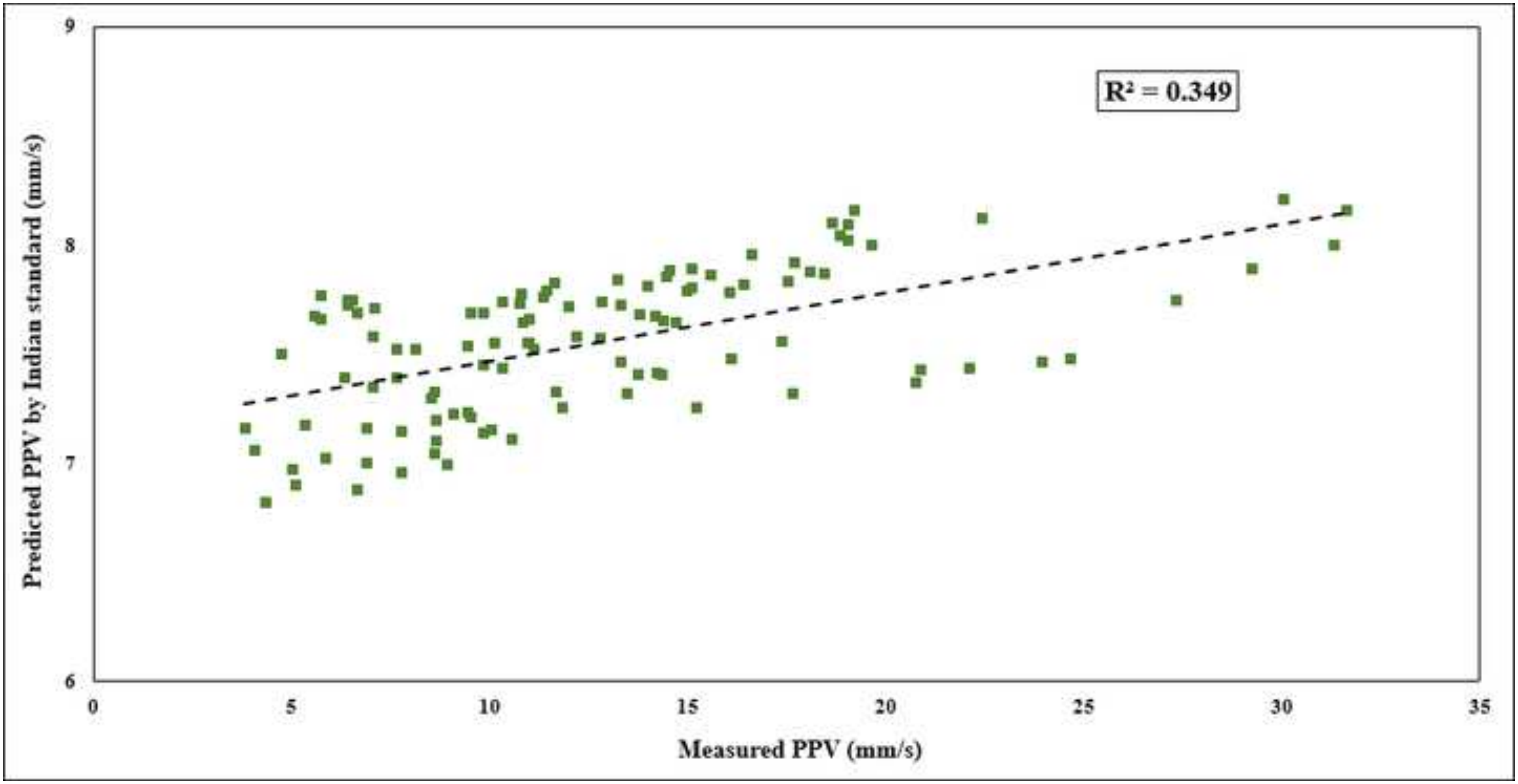

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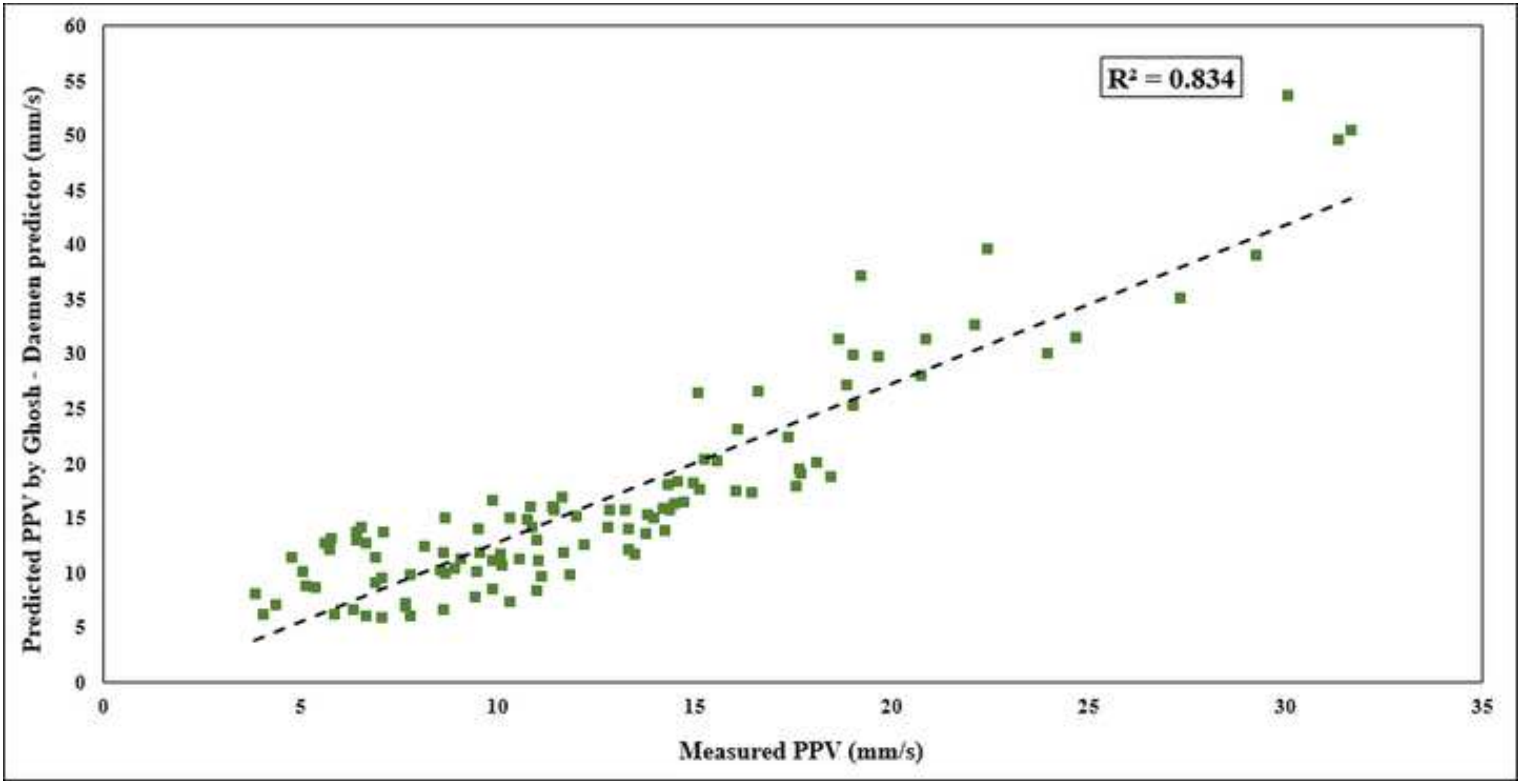

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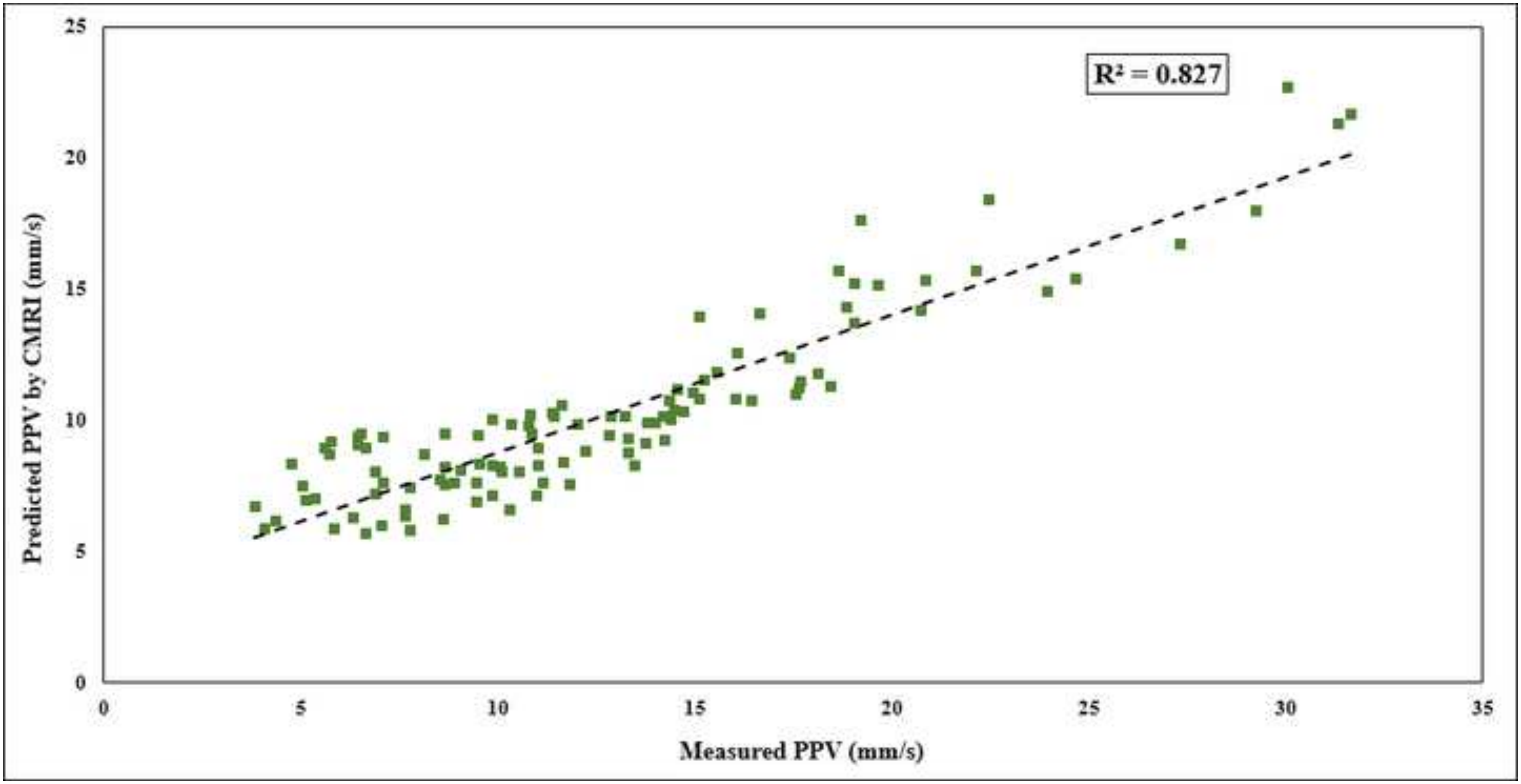

Table 1

Table 1 Recent works on PPV prediction using soft computation techniques

Reference	Technique	Input	No. of dataset	R^2
Khandelwal and Singh (2009)	ANN	BI, S, B, HD, D, VOD, Vp, E, υ, C	154	$R^2 = 0.98$
Monjezi et al. (2010)	ANN	BS, N, D, UCS, C, DPR	269	$R^2 = 0.95$
Monjezi et al. (2011)	ANN	HD, ST, D, C	182	$R^2 = 0.95$
Khandelwal et al. (2011)	ANN	D, C	130	$R^2 = 0.92$
Mohamed (2011)	ANN, FIS	D, C	162	$R^2_{ANN} = 0.94$ $R^2_{FIS} = 0.90$
Fisne et al. (2011)	FIS	D, C	33	$R^2 = 0.92$
Li et al. (2012)	SVM	D, C	32	$R^2 = 0.89$
Mohamadnejad et al. (2012)	SVM, ANN	D, C	37	$R^2_{SVM} = 0.89$ $R^2_{ANN} = 0.85$
Ghasemi et al. (2013)	FIS	B, S, ST, N, C, D	120	$R^2 = 0.95$
Monjezi et al. (2013)	ANN	C, D. TC	20	$R^2 = 0.93$
Jahed Armaghani et al. (2013)	ANN-PSO	HD, S, B, ST, PF, C, DI, N, RD, SD	44	$R^2 = 0.94$
Hajihassani et al. (2014b)	ANN-ICA	BS, ST, D, C, Vp, E	95	$R^2 = 0.98$
Ghoraba et al. (2015)	ANN	BS, D, C, ST, HD	115	$R^2 = 0.98$

Spacing (S); burden (B); stemming (ST); powder factor (PF); specific drilling (SD); support vector machine (SVM); charge per delay (C); hole diameter (DI); hole depth (HD); rock density (RD); number of row (N); particle swarm optimization (PSO); sub-drilling (SD); distance from the blasting face (D); total charge (TC); blastability index (BI); velocity of detonation of explosive (VOD); p-wave (Vp); Young's modulus(E);poison's ratio(υ); burden to spacing ration (BS); delay per rows (DPR); imperialist competitive algorithm (ICA).

Table 2

Table 2 Parameters used in the predictive model with their categories

Parameter	Category	Unit	Symbol	Minimum	Maximum	Average
Maximum charge per delay	Input	(Kg)	MC	106	374	255.47
Distance*	Input	(m)	D	125	670	346.37
Peak particle velocity	Output	(mm/s)	PPV	3.83	31.65	12.72

* Distance between monitoring point and blast-face

Table 3

Table 3 Recommended number of nodes for hidden layers (Sonmez et al. 2006)

Heuristic	Reference
$\leq 2 \times N_i + 1$	Hecht-Nielsen (1987)
$3N_i$	Hush (1989)
$(N_i + N_0)/2$	Ripley (1993)
$\frac{2 + N_0 \times N_i + 0.5\, N_0 \times \left(N_0{}^2 + N_i\right) - 3}{N_i + N_0}$	Paola (1994)
$2N_i/3$	Wang (1994)
$\sqrt{N_i \times N_0}$	Masters (1994)
$2N_i$	Kaastra and Boyd (1996) Kannellopoulas and Wilkinson (1997)

N_i: number of input neuron, N_0: number of output neuron.

Table 4

Table 4 Performances of trained ANN models to predict PPV

Model No.	Nodes in hidden layers	Network Result									
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5	
		RMSE		RMSE		RMSE		RMSE		RMSE	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	2.709	2.778	2.755	2.387	2.608	3.013	2.655	2.839	2.714	2.587
2	2	2.585	2.583	2.689	2.705	2.071	2.781	2.206	2.759	2.329	2.182
3	3	1.865	2.507	2.112	2.539	2.091	2.438	1.976	2.665	2.059	2.410
4	4	1.949	2.220	2.021	2.118	2.163	2.471	2.055	2.393	1.825	2.491
5	5	1.425	1.777	1.684	2.285	1.662	2.250	1.377	2.173	1.418	1.673
6	6	1.261	1.726	1.327	1.538	1.576	1.653	1.597	1.654	1.698	2.473

Table 5

Table 5 Performances of the 5 ANFIS models in predicting PPV

ANFIS Model	RMSE	
	Train	**Test**
1	1.114	1.642
2	1.217	1.599
3	1.020	1.252
4	0.983	1.017
5	1.303	1.595

Table 6

Table 6 Empirical PPV models

Reference	**Equation**	**Site Constant for Granite**
Langefors - Kihlstrom (1963)	$PPV = K[\sqrt{(MC/D^{2/3})}]^B$	K: 44.43, B: -1.18
General predictor by Davies et al. (1964)	$PPV = KD^{-B}(MC)^A$	K: 212.27, B: 1.09, A: 0.52
Bureau of Indian Standard (1973)	$PPV = K[(MC/D^{2/3})]^B$	K: 6.33, B: 0.22
Ghosh - Daemen predictor (1983)	$PPV = K[D/\sqrt{MC}]^{-B}e^{-\alpha D}$	K: 780.36, B: 1.26, α: 0.0004
CMRI by Roy (1993)	$PPV = n + K[D/\sqrt{MC}]^{-1}$	K: 168.91, n: 1.57

PPV: Peak particle velocity (mm/s), MC: Maximum charge per delay (kg), D: Distance between blast face and vibration monitoring point (m), K, B, A, α, n: Site constants.

Table 7

Table 7 Performance indices of all utilized models for prediction of PPV

Predictive Model	Performance Indices		
	R^2	RMSE	VAF (%)
Langefors - Kihlstrom	0.315	10.473	-128.274
General predictor	0.831	6.391	69.293
Indian Standard	0.349	7.821	6.024
Ghosh - Daemen predictor	0.834	6.233	37.996
CMRI	0.827	4.078	72.068
Proposed model based on USBM	0.836	2.469	83.629
ANN	0.949	1.372	94.895
ANFIS	0.973	0.987	97.345